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Intelligent IoT Platform for Prediction of Failures in the Reception of Equipment Telemetry Requests

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Abstract. Artificial intelligence and IoT based technologies have generated new opportunities to prevent and identify failures in equipment or machines of all kinds, such as predictive maintenance. This paper presents an implementation of an IoT platform that shows the telemetry of equipment through temperature sensors, magnetic sensors, actuators and voltage detection, which allows the application of statistical and linear regression formulas to analyze the behavior and prediction in the reception of information from the electronic device to the IoT platform.

Keywords: IoT, sensors, telemetry, linear regression, predictive maintenance.

1 Introduction

The Internet of Things (IoT) has revolutionized telemetry as it facilitates the remote monitoring of equipment to observe the behavior of electronic devices in sending alerts to a control center that allows visualization through a web platform [1], in order to supervise that the operation is safe and efficient.

The IoT is increasingly used in the industry and the benefits it offers to companies is increasing justifying the investment required for the implementation of an IoT system, as it guarantees an improvement in the management of resources [2], however, this leads to the maintenance of such devices. There are different types of maintenance; these are classified into three types: corrective, preventive and predictive.

At the beginning, only the term corrective or reactive maintenance was used, which consists of repairing failures as they occur, however over time industries realized the advantage of early detection of a severe failure or the early change of a component with high potential for failure in machines, which gave way to preventive maintenance, which is based on conducting periodic inspections to anticipate the failure and finally periodic monitoring through inspections led to the development of predictive maintenance [3].

Predictive maintenance is based on constantly analyzing the data generated by the equipment to anticipate any possible failure or problem before it occurs, avoiding production downtime and extra costs [4].

The way it is carried out is by defining the normal parameters in which it should operate, and then detecting or predicting alterations or lags in the devices that indicate a possible problem in the system, so the process to define the predictive maintenance of a piece of equipment or device can be subdivided into three stages [5]:

1 The identification and evaluation of maintenance needs.

2 Prioritization of these needs.

3 Formulation of a predictive maintenance program.

Predictive maintenance has been applied to different branches and different techniques have been used for the identification and evaluation of maintenance needs, below, different application models are listed:

1 Fleet management project reporting to the central database where the general details of those equipment are revealed. This research mentions that critical attention should be paid to this area of IoT application so that predictive/preventive maintenance can be performed on equipment and machinery to avoid delays and reduce the adverse effects of carbon emissions to people and the environment [6].

2 Efficient sensor fault management system in IoT smart environments during the operational phase of a building. For effective predictive maintenance planning, machine-learning techniques can be integrated into the workflow, developed to efficiently predict the future condition of individual IoT components, such as data loggers and sensors [7].

3 Prototype that acts as an accessible and interactive option for energy consumption monitoring through BIM (Building Information Modeling), which contributed to predictive maintenance and facilitates the understanding of the condition and performance of building systems [8].

There are techniques that contribute to the prediction of the behavior of a variable such as biased regression or linear regression that seeks to calculate a straight line through the prediction, measuring the error with respect to the sample taken [9]. Through the IoT platform can be collected data and really useful information about the environment and the conditions in which the equipment is, however, also gives us information about the state of the modules that make up the device to achieve predict failures [10].

Therefore, in the proposed project it was determined the development of an IoT platform to receive, store and display telemetry, as for the machine it is necessary to collect data through sensors. This information is very important because it will provide the traceability or historial with which samples are taken from blocks of information and with it to apply statistical models to know the efficiency in the requests. The same sample used previously will be used to apply the linear regression method to predict the behavior in the reception of requests.

