International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2018): 7.426

Health 4.0: Prediction of Machine Break in Diagnostic Medicine

Tatiana Mallet Machado[1], Francisco Ignácio Giocondo César[2], Ieda Kanashiro Makiya[3]

[1]Campinas State University (UNICAMP), Faculty of Applied Sciences, R. Pedro Zaccaria, 1300, CEP 13484-350, Limeira – SP – Brazil

[2]Federal Institute of Education, Science and Technology of São Paulo (IFSP), Faculty of Mechanics, R. Diácono Jair de Oliveira, 1005, CEP 13414-155, Piracicaba – SP – Brazil

[3]Campinas State University (UNICAMP), Faculty of Applied Sciences, R. Pedro Zaccaria, 1300, green block, 2A, room 3, CEP 13484-350, Limeira – SP – Brazil

Abstract: ***Machine break in the image diagnostic medicine area for magnetic resonance, tomography, mammography and others lead to significant loss of revenue and customer satisfaction. Thus, the proper prediction or correlation between variables can create preventive or corrective measures before this kind of event happens. The objective of this article is to show the correlation between call openings parameters, machine break and your behavior that preceded a break for the purpose of making a reduction in machine downtime leading to revenue loss at health companies, that attends the Brazilian public and private sector. In other words, to develop a predictive maintenance methodology (based on changes in system behavior) to anticipate the failure. From an exploratory literature search and a case study made by a technology and process company in three health companies (one that attends the public sector and two the private sector), it will be started the study of existing correlations and monitoring to feed future studies and new technologies implementation aiming the deploy of a predictive maintenance system.***

Keywords: Diagnostic medicine, Image diagnostic medicine, Monitoring equipment, Predictive maintenance, Industry 4.0

1. Introduction

Currently, diagnosis, originating from the Greek term "gnosis" meaning knowledge, is the process of identifying the nature of a disease or disorder from symptoms, signs, and results of laboratory and imaging tests. This type of fast and more accurate diagnosis has only been possible through various technological advances since the 19th century, being the x-ray discovered in 1895 by the German Wilhelm Conrad Roentgen, considered to be the largest modern laboratory and imaging tool [27].

For an initial diagnosis to be made, it is necessary to go to a doctor, present the symptoms and signs and be examined. From this first contact, the doctor will order laboratory and imaging tests to be able to make the final diagnosis.

Laboratory analysis will study a substance or material, for example urine, blood or others, showing data or characteristics that may indicate disorder or medical condition through tests such as complete blood count, glucose, urea, creatinine, total cholesterol, triglycerides, uric acid, parasitological, bacteriological culture and antibiogram. Meanwhile, the image analysis will obtain information about the human body noninvasively through different methods such as radiography, mammography, CT scanner, magnetic resonance, ultrasound, nuclear medicine and angiography [2].

These diagnostic tests require machines and equipment to obtain the results, that is, they need to be continuously available and fully functioning, thus requiring constant maintenance.

There are currently three types of maintenance strategies: corrective maintenance consisting of the machine producing until an unexpected break occur; preventive maintenance that stops the device at smaller and planned regular intervals; and predictive maintenance that is based on monitoring the equipment behavior for early failure detection and lifetime maximization [19].

Predictive maintenance makes it possible to identify when and how the failure will happen. For proper monitoring of diagnostic analysis machines, initially it is necessary to measure which equipment has the greatest impact on production through indices such as Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), uptime and correlations [19].

In Brazil there are 22,440 clinical analysis establishments, of which 7,388 in the public sector (SUS) and 36,969 diagnostic imaging establishments, of which 5,698 in the public sector (SUS) [21].

Initial equipment investment is around R$ 85,000 for the laboratory area [30] while a single imaging equipment costs approximately R $ 300,000 [26].

The average price paid by SUS for people to do the main laboratory and imaging exams in hospitals and clinics, and the price paid by the person to make the exam in private, plus the average daily amount were listed in

Table 1.

Table 1: Average price in 2019 and average amount per day in 2018 of exams in public and private sector of the main laboratory and imaging exams in Brazil [1], [21], [22]

Exam	*Avr. price public*	*Avr. qty./day public*	*Avr. price private*	*Avr. qty./ day private*
Uric acid, Total cholesterol, Creatinine	R$ 1.85	227,316	R$ 15.00	-
Antibiogram	R$ 9.155	34,874	R$ 50.50	-
Bacteriological culture	R$ 7.935	24,396	R$ 23.50	-
Glucose	R$ 1.85	120,536	R$ 17.00	-
Complete blood count	R$ 4.11	219,104	R$ 16.00	-
Parasitological	R$ 1.65	35,785	R$ 12.50	-
Urea	R$ 1.85	97,864	R$ 16.00	-
Triglycerides	R$ 3.51	78,710	R$ 17.00	-
Mammograph	R$ 33.75	11,769	R$ 156.00	13,698
X-Ray	R$ 60.175	195,302	R$ 129.50	87,186
Magnetic resonance	R$ 268.75	3,420	R$ 982.00	21,656
CT scanner	R$ 112.69	14,938	R$ 618.50	20,238
Ultrasound	R$ 89.91	45,049	R$ 551.50	42,345

Estimating the revenue generated daily by exams in the public and private sector through the average price and the average quantity in Table 1, we have the numbers in Table 2.

