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Mitigating Electromagnetic Noise When Using Low-Cost Devices in Industry 4.0

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ABSTRACT Transitioning toward Industry 4.0 requires major investment in devices and mechanisms enabling interconnectivity between people, machines, and processes. In this article, we present a low-cost system based on the Raspberry Pi platform to measure the overall equipment effectiveness (OEE) in real time, and we propose two filtering mechanisms for electromagnetic interferences (EMIs) to measure OEE accurately. The first EMI filtering mechanism is the database filter (DBF), which has been designed to record sealing signals accurately. The DBF works on the database by filtering erroneous signals that have been inserted in it. The second mechanism is the smart coded filter (SCF), which is used to filter erroneous signals associated with machine availability measurements. We have validated our proposal in several production lines in a food industry. The results show that our system works properly, and that it considerably reduces implementation costs compared with proprietary systems offering similar functions. After implementing the proposed system in actual industrial settings, the results show a mean error (ME) of −0.43% and a root mean square error (RMSE) of 4.85 in the sealing signals, and an error of 0% in the availability signal, thus enabling an accurate estimate of OEE.

INDEX TERMS Industry 4.0, low-cost devices, electromagnetic interference, filtering software, Raspberry Pi.

I. INTRODUCTION

The fourth industrial revolution—or Industry 4.0—represents the development of current production systems after industrial automation and information technology merged. The technological innovation of Industry 4.0 features the integration of manufacturing systems, management during the product lifecycle, and the decentralization of IT resources [1].

The broad spectrum of devices and equipment used in Industrial Internet of Things (IIoT) mostly comprises manufacturers' exclusive systems, is costly to implement, and has communication and interoperability protocols with low standardization. Modbus [2], BACnet [3], LonWorks [4], and KNX [5] are a few of the many protocols currently used in industry. Several wireless communication technologies and protocols can be used to link devices implemented in industry, for example, Internet Protocol version 6 (IPv6) through low-power wireless personal area networks (LoWPANs), Zigbee, Bluetooth Low Energy (BLE), Z-Wave and near-field communication (NFC) [6].

Based on our research, and considering these drawbacks, we propose using systems capable of performing the same operations as other well-known proprietary systems, but with a lower financial investment. Consequently, we aim to implement low-cost devices such as Raspberry Pi—used alone or in combination with other peripherals—in industrial processes to monitor and control variables, analyze data, and, in short, link to the state of the machine for real-time analysis of how manufacturing processes are operating. However, these low-cost electronic devices have some disadvantages related to the electromagnetic setting where they are usually located, normally in insulated switchboards alongside other

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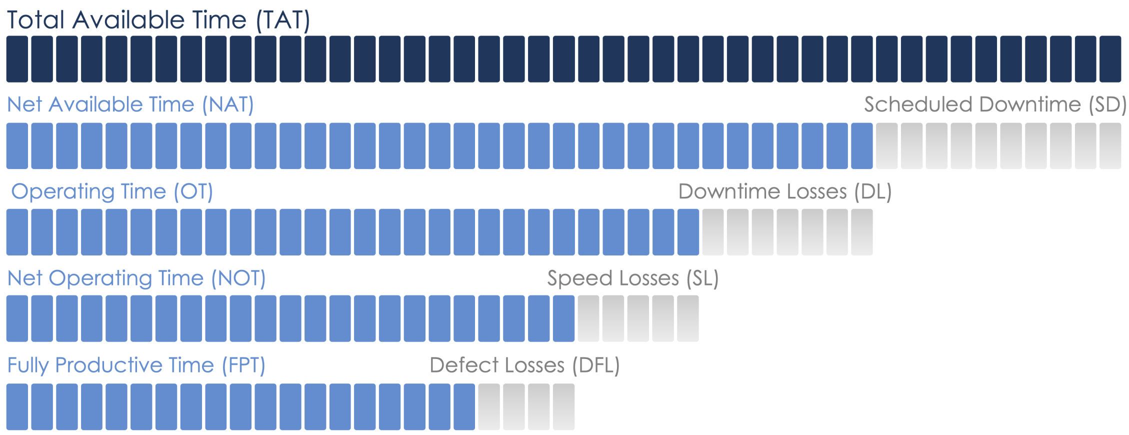


FIGURE 1. OEE parameters.

automated systems, power supplies, and other elements causing electromagnetic interferences (EMIs). EMIs occur when electronic devices operate close to each other and almost at the same frequency, which has an obvious impact on the performance and reliability of electronic equipment [7], [8]. Electromagnetic compatibility is a serious problem, since this physical phenomenon can affect the correct operation of this type of facility and system, causing errors and faults that can have fatal consequences. Raspberry Pi is a system with electronic elements sensitive to EMIs [9], and, therefore, one of the main focuses of the present proposal.

In this article, we propose a low-cost system based on Raspberry Pi and designed to monitor the variables used in calculating overall equipment effectiveness (OEE) so that it can improve production parameters, such as availability, performance, and quality. We have designed and implemented two filtering mechanisms to prevent the negative effect of EMIs on the OEE calculation. These mechanisms—the database filter (DBF) and the smart code filter (SCF)—can filter erroneous signals caused by EMIs.

These EMIs are usually corrected using hardware that eliminates anomalous signals using physical elements and filtering circuits. However, the mechanisms presented in this article are based on software filtering and allow optimal filtering of EMIs irrespective of their origin, thus eliminating the problem and avoiding the need to install several types of hardware depending on the type of interference. Our device can be installed in all kinds of settings as it is highly flexible concerning installation location and the electromagnetic noise levels it is exposed to.

The article is structured as follows: the variables used in measuring OEE, the scenarios where our proposal has been tested, the low-cost architecture we have proposed for Industry 4.0, and the type of signals our system handles are presented in Section II. Section III contains the details of the EMI filtering mechanisms we propose—the DBF and the SCF—which have been especially designed to measure accurately data on performance and availability, respectively. Section IV includes the most relevant studies on using low-cost devices in industry and the effects of EMIs on these devices. Lastly, the research conclusions are drawn in Section V.

II. BACKGROUND & MOTIVATION

Task automation, cost savings, systematic management, compliance with standards, and resource efficiency are important factors in industry, and they will be improved by developments in Industry 4.0. However, implementing new Industry 4.0 processes and services can lead to problems, especially in small and medium-sized enterprises that usually suffer capital, skill, knowledge, and technological limitations [10]. In these cases, adopting more affordable low-cost measures facilitates and accelerates the transition toward Industry 4.0.

A. OVERALL EQUIPMENT EFFECTIVENESS

The OEE measurement tool was based on the total productive maintenance (TPM) concept devised by Nakajima [11]. The purpose of TPM was to eliminate all faults caused by equipment, as far as possible, so as to directly improve the production rate, reduce costs and inventory, and increase labor productivity. OEE is defined as a complete performance measurement of equipment, in other words, the extent to which the equipment is doing what it is supposed to do [12]. This metric enables us to classify the main reasons why a deficient performance occurs, and, therefore, it provides the basis for establishing improvement priorities and analyzing the cause of the defects.

Figure 1 shows the main parameters considered to calculate OEE. They are as follows:

- Availability: The following times are considered to measure availability: (i) Net Available Time (NAT), obtained by subtracting Scheduled Downtime (SD) from Total Available Time (TAT); and (ii) Operating Time (OT), which is the time resulting from subtracting the time lost due to Downtime Losses (DL) from NAT.
- Performance: The following times are considered to measure performance: (i) OT; and (ii) Net Operating

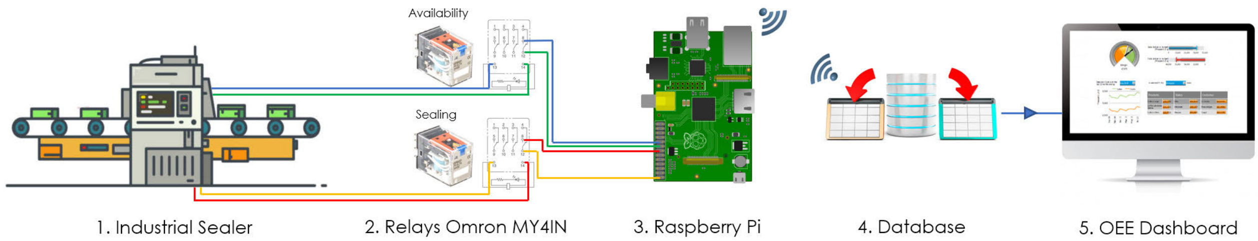


FIGURE 2. System Architecture.

Time (NOT), which is obtained by subtracting the time lost due to Speed Losses (SL) from OT.
- Quality: The following times are considered to determine this component: (i) NOT, which is the time actually available for producing; and (ii) Fully Productive Time (FPT), obtained by subtracting time lost due to Defect Losses (DFL) from NOT.

