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RESEARCH PAPER

Performance measurement of legacy equipment through its connection to the cloud

Gleison Hidalgo Martins[1] Fernando Deschamps[1] Pablo Deivid Valle[1] Silvana Pereira Detro[1]

[1]Federal University Paraná (UFPR), Curitiba, Paraná, Brazil.

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ABSTRACT

Goal: Objective focuses on development and application of an architecture for measuring the performance of legacy equipment through its connection to the cloud.

Methodology: The research was approached by the Design Science Research (DSR) method, which focuses on the development and evaluation of the application of the artifact (legacy equipment performance measurement system) through its technological base.

Results: Both in the development and in the evaluation of the application of the system architecture in a real manufacturing system, the results were satisfactory through the accuracy obtained of 86% in the measurement carried out. Regarding equipment performance measurement, the measured index achieved an OEE of 27% efficiency, which is considered low compared to the average of companies with world-class manufacturing. It is concluded that the results made it possible to verify the reliability of the information generated by the architecture of the application system and to measure the performance of the equipment through its applicability in a real manufacturing scenario with a focus on manufacturing management.

Search limitations: The development of this research is limited to the application architecture for measuring performance for bread production line.

Practical Implications: The cloud architecture contextualizes the use of IIoT technologies (sensors, devices, among others) through cloud application architecture and how this has been transforming the industry and helping in the management of manufacturing operations.

Originality / Value: This research underscores the efficacy of a customized integration approach for leveraging existing technologies. While cloud-based Industrial Internet of Things (IIoT) solutions are readily available, this work transcends the limitations of off-the-shelf options by tailoring the architecture to the specific requirements of a real-world production line. This focus on customization enables the architecture to be adapted to a broad spectrum of legacy equipment and production lines across diverse industries, thereby unlocking the full potential of IIoT technologies. Consequently, this research demonstrates the replicability of the proposed methodology for various manufacturing scenarios.

Keywords: Connected Manufacturing; Intelligent Manufacturing; Cloud System; Performance Measurement; IIoT.

1 INTRODUCTION

The transition to industry 4.0 challenged mainly small and medium-sized manufacturing industries to innovate by implementing IIoT in their legacy system for online monitoring of processes and remote management of operations. (TEDESHI et al., 2018; CHIVILIKHIN et al., 2019). The advancement of technology through industry 4.0 has been gaining strength in recent years and many factories have not updated their industrial parks, keeping their legacy systems "Obsolete",

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the reason given is always the high value for investment in new technologies (LAI et al., 2019).

Thus, reengineering seems to be a promising approach to revamp the existing legacy system. Many industries have been applying improvements through reengineering because it is an economical and less risky process. Also focusing on reducing costs and risks associated with the evolution of the manufacturing system, offering an equalization between continued maintenance and the replacement of a legacy system (BATTAGLIA et al., 1998; WARREN; RANSOM, 2002). For Hossain (2023), conducting studies in developing nations are those that face the most restrictions, but see the most potential regarding Industry 4.0.

In recent decades, many research projects have been proposed for the development of remote systems for measuring online performance through IIoT devices (TEDESHI et al., 2019; GOVINDARAJAN et al., 2020). These applications take place through procedures based on industry 4.0 standards for digital transformation, focusing on the integration of legacy systems with IIoT (ORELLANA; TORRES, 2019). For this reason, digitization focuses on sensing and IIoT-based systems, allowing non-compliant legacy equipment to be used as the new industry 4.0 standards. (LIMA et al., 2019). These techniques are used for the integration of legacy equipment in the manufacturing industry, establishing the conditions for carrying out online monitoring through the collection of machine data with a focus on preventive maintenance, condition monitoring and machine availability for measuring the performance of legacy equipment in manufacturing system (AL-ALI et al., 2019; CHIVILIKHIN et al., 2019; GOVINDARAJAN et al., 2020).

It should be noted that, in addition to the development of devices, which can be controlled via a cloud system, it also allows remote access for data collection activities on any legacy equipment (BATISTA JUNIOR; OLIVEIRA, 2017; JÓNASDÓTTIR et al., 2018). Other solutions for modernization were created to update the cloud-based industrial park aimed at sharing and optimizing data through online monitoring, to meet the need for communication of the legacy system of small and medium industries with the IIoT (QURESHI et al., 2017; LIMA et al., 2019; MAMO et al., 2019; GOVINDARAJAN et al., 2020). The main objective of processing this data is to feed key performance indicators (KPIs) to align processes with the organization's strategy, providing insights for decision-making based on machine data to assist in building rapid real-time feedback on the performance of key processes at all levels of the plant (ORELLANA; TORRES, 2019).

In this context, a gap was observed since small and medium-sized industries have difficulties in using machine data to manage operations, due to their industrial park having low adoption of technologies made up of a legacy manufacturing system. Thus, the focus of study is the development and application of an architecture for measuring the performance of legacy equipment through its connection to the cloud. In this way, the research aims to interact intelligently between people, the machine and the cloud, focusing on providing the manufacturing manager with information on measuring the performance of the process relevant to the operation, such as: machine availability, Performance and quality, so that manufacturing management can act on production strategies and obtain better efficiency in the performance of manufacturing operations based on machine data through connection to the cloud.

2 LITERATURE REVIEW

The proposal created in Germany in 2011 for the economic development of the country with a focus on high-complexity technology has driven the transformation of the 4th industrial revolution known as “Industry 4.0” based on manufacturing and service innovation enabled by a cyber-physical production system (CPS) (ROJKO, 2017), which (BYRNE et al., 2016; CRNJAC BANDUKA, 2017) connect machines, sharing information autonomously, monitoring activities and controlling processes independently with productive gains, making industries more competitive.

These concepts led several countries to adopt initiatives focused on this transformation and created programs to update and modernize industrial manufacturing as a national competitiveness strategy. “Some of them are mentioned, such as: the “industrial Internet of Things (IIoT)” implemented by the US; “New Robert Strategy” by Japan; "The Industrial Value Chain Initiative," South Korea's program; “Made in China 2025” developed by China (SUN et al., 2017; LENZ et al., 2018). Among others, Brazil with the program “Towards Industry 4.0” (DALENOGARE et al., 2018).

All these initiatives focus on a common goal in the use of manufacturing data and machine tools (LENZ, 2018; DELANOGARE et al., 2018; SUN et al., 2017). The application of online monitoring in the manufacturing process brings insights, which can be accurately translated to allow improvements in the operation of the production stages (TAO et al., 2018). For Rymaszewska et al., (2017) smart, connected devices generate immense amounts of data, which can be transmitted through various business intelligence and analysis tools.

Technologies based on online monitoring transform manufacturing facilities into a proactive approach, being able to respond quickly without interruptions to ongoing operations (KAMBLE et al., 2020). Therefore, performance measurement becomes essential for all industries and fundamental for gaining competitiveness using performance measurement tools (SCHIRALDI; VARISCO, 2020). Industries must be equipped with technologies for measuring equipment performance, to identify gaps between planned and actual providing future actions, reducing 4M losses (raw material; labor; material; machine), (NWANYA et al., 2017; PUVANASVARAN, et al., 2020).