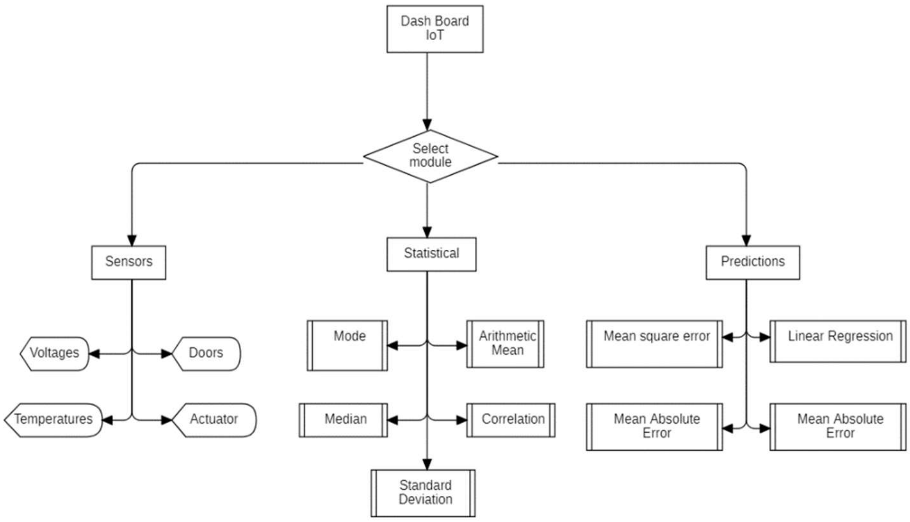

Fig. 1. Structure of the Dash Board of the IoT platform. [Own creation].

2 Methodology

The development of the IoT platform has a visual part that allows the user to access the information in a simple way; a panel of modules, divided into sections, separates the data:

1 Machine telemetry history.
2 Samples collected for the use of statistical methods.
3 Samples for prediction by applying regression method lines and obtaining the prediction data.

In the telemetry part of the equipment, the following data will be obtained: Gate detection, voltage supply, Temperature and Actuators. In the statistics part, the following data will be obtained from the request analysis: Correlation, Arithmetic Mean, Median, Mode and Standard Deviation. In the linear regression part, the prediction will be obtained and the Mean Absolute Error (MAE), the Mean Squared Error (MSE) and the Median Absolute Error (MedAE) will be calculated to check the quality of the prediction. The dashboard diagram includes subdivisions for each module, as shown in image 1.

2.1 Software Description

For the implementation of the IoT platform, we used the Laravel Framework that allows the use of a refined and expressive syntax to create code in a simple object-oriented way [11], this implementation is based on Model-View-Controller (MVC) technology and has a high compatibility for the use of composer packages.

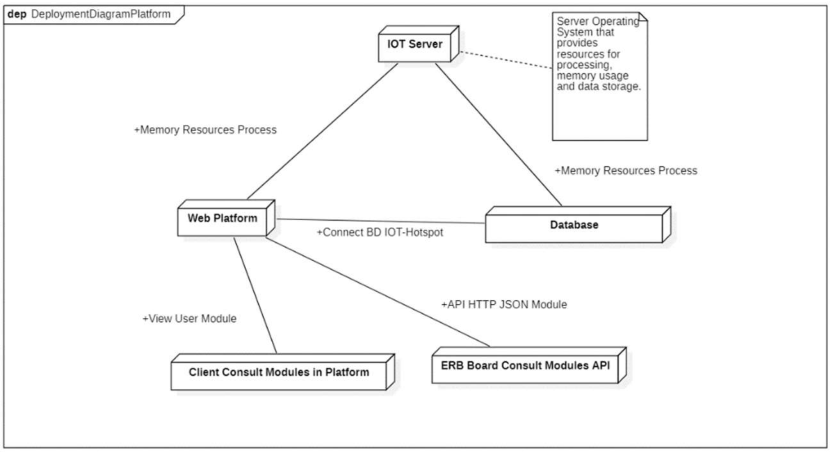

Fig. 2. IoT platform architecture diagram [Own elaboration].

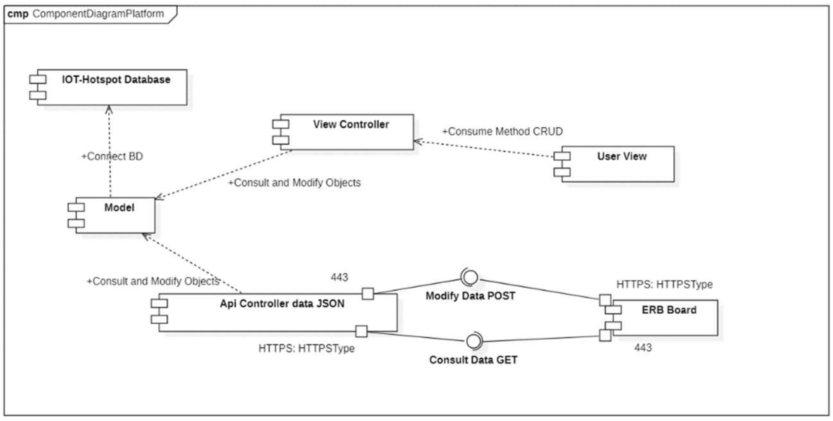

Fig. 3. Diagram of components for the IoT platform [Own elaboration].

