A Prototype for Monitoring Railway Vehicle Dynamics Using Inertial Measurement Units

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***Abstract*—The dynamics of railway vehicles have changed from an essentially mechanical application into one that requires knowledge of sensors, electronics and computational processing. Industry 4.0 is a term that describes industrial activity by intelligent systems and solutions established on the concept of the Internet of Things (IoT). The present work illustrates the application of a conceptual cycle of an Internet of Things building a prototype, consisting on acquisition, processing and communication of data in the industrial context. Specifically, the monitoring of the dynamics of wagons using inertial sensors and algorithms that establish the fusion of sensors. The use of refined methods shows more reliable results in the use of low-cost sensors. Furthermore, the implementation of wireless communication enables the use of data in the creation of more complex analyses that can be applied in computational and instrumentation tools.**

***Index Terms*—railway vehicle dynamics, internet of things, sensor fusion, Kalman filter.**

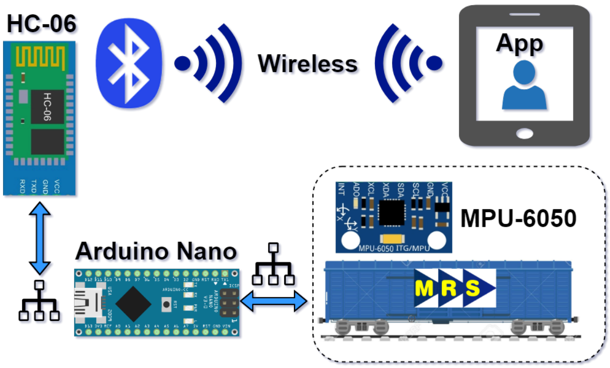

Fig. 1. Process overview, presenting the work steps.

I. Introduction

In recent years, the concept of Internet of Things (IoT) proposes a serie of innovations in several situations: for urban applications in construction of smart cities [1], in monitoring of human health [2], in security using tracking by detection, and also responsible for several changes in the industrial scenario [3]. The inclusion of IoT in industry is considered the new industrial transformation and one of the factors in the designated Industry 4.0. The expression Industry 4.0 is new, and its approach started to be accepted with increased researches and academic research on the subject. The understanding of Industry 4.0 consists in running virtual systems to monitor industrial processes [4], [5].

The application of IoT concept in industry is possible by adding flexible and programmable sensors which communicate using the internet, as well as with other machines. The railway dynamics is the study of the movements of a vehicle and their causes. In order to understand the dynamic behavior of the railway vehicle, it is necessary to establish the conditions of the vehicle itself and the railway. In this way, the computational and instrumentation tools help to understand the rail-wheel interaction problem. [6].

There is mistrust and lack of incentives for initiation projects using the concept of IoT. Due to that the industry 4.0 application process remains at an early stage, evolves slowly and the such projects cost dearly. One extremely importance of IoT application in industry is shown in this work. The present article monitors the dynamics of a railroad, an essential factor which increases the competitiveness of the railroad, avoid accidents and minimize the mechanical wear of railway vehicles.

The main objective of this article is the use some IoT concepts in application of industrial components. Moreover, presents the use of prototypes as an alternative to reduce project costs, applying general aspects of instrumented system [7]–[9]. Besides that, the project seeks to help in the development of research and for educational purposes, encouraging the involvement of research in industry; the project lays out an application that could be efficiently executed in industrial processes at a low-cost.

Aiming at the best cost benefit, some related works adopts the use of sensor fusion, using optimization algorithms. They show the fusion of sensors for position estimation, and orientation using accelerometers and gyroscopes [10]. By adopting

This work was supported by MRS Logística S.A..

978-1-5386-7995-1/18/$31.00 ©2018 IEEE

ISBN 978-1-5386-7995-1

algorithms such as the Kalman filter or complementary filter, it is possible to merge the data collected by the sensors and estimate more reliable data. In this context, a practical example of sensors use is presented to determine the carbody vibration of a wagon prototype in a railroad track.