In recent years, measurements taken in manufacturing through OEE have gained important dimensions in industries by pointing out losses and improving production efficiency in the process (ABD RAHMAN, et al., 2020; ANUSHA; UMASANKAR, 2020). Some related research has been confirming the presence of solutions for measuring performance in the transition to Industry 4.0, such as: cost reduction, improvement in product quality, optimized Performance, online process monitoring, among others, which can be considered as the competitive benefits resulting from investments in an intelligent manufacturing system (KAMBLE[1] et al., 2020). Studies point out that for the implementation of a reliable system for measuring performance, factors such as the interconnectivity of intelligent manufacturing must be considered (ZARREH et al., 2019). Research carried out using IIoT has played an essential role, as work has addressed methodical models through an IIoT device for data acquisition capable of self-learning during machine operation time (Lopes Miranda Junior at al., 2017; TEDESCHI et al., 2017). The model exposed by Seiichi Nakajima in the 1980s, using production resources to improve the production system by measuring machine performance at Nippondenso, became one of the pillars of the Toyota Production System (TPS) (NAKAJIMA, 1989). OEE is an analytical method (YAZDI et al., 2018) used for measuring the performance of the equipment, focusing on evaluating the proportional measurement of the equipment in relation to its maximum capacity, emphasizing the monitoring of losses (DOMINGO; AGUADO, 2015; PUVANASVARAN et al., 2017; DURÁN et al., 2018). Characterized according to equipment (YAHYA, 2017). Metrics are calculated based on equipment performance indicators (NAKAJIMA, 1989; PRASAD; RADHAKRISHN, 2019). Nowadays, it has been the focus of several studies and applications by several authors, such as (RON; RODA, 2005; MUTHIAH et al., 2008; DJATNA; IHSAN, 2015; MASTANG; PAHMI, 2019; SCHIRALDI; VARISCO, 2020; HIDALGO MARTINS et al., 2020).

It is considered a quantitative and relevant metric to measure performance in manufacturing operations (Turanoglu Bekar et al., 2016). In addition to providing data, which allows managers to monitor equipment performance, it helps to identify opportunities to improve the process and product quality (PRASAD; RADHAKRISHN, 2019; PARK; HUR, 2020). A quick response, underlying production losses, in the process under analysis, in fact, provide insights into improvements in production processes, on where it is necessary to act to improve the productive performance of the equipment (MIRAGLIOTTA et al., 2018). Park: Hur (2020) points out that these losses need to be well defined, since the optimization for measuring performance through OEE occurs due to the reduction of anomalies such as losses due to stops, speed, quality, among others.

3 RESEARCH DESIGN

3.1. Contextualization and objectives of Design Science Research

The methodological approach by DSR presents as the fundamental principle, that the construction of knowledge is conceived in the construction in the conception of an artifact and in the contextualization of a specific cause (FREITAS JÚNIOR, 2015). Artifacts (Constructs, Models, Methods, and Instantiations) presented in TABLE 1 are items, which can be transformed into a material or artificial existence (MANSON, 2006; GREGOR; HEVNER 2013; CHATTERJEE, 2015). The artifacts provide the construction of knowledge and are used to design technology-based solutions (MARCH; SMITH, 1995; LACERDA et al., 2013). Allowing artifact evaluation, generating feedback to improve product quality and process design (HEVNER et al., 2004).

Table 1 - types of artifacts

Constructs	They explain the description of the specific causes of an artifact to detail the respective solutions. They are used to portray thinking about tasks, invaluable to designers and researchers.
Models	These are sets of arguments to clarify the links between constructs. In DSR, the "model" symbolizes situations of obstacles and solutions. This term must confine the structure of reality to be a useful representation.
Methods	They focus on steps followed to perform tasks based on a set of constructs and a model for solving a problem.

Instantiations	It materializes the artifact and prepares to precede the connections of constructs, models, and methods, demonstrating the feasibility and success of the artifacts.

Source: Adapted from Hevner et al., (2004) and Lacerda et al., (2013).

The structure of the (DSR) consists of seven guidelines presented in TABLE 2 and it is recommended that each of them be addressed, so that the research can be completed successfully (HEVNER et al., 2004; INAN; BEYDOUN, 2017). For Vaishnavi, Kuechler (2005) results can be produced in at least two ways: 1). The research construction of the project can be an experimental proof of the method or an experimental exploration of the method or both; two). Artifacts can expose the relationships between their components, that is, a new understanding has been produced.

Table 2 - dsr guideline

1 - Design as an artifact	The research must generate the production of a viable artifact.
2 - Relevance of the problem	Focuses on developing technological solutions to managerial inconveniences.
3 - Design evaluation	The purpose, characteristic and efficiency of the artifact must be presented by methods consisting of evaluations.
4 - Research contribution	The investigation must provide clear and auditable benefits in the artifact design zones.
5 - Rigor of research	It follows based on the application of precise methods both in the survey and in the qualification of the artifact.
6 - Design as a research process	The search for an effective artifact to the problem requires the use of available means to match the determined objective.
7 - Research communication	The investigation must be presented in a positive light to both audiences.

Source: Adapted from Hevner et al., (2004); Lacerda et al., (2013).

3.2 Design Science Research Application

The method applied by DSR is considered as a logical process, both theoretical and objective, that is, assessments are reviewed using abduction, deduction, and circumscription according to the evolution of the research. The DSR illustrated by FIGURE 1 details the fundamental processes (knowledge flow, stages of the DSR cycle and outputs) to achieve the objectives based on the authors' research (TAKEDA et al., 1990; VAISHNAVI; KUECHLER, 2005). Unfolding continuously, offering the opportunity for improvements throughout its entire process (FREITAS JÚNIOR et al., 2013).

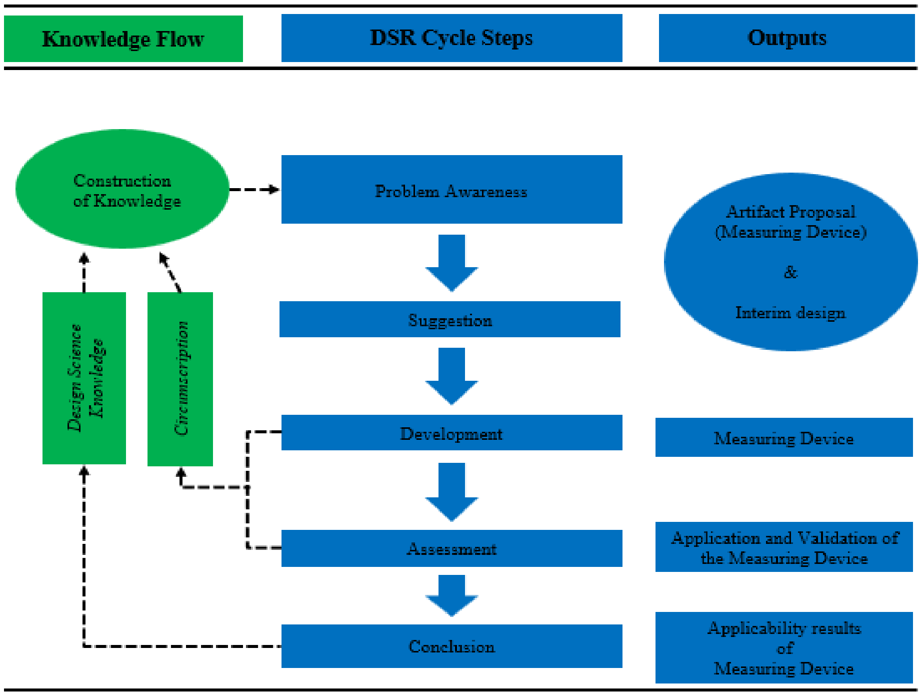


Figure 1 - Diagrama do fluxo de design science research
Source: Adapted from TAKEADA; VEERKAMP (1990); VAISHNAVI; KUECHLER (2005); MANSON (2006).

The construction of knowledge generated through the development and evaluation of the artifact guided by FIGURE 1 are labeled in the knowledge flow by Circumscription and Design Science Knowledge: Circumscription is a formal logical method applied to resolve the inconsistency found through abduction and deduction of positive reasoning (McCARTHY, 1980; TAKAEDA et al., 1990). Essential to understand the DSR process, which could be obtained only in the specific act of constructing the artifact (VAISHNAVI; KUECHLER, 2005; MANSON, 2006). Design science knowledge is the result of a research project and to understand how this form of knowledge can be expressed, it is necessary to understand the potential types of contributions of the DSR methodology. In the model, the stages of the DSR cycle are comprised of a cycle composed of five stages:

(1). Problem awareness: required from multiple sources of concepts, theories and relationships including new developments. The output is formal or informal construction of the initial construction of the investigation process to resolve a problem;

(2). Suggestion: Proposal of one or more design attempts contextualized in relation to the main concepts extracted from the knowledge bases to generate the problem resolution proposal. An essentially creative stage, whose abduction is used to expand the designer's thinking based on a new configuration of existing or new elements;

(3). Development: The solution is developed in this phase when the designer, through deductions, wants to obtain relevant information about the artifact, which is available for building the designer's knowledge. If something unresolved is found, it becomes a new problem, which must be resolved in a new development cycle;

(4). Assessment: The artifact must be evaluated in relation to the criteria implicit or explicitly contained in the proposal. The appreciation phase conceives an analytical subphase built by deductions and hypotheses about the performance of the artifact and any deviation must be tested experimentally.