Equation 1 shows the OEE calculation.

$$OEE = Availability \cdot Performance \cdot Quality \tag{1}$$

where: $Availability = \frac{OT}{NAT}$, $Performance = \frac{NOT}{OT}$, and $Quality = \frac{FPT}{NOT}$.

OEE results allow production units in industry to be monitored and compared. Specifically, OEE provides significant data that make it possible to optimize resources and reduce working time, which is why it is used to increase system performance and constantly improve work. OEE can also reveal cases of high work demand and low production, which will make it possible to adopt better practices in industry [13].

Our proposal is based on using a Raspberry Pi to measure the parameters contributing to the OEE calculation. Specifically, it consists of measuring the availability times of the machine by determining wait times, shift shutdowns, maintenance shutdowns and shutdowns due to breakdowns. Monitoring the sealing signal also provides the times when the machine is operating more effectively, and the number of products manufactured. In short, OEE availability and performance parameters can be calculated accurately with the proposed system.

B. INDUSTRIAL SETTING WHERE OUR PROPOSAL WAS DEPLOYED

We deployed our system in a factory in the food sector—specifically, in a dairy industry—to validate its correct operation, and also to address scalability and requirements in other industrial settings. In this industry, we incorporated our system into the thermoplastic sealing lines of product packaging.

The dairy industry where we deployed our system mainly manufactures cheeses and milk preparations. This company has several packaging lines, although the products processed in these lines have different formats and sizes: cheese quarters, wedges, half cheeses, and whole cheeses.

C. SYSTEM ARCHITECTURE

Our proposal is configured to measure variables in the OEE calculation using a low-cost system that filters erroneous signals produced by EMIs. The system comprises five clearly differentiated elements (Figure 2), namely:

- Industrial sealer: Packaging device in the production chain.
- OMRON MY4IN relays: They receive electrical pulses from the machine concerning sealing and availability signals.
- Raspberry Pi: Low-cost microcomputer programmed to receive signals, manage the database, and apply EMI filtering mechanisms (i.e., DBF and SCF).
- Database: This stores the signals from each line.
- OEE dashboard: This allows monitoring of processed data.

The sealer emits two types of signal: sealing and availability. The sealing signal comprises a joint ON and OFF. More specifically, sealing occurs with a 1 and a 0 signal (corresponding to the lowering and raising of the sealing piston). The system registers sealing when the two signals appear consecutively. The availability signal indicates whether the machine is ready to operate. Consequently, this signal can be one of two types: ON (1), when there is availability, and OFF (0), when the sealer is not available.

The procedure the system follows is to wait for signals to arrive, process and separate them depending on their origin (sealing or availability), and then check that they have been inserted into the database correctly. If there is no connectivity with the database, the signals are stored in the device and inserted in the database when the connection is restored.

D. PERFORMANCE SIGNAL

The sealing signal measured by the proposed system provides the data needed to determine the performance of the industrial machine. This signal tells us how many sealings have been completed, and exactly when they occurred, thus determining the elements intervening in performance to calculate the OEE factor.

The sealing signals form a clear pattern depending on how long the machine takes for the sealing. The time the machine remains in state 1 is the time during which the piston is sealing the thermoplastic. Consequently, this is considered the time the machine takes to perform a sealing operation. The time

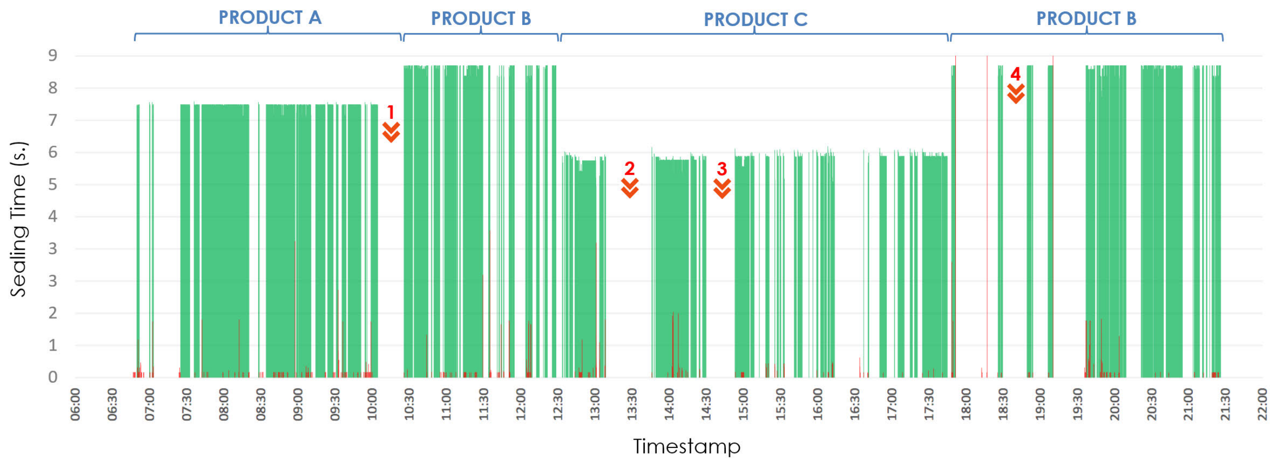


FIGURE 3. **Representation of the Performance signals and EMIs.**

the machine remains in state 0 (piston raised) is considered the time between sealings.

As the sealing signal is characterized by consistent behavior patterns in sealing times, which tend to constantly repeat, any anomalous alteration of these patterns in the manufacturing shifts indicates the presence of electromagnetic noise. These patterns are variables that depend on the product being sealed and the industrial sealer used; in other words, the time it takes to seal a cheese wedge differs from the time it takes to seal a whole cheese or cheese quarters. However, our proposal adapts to this circumstance and works properly in all cases.

Figure 3 shows an example of the information the system gathers on the sealing process during a shift. The packaged products can be differentiated from the shutdowns. The green lines represent the sealing time (Ts) of several products, while the red lines represent the values that do not correspond to the sealing pattern of the product, and that clearly highlight the electromagnetic noise produced in the device. More specifically, Figure 3 shows the sealing of the three different products: cheese quarters (Product A), whole cheeses (Product B) and cheese wedges (Product C). Whole cheeses (Product B) were sealed at two different times during the shift, and it is the process that introduces the longest sealing time: 8.38 seconds. Cheese quarters (Product A) take less time to be sealed (7.32 seconds) than whole cheeses, and wedges (Product C) take even less time, specifically 5.83 seconds. The shutdowns in the various products during the shift can also be clearly seen. By way of example, scheduled shutdowns for staff breaks and changeovers can be observed at 10:00 and 13:00 (1 and 2, respectively), as well as a shutdown for maintenance at 14:30 (3) and to replace the roll of plastic at 18:30 (4). Besides the shutdown for a staff break at 19:00, the other shutdowns were not scheduled.

Therefore, products and shutdowns can be identified, and the electromagnetic noise EMIs produced can be observed. Specifically, in the example presented here, 3,916 sealings were counted, while the actual number of sealings was 2,540, equating to 35.14% of erroneous signals due to EMIs. As we have seen, we can even determine which products were made during the shift, without eliminating the noise, but a correct estimate of OEE in terms of productivity cannot be made as the number of sealings actually produced was not obtained.

E. AVAILABILITY SIGNAL

Availability is another of the parameters forming the OEE factor that our system measures considering the state of the machine (ON/OFF). The analysis of this signal helps to determine the times when the machine is and is not available. In this way, we can also establish when the machine is ready to perform tasks—but has not performed any—and also the shutdown times, and compare them to scheduled production shutdowns.

Detecting erroneous signals in availability is more complex. Unlike the sealing process, signals indicating machine availability are unitary; in other words, they present either a 1 or a 0, not a set of two values. They are also asynchronous and do not present a pattern, as in the case of the sealing signals. The presence of EMIs indicates the appearance of consecutive signals of the same type; in other words, if the machine has stopped (0), it cannot send another shutdown signal (0), and the same would occur if the machine had a state (1). EMIs can also be detected in availability when the sealing signals are contrasted with the state of the machine; in other words, if the machine is sealing, it would not have to send a (0) signal regarding availability.

