EMERGING TECH CONFERENCE – Edge Intelligence

Volume 02, 2023, Page 16 – 20

Proceedings of Emerging Tech Conference:
Edge Intelligence 2023

Advanced Monitoring System of Industrial Refrigeration (ADMOSIR)

T. Athanasopoulos[1], G. Mavropoulos[1], A. Depastas[1], P. Vlagopoulos[1],
K. Spyropoulou[1], E. Zervakis[1]

[1] *European Sensor Systems, 62 I. Metaxa str, Koropi-Athens,19441, Greece*

Abstract

The food supply chain industry often uses large scale industrial refrigeration systems with high installation and maintenance cost. In the same time, there are no permanent installations of systems that will monitor the parameters of the refrigeration systems and predict a malfunction (e.g. cooling fluid leak) or even improve the efficiency in order to reduce its power consumption. For example, a refrigeration system that contains 1500kg of cooling fluid will need 7500€ more electrical power if its efficiency drops by only 10% due to fluid leak.

1 Introduction

The European Union, towards the containment of the greenhouse effect has placed strict regulations (EE 517/2014) for the management of HFCs, fact that increased their cost and made leak detection management a necessity towards reducing the impact of cost.

Until now, most of the large industrial refrigeration installations are trying to solve the problem by having technicians performing preventive maintenance tasks. These procedures do not prevent leaks of HFCs and are essentially repair activities performed after the problem becomes apparent. The existing solutions of leak prevention are very complex and far too expensive to be used. ES Systems has implemented an innovating way of monitoring the refrigeration installation with wireless sensors and with the aid of Edge Machine Learning which leads to leak detection at the earliest possible stage and rate.

2 System Description

In order to effectively monitor the refrigeration system, a series of wired and wireless sensors must be installed in strategic places depending on their functionality. The system is composed of the following:

- A main processing unit that collects all the data wirelessly as well as wired.
- Wireless Temperature sensor.
- Wireless Pressure sensor.
- Wired power meter.
- A cloud server that will run the Edge Machine Learning

- Dashboard for depicting the results.

The main processor collects the data from the sensors and performs a pre-process algorithm in order to assist the Edge ML. When the pre-process has generated metadata, these are sent to the cloud server to perform the Edge ML and generate the algorithm. Data from there are displayed on the Thingsboard platform for the user/operator to fully understand the current situation but also see if there is a fault trend in the system. A complete overview of the system is shown in Figure 1.

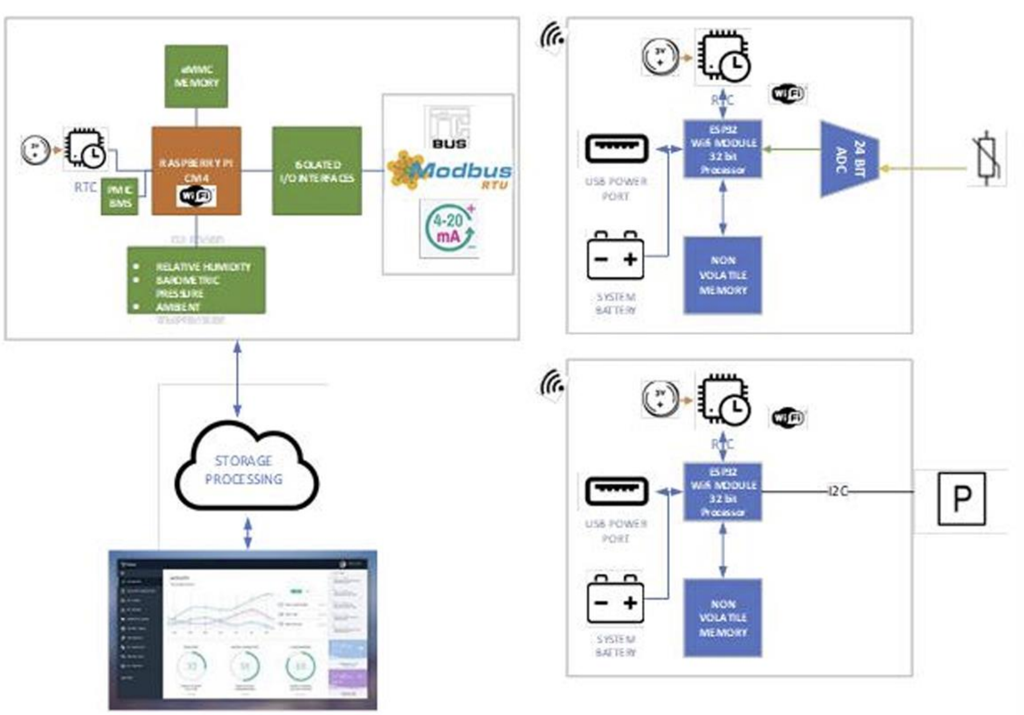

Figure 1. ADMOSIR System Description.