(5). Conclusion: Conclusion indicates the end of a design science research cycle. In this phase, the creative cognitive processes of reflection and abstraction are used, which add values to the knowledge of design science.

For Vaishnavi; Kuechler (2005) results can be produced in at least two ways: 1) The design research construct can be an experimental proof of the method or an experimental exploration of the method or both: 2) Artifacts can expose the relationships between their components, that is, a new understanding was produced.

3.3. DSR in research

The research was conducted with a focus on the bread production line of the "Indústria de Alimentos" Group, which has been providing collective food services since the 60s. The Figure 2 application architecture presented a common objective of using machine data to assist manufacturing management by measuring the performance of legacy equipment through its connection to the cloud, being developed and evaluated as a means for a performance measurement solution. performance of legacy equipment, to be used as a reference in relation to the difficulties presented by small and medium-sized industries in using machine data to manage operations (KIBIRA, 2016; SYAFRUDIN, et al., 2017; GHOBAKHLOO, 2018; FATORACHIAN, KAZEMI, 2018; HIDALGO MARTINS et al., 2020a).

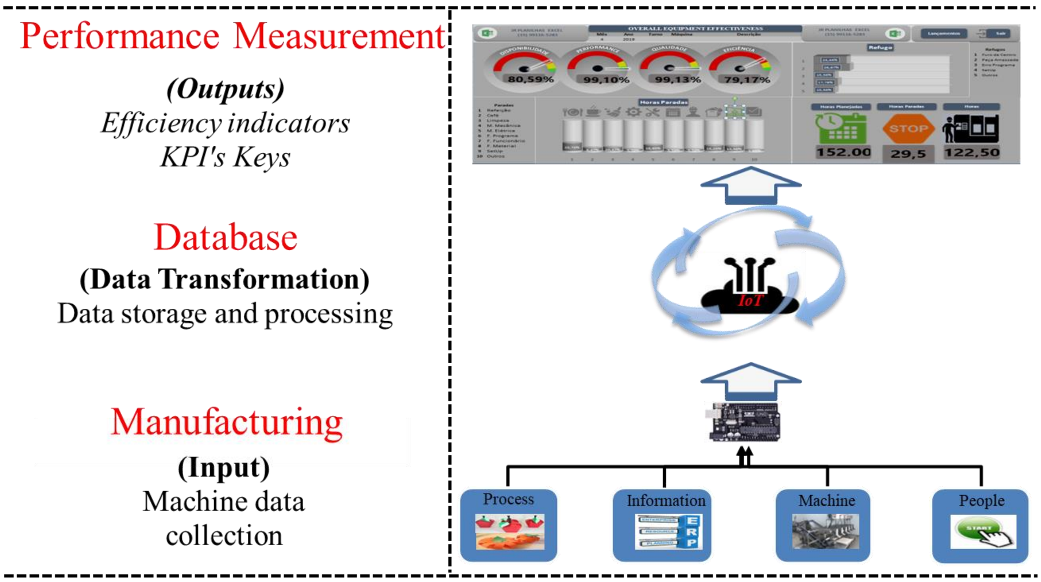


Figure 2 - Proposed application architecture
Source: author (2021).

Manufacturing (Inputs): Information on process operations can be collected through devices/sensors installed in machines/equipment, to provide more accurate information.

Analysis of analytical data (Data transformation): Data is collected by means of devices/sensors and sent to the cloud system, an application architecture composed of (hardware and software).

Performance measurement (Outputs): This information will be available to be monitored online/offline by the cloud system, with a focus on generating information to assist and contribute to decision-making in manufacturing management.

The research application flow Figure 3 presents the process contemplating the five phases of the DSR methodology flow, this time, helping the researcher in the construction of the artifact for the awareness of the problem, followed by the construction of the suggestion, development and evaluation of the proposal with its possible updates, ending with the conclusions through results generated in the research and assists the researcher in decision-making in the construction of artifacts to achieve pre-established objectives.

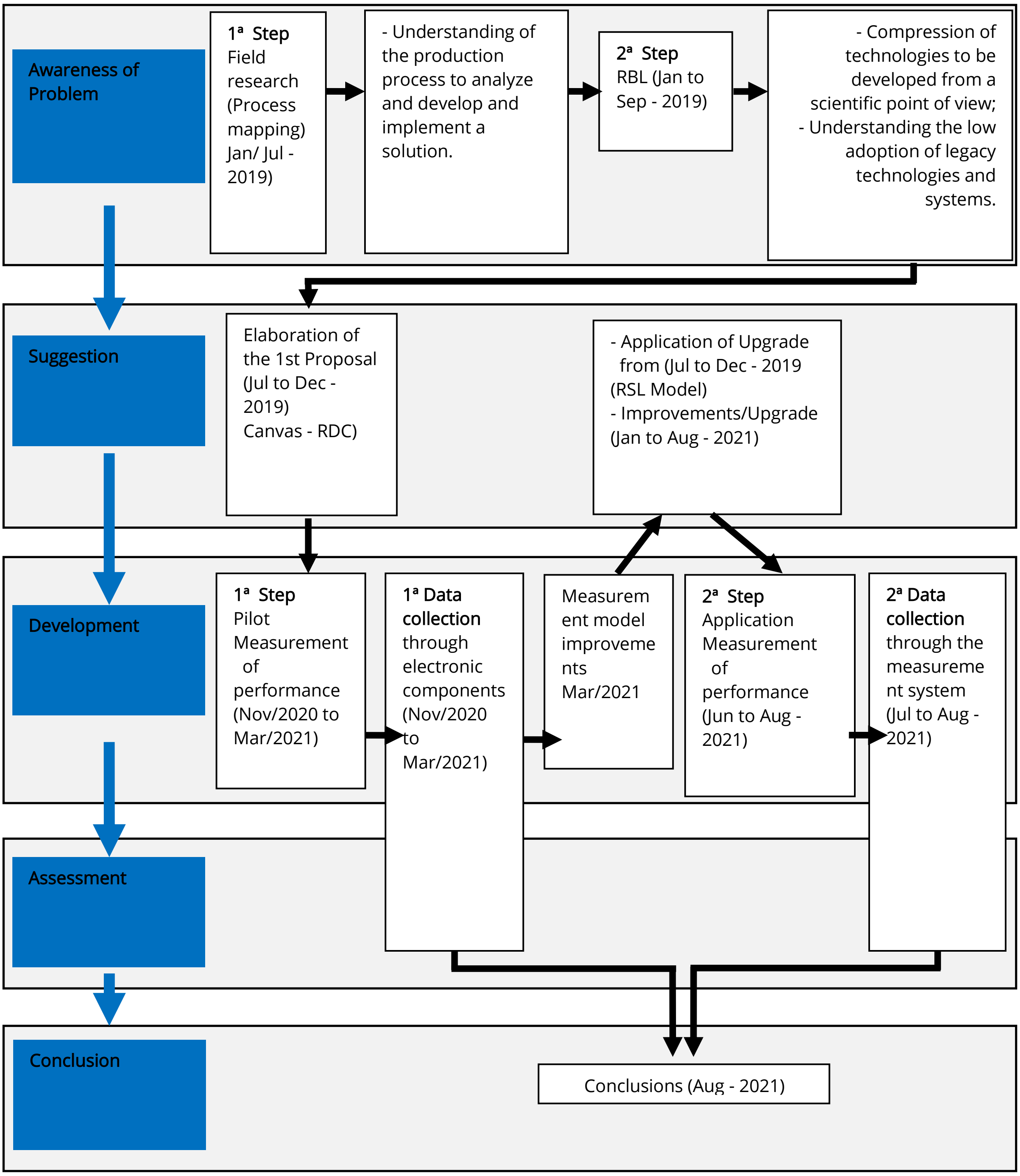


Figure 3 - research flow diagram
Source: elaborated by the author (2021).