Figure 4 shows an example of the values obtained relating to the availability of the machine during a complete shift. There are characteristic points indicating several incidences that occurred during the process. The shutdown at 06:50 (1) serves as an example, as it represents a readjustment of the plastic used in the blister sealing operation. In contrast, the shutdowns from 10:00 to 10:30 (2) and from 14:30 to 15:00 (3) are scheduled shutdowns: the first is for a staff break, and the second to change over personnel. The red lines represent the EMIs that have occurred in the shift. Besides

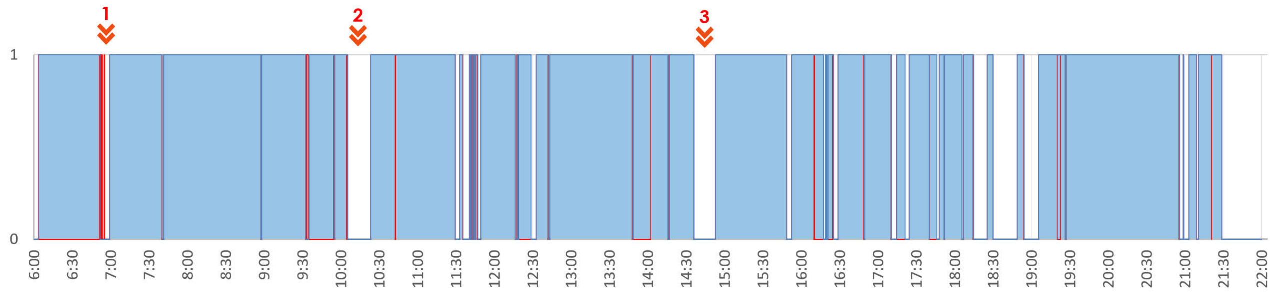


FIGURE 4. Representation of the Availability signals and EMIs.

shutdowns to change the roll of plastic at 18:30 and for a staff break at 19:00, the other shutdowns were not scheduled.

In short, the figure clearly shows when the machine was available and when it was not, as well as the alterations caused by EMIs in the availability signal. More specifically, the signals shown in Figure 4, which include noise, demonstrate an availability of 69.12% (11 hours and 3 minutes); however, if we eliminate the signals produced by EMIs, availability is 81.49% (13 hours and 2 minutes). The total number of signals recorded by the device is 707, but only 163 are valid; in other words, 76.94% of the signals are erroneous. These data show the need to eliminate EMIs to calculate OEE more accurately.

III. FILTERING MECHANISMS OF ELECTROMAGNETIC INTERFERENCES: DBF AND SCF

In this section we present the two mechanisms designed for filtering EMIs, the DBF, applied to sealing signals, and the SCF, applied to availability signals.

A. DBF MECHANISM: EMI FILTERING IN PERFORMANCE SIGNALS

The DBF is the mechanism we have designed to mitigate the presence of erroneous signals due to EMIs in performance signals. This mechanism filters signals from electromagnetic noise to determine valid signals and improve the precision of our system when estimating OEE. To this end, we considered the behavior and nature of the sealing signal. It is important to note that the start and end times for every product in every shift are known.

After the signals are stored in the database, they are processed by Algorithm 1. Initially, signals are filtered to obtain those that last longer than one second, since the system start-up has shown that no thermoplastic sealing signal lasts more than one second (getCandidateSignalsDB). The DBF also rules out erroneous signals to comply with a logical order of the values forming a sealing signal. A signal cannot be considered valid if the logical values are repeated one after another, in other words, a 0 followed by another 0 or two consecutive 1s (filterLogicSignals). Once the DBF has performed these two steps, it obtains the start and end timestamps of every product, which have been previously planned and stored in the database (getProductTimesDB).

Next, the DBF generates an array with the signals for every product (getProductSignals), thus identifying the sealing time value that repeats the most in the sealing process (mode). Figure 5 shows an example of a specific product. As can be seen, the most frequent sealing time is 6.05 seconds, which is the time established as the sealing time of this product.

The upper and lower limits are determined next using the established offset. Then, the valid signals of each product (dbfSignals), that is, those with a Ts within the fixed interval, are obtained by filtering using this criterion.

The offset value was established after an exhaustive analysis of the sealing operations, their duration times, and the errors occurring in each of the shifts and products considering deviations in the sealing duration. The primary aim is to obtain all the signals corresponding to the actual operation, and to establish an offset value generating a minimum error in all the shifts and products. As shown in Figure 6, if we consider an offset of 13%, the percentage of erroneous signals is less than 1% for all the shifts and products analyzed. This is a very low error that barely impacts the OEE calculation.

In line with the above, the DBF considers that signals whose sealing times are far from the mode (in a higher percentage than the offset) would have been generated by electromagnetic noise. By way of example, signals with times from 1.47 to 2.07 seconds shown in Figure 5 will not be considered valid. As a result, the DBF can eliminate the noise caused by the EMIs in the sealing signals.

Figures 7.a and 7.c show the sealings gathered in two example shifts. The duration of the sealing signals at the exact time when they occur is represented in green, and the signals caused by EMIs in red. Figures 7.b and 7.d also show valid signals, once the EMIs have been filtered using the DBF mechanism. As can be seen, the DBF eliminates noise signals as it assumes that only signals within the interval set by the mode and the established offset are the good ones ($\pm 13\,\%$).

After filtering the erroneous signals, Figure 7.b shows the number of products that have formed part of the production shift. There are three: whole cheese sealing, cheese quarter sealing, and cheese wedge sealing. The distinction between the products is obvious during the shift. Whole cheeses are sealed from 6:30 to 15:00, with a sealing time

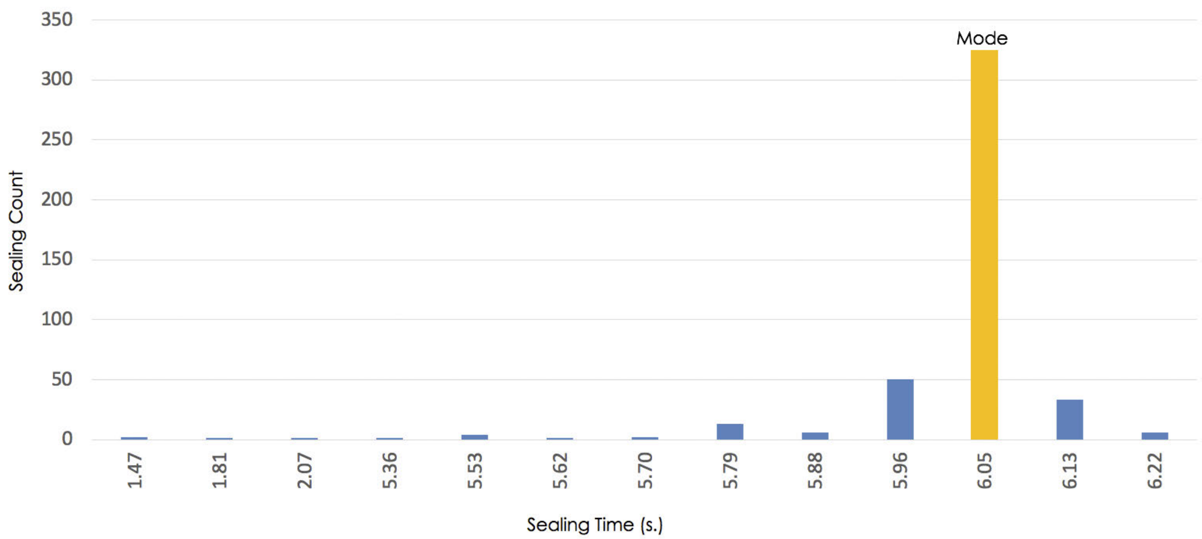


FIGURE 5. Sealing Time frequency analysis. Mode determination.