The prototype is composed of sensors that measure the carbody acceleration. The data is later processed in a microcontroller and through wireless communication devices, they are sent to an application that displays and analysis it to report wagon movement irregularities on railroad. The collected and treated inputs can be used to calculate other defects as well as check the tracks quality [11], [12]. The project was carried out with the association between Federal University of São João del-Rei and the railway concessionaire MRS Logística S.A..

II. Proposed System

This section presents a brief review and an description of the technologies used in this work, evidencing as well the electronic resources.

A. System Background

A structured monitoring system which can directly track the activities of a carbody [13], is shown by Fig. 1 and is divided into the following steps:

- Inertial tracking subsystem;
- Communication subsystem;
- Platform development (data visualization).

The system consists of the MPU6050 sensor based on accelerometer and gyroscope embedded in the wagon prototype, which are coupled on the Arduino Nano microcontroller platform by a conditioning circuit. The microcontroller has the fusion processing algorithm of Kalman Filter sensors and the conversion calculations of angles (deg). The processing is shipped in the system, where data is sent by a wireless device (HC06) via Bluetooth communication to an Android application created by App Inventor. The application consists of sampling the data and establishing notifications through the limits set by the user. The following sections explain each device and algorithm used, as well as procedures and results.

B. MPU6050 Module

MPU6050 equipment incorporate a 3-axis gyroscope, and a 3-axis accelerometer in the equivalent component with a Digital Motion Processor, representing measuring values angle and acceleration values in the three orthogonal directions. The module is an Inertial Measurement Unit (IMU) that has six 16-bit digital-analogue converters and has the option to change the sampling rate of the gyro accelerometer. The sensors are Micro Electro Mechanical System (MEMS), where the gyroscope quantifies the angular velocity and the accelerometer measures acceleration of the carbody.

C. Arduino Nano Platform

The Arduino Nano is a board with a tiny size compared to other boards on the market. It is based on the ATmega328 and, in general, has the same functionalities as other Arduino platforms. The Nano can be powered via Mini-B USB connection, unregulated external $6-20$ V power supply (pin 30) or 5V regulated external power supply (pin 27). The power source is automatically selected for highest voltage source. Its small size and processing are essential for embedded projects.

D. Bluetooth Module HC-06

Bluetooth technology is widely used. In IoT is another simple and inexpensive way to send and receive information remotely. The Bluetooth module HC-06 is used for wireless communication between devices. In the present work, the data is received or acquired by the module and transferred to the Arduino Nano via serial communication. The following wireless module clarify an essential part in the application of the IoT concept, representing the analysis and visualization of data obtained from the sensors through supervisory.

E. MIT App Inventor

App Inventor for Android is an open source Web application initially provided by Google and now maintained by the Massachusetts Institute of Technology (MIT). The interface allows programming software applications for Android operating system. A graphical block interface is used and simplifies programming and use of its functions. The App Inventor builds on by the theories of constructionist learning, which makes it possible to modify and add new features quickly.

F. Wagon Oscillations

The traffic of railway vehicles in a permanent way (rails) does not exhibit simple characteristics, instead it runs a variety of oscillations. This type of effect can undermine the operation of their mechanical parts, related to their damping, service life and the unbalance on the railroad, which can cause accidents.

A railroad car has six degrees of freedom, three translational and the other three rotational. The axes are considered as follows:

- X-axis: Along the permanent path (longitudinal movements);
- Y-axis: Transversal to the permanent path (lateral movements);
- Z-axis: In the vertical direction (vertical movements).