Awareness of the problem: The understanding of the awareness of the problem related to the research theme, emerged through the approach of two researches: The first being an A3 titled as: "Optimization of the Pasta Production Line in the Collective Food Industry" published by (HIDALGO MARTINS et al., 2020) in the Journal of Lean systems Vol.5, nº3, p.138 (2020), points out as problematic, the low index of overall efficiency of the equipment (OEE) of 33%, when compared to the industrial average, with the index of OEE of Industries with world-class manufacturing with 85% and the research of literature review, and the second research, article titled: "Performance measurement based on data for machines: Systematic literature review", published by (HIDALGO MARTINS et al., 2020a), at the X International Congress of Production and Research (ICPR of the Americas) portraying the difficulties observed by small and medium industries in using machine data in manufacturing management and the proposed application architecture model. The surveys have in common the absence of tools for measuring performance, which directly affects production management in legacy manufacturing systems. For the authors Mello, (2015) apud Mcafee;

Brynjolfsson, (2012); Galdino, (2015) point out that it is impossible to manage if the process is not measured.

Suggestion: The construction of the suggestion for the development of alternative technologies, which could contribute to the measurement of performance, considered that, currently, there are already mature tools, algorithms, techniques and technologies for data analysis, which are used in other processes and justified based on the results of research published in the journal "Journal of Lean Systems" and in the congress "ICPR of the Americas", contributing to a potential application in problem solving through the research proposal. In this case, the suggestion focuses on contributing to the design of an application architecture for performance measurement for small and medium industries, which operate with a legacy manufacturing system and have difficulties in managing data to measure equipment efficiency.

Development: In this development phase, it considered the customization of the application architecture in a cloud platform and devices, already existing using a cellular internet mobile network (4G). The development was carried out in two phases: The first phase with the installation of the TR-IO flex module using a 50mA current measurement sensor, enabling the collection of data through electrical signals and transmitting them via 4G connection to a system in cloud. The second phase continued based on the circumscription stage in the construction of knowledge of the evaluation analyzes of the 1st phase with improvements applied to the project with a focus on the evolution of the count through image processing and customization of the dashboards (availability, Performance and quality), panels that show the indicators for measuring the performance of the operation, facilitating the understanding of the information generated in the process, are illustrated by Figure 5.

Assessment: The comparison made between the data collected by the measurement system and the manual collection was satisfactory, in terms of the accuracy of the information and for measuring the performance of the equipment. For more information, about the evaluations carried out on the measurement system.

Methodological conclusion: The methodological approach contributed to the generation of the flow of knowledge by applying the circumscription in the resolution of the inconsistencies found through the abduction and deduction of the reasoning in the stages of the flow cycle of the DSR (awareness of the problem, suggestions, development, evaluation and conclusions). Building knowledge and collaborating in the development of the artifact, motivated by the search for technologies to measure the performance of legacy equipment due to the low adoption of technologies by small and medium industries with difficulties in using machine data for manufacturing management in industry 4.0.

4 RESULTS AND DISCUSSIONS

4.1. Performance measurement system

For the application of this technological project in a real manufacturing scenario, a low-cost technology-based solution was developed, consisting of a microcomputer board (Raspberry) connecting sensors for machine data collection via a 4G gateway device without the need for a local internet, illustrated by Figure 4 and the generic interface for data transmission via the cloud Figure 5.

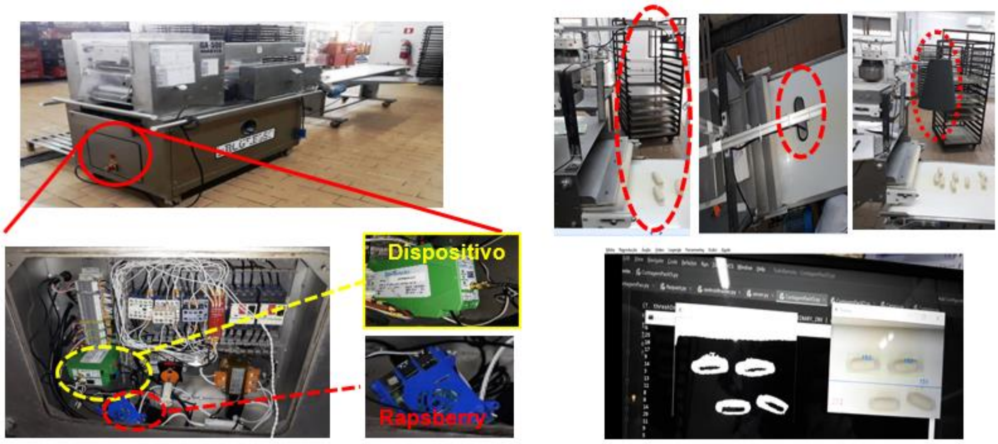


Figure 4 - Measurement system infrastructure
Source: elaborated by the author (2021).

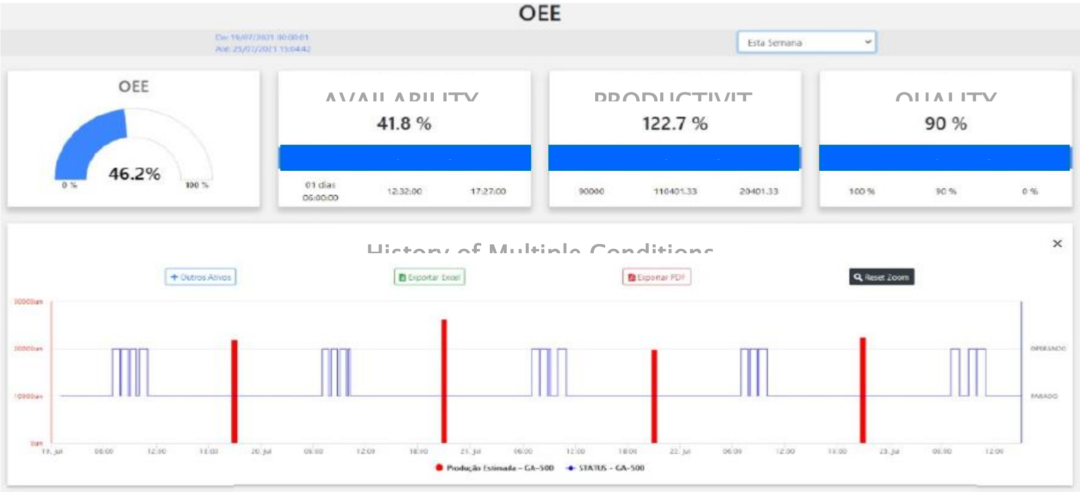


Figure 5 - interface for measurement system
Source: elaborated by the author (2021).

4.2 Application result in a real manufacturing scenario

This item presents the results obtained from the application of the performance measurement system in a real bread production manufacturing scenario, by collecting data from the equipment with a focus on generating information through its connection to the cloud. For this analysis, the data were stratified from the measurement system into Excel spreadsheets and the results will be shown below using the OEE analytical method as a basis for calculation.

4.3 Result of the application for the Availability rate

As mentioned, the availability rate Formula (1) and (2) is the ratio between the time planned for the operation of the equipment in relation to the time consumed in the operation.