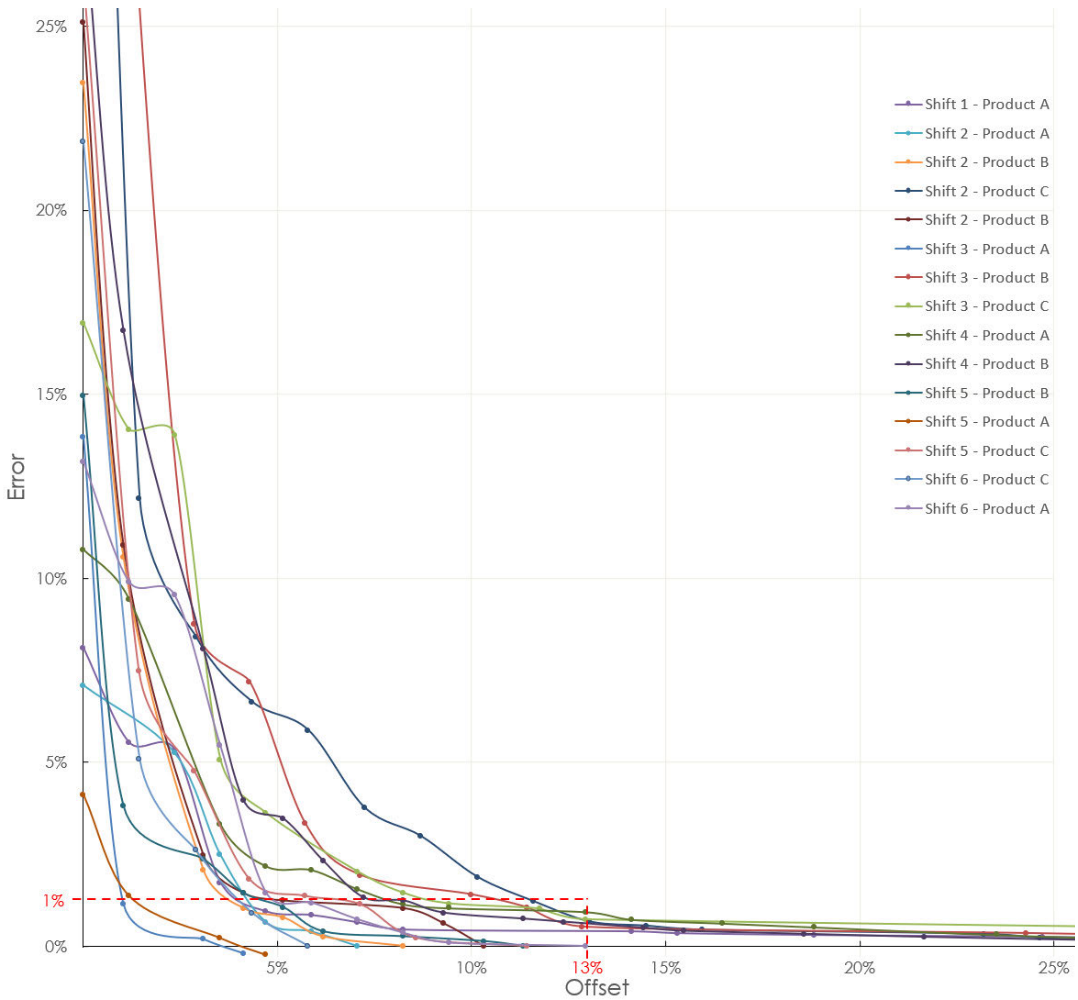
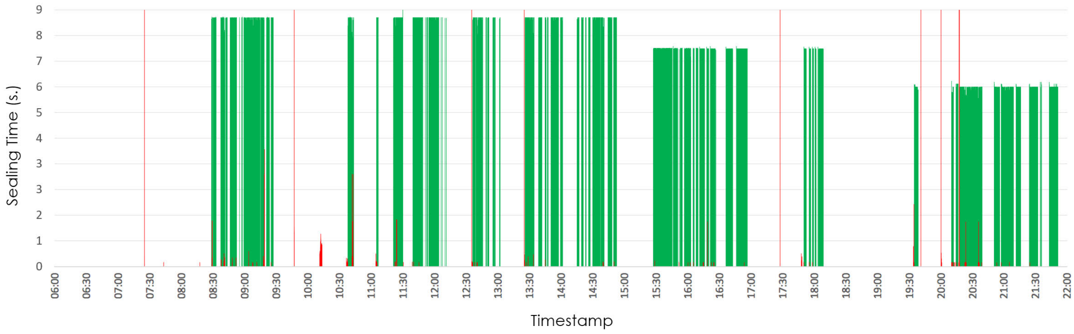
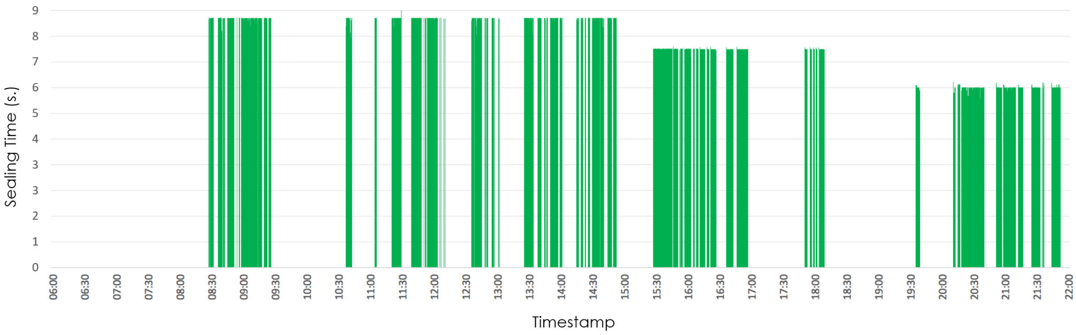


FIGURE 6. Error made during the filtering process when varying the offset.

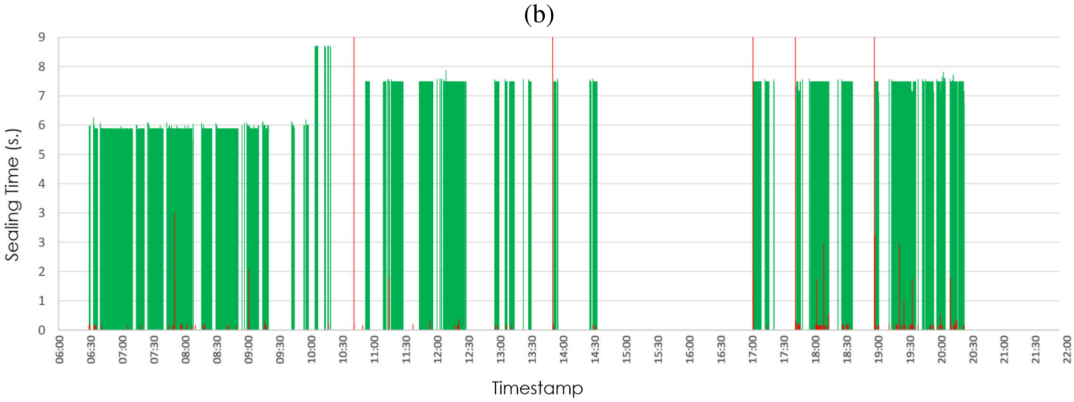
of 8.41 seconds; cheese quarters are sealed from 15:30 to 18:10, with a sealing time of 7.34 seconds; and, lastly, cheese wedges are sealed in the final shift zone, from 19:30 to 22:00, with a sealing time of 6.05 seconds.



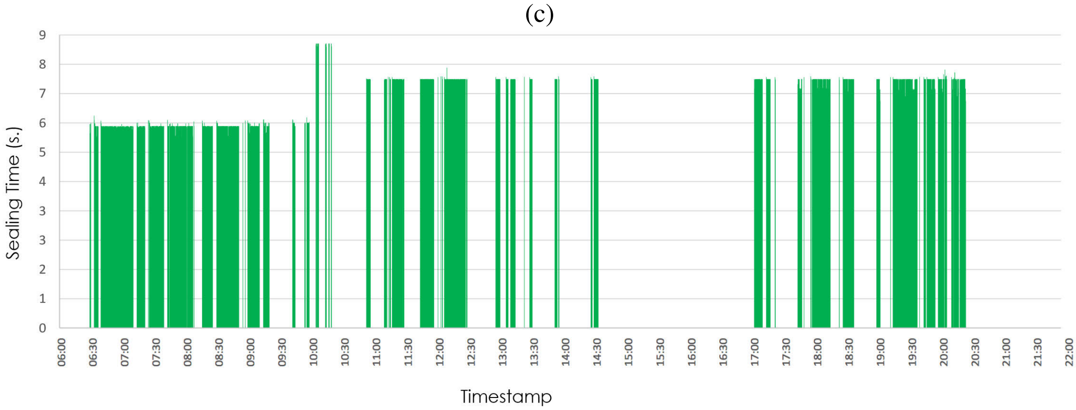
(a)



(b)



(c)



(d)

FIGURE 7. Sealing signals: (a) RAW and (b) Filtered by DBF in Shift 5, and (c) RAW and (d) Filtered by DBF, in Shift 6.

Electromagnetic noise is observed throughout the shift, since the system records 1,377 erroneous signals in total, representing 45.6% of signals that should be eliminated.

The same products as in shift 5 are in shift 6, which are reproduced in Figures 7.c and 7.d. The first product observed is wedge sealing, which starts the shift at 6:30 and lasts

Algorithm 1 DBF

```
/* ***********                          */
/* candidateSignals: array which
   includes all the signals except
   those lower than one second;         */
/* prefilteredSignals: array which
   includes the signals filtered by a
   logic order (0-1);                   */
/* productTimes: array which includes
   product start and end times;         */
/* signalsByProduct: array which
   includes signals between start and
   end times for each product;          */
/* mode: most repeated sealing time
   during the process;                  */
/* offset: time added or subtracted
   to the mode to determine the
   sealing values valid range;          */
/* maxLimit: upper offset limit;        */
/* minLimit: lower offset limit;        */
/* dbfSignals: array which includes
   all the sealing signals filtered
   by the DBF;                          */
/* ***********                          */
candidateSignals[] = getCandidateSignalsDB(shift);
prefilteredSignals[] =
filterLogicSignals(candidateSignals[]);
productTimes[] = getProductTimesDB(shift);
foreach product in productTimes[] do
    signalsByProduct[] =
    getProductSignals(prefilteredSignals[],
    product.TimeInit, product.TimeEnd)
    mode = getMode(signalsByProduct[])
    foreach signal in signalsByProduct[] do
        maxLimit = mode + offset;
        minLimit = mode - offset;
        if (signal < maxLimit)&&(signal > minLimit)
        then
            dbfSignals.add(signal)
        end
    end
end
```

until 10:10; its sealing time is 5.93 seconds. The second process observed is the sealing of whole cheeses, with a sealing time of 8.34 seconds. The last product sealed taking up most of the shift time (from 10:55 to the end of the shift at 20:20) is the packaging of cheese quarters, with a sealing time of 7.36 seconds. Figure 7.c shows the effect of EMIs, and Figure 7.d reveals how the erroneous signals have been eliminated. Specifically, 755 signals were eliminated by the DBF, in other words, 27.3% of all the signals initially recorded by the system.