Table 2: Average revenue per day in public and private sector of the main laboratory and imaging exams [1], [8], [21], [22]

Exam	*Avr. R$/day public*	*Avr. R$/day private*
Uric acid, Total cholesterol, Creatinine	R$ 420,534.60	-
Antibiogram	R$ 319,271.50	-
Bacteriological culture	R$ 193,582.30	-
Glucose	R$ 222,991.60	-
Complete blood count	R$ 900,517.44	-
Parasitological	R$ 59,045.25	-
Urea	R$ 181,048.40	-
Triglycerides	R$ 276,272.10	-
Mammograph	R$ 397,203.75	R$ 2,136,888.00
X-Ray	R$ 11,752,297.85	R$ 11,290,587.00
Magnetic resonance	R$ 919,125.00	R$ 21,266,192.00
CT scanner	R$ 1,683,363.22	R$ 12,517,203.00
Ultrasound	R$ 4,050,355.59	R$ 23,353,267.50

Since initial investment and revenue in the imaging area are higher than in the laboratory area, then this study will analyze in detail the correlation of call opening and machine break, Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), and uptime only for diagnostic imaging devices. These numbers will be shown in a case study of one public and two private companies to initiate predictive maintenance strategies in this sector. Topic 2 will treat the theoretical references based on keywords, topic 3 will be about methodology of the work, in topic 4 the research will be highlighted step by step, in topic 5 the results will be analyzed and topic 6 will show final considerations of this article.

2. Theoretical References

Next, it will be discussed the main themes involved in the research, with the aim of improving the knowledge of the subject matter hereof.

2.1. Diagnostic medicine

Diagnostic medicine is defined as a group of medical skills focused on complementary exams to the diagnostic aid. This includes laboratory, imaging and other diagnostic activities [3].

The evolution of diagnostic medicine begins with the discovery of x-ray in 1895 by German physicist Wilhelm Conrad Roentgen, the creation of ultrasound equipment in 1948 by American physician Douglas Howry and of CT scanner in 1972 by English engineer Godfrey Hounsfield and the significant growth of laboratory tests in the last 60 years. Thus, there was an increase in diagnosis, early intervention and life expectancy [18].

Since last century, the sector has undergone several innovations and improvements, increasing the type of exams from 60 in the 50's to 2,000 in 2006. This shows that the search for knowledge and the incorporation of new technologies will place the focus of this sector in accuracy and patient safety [13].

Despite all these changes, it is estimated that 400 million people still do not have access to basic health, so industry 4.0 has the potential to change this scenario, either through nanotechnology in monitoring, diagnosis and noninvasive treatment [20], or artificial intelligence for quick and accurate diagnosis with fewer errors and lower costs [17].

2.2. Image diagnostic medicine

The evolution in imaging diagnosis in recent years has been rapid and consistent in both technology and team expertise, allowing the diagnosis so early that the chances of successful treatment have multiplied. New imaging techniques for liver density, detection of iron and fat deposits in the liver, prostate and breast exams, dynamic joint analysis and more, and recent advances in nuclear medicine equipment and drugs have made exams and diagnoses faster and more effective with lower patient risk [11].

Process evolution and industry 4.0 advances has raised great doubt regarding the replacement of technical and medical work through process virtualization and centralization, and artificial intelligence with voice recognition tools and image reconstructions. A contributing factor to this issue was the standardization of tele-radiology, which established standards for clinical data transmission, patient authorization, human responsibilities, operational standards, image viewing and processing, and security and privacy [7]. Other contributing factors were tele consultation, tele report and automated reports that are starting to gain strength in the market [13].

In today's world with big data and google, patients are becoming more and more informed, wanting to know about protective gear, the amount of radiation from each exam, etc., so there will be a concern about the amount and quality of exams performed and the elimination of ionizing radiation. Furthermore, humanization is increasingly in question, not only in the patient-physician relationship but also in the environment and patient relationship, making environments more comfortable and receptive [13].

2.3. Monitoring equipment

Medical equipment undergoes specific technical and quality compliance certifications from ANVISA and INMETRO before going into operation to ensure the protection of the patient's physical integrity. But there is no mandatory regulation to ensure the reliability and performance of equipment with calibrated traces during its life cycle [24].

Magnetic resonance equipment is the most complex and most promising for not using ionizing radiation. These equipment have uptime suggested by manufacturers of 98%, that may be impacted by failures in the conditions of infrastructure and equipment like chillers, voltage stabilizers, air conditioning and exhaust fans systems, and power grid fluctuations [33].