In this development it was decided to use the NGINX web server applying a client server type architecture, so for this service the HTTPS communication protocol is used in requests with get() and post() methods for both the visual part of the platform as well as in the rest api.

The telemetry information is sent by the device to the server and then stored in a Maria DB database. This set of configurations is implemented in web services and is known as LEMP SERVER or LAMP SERVER, commonly used for the development of web platforms and in this particular case to develop the IoT platform [12].

2.2 IoT System Architecture

Within the web platform there are two services; the first one is the communication where the Client information is displayed (Client Query Modules in Platform) and the second one is the ERB Card communication (ERB Card Query Modules API).

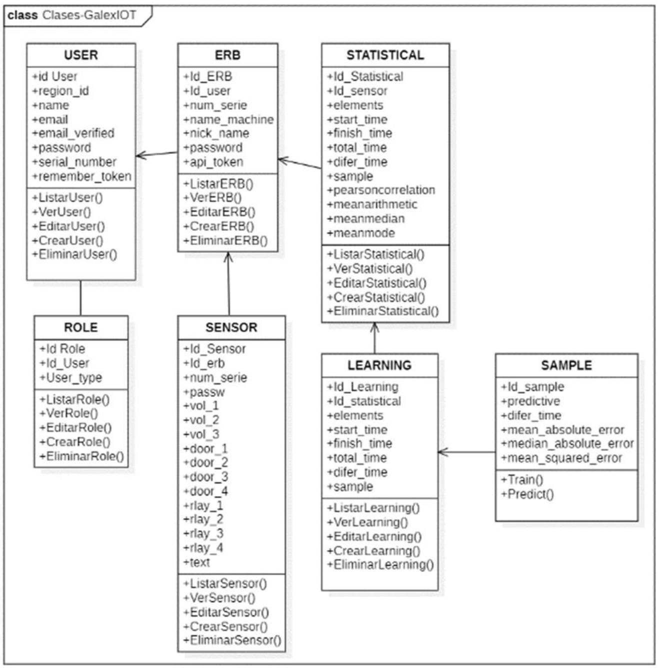

Fig. 4. Class diagram of the IoT platform [Own elaboration].

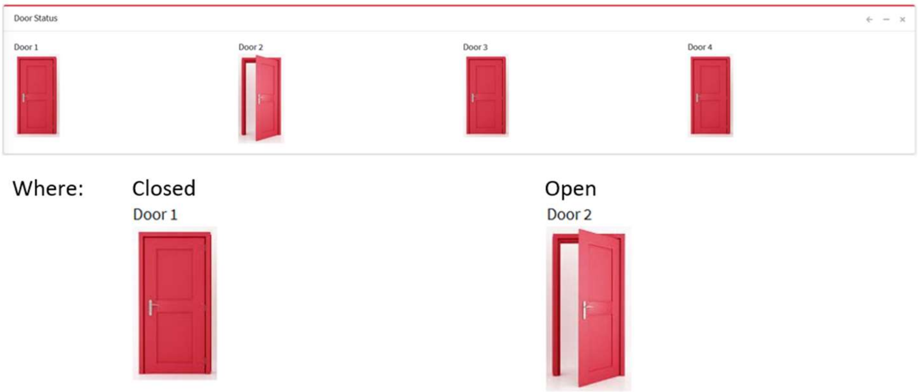

Fig. 5. Door status detector [Own elaboration].

The services pass from the web platform to the database and together they allow saving or querying the information inside the IoT server as shown in image 2. The functionality of the two services mentioned above follows the same pattern. Image 3 shows how the database is related to the model.

The model communicates with the controllers and these in turn communicate with the view, this addressing is triggered by the queries generated either from the user or from the card.

The database has 7 tables, as shown in the class diagram in image 4, which are related

Fig. 6. Voltage detector. [Own elaboration]

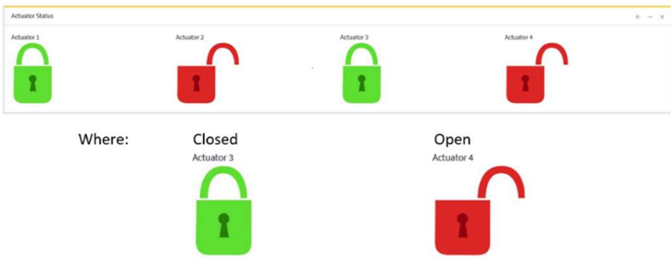

Fig. 7. Status of actuators [Own elaboration]

to each other in order to give integrity to the data of the IoT platform, the relationship of the tables has a unique id and in turn an id foreign.