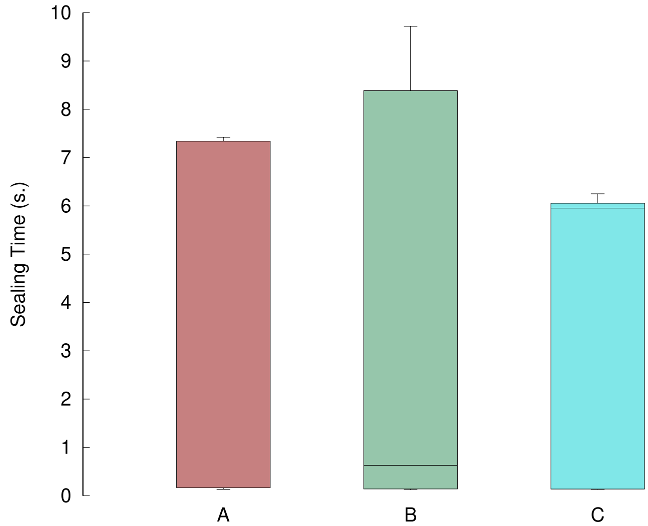


FIGURE 8. Distribution of RAW sealing signals in shift 5, grouped by product.

Table 1 shows the detailed results obtained from applying the DBF mechanism in all the analyzed shifts. The first column indicates the shift and the product that was analyzed, and the second shows the actual signals, that is, the sealings that actually occurred. These observations were made onsite by videorecording the operation of the sealer so as to compare its actual behavior with the data recorded by the system. The third and fourth columns (RAW) contain the signals the device received without applying the DBF filtering mechanism, and also the error made between the received and actual signals. The signals obtained after applying the DBF mechanism are included in the fifth and sixth columns (DBF).

We have obtained results from the sealing process of three products in six shifts. The products involved in the processes were cheese quarters (Product A), whole cheeses (Product B) and cheese wedges (Product C). Without filtering EMIs, their incidence on these processes would not enable us to properly calculate performance, and, therefore, OEE, since the errors are high, up to 64.49%.

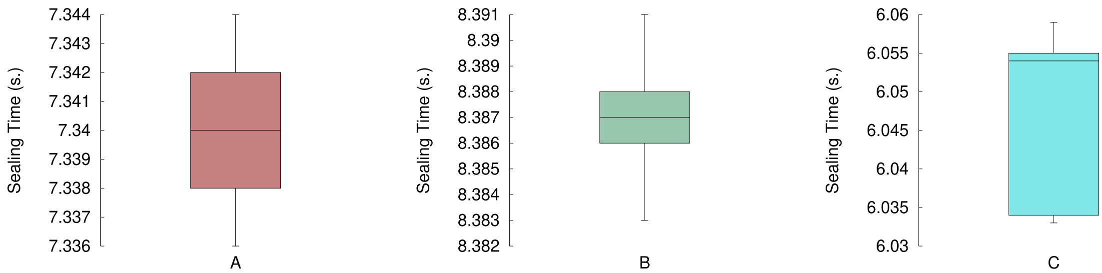
EMI filtering by DBF is considered effective since its errors are acceptable for a correct OEE calculation, as far as performance is concerned. More specifically, the data indicates a mean error (ME) of -0.43% and a root mean square error (RMSE) of 4.85, a minimum error that barely affects the OEE calculation.

Now, we present the distribution of sealing signals before and after using our DBF mechanism. In particular, Figure 8 shows the RAW sealing signals collected during shift 5, whereas Figures 9.a, 9.b, and 9.c present the sealing signals that were obtained after applying the DBF scheme.

As shown, the RAW sealing signals are far from being symmetrically distributed (see Figure 8). In fact, data are very scattered, and the signal values range from very low values (close to 0) to values between 6 and 10, depending upon the specific product. Although data for all the products is skewed, there are significant differences among the signals of the three

TABLE 1. Results of the Sealing signals obtained in the six shifts analyzed.

Shift	Real Signals	RAW		DBF	
		Received Signals	Erroneous signals	Filtered Signals	Erroneous signals
1 Product A	2023	5697	64.49%	2014	-0.45%
2 Product A	762	1394	45.34%	762	0.00%
2 Product B	388	505	23.17%	388	0.00%
2 Product C	904	1166	22.47%	893	-1.23%
2 Product B'	486	851	42.89%	487	0.21%
3 Product A	520	717	27.48%	521	0.19%
3 Product B	571	971	41.19%	568	-0.53%
3 Product C	691	1247	44.59%	687	-0.58%
4 Product A	965	1750	44.86%	956	-0.94%
4 Product B	1214	2487	51.19%	1206	-0.66%
5 Product B	762	1650	53.82%	762	0.00%
5 Product A	437	609	28.24%	438	0.23%
5 Product C	441	759	41.90%	441	0.00%
6 Product C	883	949	7.06%	884	0.23%
6 Product B	31	31	0.00%	30	-3.33%
6 Product A	1101	1790	38.49%	1101	0.00%
Average			**36.07%**		**-0.43%**
RMSE			**458.37**		**4.85**



(a) (b) (b)

FIGURE 9. Distribution of DBF sealing signals in shift 5: (a) cheese quarters (Product A), (b) whole cheeses (Product B), and cheese wedges (Product C).

products. In fact, more than 50% of the signals correspond to a sealing time higher than 6 s, whereas most sealing signals in product B are concentrated around 1 s.

Regarding the effect of DBF, Figures 9.a, 9.b, and 9.c confirm the effectiveness of our filtering mechanism, as once the DBF is applied (and so the erroneous signals are eliminated), the data are more symmetrically distributed, especially in products A and B. In addition, we observe that sealing times for each product differ from less than 3 hundredths of a second, even in the worst case (i.e., product C).

Finally, Figure 10 shows the distribution of erroneous sealing signals due to EMIs, collected during all shifts. As shown, these signals do not depend on the shift or the product packaged. In fact, it is remarkable that the vast majority of the erroneous signals are concentrated around 0.14 s. However, there are also some products whose erroneous sealing signals vary greatly compared to the rest, especially those presented in 2C (i.e., erroneous signals collected when sealing product C in shift 2).

B. SCF MECHANISM: EMI FILTERING IN AVAILABILITY SIGNALS

Considering how unique erroneous availability signals are, and how they differ from sealing signals—and given that it is impossible to identify patterns—we designed the SCF to filter erroneous signals concerning availability. The SCF avoids introducing erroneous signals into the system, thus allowing for more precision in the availability calculation and, therefore, in the OEE calculation [14].

Algorithm 2 GPIO Sender

```
/* ***********                              */
/* pause: pause time in milliseconds;
   */
/* pattern: pattern sent with the
   determined durations;                    */
/* ***********                              */
int pause = 500;
int pattern[] = [50,150,75,125,100];
while rpiON do
    foreach time in pattern do
        send(changeState);
        sleep(time);
    end
    sleep(pause);
end
```