Monitoring x-ray and ultrasound equipment has been done through physical and mechanical inspections and performance tests with the help of invasive and non-invasive systems to achieve quality control and assurance of service, which take from 20 minutes to 2 hours to be completed depending on its complexity [35]. This is done to prevent damage, corrective maintenance and degradation in image quality [4], [28].

2.4. Industry 4.0

Revolution means an abrupt and radical change in social structures and economic systems as a result of new technologies and ways of perceiving the world [29]. Currently, four stages related to technological evolution have been verified. The first in the late 18th century was due to the use of water and steam mechanical installations, the second in the early 20th century with the use of electrical technologies in mass production, the third in the late 20th century (around 1970) with the application of electronics and information technology to automation and the fourth was born from Germany's term industry 4.0 in 2011 with the introduction of Cyber Physical Systems (CPS) and a complete integration of virtual and physical worlds [16].

There are several technologies that can be applied to industry 4.0 implementation. These are called enabling technologies and include CPS, Internet of Things (IoT), cloud computing, blockchain, information integration, and others related [34].

Advances in medical technology alone are not sufficient to meet the demand for healthcare services, so it is necessary to use industry 4.0 enabling technologies to improve service quality and efficiency and reduce maintenance and management costs, thereby increasing decision-making capacity and flawless operating activity of equipment [5].

2.5. Predictive maintenance

The first industrial revolution originated what it's call maintenance in order to ensure continuity of work, and also corrective maintenance with error repair and equipment unavailability only after the fact itself occurs. Another term set after World War II, in the second industrial revolution, was preventive maintenance, where the monitoring of machines between time intervals was practiced. Regarding corrective maintenance, preventive maintenance has increased equipment reliability and availability, and decreased safety and health-related worker risks, but product costs have increased due to constant downtime and rising costs. The significance of predictive maintenance emerged in the third industrial revolution with the development of fault measurements, analysis, criteria and predictions. This has brought advantages in increased process reliability and machine availability, reduced intervention time, improved intervention accuracy, improved environmental and safety conditions, and better integration with the production itself [6].

Thus, predictive maintenance compared to other maintenance types has numerous advantages, but has challenges in its implementation, such as integrating multiple data-owning systems, the ability to handle big data, and the accuracy of prediction [15].

In addition, industry 4.0 promotes predictive maintenance using advanced predictive tools, transforming machine health data into information that can explain uncertainty, optimizing plant management, maintenance scheduling and machine safety [14].

The importance of predictive maintenance in hospitals has become increasingly important in recent years, encouraging discussion of its management and new model solutions to ensure the maximum interval between medical-hospital equipment repairs and its quality [12].

For the implementation of predictive maintenance and equipment monitoring to be facilitated in hospital environments, the six steps of [19] can be applied, as it consists of: "(i) equipment assessment, (ii) monitoring standard definition, (iii) monitoring technique determination, (iv) data collection implementation, (v) machine database creation and (vi) implementation of corrections in the monitoring plan".

3. Method & methodology

In its first phase, this article conducts an exploratory bibliographic research, then it is by nature an applied research to provide ideas for solving practical problems. In addition, it will have an approach form of quantitative research, translating information into numbers, so that is possible to analyze the results obtained. Regarding the objectives, this article is classified as a descriptive research, describing the characteristics and relationships between variables. The technical procedures used are an exploratory bibliographic research followed by a case study, allowing the wide and detailed investigation of objects in their real application.

4. Research

The company to be studied has been operating since 1991, is in the technology and process industry, has approximately 100 employees, located in the State of São Paulo – Brazil, and its mission is to deliver business results with speed, safety and excellence. This company provides services to diagnostic medicine companies in their equipment, both from public and private national sector and has a data lake with information of clinical engineering equipment and infrastructure, representing 1.2% of the diagnostic imaging equipment in use in Brazil, as shown at Table 3.

Table 3: Number of diagnostic imaging equipment in Brazil and the company to be studied [21]

Equipment	*Existing Brazil*	*In use Brazil*	*Existing study*
Mammograph	6,066	5,828	128
X-Ray	84,557	78,818	467
Magnetic resonance	2,718	2,639	143
CT scanner	5,030	4,859	138
Ultrasound	42,741	41,077	663
TOTAL	141,112	133,221	1,539

The company to be studied implemented a centralized and digitized call opening system in a single environment for the customer' clinical engineering equipment and infrastructure, through process improvement studies. By means of this first improvement and some further process studies, it was possible to identify that the main problem presented by the diagnostic medicine companies was the lack of a predictive maintenance methodology. Secondary problems are connected to engineering processes with improvements in patient care rates, equipment service rates and maintenance service levels. All of these problems lead to some revenue loss and increased costs due to machine downtime and inability to care for patients.