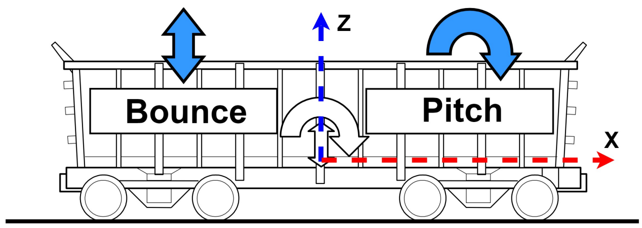

Fig. 2. Modes of oscillation in the vertical (Bounce) and rotational (Pitch) in the X-axis and Z-axis.

Hence, the wagon has six degrees of freedom, or modes of oscillation, which are shown in Fig. 2, 3 and 4. In addition to structure oscillations, the other components of the vehicle also suffer oscillations. Wheelset and consequently the trucks suffer several oscillations due to the irregularities effects on wheel and rails [14]. The combined oscillation of Roll and Yaw when they happen in a violent way generate a phenomenon called hunting. In general, there are two categories of oscillations:

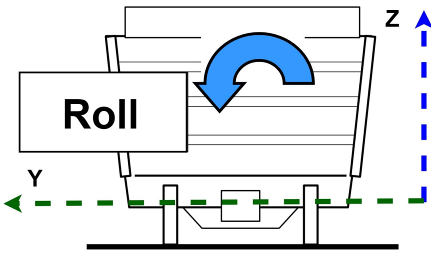

Fig. 3. Modes of oscillation in the rotational (Roll) in the Y-axis and Z-axis.

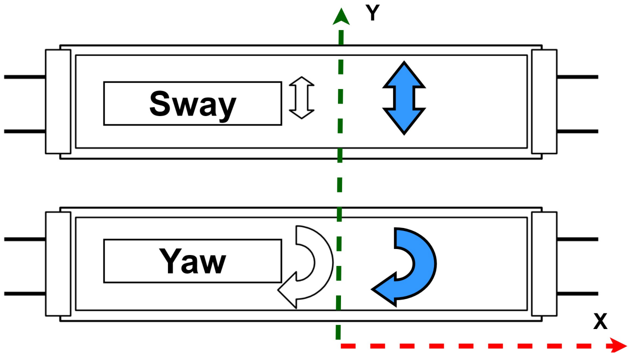

Fig. 4. Modes of lateral (Sway) and rotational (Yaw) oscillation in the X-axis and Y-axis.

- Self-excited: Due to taper (imperfections) of wheel;
- Non-self-excited: Due to rail irregularities, traction elasticity characteristics, vehicle suspension characteristics and load arrangement in vehicle.

III. Development and Analysis

A. Estimation of Pitch and Roll

Through the accelerometer included in the MPU6050 module the obtaining the inclination angles is possible. The sensor readings should be converted to unity in g ($9.8m/s^2$) and applied in the appropriate equations. The process of obtaining and converting the accelerometer readings depends on the characteristics of the hardware used. The MPU6050 has a resolution of 16 bits and range of $(\pm 2g, \pm 4g, \pm 8g, \pm 16g)$.

Generally, the formula used to calculate the acceleration readings using the resolution and range values is described as follows:

$$G_{Accel} = Raw_{Accel} \left(\frac{Range}{2^{Resolution-1}} \right). \tag{1}$$

Calculated the correct acceleration components, we can determine the pitch and roll movements using the following equations:

$$pitch = arctan \left(\frac{G_y}{\sqrt{G_x^2 + G_z^2}} \right), \tag{2}$$

$$roll = arctan \left(\frac{-G_x}{G_z} \right). \tag{3}$$

The calculated values are integrated to the algorithm of the Kalman Filter, and together with the values obtained from the gyroscope, a better estimation is reached. Using statistical interactions of sensor contributions, it is possible to measure a specific effect with more reliability.

B. Implementing the Kalman Filter

The Kalman filter is a widely known algorithm due to the many applications in technology. Commonly used in guiding, navigating and controlling vehicles, this recursive algorithm can be implemented in real time using the current measurement, the previously calculated state, and an uncertainty matrix [15].