2.3 Telemetry of the Equipment

Telemetry is a technology that allows the remote measurement of physical variables of a device through data that are transferred to a server [13]. This telemetry was performed by means of wireless communication through get and post requests containing the information of:

– Door status detector: the equipment has two front doors and two rear doors, which must be kept closed, unless the detection of the opening of any of the doors is registered in the device, this is possible through the use of a magnetic sensor that allows the presence or absence of a high pulse to detect that the door is open or a low pulse to detect that the door is closed. On the platform, the detection of the status of the doors is shown as in image 5.

– Voltage detection: the equipment must feed 3 subsystems, which are door power supply, temperature sensors and actuators. Therefore, if no faults are found in any of them, they should be powered all the time. In the platform, voltage detection is shown as in image 6.

– Temperature: the equipment has 4 temperature sensors; these are distributed inside the equipment. The regular temperatures that the equipment supports are from 0 degrees Celsius to 35 degrees Celsius, however, it can reach 65 degrees Celsius and continue working, but from 65.1 degrees Celsius the temperature is considered too high and could cause damage. The graph of the temperature ranges is shown in image 7.

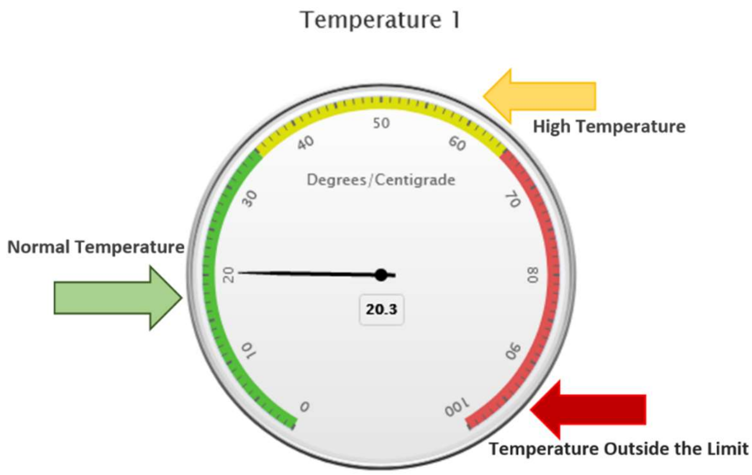

Fig. 8. Temperature graph [Own elaboration].

– Actuators: the units have 4 actuators that are distributed inside the unit. Depending on the equipment, the actuators can be in an open or closed state. On the platform, the detection of the actuator status is shown as in image 8.

2.4 Analysis of Requests

The sending of requests from the equipment to the IoT platform will take 10 minutes; however, there are possible problems that may cause packets not to be sent [14,18], the following is a description of the possible causes:

– Outdated information: if a sensor takes longer than usual, it may delay the sending of requests.

– Slow loading: if the loading takes longer than normal, the server will reject the connection and you will have to try again.

– Interruption in uploads: Due to the slowness, requests may be completely interrupted, taking longer than normal, which will result in the rejection of the request.

– Connection closure: if a connection closure occurs, the equipment will try to recreate the connection and try again.

– Incomplete information: if the information in the get or post request is incomplete, the reception will be rejected and the team will reassemble the information to retry the request.

– Damaged hardware. If there is a physical problem in the hardware that handles network traffic, it is very likely that packet loss will occur.

– Hardware capacity (bottlenecks).

In the analysis of requests, the application of mathematical concepts is contemplated to obtain metrics that help us to understand the data [15], such as:

- Correlation: this metric reflects the measure of association between the number of requests and the time elapsed between them; a correlation close to zero is sought, since it is expected that the values of the samples do not have an increasing or decreasing behavior.
- Standard deviation: is the most common measure of dispersion, indicating how scattered the data are around the mean. A standard deviation value higher than the mean indicates a greater dispersion of the data, implying that the sample values are not similar. In this case the standard deviation will be used to establish a reference value for estimating the overall time variation between requests. For this project, an acceptable standard deviation is considered when the standard deviation is less than 10, taking into account the value should be in 600 with tolerance of ±10.
- Arithmetic mean: it is used as an indicator when the distribution of the sample is normal, which means that it contains a low number of very distant values, which is the ideal.
- Median: it is the midpoint of the sample and indicates the central tendency.
- Mode: is the value that occurs most frequently in the sample and is used along with the mean and median to provide a general characterization of the distribution of the sample data.