Available time = (TT – SS) (1)

Availability = ((AT – US) / AT) x100 (2)

SS = Scheduled Stops
AT = Available time
US = Unscheduled Stops

Contextualizing, the Total Time (TT) planned for the availability of the equipment was 02h00min, for the measurement period no Scheduled Stop was planned (SS). The data for the purposes of verifying the availability rate are shown in the TABLE 1, Availability Times being determined (AT) equipment based on downtime (US). In this measurement, it is possible to see that the equipment was out of operation (US) on average 00h56min, that is, in this period, the machine was stopped in (48%) of the available time (AT).

Table 1 - Data for availability measurement

Date	Start Shift	Start Operation	End Plan	Time Available (at)	Hours Stops (us)	Hours Stops %	Hours Worked	Avai (%)
18- aug	6:00	6:52	8:00	2:00	0:57	48%	1:03	52%
19- aug	6:00	6:32	8:00	2:00	0:47	48%	1:13	61%
20- aug	6:00	6:31	8:00	2:00	0:36	48%	1:24	66%
23-aug	6:00	6:45	8:00	2:00	1:02	48%	0:58	48%
25-aug	6:00	6:48	8:00	2:00	1:01	48%	0:59	49%
26-aug	6:00	6:56	8:00	2:00	1:05	48%	0:55	46%
27-aug	6:00	6:50	8:00	2:00	1:05	48%	0:55	46%

Average		6:45		2:00	0:56	48%	1:03	52%

Source: author (2021).

In this scenario, the equipment reached an average of 52% in the availability index. Considering the graphic reference indication scale as red (Bad), yellow (Good) and green (Excellent), the availability of 52% is classified as a good index, but requires attention with opportunities for improvement, seen in this measured scenario, waste with equipment availability times, consists of a low performance.

4.4. Result of the application for the Performance rate

This metric makes a comparison between the production carried out by the planned production, that is, it is the proportion of the total production in relation to what should be produced Formula (3).

$$\textbf{Performance} = (PP / PPlan) \times 100 \tag{3}$$

PP = Production Performed
PPlan = Planned Production

The first step in measuring Performance was to measure the average hourly production performed on the production line, according to TABLE 2, the Performance measured in the period from 7:00 am to 8:00 am produced an average of 8,604 units/hour. For later calculation purposes, this average of 8,604 loaves of bread was rounded to 9,000 units per hour.

Table 2 - Average hour production

Date	Hours	Amount
18-aug	7-8	9.576
19-aug	7-8	8.856
20-aug	7-8	8.856
23-aug	7-8	8.496
25-aug	7-8	9.360
26-aug	7-8	8.352
27-aug	7-8	9240
Average		8.604

Source: Autor (2021).

The second step was to work with the Planned Production (PPlan), according to TABLE 3, the planned production (PPlan) follows based on the available time (two hours) multiplied by the determined average production of (9,000 units/hour), that is, for this production, the planned quantity will be 18,000 units of bread. The third step is to measure the amount of Accomplished Production (PR), for the construction of the Performance metric between accomplished (PR) versus planned (PPlan). The Performance measurement data shown in TABLE 3, makes the relationship between the average production carried out between the periods of August 18th to 27th, in the period of two hours, with the planned production of 18,000 loaves of bread for the period.

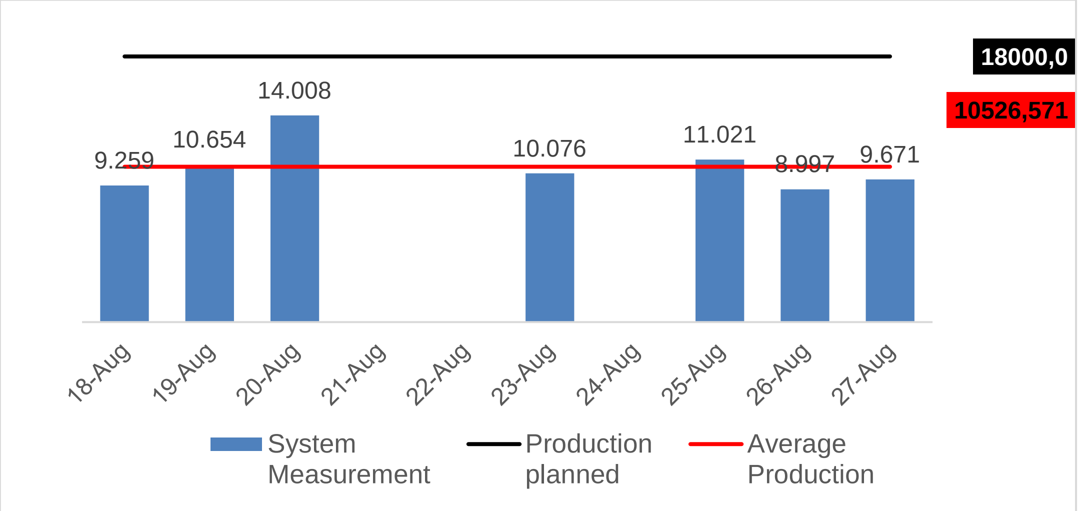
Table 3 - Data for performance measurement

Date	Time Planned	Production Planned (PPlan)	Production Performed (PP)	Average Production	Performance (%)
18-aug	02:00	18.000	9259	10.527	51%
19-aug	02:00	18.000	10654	10.527	59%
20-aug	02:00	18.000	14008	10.527	78%
23-aug	02:00	18.000	10076	10.527	56%
25-aug	02:00	18.000	11021	10.527	61%
26-aug	02:00	18.000	8997	10.527	50%
27-aug	02:00	18.000	9671	10.527	54%
Average	02:00	18.000	10.527		58%

Source: author (2021).

The data illustrated by Chart 1, the daily production measured by the application architecture reached an average of 10,527 units of bread produced in the period. A Performance of 42% below the plan.

Chart 1 - Planned versus realized performance



Source: author (2021).

In this context, in which the Actual Production data of 10,527 units of bread produced are compared with the 18,000 units of bread that were planned for the period, the results reached 58% of this Performance. The 58% performance index, considering indication scale with red (Bad), yellow (Good) and green (Excellent), fits in a scale of a good indicator, but opens the way for opportunity for improvements to increase Performance in the production line.

4.5. Result of the application for the Quality rate

The Quality Indicator (4) was worked through a constant of 90% derived from a survey and published through a case entitled: "Optimization of the Pasta Production Line in the Collective Food Industry" published by (HIDALGO MARTINS et al., 2020), which indicated an average of 9% of losses with rework activities and 1% with scrap.

Quality = ((NPP – NPR) / NPP) x 100 (4)