The proposed solution was to extract data from system call entries from 1st January 2018 until 31st October 2019 to:

a) Show reasons for opening calls and breaks with correlations;
b) Measure which equipment has the greatest impact on production through Mean Time Between Failure (MTBF), Mean Time To Repair (MTTR) and uptime rates;
c) Predict when an equipment will break and need maintenance with behavioral charts.

According to the diagnostic imaging machine manufacturers' manual [9], [10], [25], [31], [32], the external factors that exclude equipment from warranty and impact in their operation are:

1) Mammograph: ambient temperature, humidity and pressure and electric power;
2) X-Ray: ambient temperature, humidity and pressure and electric power;
3) Magnetic resonance: ambient temperature and humidity, water temperature and electric power;
4) CT scanner: ambient temperature and humidity and electric power;
5) Ultrasound: ambient temperature, humidity and pressure and electric power.

The idea of using correlations is to understand if equipment and external factors have some kind of relationship, so that when one varies the other also varies. The correlation of opened calls compared to the break for a diagnostic medicine equipment makes it possible to show reasons with which the equipment calls are opened and the reasons for machine break, as well as checking the maintenance and call system behavior.

Initially, in the calculation of call and break correlations, system entries were filtered to a list with only non-duplicated call numbers and another list with only non-duplicated call numbers of equipment classified as inoperative, reducing entries from 99,047 to 26,993 and to 4,200 respectively.

Afterwards, the filtered entries were distributed month by month in their respective equipment and external factors and their correlations were calculated by a function in Excel.

Thus, the correlations of the diagnostic imaging equipment linked to the verified external factors are at Table 4. In this, it is possible to resume the problems as follows: (i) Ambient: problems related mainly to the air conditioning, known for regulating temperature, humidity, cleanliness and movement of indoor air, (ii) Electric: problems related to energy, (iii) Water: problems related mainly to the Chiller, considered a water chiller used mainly at the magnetic resonance compressor.

Table 4: Calls and breaks correlation between imaging diagnostic equipment and external factor

Equipment	*External factor*	*Call correlation*	*Break correlation*
Mammograph	Ambient	65%	55%
	Electric	58%	35%
X-Ray	Ambient	30%	8%
	Electric	34%	18%
Magnetic resonance	Ambient	53%	23%
	Electric	50%	28%
	Water	47%	8%
CT scanner	Ambient	59%	25%
	Electric	58%	37%
Ultrasound	Ambient	71%	17%
	Electric	64%	45%

By measuring the equipment impact on production, the performance indices were chosen because they indicate uptime and equipment capacity with regard to Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR). All indicators are in percent for easy reading and quick comparison to 100% of total available hours. They have the following formulas:

$$MTBF[\%] = \frac{total\_available\_time - time\_lost}{number\_of\_stops * total\_available\_family\_time} * 100 \quad (1)$$

$$MTTR[\%] = \frac{total\_repair\_time}{number\_of\_stops * total\_available\_family\_time} * 100 \quad (2)$$

$$Uptime[\%] = \frac{uptime[hr]}{total\_available\_family\_time} * 100 \quad (3)$$

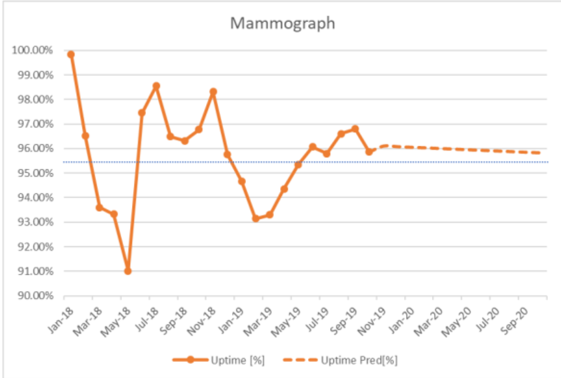
Being the total available family time equal to the equipment. family quantity multiplied by total available hours in period

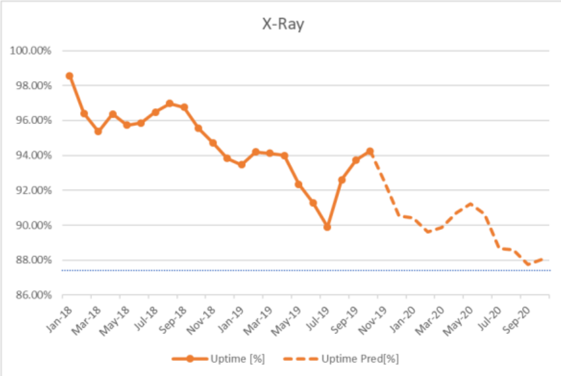
The results of MTBF, MTTR and uptime calculations of all calls are shown at Table 5.