If it is considered that the requests are repetitive in a period of time of every 10 minutes which is equivalent to 600 seconds. For this reason, in the ideal case for the project, the arithmetic mean, median and mean should be close to 600, since, if the data are symmetrical, then the mean and median should be similar.

2.5 Linear Regression for Prediction

The prediction or linear regression model is one of the methods used to predict a desired value from a sample [16], in this case it will be used to represent the relationship between the number of the position of the requests and the time that has elapsed between one and another. The model is expressed in a logical-mathematical form and allows to make predictions of the values where the time that has elapsed between one request and another will be taken, starting from the number of the next position of the request.

It is possible to apply the above-mentioned algorithm since there is a linearity in the input data because each request received is expected to have an approximate time of 600 seconds between one request and another, which is equivalent to a request every 10 minutes. The equation used by the linear regression model for training is given by:

$$y = A + B * X , \tag{1}$$

The least squares method consists of minimizing the sum of the squares of the errors:

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 . \tag{2}$$

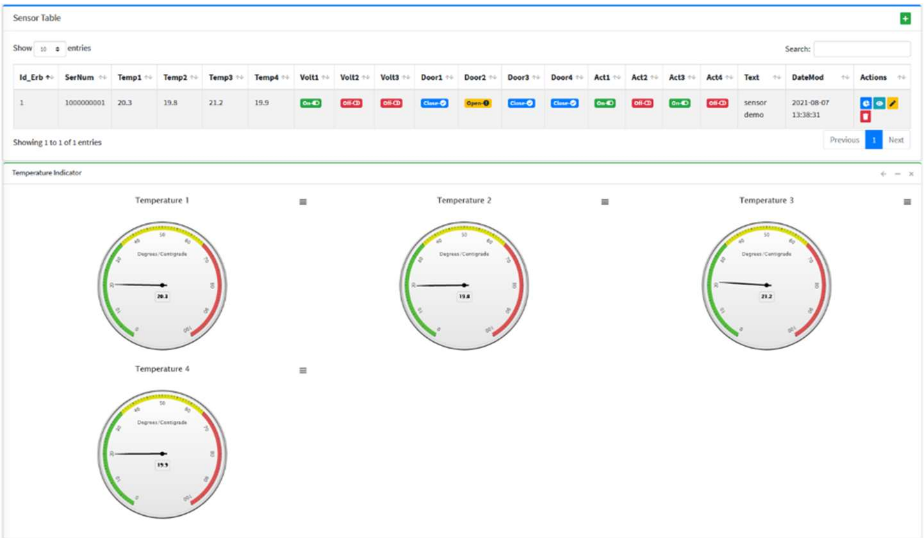

Fig. 9. Status of temperature sensors [Own elaboration].

That is, the sum of the squares of the differences between the actual observed values (y_i) and the estimated values ($\hat{y_i}$). Regression metrics are used to measure the performance of some regression mode and for this project, they are:

– Mean Absolute Error (MAE) will serve to quantify the accuracy of the prediction by comparing the estimated value against the value that is estimated. It is considered a good prediction if it is less than 7 since that represents an error of 1.2% over the desired amount (600), which implies that it is a negligible error.
– Mean Squared Error (MSE) evaluates the quality of the predictions in terms of their variation and the degree of bias, for the purposes of this project it is sought to be less than 41 which represents a negligible error of less than 1.2% over the desired amount (600).
– Median Absolute Error (MedAE) as well as the Mean Absolute Error is considered a good prediction if it is less than 7 since that represents an error of 1.2% over the desired amount (600), which implies that it is a negligible error.

3 Results

The experimentation was carried out under certain conditions that allowed the veracity of the results:

– The conditions of the cloud server were optimal.
– The machines have power supply.
– The machines were free of external agents that could cause failures.
– The internet service was stable for uploading and downloading requests from the machine to the server.