The sensors measuring the required physical properties send their data wirelessly at regular intervals to the "local" data collection and processing system. The current measurement data in relation to the data of the previous measurements compose the time profiles of the operating parameters of the refrigeration system. These profiles are processed by the intelligent algorithms which have been developed and "trained" in the stage of machine learning. During the training stage, the algorithms are implemented on the edge devices as well as on the IoT platform that provides this function where it is fed with sensor data through the cloud. When the results of the algorithms are considered reliable in relation to the expected results template data, these are transferred and implemented in the built-in local processor software. The innovation of the implementation lies in the following factors:

- The measurements, their processing and the alert generation / reporting is taking place at almost real time. The use of local processing with intelligence contributes to this algorithms so as to prevent failures (leaks etc.) before they happen or in their very early stages. Similar low-cost, real time system does not exist.
- The developed solution is a predictive maintenance based solution

- The sensors selected are modified accordingly (wireless, stand-alone) so that they can be installed easily and at low cost in existing facilities where they were not foreseen.

The solution briefly includes:

- Design and development of a conversion package for conventional or industrial use, of sensors in wireless and wired sensors
- Design and development of data collection and processing node with the use of smart algorithms and ability to generate alerts and reports
- Design and development of algorithms on an IoT platform with processing data tools for the creation and training of the algorithms
- Data visualization platform
- Manufacturing and laboratory confirmation of prototypes (conversion package, wireless node)
- Application and field testing in refrigeration plants.

3 Edge Machine Learning

One of the stages of the system is to predict leaks to optimize the operation and increase the system efficiency. The prediction problem is solved by using Machine Learning techniques. The final goal of the system is to reduce operating costs, as well as to avoid system failures that have a large cost to the business. As Machine Learning in the past few years has shown encouraging results and applications in the edge environment, we applied inference at the edge, which refers to running pre trained machine learning models directly on edge devices.

Inference on the edge allows sensitive data to remain on the device, reducing the risk of data breaches during data transmission. This enhances privacy and data security, making it particularly important for applications involving personal or sensitive information. Edge devices can perform inference locally, reducing the time taken to process data and make decisions. This low-latency capability is essential for applications that require real-time or near-real-time responses, such as autonomous vehicles and smart surveillance systems. Furthermore, can perform inference locally, leading to a more distributed and scalable approach. This enables applications to handle increasing workloads without overwhelming centralized servers. Finally, running inference on the edge reduces the need for expensive cloud computing resources, resulting in cost savings, especially in deployments with a large number of edge device.

In summary, inference on the edge solves various challenges associated with traditional cloud based inference, offering benefits such as reduced latency, enhanced privacy, scalability and cost efficiency.

Data

The system consists of 5 features. One of these features pertains to the power consumption of the cooling unit in Watts. The other 4 features relate to the output of the condenser and the input of the compressor. For the condenser output, data is collected for the temperature in Celsius degrees and the pressure in bar. Similarly, for the compressor input, measurements are taken for the temperature and the pressure. Since there is no output/target value in the stored data, unsupervised learning algorithms were used for predicting leaks, specifically clustering algorithms or outlier detection algorithms.

Algorithms

The algorithms used follow different approaches. Specifically, the following three algorithms were applied:

1. Clustering Algorithm: The clustering algorithm was used to separate data into different groups based on their characteristics, without using output labels. This allows the detection of distinct behaviors and patterns in the data.
2. Support Vector Machines (SVMs): SVM algorithm was applied to create a hyperplane that separates data categories with the largest possible distance between them. This hyperplane is then used to predict the category or behavior of new data.
3. Decision Trees: The decision tree algorithm was used to create a tree that classifies data based on their characteristics. Each node of the tree represents a choice for a feature, and each leaf corresponds to a category or behavior.

With these algorithms, the detection and categorization of different system behaviors based on the data collected for the cooling units can be achieved.

Results

Firstly, the DBSCAN clustering algorithm was applied, achieving an accuracy close to 88%. Similarly, good values were obtained for Precision and False Positive Rate. However, the Recall and False Negative Rate did not perform as well. The OCSVM algorithm, which incorporates techniques from Support Vector Machines (SVMs), was then applied, but its results were worse than DBSCAN's, as well as the subsequent Isolation Forest algorithm. A detailed analysis of the results is presented in Table 1. Observing the table, the Recall for all three algorithms is relatively low. In practice, this indicates that none of the three algorithms correctly recognize the extreme values, highlighting their poor effectiveness in detecting system leaks.

According to the literature, proposed solutions that could be implemented in future work include tuning the hyperparameters of the algorithms, increasing the dataset size with longer experiments, and augmenting the dataset artificially.

Algorithm	**Accuracy (%)**	**Precision**	**Recall**	**F1**	**False Positive Rate**	**False Negative Rate**
DBSCAN	87.5	0.99	0.50	0.67	0.001	0.49
OCSVM	80.37	0.77	0.31	0.44	0.030	0.69
Isolation Forest	83.50	0.97	0.35	0.51	0.003	0.65

Table 1. DBSCAN vs OCSVM algorithm.

4 Conclusion

A system has been developed using conventional sensors that have been modified accordingly to fit the measurement environment variables. This includes power autonomy, transmission medium (wired, wireless), communication protocols and electromechanical interfaces. This enabled one of the key system characteristics, the retrofitting.

The system developed has been trained using data from a refrigeration test set up with controlled inputs and outputs so as to get all the system performance signatures for the algorithms training. However, training has been proven not sufficient due to the limited dataset sizes required. This has been proven in both ML evaluation using different algorithms as well as real field testing on a standard large scale refrigeration system.

The main reason is the significant difference in system behavioral parameters due to the system scale as well as the limited dataset.

The system is currently further improved by collecting more data of the same large refrigeration system to continuously improve the training algorithms.