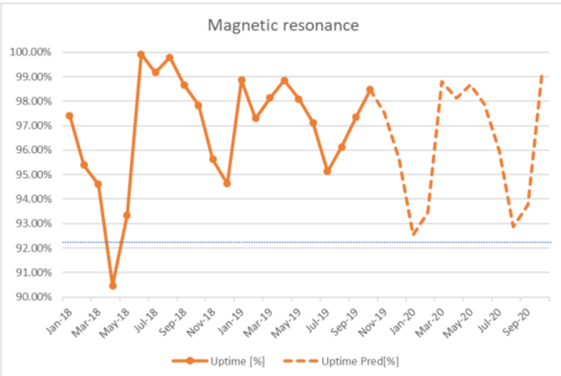
Table 5: Performance indices of average MTBF, MTTR e uptime by equipment family

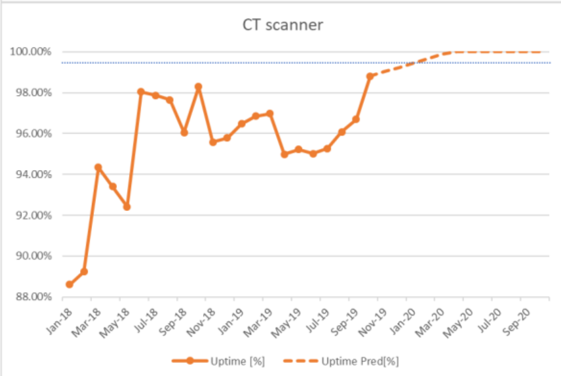
Equipment	*Avr. MTBF [%]*	*Avr. MTTR [%]*	*Avr. uptime [%]*
Mammograph	14.43%	0.57%	95.73%
X-Ray	2.34%	0.13%	94.66%
Magnetic resonance	24.02%	0.81%	96.92%
CT scanner	7.92%	0.38%	95.44%
Ultrasound	6.35%	0.12%	98.13%

For the behavioral charts of uptime indicators, system entries only with diagnostic medicine equipment were considered for the uptime calculation. These were accounted in the continuous line with dots in % at the y-axis month by month at the x-axis. And the predictions in the dashed line were done with an Excel formula considering trend and seasonality of the data's entries. In these curves presented in **Error! Reference source not found.** it is possible to predict when an equipment will break and need maintenance, as well as set thresholds (blue) for the automatic call openings for each type of diagnostic medicine equipment.









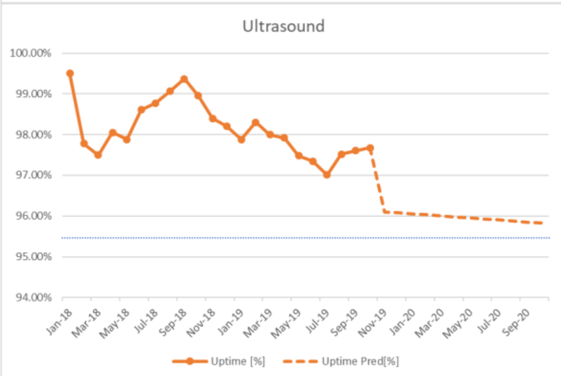


Figure 1: Behavioral charts and thresholds of mammograph, x-ray, magnetic resonance, CT scanner and ultrasound in sequence

5. Results Analysis

The data collected in the previous section will be analyzed and interpreted in this chapter so that a predictive maintenance methodology for imaging diagnostic equipment can be developed.

Table 6 presents the call correlation, the break correlation and the difference between the equipment correlations. It is possible to observe that most equipment has a positive and strong relation of the calls with the external factors, since the correlation values (30-71%) are positive and tend to 100%. In addition, strong call correlation does not indicate a break correlation at the same rate and ratio, most having a weak ratio (8-55%) below 50%. Another point is the medium difference between call and break correlations (10-54%), which may indicate that there were many calls for the same event or that the external factor call took time to be completely resolved, breaking the equipment, but not the factor itself or that the call was opened as break by the user only for maintenance priority reasons.

In detail, what can be observed in Table 6 for each equipment is:

(i) Mammograph: regarding the ambient factor there is a high-medium call ratio (between 60% and 80%) and medium break ratio (between 40% and 60%), resulting in low difference between call and break correlations (<20%). Regarding the electric factor, there is a medium call ratio (between 40% and 60%) and low-medium break ratio (between 20% and 40%), resulting in a medium-low difference between call and break correlations (between 20% and 40%);

(ii) X-ray: regarding the ambient factor there is a medium-low call ratio (between 20% and 40%) and low break ratio (<20%), resulting in a medium-low difference between call and break correlations (between 20% and 40%). Regarding the electric factor there is a medium-low call ratio (between 20% and 40%) and low break ratio (<20%), resulting in a low difference between call and break correlations (<20%);

(iii) Magnetic resonance: regarding the ambient factor there is a high-medium call ratio (between 60% and 80%) and medium-low break ratio (between 20% and 40%), resulting in a medium-low difference between call and break correlations (between 20% and 40%). Regarding the electric factor there is a medium call ratio (between 40% and 60%) and low-medium break ratio (between 20% and 40%), resulting in a medium-low difference between call and break correlations (between 20% and 40%) Regarding the water factor there is a medium call ratio (between 40% and 60%) and low break ratio (<20%), resulting in a medium-low difference between call and break correlations (between 20% and 40%);