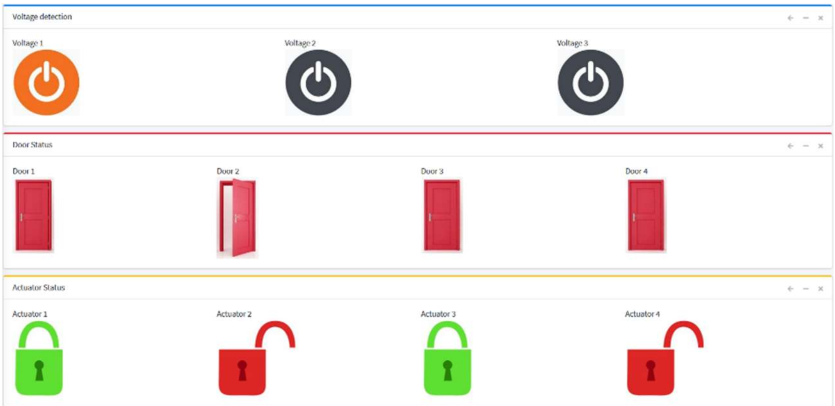

Fig. 10. Status of voltage sensors, gates and actuators [Own elaboration].

Table 1. Petition analysis [Own elaboration].

ID	Correlation	Average Arithmetic	Median	Mode	Standard Deviation
1	0.057291	602	600	605	6.187339
2	0.116996	598	600	602	5.521691
3	-0.083445	595.5	600	595	5.919587
4	-0.096358	600	600	609	6.114546

3.1 Telemetry of the Equipment

The temperature of the equipment is within the desired parameters, which indicates that they are operating at the appropriate temperatures as shown in image 9. As for the voltage detection, the three sensors are on status, as well as the doors and actuators of the equipment are closed as shown in image 10.

3.2 Analysis of the Requests

Four samples were analyzed, each one with 144 requests, these are equivalent to 24 hours or the equivalent of one day of requests in which it is observed that the arithmetic mean, median and mode are close to 600, which implies that the data are symmetrical, it is also observed that the correlation is close to 0 which indicates that it does not have an increasing or decreasing trend, the standard deviation is within acceptable parameters as can be seen in image 11.

3.3 Prediction of Request Failures

For the demonstration of this project and through the use of 4 samples, each one of 144 requests equivalent to one day, these samples were from consecutive days and the prediction of the following day was generated, the start and end time was taken, and the difference and the total time of the samples were obtained, as shown in image 12.

Table 2. Prediction of request failures [Own elaboration].

Id	Elements	Start time	Final time	Total Time	Difference
1	144	2021-07-24 13:38:12	2021-07-25 13:39:35	86483	83
2	144	2021-07-25 13:36:15	2021-07-26 13:38:28	86533	133
3	144	2021-07-26 13:36:12	2021-07-27 13:30:46	86074	-326
4	144	2021-07-27 13:37:09	2021-07-28 13:32:02	86093	-307

Table 3. Details of the prediction of the request [Own elaboration].

Sample	Start time	End time	Pass time	Differ time	Mean absolute error	Median absolute error	Mean squared error
1	2021-07-24 13:38:12	2021-07-24 13:48:12	600	0	5.4514	5	38.0347
2	2021-07-25 13:36:15	2021-07-25 13:46:15	600	0	4.6458	4	30.9375
3	2021-07-26 13:36:12	2021-07-26 13:46:11	599	1	5.1597	5	35.7569
4	2021-07-27 13:37:09	2021-07-27 13:47:08	599	1	5.3125	5	39.0764

To review the generated metrics, access the sample details, in this case a table was generated with the information of sample number, start time, end time, pass time, Difer time, Mean absolute error, Median absolute error, Mean squared error, as shown in image 13. As shown in Figure 13, the Mean absolute error is less than 7, the Median absolute error is less than 7 and the Mean squared error is less than 41, which implies that the errors are less than 1.2% taking as a reference the expected value of 600, so the predictions obtained are within the acceptable parameters, generating an acceptable prediction.

4 Conclusions

Using an IoT platform is essential to centralize the information collected from the equipment, in such telemetry is important to establish what data needs to be collected, such as the time of receipt of the request and the time that exists between them.

Another important point to take into account is to manage the traceability of the telemetry generating a history, if this information is performed a statistical analysis and a predictive method [17], it can generate valuable information, in this case focused on the reception of requests and thus determined the functionality between the equipment and the IoT platform.

The results obtained show that the development of the IoT platform for the equipment was favorable, demonstrating that it is possible to predict failures in the reception of requests, this helps to schedule maintenance visits to the equipment, preventing possible failures that require equipment replacement and thus avoiding an increase in costs.

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