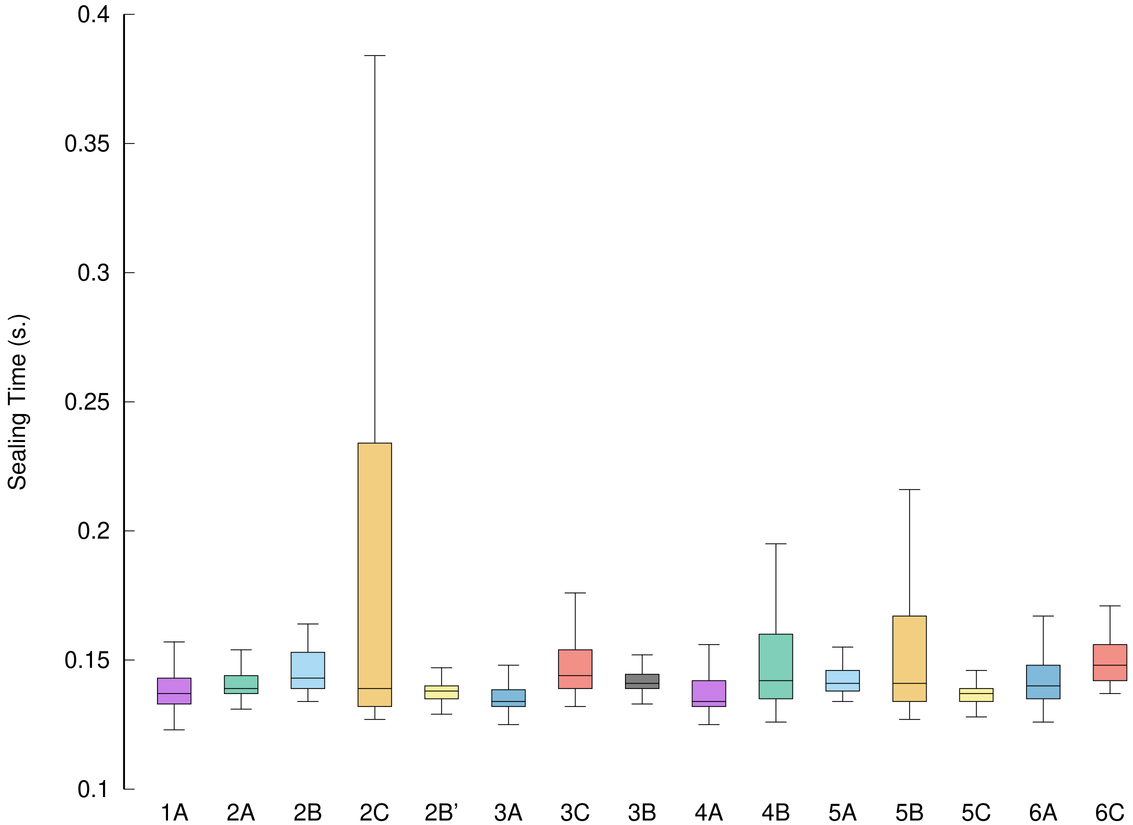


FIGURE 10. Distribution of erroneous sealing signals collected during all shifts.

The SCF operation is determined by the following processes, which are run in parallel in the Raspberry Pi, and whose code appears in Algorithms 2, 3 y 4. These three processes allow suitable filtering of erroneous signals. To that end, the GPIO sender (Algorithm 2) is the process that sends a coded message with the aim of indicating that the machine is available, sending a signal pattern within a specific time. The GPIO listener (Algorithm 3) receives the message and estimates whether the machine is available. For that purpose, it checks that the pattern has been received a minimum number of times (MINPATTERN). Finally, the inactive machine checker (Algorithm 4) detects that the sealer is not active.

Algorithm 3 GPIO Listener

```
if counter < MINPATTERN then
    if patternComplete() then
        counter++;      // checking that the
        signal received is the last of a
        right pattern
        if counter >= MINPATTERN AND !active then
            insertDB(currentMillis(), 1);
            active = 1;
        end
    end
end
```

Algorithm 4 Inactive Machine Checker

```
while rpiON do
    if counter < MINPATTERN AND active then
        insertDB(currentMillis(), 0);
        active = 0;
    end
    counter = 0;
    sleep(TIMEOUT);
end
```

Below we explain each of the abovementioned processes in more detail. Concerning Algorithm 2, a specific state (0 or 1) cannot be sent in the library used for code implementation, and instead, change of state messages (changeState) are sent. Consequently, the GPIO sender sends a pattern of changes of state through a GPIO, in a fixed time pattern (50 ms, 150 ms, 75 ms, 125 ms, and 100 ms). The system emits a change of state, waits 50 ms, then sends another change of state and waits 150 ms, sends another change of state, waits 75 ms, and so on, until the time pattern is complete. Once complete, it waits 500 ms before repeating the process again.

The GPIO listener process monitors the signals received and waits for the acknowledgement of the pattern sent by the GPIO sender process. The GPIO listener automatically runs every time an interruption is received due to a change in state.

TABLE 2. Results of the Availability signals obtained in the six shifts analyzed.

Shift	Real Signals	RAW		SCF Signals		Availability		
		Received Signals	Erroneous Signals	Signals	Erroneous Signals	w/o SCF	w/ SCF	Diff
1	52	1,385	96.25%	52	0.00%	31.84%	72.19%	40.35%
2	82	354	76.84%	82	0.00%	69.12%	81.50%	12.38%
3	117	172	31.98%	117	0.00%	66.16%	77.43%	11.27%
4	28	88	68.18%	28	0.00%	80.27%	82.94%	2.67%
5	51	79	35.44%	51	0.00%	49.72%	74.06%	24.34%
6	29	67	56.72%	29	0.00%	59.87%	80.20%	20.33%

If it receives the pattern twice (MINPATTERN), it establishes that the machine is available (active=1) and inserts this in the database. The inactive machine checker runs independently of the GPIO listener. It is responsible for checking whether the machine is available every 10 seconds (TIMEOUT). In this case, it checks that the number of messages received during this period is less than the MINPATTERN value. If this condition is met, it considers that the machine in inactive (active=0) and inserts this in the database. The twofold check allows the system to ensure that the signals received are not due to EMIs.

The GPIO listener and the inactive machine checker use common variables that will be detailed below:

- MINPATTERN: This indicates the minimum number of times the pattern sent by the GPIO sender must be repeated to consider the machine is active. Its value is 2 to completely ensure that the message received has not been produced by EMIs.
- TIMEOUT: This is the maximum time considered for conditions to be met to establish whether the machine is active or not. Its value is 10,000 ms.
- counter: This is the variable that counts patterns and its initial value is 0.
- active: This indicates the state of the machine and has an initial value of 0.

Table 2 shows the results for all the analyzed shifts. The first column represents the studied shift, while the second the actual signals, the third and fourth (RAW) indicate the availability signals of the system without any type of filtering and the errors made, respectively. The fifth and sixth columns (SCF signals) show the values obtained after applying the SCF filtering algorithm. As shown, the percentage of erroneous signals introduced into the system without filtering the noise fluctuates from 31.98% to 96.25%, while the error, after filtering the signals with SCF, is 0% in every shift. This validates the EMI filtering mechanism as a reliable method to obtain data on machine availability.

Nevertheless, it is important to realize that the abovementioned error is related to the number of availability signals received, but not with the machine's availability times. The seventh and eighth columns in the table show the availability percentages compared with the total shift duration, considering RAW signals and when the signals are filtered by the SCF mechanism. The difference is shown in the last column. As can be seen, the error in the number of signals received is not directly related to the error made in terms of duration of the availability of the machine. By way of example, there is an error of 214.29% in signal reception in shift 4, while in availability percentage terms, the error is 2.67%. Conversely, a smaller error is observed in signal reception in shift 5 compared with shift 4, specifically 54.90%, but the availability difference is substantial (24.34%).

Table 2 reveals that shift 1 has a high number of signals received in RAW, which is also shown in the availability data without SCF filtering. There are 1385 signals in RAW in this shift, and an error of 2,563% compared with actual signals, a very high number of erroneous signals in RAW that also logically has repercussions on availability estimation. In this case, the availability difference is 40.35%, which would not enable us to estimate OEE accurately.

In conclusion, the erroneous signals caused by EMIs negatively affect the results when estimating machine availability and randomly increase or decrease the availability percentage, although, based on the deployment results, the availability obtained is always less than the actual availability. In any event, we can see that it is especially important to ensure all signals are correct, since just one signal could significantly affect availability. Consequently, using our SCF filtering mechanism is absolutely essential in this type of setting with EMIs.

Figures 11 and 12 show the difference between the unavailabilities obtained without filtering and those including SCF filtering in two example shifts. Comparison of Figures 11.a and 11.b reveals the erroneous signals caused by EMIs. Two of the most visible errors appear from 11:30 to 12:15, when the device detects that the machine stops and starts twice, while with the SCF filtering these signals are ignored.

Figure 11.b shows the shutdowns made in the shift for varying reasons. Specifically, a product change from 11:00 to 11:20 to seal a short series, a planned shutdown from 11:30 to 13:00, a shutdown for a staff changeover from 14:00 to 14:30, a shutdown to change the plastic at 19:30, and another production change at 20:00.