(iv) CT scanner: regarding the ambient factor there is a medium call ratio (between 40% and 60%) and low-medium break ratio (between 20% and 40%), resulting in a medium-low difference between call and break correlations (between 20% and 40%). Regarding the electric factor there is a medium call ratio (between 40% and 60%) and low-medium break ratio (between 20% and 40%), resulting in a medium-low difference between call and break correlations (between 20% and 40%);

(v) Ultrasound: regarding the ambient factor there is a high-medium call ratio (between 60% and 80%) and low break ratio (<20%), resulting in medium difference between call and break correlations (between 40% and 60%). Regarding the electric factor there is a high-medium call ratio (between 60% and 80%) and medium break ratio (between 40% and 60%), resulting in a low difference between call and break correlations (<20%).

Table 6: Calls and breaks correlation between imaging diagnostic equipment and external factor and difference between correlations

Equipment	*External factor*	*Call correlation*	*Break correlation*	*Difference between correlations*
Mammograph	Ambient	65%	55%	10%
	Electric	58%	35%	23%
X-Ray	Ambient	30%	8%	22%
	Electric	34%	18%	16%
Magnetic resonance	Ambient	53%	23%	30%
	Electric	50%	28%	22%
	Water	47%	8%	39%
CT scanner	Ambient	59%	25%	33%
	Electric	58%	37%	21%
Ultrasound	Ambient	71%	17%	54%
	Electric	64%	45%	20%

Looking at the performance indices of uptime summarized with the average revenue loss in the public and private sector at Table 7, the equipment that has the greatest impact on production is the x-ray and the one that has the least impact is the mammograph. Thus, the priority focus of maintenance and process improvement can be defined by the average revenue losses generated by machine downtime.

Table 7: Performance indicator of uptime and average revenue loss by equipment and focus priority order [1], [21], [22]

Equipment	Avr. uptime [%]	Avr. R$ loss/ day public	Avr. R$ loss/ day private	Priority
Mammograph	95.73%	R$ 16,960.60	R$ 91,245.12	5
X-Ray	94.66%	R$ 627,572.71	R$ 602,917.35	1
Magnetic resonance	96.92%	R$ 28,309.05	R$ 654,998.71	2
CT scanner	95.44%	R$ 76,761.36	R$ 570,784.46	3
Ultrasound	98.13%	R$ 75,741.65	R$ 436,706.10	4

Considering the average uptime and threshold of each equipment family at Table 8, the equipment with the highest expected uptime are: 1st place: CT scanner and 2nd place: Magnetic resonance. In addition, three out of five equipment families will have worse uptime indices and generate even greater loss if a more efficient predictive maintenance methodology is not implemented in the diagnostic medicine field.

Paper ID: ART20204110 DOI: 10.21275/ART20204110

Table 8: Average uptimes and thresholds for each equipment

Equipment	*Avr. uptime [%]*	*Avr. Uptime predicted [%]*	*Difference between avr. uptimes [%]*	*Threshold [%]*
Mammograph	95.73%	95.96%	+0.23%	95.50%
X-Ray	94.66%	90.22%	-4.44%	87.50%
Magnetic resonance	96.92%	96.37%	-0.55%	92.25%
CT scanner	95.44%	99.70%	+4.26%	99.50%
Ultrasound	98.13%	96.10%	-2.03%	95.50%

6. Final Considerations

From the analysis made, it is possible to develop a predictive maintenance methodology for each equipment family, having the following recommendations:

- The difference between call and break correlations in Table 6 of the previous chapter should be monitored and might point to the efficiency and effectiveness of overall maintenance or call opening classification by the user, and is better when the call and break correlations tend to have a difference of 0%;
- By combining the call correlation value with the average uptimes, it is also viable to define overall priority of external factors by equipment (Table 9), always thinking about the revenue loss. The external factors should be automatically monitored through sensors, generating data for automatic call opening before the equipment break;
- From the maintenance and process improvement priority focus and the expected average uptime, the system should also change the maintenance prioritization in real time through machine learning of prediction calculations, taking as an example the prioritization adjustment at Table 9.
- Table 9 presents a predictive maintenance prioritization schedule based on expected average uptime, considering equipment prioritization in the following order: (1) X-ray, (2) Ultrasound, (3) Magnetic resonance, (4) Mammograph, (5) CT scanner.