NPP = Nº Processed Products
NPR = Nº Rejected Products

4.6. Application result for the OEE index

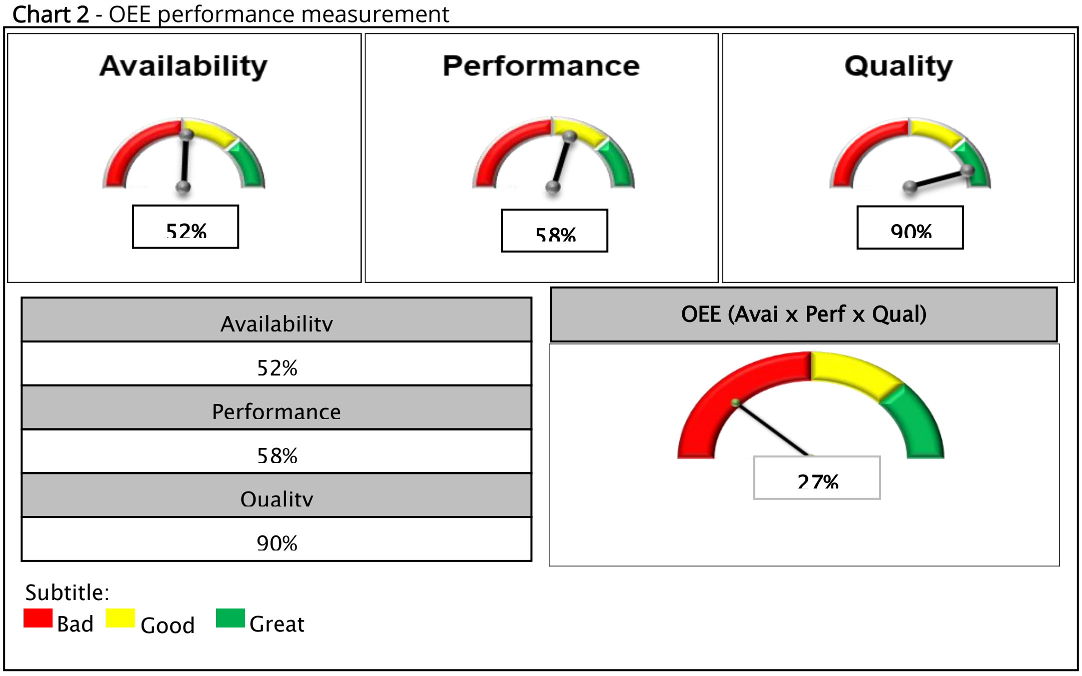
The measurement of OEE performance addressed in the research by Formula (5), is about the combinations of the three metrics (availability x Performance x quality). The OEE index considered ideal by industries with world-class manufacturing is 85% (DJATNA; IHSAN, 2015; MIRAGLIOTTA et al., 2018; CHEN, 2020).

OEE = (Availability x Performance x Quality) (5)

Chart 2 reveals that equipment was only operational for 52% of the total available machine time, resulting in 48% downtime. This directly impacts performance, as higher availability leads to greater production output. Consequently, of the planned 18,000 bread units, only 10,527 (58%) were produced. The remaining 7,473 units (42%) were not completed due to process deviations.

For the quality metric, based on previous surveys indicating a rework/reprocessing rate of around 10%, we assumed a constant value of 90% for this initial analysis. This is because the system only counts compliant products, with non-compliant ones being addressed as detailed in section 4.2.3.

Chart 2 - OEE performance measurement



Source: author (2021).

5 CONCLUSIONS

Research on the topic of performance measurement for legacy equipment has shown its importance and contribution to understanding changes, especially for small and medium-sized manufacturing industries with low adoption of technologies in the transition to industry 4.0 and the challenges of innovation and implementation of IIoT in your manufacturing system. For these reasons, the search for alternative technologies for measuring performance for legacy equipment contributed to the design for the development and application of an architecture for measuring the performance of legacy equipment through its connection to the cloud, using hardware and existing software, with a focus on providing the inclusion of small and medium-sized industries in digital transformation to take advantage of the benefits of IIoT in Industry 4.0 connectivity.

The methodological approach contributed to the generation of the flow of knowledge by applying the circumscription in the resolution of the inconsistencies found through the abduction and deduction of the reasoning in the steps of the flow cycle of the DSR, building the knowledge and collaborating in the development of the artifact, motivated by the search for technologies to performance measurement of legacy equipment due to the low adoption of technologies by small and medium industries with difficulties in using machine data for manufacturing management in industry 4.0.

The responses to the measurements carried out by the architecture applied in a real manufacturing system obtained the following results, considering that the OEE methodology was used for this measurement using the three metrics, Availability, Performance and Quality. The measured availability of the equipment was 52%, that is, 48% of the time the equipment was stopped without production and without any corrective maintenance intervention. In this context, the performance index was also impacted in relation to the planned volume reaching 58% of its capacity and the quality metric was measured at 90%. Overall, OEE presented an index of 27%, a result below expectations, considered a low index when compared to 85%, a reference for industries with world-class manufacturing (WCM).

Other important results measured and fundamental to the contribution of research to industry are linked to opportunities for improvements to be applied by managers in the manufacturing sector, of the industry subject to research. The measurements considered losses for a working day with two 8-hour shifts. performance showed the biggest loss with 42%, where, out of the planned production of 18,000 units, only 10,527 units of bread were produced. Availability lost 7.7 hours without corrective stops, that is, the approximate loss of a production shift. Another fact is the loss of 10% in quality, in which 1,345 units needed to be reworked.

Therefore, it is believed that the pre-established objectives for this research were achieved through the results obtained by the development and application of the measurement system in a real manufacturing scenario. It is also worth mentioning that the “artifact” can contribute other process information through the data presented, helping manufacturing management to develop work aimed at reducing waste with labor, material, machine and method. Although the development of this research through the application architecture has been limited to performance measurement for bread production lines, it is recommended for future research that, by implementing the above recommendations, the proposed performance measurement model has the potential to become an even more powerful and versatile model. tool to optimize industrial performance in various sectors, mainly small and medium-sized companies. The ability to adapt to different environments, monitor different types of machines, validate in multiple production areas and have an improved and secure measurement system allows the tool to help companies make more effective strategic decisions, increasing productivity, quality and market competitiveness.

For such implementations, modular and flexible approaches must be adopted to make the architecture more adaptable to different types of legacy equipment, reducing the need for significant modifications to each piece of equipment and facilitating its integration into Industry 4.0, contributing to the optimization of production. and more assertive decision-making by small and medium-sized industries. Incorporating advanced technical analytics, such as machine learning and predictive maintenance, into application architecture to measure legacy equipment performance leads to deeper, richer analysis of performance data, enabling significant optimizations in manufacturing management. Standardization of performance measurement protocols and data formats is crucial for the integration of legacy equipment in Industry 4.0. This integration is essential to achieve modern, connected manufacturing, enabling efficient communication between heterogeneous devices, the exchange of relevant information and process optimization. Developing easy-to-use interfaces with intuitive visualizations and actionable alerts is essential to creating systems that are efficient, effective, and enjoyable to use. By following the principles and practices described in this document, it is possible to create interfaces that meet users' needs and contribute to the success of the system.

These approaches contribute to reducing implementation costs, increasing equipment availability, improving product quality and extending the useful life of legacy equipment, boosting the competitiveness of small and medium-sized industries in Industry 4.0.

REFERENCES

Abd Rahman, M.S., Mohamad, E. and Abdul Rahman, A.A. (2020), "Enhancement of overall equipment effectiveness (OEE) data by using simulation as decision making tools for line balancing", Indonesian Journal of Electrical Engineering and Computer Science, Vol. 18 No. 2, pp. 1040–1047. https://doi.org/10.11591/ijeecs.v18.i2.pp1040-1047.

Anusha, C. and Umasankar, V. (2020), "Performance prediction through OEE-model", International Journal of Industrial Engineering and Management, Vol. 11 No. 2, pp. 93–103. https://doi.org/10.24867/IJIEM-2020-2-256.

Ardolino, M., Rapaccini, M., Saccani, N., Gaiardelli, P., Crespi, G. and Ruggeri, C. (2018), "The role of digital technologies for the service transformation of industrial companies", International Journal of Production Research, Vol. 56 No. 6, pp. 2116–2132. https://doi.org/10.1080/00207543.2017.1324224.

Batista Jr, P.A. and Oliveira, S.C. (2017), "Node indústria 4.0: integrando sistemas legados à indústria 4.0", Revista de Engenharia e Pesquisa Aplicada, Vol. 2 No. 4, pp. 30–37. https://doi.org/10.25286/repa.v2i4.586.

Byrne, G., Ahearne, E., Cotterell, M., Mullany, B., O'Donnell, G.E. and Sammler, F. (2016), "High Performance Cutting (HPC) in the New Era of Digital Manufacturing - A Roadmap", Procedia CIRP, Vol. 46, pp. 1–6. https://doi.org/10.1016/j.procir.2016.05.038.

Chatterjee, S. (2015), "Writing my next design science research masterpiece: But how do I make a theoretical contribution to DSR?", 23rd European Conference on Information Systems, ECIS 2015, pp. 0–14. https://doi.org/10.18151/7217289.