It consists of a recursive algorithm using a series of measures over time, which in this context, measures derived from the accelerometer and gyroscope. Measurements have noises that contribute over time to measurement errors. Therefore, the Kalman filter is intended to estimate the states of the measurement system, based on current and previous states, which tend to be accurate than just simple measurements. In this case, the accelerometer presents noises when it is used to measure gravitational acceleration and the gyroscope displays data that fluctuates over time.

The filter consists basically of two steps, prediction and correction, based on recursive techniques of the system represented in state spaces, being an estimation of the dynamics of the system [16]. During the first step, a prediction about the dynamics of the model is performed and in the second step a correction, acting on the covariance of the error. In this sense, the Kalman filter functions are an estimator and state optimizer x_k with a measurement of z_k.

$$x_k = F x_{k-1} + B u_k + w_k, \tag{4}$$

where F is the state transition model, applied in the previous state x_{k-1}, B is the control inputs model applied to the control input vector u_k. The matrices F and B are obtained from the constructive properties of the accelerometer and can also be obtained with information from the manufacturer.

$$x_k = \begin{bmatrix} \theta \\ \dot{\theta}_b \end{bmatrix}_k. \tag{5}$$

In (5) the filter output will be the angle θ representing the actual output, but also the drift (slip) $\dot{\theta}$ calculated in degrees per second and based on accelerometer measurements and gyroscope. The flow is the amount of gyro deviation, meaning that it is possible to obtain the real rate by subtracting the gyro measurement trend. Thus, the input is a real variable also given in degrees per second, represented by:

$$u_k = \dot{\theta}_k. \tag{6}$$

The F matrix is the state transition model that is applied in the previous state x_{k-1}. In this case, the matrix F can be defined as:

$$F = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix}. \tag{7}$$

The B matrix is called the control input model, where it is defined as follows:

$$B = \begin{bmatrix} \Delta t \\ 0 \end{bmatrix}. \tag{8}$$

Equation (8) is confirmed since the angle θ is obtained when the rate $\dot{\theta}$ is multiplied by the time rate of Δt, and since it is not possible to calculate the deviation directly based on the rate $\dot{\theta}$, we will define the second line of the matrix B as 0. In (9), w_k is the noise process, represented by the Gaussian distribution with zero mean and covariance Q in time k:

$$w_k \sim N(0, Q_k), \tag{9}$$

where Q_k is the covariance matrix of the noise process. In this case Q_k is the covariance matrix of the estimate of the state of the accelerometer and the drift of the gyroscope. The estimated drift and accelerometer values are considered independent, then, it is precisely equal to the variance of the accelerometer and drift estimation. The final matrix is defined as:

$$Q_k = \begin{bmatrix} Q_\theta & 0 \\ 0 & Q_{\dot{\theta}_b} \end{bmatrix} \Delta t. \tag{10}$$

The covariance matrix Q_k depends on the current time k, so the accelerometer variation Q_θ and the drift variance $Q_{\dot{\theta}_b}$ is multiplied by the time rate Δt. Then it is informed that the noise process is larger because the last state update occurs. It is interesting to note that if you set higher values, in other words, add more noise in the state estimate, and if the angles start to deviate, you need to increase the value of $Q_{\dot{\theta}_b}$. On the other hand, if the estimate tends to be slow, the confidence in the angle estimation is large and the Q_θ value should decrease, making the system more weighted.