Figure 12.a represents the significant number of errors caused by EMIs in shift 5. Specifically, availability errors appear from 07:00 to 08:30, from 13:00 to 14:00, 17:00 to 18:00, and from 19:30 to 20:00. The actual availability of the machine is shown in Figure 9.b, where the SCF

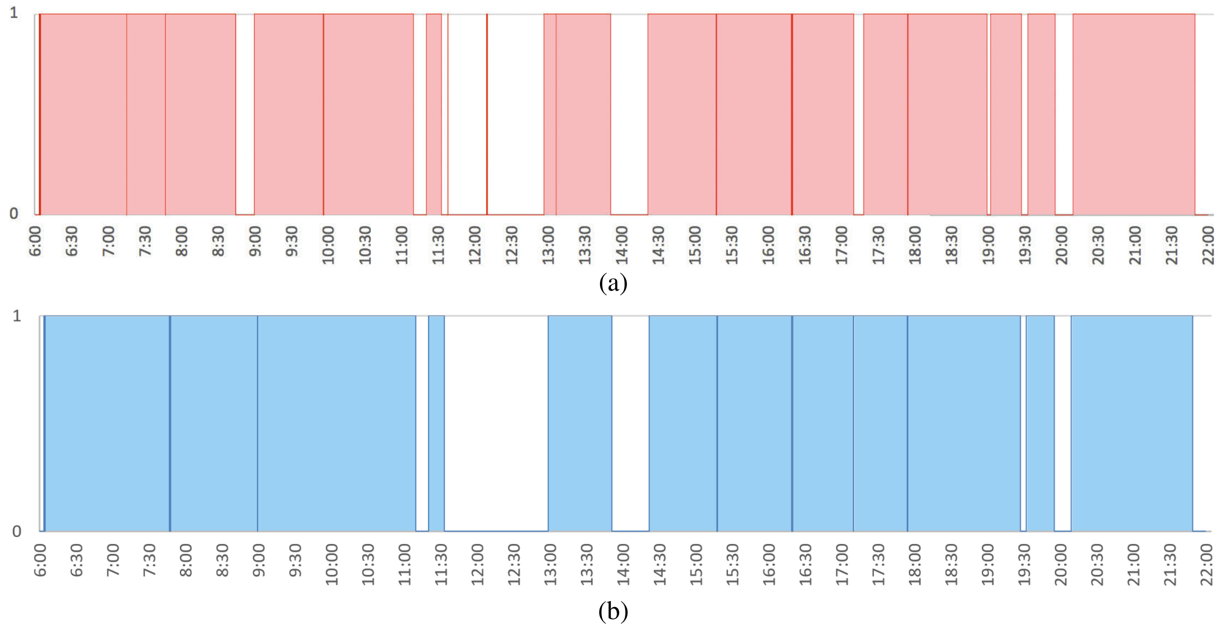


FIGURE 11. Availability of shift 4: (a) RAW signals and (b) Signals filtered by SCF.

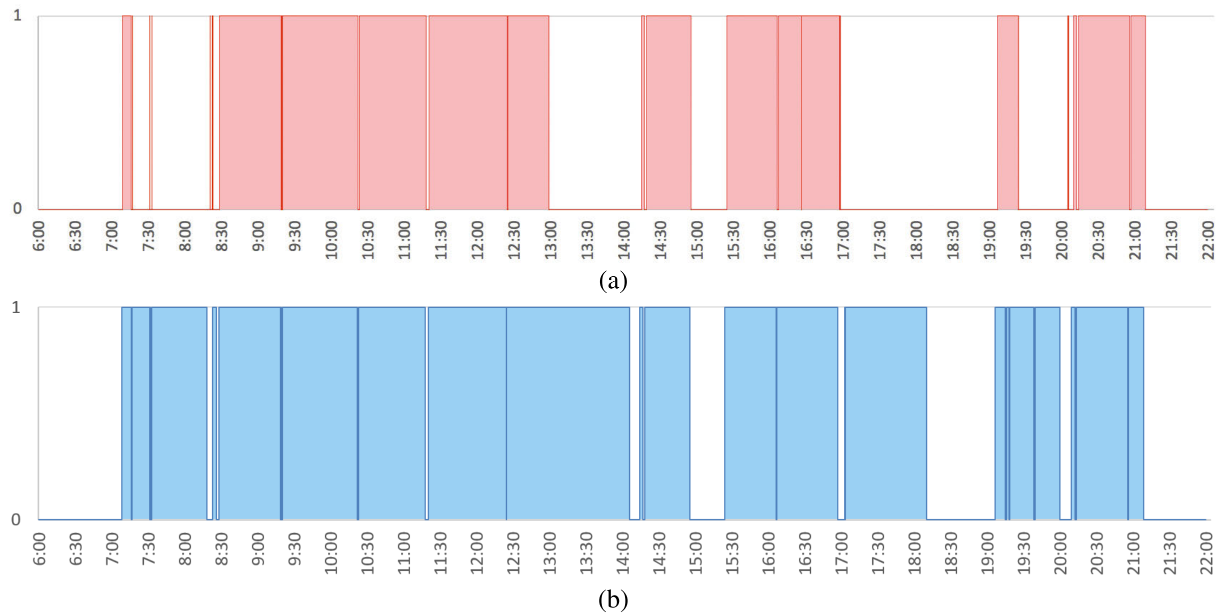


FIGURE 12. Availability of shift 5: (a) RAW signals and (b) Signals filtered by SCF.

makes it possible to obtain the actual availability of the sealer.

If we focus on the OEE calculation in shift 4, the availability difference without applying the SCF mechanism and after applying the SCF would impact the OEE calculation, increasing from 80.27% to 82.94%, although it is more noticeable in shift 5, with an availability of 49.72% without the SCF, and an actual availability of 74.06% of the total time of the shift after applying the SCF.

The main purpose of signal filtering is to obtain signals without any noise, since OEE cannot be determined correctly without eliminating erroneous signals. Nevertheless, the system provides benefits besides our proposal: a considerable reduction in the number of unnecessary transactions, and in the amount of data to be stored in the database, which could overload the system.

The results show that we can obtain the exact availability data involved in calculating OEE using the SCF to monitor

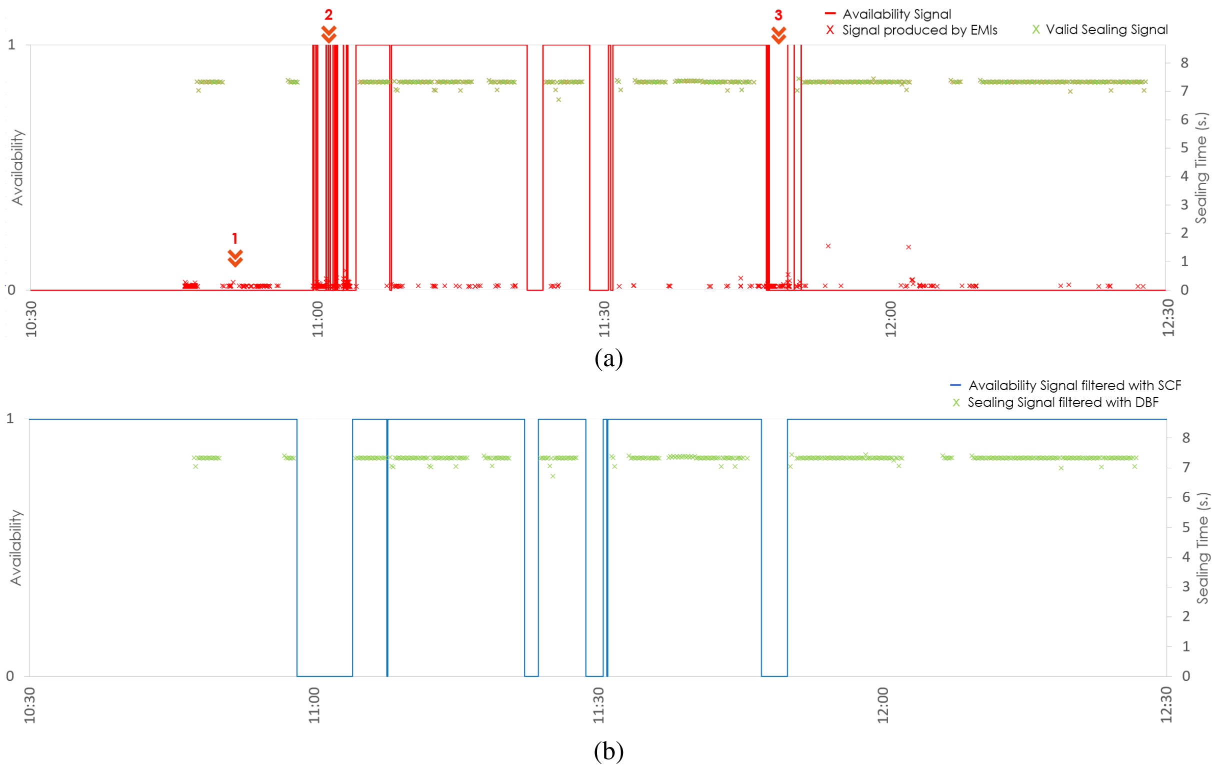


FIGURE 13. Comparison of sealing and availability during two hours of production: (a) RAW signals and (b) Signals filtered by DBF & SCF.

signals, since our proposal completely filters incorrect signals caused by electromagnetic noise.

C. PUTTING IT ALL TOGETHER

To provide an overview of our proposal, below we show the two signal types—availability and sealing—in the same graph, comparing the signals received by the device, and also the signals obtained by applying the proposed filtering mechanisms.