Chen, X. and Voigt, T. (2020), "Implementation of the Manufacturing Execution System in the food and beverage industry", Journal of Food Engineering, Vol. 278, p. 109932. https://doi.org/10.1016/j.jfoodeng.2020.109932.

Chivilikhin, D., Patil, S., Cordonnier, A. and Vyatkin, V. (2019), "Towards automatic state machine reconstruction from legacy PLC using data collection", IEEE International Conference on Industrial Informatics (INDIN), pp. 147–151. https://doi.org/10.1109/INDIN41052.2019.8972143.

Crnjac, M. and Banduka, N. (2017), "From Concept to the Introduction of Industry 4.0", International Journal of Industrial Engineering and Management (IJIEM), Vol. 8 No. 1, pp. 21–30.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F. and Frank, A.G. (2018), "The expected contribution of Industry 4.0 technologies for industrial performance", International Journal of Production Economics, Vol. 204, pp. 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019.

Djatna, T. and Ihsan, M.R. (2015), "A Fuzzy Associative Memory Modeling for Production Equipment Status Assessment", Procedia Manufacturing, Vol. 4, pp. 163–167. https://doi.org/10.1016/j.promfg.2015.11.027.

Domingo, R. and Aguado, S. (2015), "Overall environmental equipment effectiveness as a metric of a lean and green manufacturing system", Sustainability (Switzerland), Vol. 7 No. 7, pp. 9031–9047. https://doi.org/10.3390/su7079031.

Durán, O., Capaldo, A. and S, P.A.D. (2018), "Sustainable overall throughput ability effectiveness (S.O.T.E.) as a metric for production systems", Sustainability (Switzerland), Vol. 10 No. 2. https://doi.org/10.3390/su10020362.

Fatorachian, H. and Kazemi, H. (2018), "A critical investigation of Industry 4.0 in manufacturing: theoretical operationalisation framework", Production Planning and Control, Vol. 29 No. 8, pp. 633–644. https://doi.org/10.1080/09537287.2018.1424960.

Freitas Júnior, C.J., Machado, L., Klein, A.Z. and Freita, A.S. de. (2015), "Desing Research: Aplicações práticas e lições aprendidas", Revista de Administração FACES Journal Belo Horizonte, Vol. 14 No. 1, pp. 95–116.

Ghobakhloo, M. (2018), "The future of manufacturing industry: a strategic roadmap toward Industry 4.0", Journal of Manufacturing Technology Management, Vol. 29 No. 6, pp. 910–936. https://doi.org/10.1108/JMTM-02-2018-0057.

Govindarajan, N., Ferrer, B.R., Xu, X., Nieto, A. and Lastra, J.L.M. (2016), "An approach for integrating legacy systems in the manufacturing industry", IEEE International Conference on Industrial Informatics (INDIN), pp. 683–688. https://doi.org/10.1109/INDIN.2016.7819247.

Gregor, S. and Hevner, A.R. (2013), "Positioning and presenting design science research for maximum impact", MIS Quarterly, Vol. 37 No. 2, pp. 337–355. https://doi.org/10.25300/MISQ/2013/37.2.01.

Hadi, M.S., Lawey, A.Q., El-Gorashi, T.E.H. and Elmirghani, J.M.H. (2018), "Big data analytics for wireless and wired network design: A survey", Computer Networks, Vol. 132, pp. 180–199. https://doi.org/10.1016/j.comnet.2018.01.016.

Hevner, A.R. (2007), "A three cycle view of design science research: A three cycle view of design science research", Scandinavian Journal of Information Systems, Vol. 19 No. 2, pp. 87–92. Available at: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.218.5386 [Accessed 01 Dec. 2021].

Hevner, A.R., March, S.T., Park, J., Lee, A.S. and Ram, S. (2004), "Design science in information systems research", MIS Quarterly, Vol. 28 No. 1, pp. 75–105. Available at: https://www.researchgate.net/publication/201168946_Design_Science_in_Information_Systems_Research [Accessed 01 Dec. 2021].

Hidalgo Martins, G., Detro, S.P., Valle, P.D. and Deschamps, F. (2020a), "Medição de desempenho baseado em dados para máquinas: Revisão sistemática de literatura", in Ediuns (Ed.), X ICPR das Américas, Bahía Blanca, pp. 875–889. Available at: https://www.matematica.uns.edu.ar/ipcra/pdf/icpr_americas_2020_proceedings.pdf [Accessed 01 Mar. 2021].

Hidalgo Martins, G., Tulio, C.D., Pereira, A. and Deschamps, F. (2020), "Optimization of the Pasta production line in the 'Collective Food Industry'", Journal of Lean Systems, Vol. 5, p. 138. Available at: https://leansystem.ufsc.br/index.php/lean/article/view/3665 [Accessed 01 Mar. 2021].

Hossain, S., Hassan, S. and Karim, R. (2023), "Assessment of critical barriers to Industry 4.0 adoption in manufacturing industries of Bangladesh: An ISM-based study", Brazilian Journal of

Operations and Production Management, Vol. 20 No. 3 Special Edition, e20231797. https://doi.org/10.14488/BJOPM.1797.2023.

Inan, D.I. and Beydoun, G. (2017), "Disaster knowledge management analysis framework utilizing agent-based models: Design science research approach", Procedia Computer Science, Vol. 124, pp. 116–124. https://doi.org/10.1016/j.procs.2017.12.137.

Jónasdóttir, H., Dhanani, K., McRae, K. and Mehnen, J. (2018), "Upgrading legacy equipment to Industry 4.0 through a cyber-physical interface", IFIP Advances in Information and Communication Technology, Vol. 536, pp. 3–10. https://doi.org/10.1007/978-3-319-99707-0_1.

Lopes Miranda Junior, H., Albuquerque Bezerra, N.R., Soares Bezerra, M.J. and Rodrigues Farias Filho, J. (2017), "The internet of things sensors technologies and their applications for complex engineering projects: a digital construction site framework", Brazilian Journal of Operations & Production Management, Vol. 14 No. 4, pp. 567–576. https://doi.org/10.14488/BJOPM.2017.v14.n4.a12.

Kamble, S., Gunasekaran, A. and Dhone, N.C. (2019), "Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies", International Journal of Production Research, Vol. 0 No. 0, pp. 1–19. https://doi.org/10.1080/00207543.2019.1630772.

Kamble[1], S.S., Gunasekaran, A., Ghadge, A. and Raut, R. (2020), "A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs - A review and empirical investigation", International Journal of Production Economics, Vol. 229, p. 107853. https://doi.org/10.1016/j.ijpe.2020.107853.

Kibira, D., Morris, K. and Kumaraguru, S. (2016), "Methods and tools for performance assurance of smart manufacturing systems", Journal of Research of the National Institute of Standards and Technology, Vol. 121, p. 287. https://doi.org/10.6028/jres.121.013.

Lacerda, D.P., Dresch, A., Proença, A. and Antunes Júnior, J.A.V. (2013), "Design Science Research: Método de pesquisa para a engenharia de produção", Gestao e Producao, Vol. 20 No. 4, pp. 741–761. https://doi.org/10.1590/S0104-530X2013005000014.

Lenz, J., Wuest, T. and Westkämper, E. (2018), "Holistic approach to machine tool data analytics", Journal of Manufacturing Systems, Vol. 48, pp. 180–191. https://doi.org/10.1016/j.jmsy.2018.03.003.

Lima, F., Massote, A.A. and Maia, R.F. (2019), "IoT energy retrofit and the connection of legacy machines inside the Industry 4.0 concept", IECON Proceedings (Industrial Electronics Conference), 2019-Octob, pp. 5499–5504. https://doi.org/10.1109/IECON.2019.8927799.

Mamo, F.T., Sikora, A. and Rathfelder, C. (2017), "Legacy to Industry 4.0: A Profibus Sniffer", Journal of Physics: Conference Series, Vol. 870 No. 1, pp. 0–6. https://doi.org/10.1088/1742-6596/870/1/012002.