The definition of the observation or measurement parameters z_k of the true state x_k is given by:

$$z_k = Hx_k + v_k, \tag{11}$$

where the H matrix is called the observation model and is used to map the true state space in the observed space since the true state cannot be observed. On the point of the measurement is only the measure of the accelerometer, the matrix H is given by:

$$H = \begin{bmatrix} 1 \\ 0 \end{bmatrix}. \tag{12}$$

The measurement noise should be defined by the Gaussian distribution, with zero mean and covariance R:

$$v_k \sim N(0, R). \tag{13}$$

The R is not an array, the measurement noise is equal to the measurement variance since the covariance of the same variable is equal to the deviation, we can define R as:

$$R = E\left[v_k \quad {v_k}^T\right] = var(v_k). \tag{14}$$

Assuming that the measurement noise is the same and does not depend on the time k we have the following equation:

$$var(v_k) = var(v). \tag{15}$$

The Fig. 5 is a schematic representation of the recursive steps of the Kalman filter. In the prediction algorithm, it is displayed the prediction $\hat{x}_k^-$ and the matrix P_k^-, which are computed representing the prediction at the later time instant, but before incorporating the z_k measurement. The prediction is obtained by incorporating the control signal u_k.

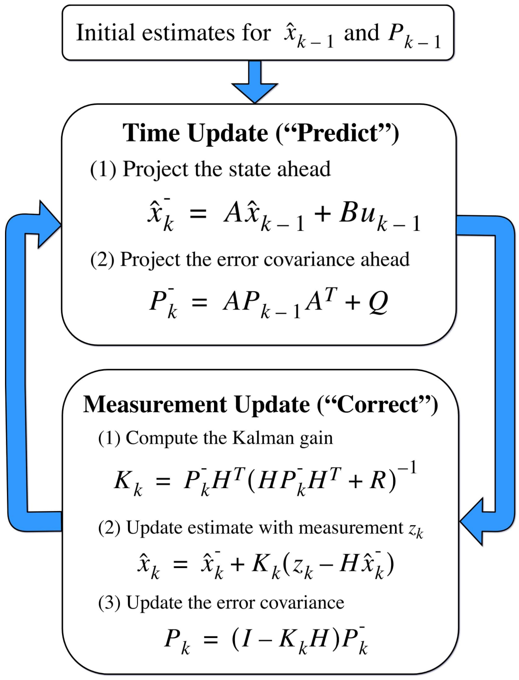

Fig. 5. Implementation of the recursive Kalman filter algorithm.

The mean is updated using the deterministic version of the state transition function, with the mean of the $\hat{x}_{k-1}$ replaced by the state value x_{k-1}.

The prediction is subsequently corrected into the desired prediction as it is incorporated the measurement z_k. The variable K_k is called the Kalman gain, which specifies how much the measurement will be incorporated into the new state estimate. The correction step handles the mean by proportionally adjusting the Kalman gain K_k, the deviation of the current measurement z_k, and the prediction of the measurement according to the probability of the measurement. Finally, the new covariance of the next prediction is calculated according to information of the gain resulting from the measure.

From the previously discussed equations, we can estimate the contribution of the values obtained by the gyroscope and accelerometer. The values calculated by the Kalman algorithm show a pitch and roll representation using sensor fusion.

C. Remote User Interface

The application was developed to show the data collected by the sensors and processed by the microcontroller. In this way, it is possible to sample the data in a fast and straightforward way [17]. The created interface allows you to change the parameters related to the established limits, which notify the data that do not match the limits entered in the application. The interface was created in App Inventor [18], software intended for the construction of Android applications. A simple and intuitive software based on the development of blocks, enabling reconfigurable programming and a structure for easy adaptation and implementation of new functions.

The Fig. 6 shows the visual interface, where Labels are used to display the text on the screen, Button indicating the user response actions and TextBox to store and edit variables. There are also hidden elements as the Notifier (an alert element to the screen), TinyDB (responsable to store the data in the application) and BluetoothClient (component responsible for the transmission of data via Bluetooth).