Figure 13.a presents a two-hour extract from a shift showing all the sealing and availability signals received, including those caused by EMIs. The left vertical axis indicates the state of availability of the machine, while the right vertical axis represents the sealing times. As can be observed, the values of the noise produced in the sealing signals exceed the pattern representing the sealing (1), in other words, sealings with durations outside the limits of the established offset. The unavailability shown by the system from 10:30 to 11:00 can also be clearly seen, demonstrating the negative effects of EMIs on availability signals and significantly altering the measurement of this parameter. Another example of availability signals not corresponding to the actual operation of the machine occurs at 11:00 (2), with EMIs manifested by very short-lasting availability values or sudden changes in state, when the machine is actually unavailable. Short-lasting sealing signals caused by EMIs that appear when the machine is actually unavailable (3) are also observed. In the last part of the example shown, we can see that the machine is not available (Figure 13.a) when it actually is (Figure 13.b). Otherwise, the sealings during this period could not be considered valid.

Figure 13.b represents sealing signals and availability signals after applying the DBF and SCF filtering mechanisms, respectively.

This example proves the negative effect of EMIs when estimating OEE. The system records 1,125 sealing signals without applying the proposed filtering mechanisms. However, there are only 390 sealings when we apply the DBF filtering mechanism. In contrast, the availability value is 33.06% without applying the SCF filtering mechanism, and after applying it, we can see that the actual availability of the machine is 89.63%.

After analyzing the results in the figure, which represents actual signals, EMIs, and signals provided by the filtering mechanisms, we can highlight the following aspects:

- The filtering mechanism works properly, filtering the sealing signals appearing when the machine is inactive.
- The signals compared with the video recorded during the shifts enable us to check the reliability of the system and the precision after applying the filtering mechanisms.
- The extremely short duration of the signals, the fact they appear when the machine is unavailable, and that they do not fit into expected patterns, allow us to determine erroneous signals.
- There is no correlation between the number of erroneous signals and the effective availability percentages;

in other words, the erroneous signals can impact estimated availability to a greater or lesser extent, although it is obviously very important to obtain precise values that allow us to correctly estimate OEE.

IV. RELATED STUDIES

As established by our proposal, low-cost devices can be used in Industry 4.0 settings to provide more flexibility in machine communication and to make organization of industrial production more effective, without involving unaffordable costs. However, these devices are more sensitive to EMIs than other systems.

When addressing these challenges, and considering the features of proprietary systems, essentially cost and exclusivity, we can find research in the literature on: (i) systems based on low-cost devices to provide solutions for Industry 4.0; and (ii) techniques to reduce EMIs.

One of these proposals for low-cost devices is put forward by Seguna *et al.* [15]. These authors demonstrate a low-cost real-time monitoring and control system for an industrial mini-climatic chamber and other climate-control systems. Their proposed system can control and monitor variables, such as temperature, using a Raspberry Pi and an STM32F microcontroller [16]. The system is implemented in an ideal setting for low-cost devices so there is no electromagnetic noise. Unlike in our research, the authors do not address the difficulties that could arise in a hostile environment, such as inside an electrical switchboard with automated systems, windings, and power supplies.

Also, based on a Raspberry Pi, and combined with other industrial devices and free software, Caiza *et al.* [17] present a solution with closed-loop controllers for industrial processes. Specifically, a proprietary system is used, FESTO's MPS® PA module, offering a set of industrial sensors. In general, the study evidences the effectiveness of the Raspberry Pi with several proprietary devices, although the tests are based on simulation and not on actual industrial settings. Implementing this type of proposal in an actual setting, as we have done, could change the results, essentially because this type of low-cost device is sensitive to EMIs.

Othman *et al.* [18] propose a remote real-time monitoring system of a photovoltaic plant using a Raspberry Pi. The system can show parameters such as voltage and temperature. The authors show that their proposal has some flexibility to adapt to a more complex installation, although the tests were simulated and not conducted in an actual facility that would be impacted by adverse weather conditions.

Molano *et al.* [19] describe a proposal for Internet of Things (IoT) architecture applied to industry, an integration metamodel (IoT, social networks, the cloud, and Industry 4.0) to generate applications for Industry 4.0. The authors present a manufacturing monitoring prototype implemented with Raspberry Pi, a cloud storage server, and a mobile device to control a production process online. However, as they do not implement it in actual industrial settings, they do not address any possible problems that may arise.

As mentioned above, EMIs cause defects and alterations in the operation of electronic devices, plates, sensors, microcontrollers, and microcomputers such as Raspberry Pi. In fact, electromagnetic compatibility (EMC) problems are becoming more prominent in the industry [20], and they occur more often when we use low-cost devices that do not usually incorporate complex systems that can prevent them.

Mach *et al.* [9] analyze and compare the near-field and far-field electromagnetic compatibility of the Raspberry Pi to determine the state of this device as a development platform. The results indicate that the Raspberry Pi contains many components generating far higher EMIs than expected, and that it is extremely susceptible to them.

Mynster and Jensen [21] describe some challenges and solutions related to EMC and EMI in IoT devices. Specifically, they pay special attention to integrated systems and radiated electromagnetic disturbances, since there are considerable differences between test environments standardized by regulations and the environments they actually operate in [21], [22].

Li *et al.* [23] expound how the increase in density of the components, and the decrease in operating voltage, have turned microcontrollers into elements that are more sensitive to EMIs. Low currents and voltages coupled to microcontrollers through their pins are the reason why they might stop working, and even damage the device. The authors also consider the effects of devices aging and the degradation of the physical parameters of the semiconductors, which could weaken protection of the devices against EMIs.

New polymer compounds that have replaced conventional metal materials in EMI screening and shielding is covered by Sankaran *et al.* [24]. These new polymers have an added value since they prevent corrosion, are lighter and they have superior thermal, mechanical, and magnetic properties that reduce electromagnetic noise.

In printed circuit board (PCB) analysis—Raspberry Pi is built on a PCB after all—Xiao *et al.* [25] propose a field-TL-circuit simulation field to analyze the impact of cable parameters on the electromagnetic coupling of PCBs in electronic equipment. The authors developed a model of an electronic device with PCB with three different cabling routes to analyze the problem of EMIs in PCBs. Their results show that the sensitive circuit must be kept away from the cabling area presenting more interference, and they propose installing suitable cables to reduce radiated EMI.

Using prohibited metallo-dielectric electromagnetic bandgap structures, Shahparnia *et al.* [26] present an effective method to suppress radiation in PCB power buses over an ultrawide range of frequencies. Their study focuses on suppressing radiation, caused by switching noise, from parallel-plate bus structures in high-speed PCBs. This noise comprises unwanted voltage fluctuations in a PCB power bus that stems from resonance of the parallel-plate waveguiding system generated by the power bus planes. The technique the authors use can extend to any wave propagation between power bus plates. They manufactured and tested PCB prototypes in the laboratory and their results show a noticeable suppression of radiated noise over certain frequency bands, thus demonstrating the effectiveness of this concept.

In short, most proposals concerning EMIs in this type of devices make measurements and quantify their effects, but they do not eliminate them. Authors addressing their elimination do so with hardware solutions, and only in certain settings. In other words, they examine interferences through the power line, limiting their studies to just one means of EMI transmission. Our proposal, however, offers a software solution to eliminate EMIs in low-cost devices. We do not differentiate between the source or means of transmission of the interferences (radiated or conducted), and we eliminate the erroneous signals impacting the device. This makes our system more flexible and able to adapt to a variety of settings.

V. CONCLUSION

EMIs represent a challenge that low-cost devices used in industry need to overcome. The insulated location of this type of device in industrial settings alongside elements generating a great deal of electrical noise poses a problem that needs to be eliminated so that this type of more economical device can be implemented to replace other less vulnerable but more expensive proprietary systems.

Our study presents a low-cost solution to measure productivity parameters in industrial settings, more specifically the variables determining the OEE, a key effectiveness indicator which enables company managers to discover the aspects they should analyze in detail to improve the efficiency of the production process, and thus increase profitability. We also propose two mechanisms that can filter EMIs in the signals the device receives, in other words, the sealing process and the machine availability signals. The first mechanism is the DBF, which applies filtering based on the conventional sealing patterns of the machine, and acts upon the data in the database to remove erroneous data. The second mechanism, SCF, fully filters EMIs to obtain the actual availability of the machine. We have checked its effectiveness after implementing it in several lines in a dairy industry, which provided evidence of the scalability and robustness of the system. The results show that the system is extremely reliable, with a mean error in obtaining sealing signals of -0.43% after applying the DBF filtering mechanism, and a reliability of 100%, in other words 0% error, in the availability signal.

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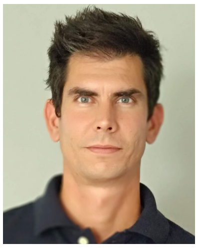

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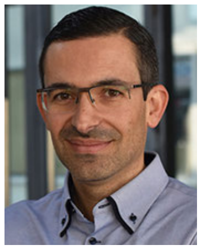

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