Manson, N.J. (2006), "Is operations research really research?", Journal of the Operations Research Society of South Africa (ORSSA), Vol. 22 No. 2, pp. 155–180.

March, S.T. and Smith, G.F. (1995), "Design and natural science research on information technology", Decision Support Systems, Vol. 15 No. 1, pp. 251–266.

Mastang and Pahmi, M.A. (2020), "Development of Raspberry Pi applied to real-time monitoring of overall equipment effectiveness (OEE)", Journal of Physics: Conference Series, Vol. 1477 No. 5. https://doi.org/10.1088/1742-6596/1477/5/052013.

Miragliotta, G., Sianesi, A., Convertini, E. and Distante, R. (2018), "Data driven management in Industry 4.0: A method to measure data performance", IFAC-PapersOnLine, Vol. 51 No. 11, pp. 19–24. https://doi.org/10.1016/j.ifacol.2018.08.228.

Muthiah, K.M.N. and Huang, S.H. (2008), "Automating factory performance diagnostics using overall throughput effectiveness (OTE) metric", International Journal of Advanced Manufacturing Technology, pp. 811–824. https://doi.org/10.1007/s00170-006-0891-x.

Nakajima, S. (1989), Introdução ao TPM Total Productive Maintenance, 1st ed., IMC, São Paulo.

Niebel, T., Rasel, F. and Viete, S. (2019), "Big data–big gains? Understanding the link between big data analytics and innovation", Economics of Innovation and New Technology, Vol. 28 No. 3, pp. 296–316. https://doi.org/10.1080/10438599.2018.1493075.

Nwanya, S.C., Udofia, J.I. and Ajayi, O.O. (2017), "Optimization of machine downtime in the plastic manufacturing", Cogent Engineering, Vol. 4 No. 1. https://doi.org/10.1080/23311916.2017.1335444.

Orellana, F. and Torres, R. (2019), "From legacy-based factories to smart factories level 2 according to the industry 4.0", International Journal of Computer Integrated Manufacturing, Vol. 32 Nos. 4–5, pp. 441–451.

Park, Y.J. and Hur, S. (2020), "Improvement of performance through the reduction of unexpected equipment faults in die attach equipment", Processes, Vol. 8 No. 4. https://doi.org/10.3390/PR8040394.

Popovic, A., Hackney, R., Tassabehji, R. and Castelli, M. (2018), "The impact of big data analytics on firms' high value business performance", Information Systems Frontiers, Vol. 20 No. 2, pp. 209–222. https://doi.org/10.1007/s10796-016-9720-4.

Prasad, N.V.P.R.D. and Radhakrishna, C. (2019), "Key performance index for overall substation performance", International Journal of Recent Technology and Engineering, Vol. 8 No. 2, pp. 6067–6071. https://doi.org/10.35940/ijrte.B3797.078219.

Puvanasvaran, P., Teoh, Y.S. and Ito, T. (2020), "Novel availability and performance ratio for internal transportation and manufacturing processes in job shop company", Journal of Industrial Engineering and Management, Vol. 13 No. 1, pp. 1–17. https://doi.org/10.3926/jiem.2755.

Qureshi, K.A., Mohammed, W.M., Ferrer, B.R., Lastra, J.L.M. and Agostinho, C. (2017), "Legacy systems interactions with the supply chain through the C2NET cloud-based platform", Proceedings - 2017 IEEE 15th International Conference on Industrial Informatics, INDIN 2017, pp. 725–731. https://doi.org/10.1109/INDIN.2017.8104862.

Rojko, A. (2017), "Industry 4.0 concept: Background and overview", International Journal of Interactive Mobile Technologies (IJIM), Vol. 11 No. 5, pp. 77–90. https://doi.org/10.3991/ijim.v11i5.7072.

Ron, A.J. de and Rooda, J.E. (2005), "Equipment effectiveness: OEE revisited", IEEE, Vol. 18 No. 1, pp. 190–196. https://doi.org/10.1109/TSM.2004.836657.

Rymaszewska, A., Helo, P. and Gunasekaran, A. (2017), "IoT powered servitization of manufacturing – an exploratory case study", International Journal of Production Economics, Vol. 192, pp. 92–105. https://doi.org/10.1016/j.ijpe.2017.02.016.

Schiraldi, M.M. and Varisco, M. (2020), "Overall equipment effectiveness: consistency of ISO standard with literature", Computers and Industrial Engineering, Vol. 145, p. 106518. https://doi.org/10.1016/j.cie.2020.106518.

Sun, B., Jämsä-Jounela, S.L., Todorov, Y., Olivier, L.E. and Craig, I.K. (2017), "Perspective for equipment automation in process industries", IFAC-Papers Online, Vol. 50 No. 2, pp. 65–70. https://doi.org/10.1016/j.ifacol.2017.12.012.

Syafrudin, M., Fitriyani, N.L., Li, D., Alfian, G., Rhee, J. and Kang, Y.S. (2017), "An open source-based real-time data processing architecture framework for manufacturing sustainability", Sustainability, Vol. 9 No. 11. https://doi.org/10.3390/su9112139.

Tao, F., Qi, Q., Liu, A. and Kusiak, A. (2018), "Data-driven smart manufacturing", Journal of Manufacturing Systems, Vol. 48, pp. 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006.

Tedeschi, S., Rodrigues, D., Emmanouilidis, C., Erkoyuncu, J., Roy, R. and Starr, A. (2018), "A cost estimation approach for IoT modular architectures implementation in legacy systems", Procedia Manufacturing, Vol. 19, pp. 103–110. https://doi.org/10.1016/j.promfg.2018.01.015.

Turanoglu Bekar, E., Cakmakci, M. and Kahraman, C. (2016), "Fuzzy COPRAS method for performance measurement in total productive maintenance: a comparative analysis", Journal of Business Economics and Management, Vol. 17 No. 5, pp. 663–684.

https://doi.org/10.3846/16111699.2016.1202314.

Vaishnavi, V., Kuechler, W. and Petter, S. (2005), "Design science research in information systems", MIS Quarterly, Vol. 28 No. 1, pp. 75–105. Available at: http://www.desrist.org/design-research-in-information-systems/ [Accessed 01 Dec. 2020].

Wang, J., Ma, Y., Zhang, L., Gao, R.X. and Wu, D. (2018), "Deep learning for smart manufacturing: Methods and applications", Journal of Manufacturing Systems, Vol. 48, pp. 144–156. https://doi.org/10.1016/j.jmsy.2018.01.003.

Woo, J., Shin, S.J., Seo, W. and Meilanitasari, P. (2018), "Developing a big data analytics platform for manufacturing systems: architecture, method, and implementation", International Journal of Advanced Manufacturing Technology, Vol. 99 Nos. 9–12, pp. 2193–2217. https://doi.org/10.1007/s00170-018-2416-9.

Yadegaridehkordi, E., Hourmand, M., Nilashi, M., Shuib, L., Ahani, A. and Ibrahim, O. (2018), "Influence of big data adoption on manufacturing companies' performance: An integrated DEMATEL-ANFIS approach", Technological Forecasting and Social Change, Vol. 137, pp. 199–210. https://doi.org/10.1016/j.techfore.2018.07.043.

Yahya, B.N. (2017), "Overall bike effectiveness as a sustainability metric for bike sharing systems", Sustainability (Switzerland), Vol. 9 No. 11. https://doi.org/10.3390/su9112070.

Yang, H., Kumara, S., Bukkapatnam, S.T.S. and Tsung, F. (2019), "The internet of things for smart manufacturing: A review", IISE Transactions, Vol. 51 No. 11, pp. 1190–1216. https://doi.org/10.1080/24725854.2018.1555383.

Zarreh, A., Wan, H., Lee, Y., Saygin, C. and Janahi, R.A. (2019), "Cybersecurity concerns for total productive maintenance in smart manufacturing systems", Procedia Manufacturing, Vol. 38, pp. 532–539. https://doi.org/10.1016/j.promfg.2020.01.067.

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