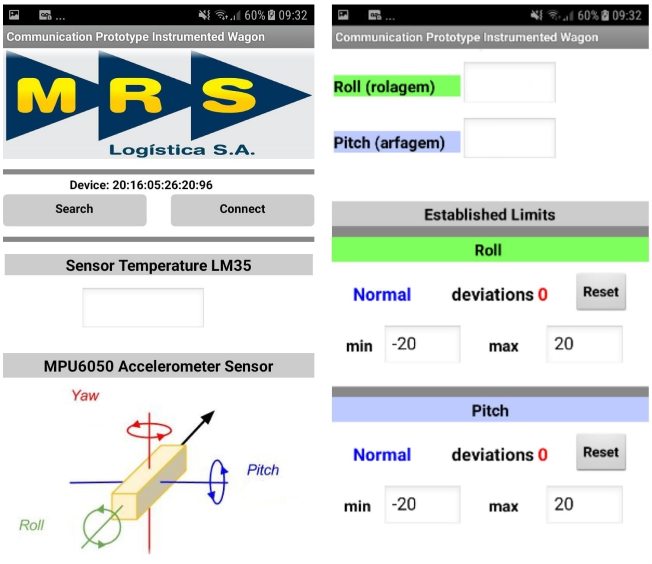

Fig. 6. Android application for monitoring and notification with microcontroller.

The application and its elements are created to establish a connection of the Android devices with the microcontrolled platform, where sound alerts are created when the limits are exceeded by the data acquired by the microcontroller. In addition, other elements have been created, such as the graphical elements to check the bluetooth connection and application startup. Finally, for communication between the Arduino and the mobile device a data protocol has been created.

IV. Results

Implementing the prototype and its acquisition, processing, and communication components, the prototype was shipped in small wagon coupled to a locomotive. The test consists of analyzing the dynamics of the movement of the locomotive and wagon assembly in a section of track with irregularities. The system illustrates the operation of the sensors and their processing using the Kalman filter. It also presents the deviations that can occur in any inertial measurement and how the introduced algorithm can work around the problem.

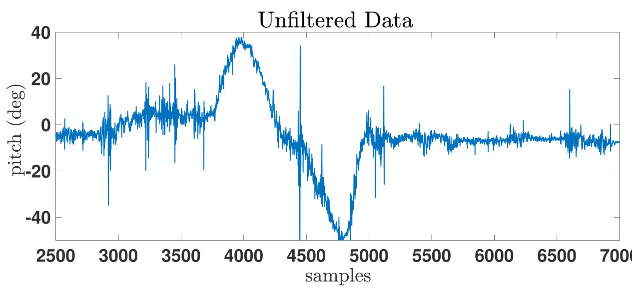

Fig. 7. Data acquired from sensor without filtering.

The Fig. 7 shows the data derived from the sensors with simple processing, it is shown that the data have a large amount of error. The irregularities are accumulated by the measurement errors of sensors, and some samples diverge from the limits with increasing errors. However, 8 shows results of estimation using the Kalman Filter, it is visualized that errors are reduced and the dynamic characteristics in time are maintained, enabling the data application for more accurate analyzes.

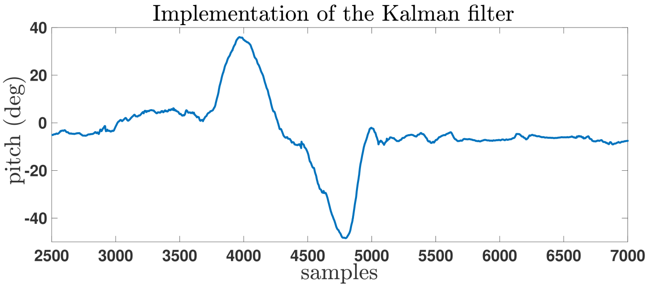

Fig. 8. Data acquired using Kalman filter.

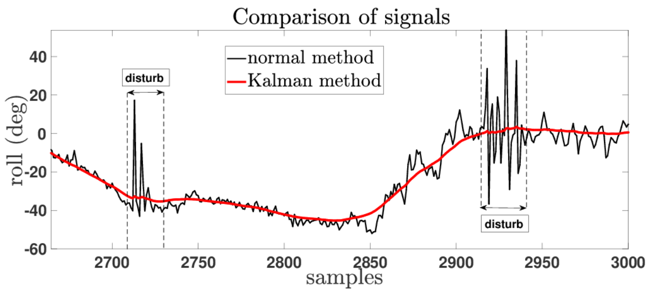

Fig. 9. Comparison of data obtained by normal method and Kalman filter.

For more accurate data analysis, Fig. 9 establishes a comparison between data processed with and without the application of Kalman filter. The filtered data preserves the trend and eliminates errors derived from the sensors. By the typical method, data exhibit several irregularities that do not represent the dynamics of the system, which some cases escape entirely and amplify the errors. In some cases, which requires analysis for notification, simple data can lead to false alerts. In cases of statistical analysis to obtain other characteristics as in case of analysis of pathways and imperfections, the data that exhibit oscillatory high amplitude values can deceive and disrupt the estimation of parameters.

The disturbances showed in the Fig. 9 and the values obtained with filtering can help to analyze effects outside those measured by sensors directly, such as structure defects and fast dynamics. In other cases, the disturbance presented may represent the numerous common effects of vehicle dynamics, which may indirectly influence the measurements made by the prototype. The kinematic oscillations with correct procedures can measure disturbances in the route by riding, which is the oscillations propagation not damped by the damping system of the wagon. Moreover, measured oscillations can aid in planning and safety decisions.

The Fig. 10 and 11 are images of the set used for dynamics tests, such as rails, locomotive, and prototype of the instrumented wagon. The goal is to illustrate the IoT project, electronic processes and algorithms which refine the results and can be easily used in real scale.

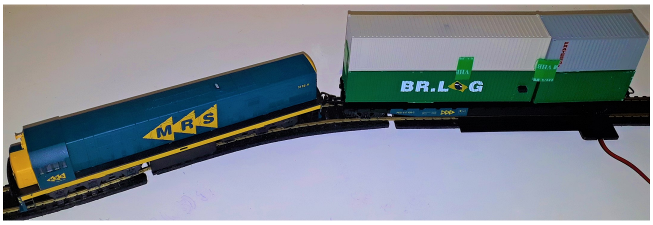

Fig. 10. Locomotive set and prototype of instrumented wagon.

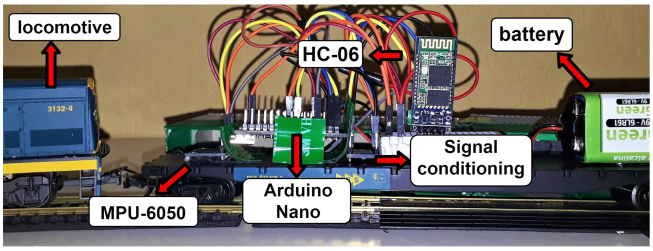

Fig. 11. Description of components of railway wagon prototype.

V. Conclusion

This paper exemplifies some applications of concepts in electronics, statistics, and computation that can be applied to problems in the industry. The work provides an intelligent, accessible and low-cost prototype, allowing the dissemination of the IoT concept in railway industry. In fact, the analysis of railway dynamics is essential to ensure economic demands, for example, influenced by accidents and equipment life.

The software used in this project is free and simple to manipulate, allowing modifications and additions of new functions, such as the modification of processing algorithm parameters and a graphical interface of the application to allow system adaptations.

Furthermore, it describes some requirements for implementation in an industrial railway - which is to obtain the dynamics of railway wagons that can be used for the analysis of operational irregularities and analysis of factors such as rail paths and operation of wagon components. The system was tested in a small prototype, which was able to exemplify the dynamics found in these types of systems and how wireless communication can aid in obtaining data from distant and moving systems.

Acknowledgment

The authors would like to thank MRS Logística S.A. for the support, and also thank Wagon Maintenance Management Team and Engineering Team. We also thank our colleagues from the Federal University of São João del-Rei and the Control and Modelling Group (GCOM).

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