Table 9: Overall priority of external factors by equipment

Equipment	*External factor*	*Call corre-lation*	*Avr. uptime [%]*	*Prev. priority*	*Avr. uptime pred. [%]*	*Fut. priority*
Mammo-graph	Ambient	65%	95.7%	10	95.9%	8
	Electric	58%	95.7%	11	95.9%	9
X-Ray	Ambient	30%	94.7%	2	90.2%	2
	Electric	34%	94.7%	1	90.2%	1
Magnetic resonance	Ambient	53%	96.9%	3	96.4%	5
	Electric	50%	96.9%	4	96.4%	6
	Water	47%	96.9%	5	96.4%	7
CT scanner	Ambient	59%	95.4%	6	99.7%	10
	Electric	58%	95.4%	7	99.7%	11
Ultra-sound	Ambient	71%	98.1%	8	96.1%	3
	Electric	64%	98.1%	9	96.1%	4

The entry of medical and hospital environments in the industry 4.0 predictive maintenance with enabling technologies can be done slowly to not affect cash flow. As shown in this article, the first steps to be done are the digitalization and centralization of call openings in a single environment, the measurement of which equipment has the greatest impact on production and which factors most affect the break. To develop a predictive maintenance methodology, the analysis results of performance indicators, correlations and priorities made should also be automated in the system in order to automatically find and adjust the predictions and thresholds presented for each equipment family through machine learning. So, it would be viable to generate alerts, maintenance call openings and schedule prioritization order.

This article had as limitations the manual call opening, since it is not possible to know if all events had a call opening in the system or if they were described according to the problem, impacting in the calculated variables. And to have low representativeness (only 1%) of the diagnostic medicine equipment in use in Brazil.

As a suggestion for future research, initially it may be cited the resolution of the limitation found in manual call opening, inserting other industry 4.0 enabling technologies in the impacting external factors with priority in the equipment that most affect the production. Thus, it would be possible to increase automatic data generation for predictive maintenance, to obtain more reliable data directly from the machines and to predict with more advanced multivariate prediction techniques when the diagnostic imaging machines break will occur and why.

References

[1] Agência Nacional de Saúde Suplementar, Mapa Assistencial da Saúde Suplementar, Rio de Janeiro, 2019.

[2] Ambra Saúde, "Conheça as 8 modalidades de diagnóstico por imagem", Jul. 24, 2017 [Online]. Available: http://ambrasaude.com.br/blog/conheca-as-5-modalidades-de-diagnostico-por-imagem/ [Accessed: Sept. 10, 2019].

[3] Campana, G. A., de Faro, L. B., & Gonzalez, C. P., "Fatores competitivos de produção em medicina diagnóstica: da área técnica ao mercado", Brazilian Journal of Patol. Med. Lab., pp. 295-303, 2009.

[4] Cardoso, F. M., & Alves, A. E., "Implantação de programa de controle de qualidade de imagem em equipamentos de ultrassom", In Proceedings of the XXIV Brazilian Congress of Biomedic Engeering, pp. 2802 – 2805, 2014.

[5] Çoban, S., Gökalp, M. O., Gökalp, E., Eren, P. E., & Koçyiğit, A., "Predictive Maintenance in Healthcare Services with Big Data Technologies", In Proceedings of the IEEE 11th Conference on Service-Oriented Computing and Applications (SOCA), p. 7, 2018.

[6] Costa, M. d., Gestão Estratégica da Manutenção: Uma Oportunidade para Melhorar o Resultado Operacional, Juiz de Fora, 2013.

[7] de Carvalho, C. A., "O futuro da Radiologia e do Diagnóstico por Imagem" [Online]. Available: https://cbr.org.br/o-futuro-da-radiologia-e-diagnostico-por-imagem/ [Accessed: Jun. 06, 2018].

[8] Dr. Consulta, "Dr. Consulta – Serviços", 2019 [Online]. Available:

https://www.drconsulta.com/servicos/exames [Accessed: Sept. 10, 2019].
[9] Fujifilm, "Manual de Operação Sistemad e Mamografia" [Online]. Available: http://www4.anvisa.gov.br/base/visadoc/REL/REL%5B37008-1-19742%5D.PDF [Accessed: Oct. 09, 2019].
[10] GE, "Instruções de Uso Equipamento Tomografia Computadorizada" [Online]. Available: http://www4.anvisa.gov.br/base/visadoc/REL/REL[33399-5-10631].PDF [Accessed: Oct. 09, 2019].
[11] HCor, "A evolução no diagnóstico por imagem" [Online]. Available: https://www.hcor.com.br/materia/evolucao-no-diagnostico-por-imagem/ [Accessed: Oct. 14, 2019].
[12] Junior, S. P., Viegas, T. V., Castañeda, W. A., Dandolini, G., & Souza, J. A., Proposta de um Modelo para Predição de Manutenções de Equipamentos Médico-Hospitalares: Um Estudo Multicasos em Hospitais da Grande Florianópolis (SC), Florianópolis, 2013.
[13] Junior, W. G., "Tendências de medicina diagnóstica e radiologia" [Online]. Available: https://www.pixeon.com/blog/medicina-diagnostica/ [Accessed: Aug. 29, 2017].
[14] Lee, J., Kao, H.-A., & Yang, S., "Service innovation and smart analytics for Industry 4.0 and big data environment", In Proceedings of the 6th CIRP Conference on Industrial Product-Service Systems, p. 6, 2014.
[15] Li, Z., Wang, K., & He, Y., "Industry 4.0 – Potentials for Predictive Maintenance", In Proceedings of the 6th International Workshop of Advanced Manufacturing and Automation, p. 6, 2016.
[16] Liao, Y., Loures, E. R., Deschamps, F., Brezinski, G., & Venâncio, A., "The impact of the fourth industrial revolution: a cross-country/region comparison", Production, vol. 28, 2018.
[17] Life 4.0, "9 Ways Artificial Intelligence is Affecting the Medical Field", [Online]. Available: https://life4-0.org/artificial-intelligence-in-the-medical-field-life-4-0-conference/ [Accessed: Aug. 25, 2019].
[18] Martins, L. O., "O segmento da medicina diagnóstica no Brasil", Rev. Fac. Ciênc. Méd. Sorocaba, pp. 139-145, 2014.
[19] Mathias, M. H., "Ferramentas de Diagnósticos de Máquinas", 2012 [Online]. Available: https://acervodigital.unesp.br/handle/123456789/46460/ [Accessed: Sept. 10, 2019].
[20] McIntosh, J., "Nanosensors: the future os diagnostic medicine?", [Online]. Available: https://www.medicalnewstoday.com/articles/299663.php [Accessed: Jan. 14, 2016].
[21] Ministário da Saúde, "DATASUS - Sistema de Informações Ambulatoriais do SUS", 2019 [Online]. Available: http://tabnet.datasus.gov.br/cgi/tabcgi.exe?sia/cnv/qauf.def [Accessed: Sept. 10, 2019].
[22] Ministério da Saúde, "CNES - Cadastro Nacional de Estabelecimentos de Saúde", 2019 [Online]. Available: http://cnes2.datasus.gov.br [Accessed: Sept. 10, 2019].
[23] Ministério da Saúde, "DATASUS - SIGTAP", 2019 [Online]. Available: http://sigtap.datasus.gov.br/tabela-unificada/app/sec/inicio.jsp [Accessed: Sept. 10, 2019].
[24] Monteiro, E. C., & Lessa, M. L., "A metrologia na área de saúde: garantia da segurança e da qualidade dos equipamentos eletromédicos", Journal of Engevista, vol. 7, n. 2, pp. 51-60, 2005.
[25] Philips, "Instruções de Uso Aparelho Ultrassom", [Online]. Available: http://www4.anvisa.gov.br/base/visadoc/REL/REL[32510-1-5].PDF [Accessed: Sept. 10, 2019].
[26] Portal Saúde Business. "Empresa paranaense aposta em solução para reduzir filas do SUS", Aug. 13, 2013, [Online]. Available: https://saudebusiness.com/gestao/empresa-paranaense-aposta-em-solucao-para-reduzir-filas-do-sus/ [Accessed: Sept. 10, 2019].
[27] Rakel, R. E., "Diagnosis", 2019 [Online]. Available: https://www.britannica.com/science/diagnosis [Accessed: Sept. 10, 2019].
[28] Ros, R. A., & Caldas, L. V., Metodologia de controle de qualidade de equipamentos de raio-x (nível diagnóstico) utilizados em calibração e instrumentos, São Paulo, 2000.
[29] Schwab, K., A quarta revolução industrial, Edipro, Geneva, 2016.
[30] SEBRAE, "Como montar um laboratório de análises clínicas", 2019 [Online]. Available: http://www.sebrae.com.br/sites/PortalSebrae/ideias/como-montar-um-laboratorio-de-analises-clinicas,2ce87a51b9105410VgnVCM1000003b74010aRCRD [Accessed: Sept. 10, 2019].
[31] Siemens, "Instruções de Uso Aparelho Raio-X", [Online]. Available: http://www4.anvisa.gov.br/base/visadoc/REL/REL%5B6474-2-2%5D.PDF [Accessed: Sept. 10, 2019].
[32] Siemens, "Instruções de Uso Equipamento Ressonância Magnética", [Online]. Available: http://www4.anvisa.gov.br/base/visadoc/REL/REL[11100-1-2].PDF [Accessed: Sept. 10, 2019].
[33] Souza, A. F., "Análise da disponibilidade em equipamentos de ressonância magnética baseada em indicadores de manutenção", In Proceedings of the 21st Brazilian Congress of Biomedic Engeenering, pp. 403 – 406, Rio de Janeiro, 2008.
[34] Xu, L. D., Xu, E. L., & Li, L., "Industry 4.0: state of the art and future trends", International Journal of Production Research, vol. 56, n. 8, p. 22, Mar 09, 2018.
[35] Zucatti, G. R., & Button, V. D., Proposta para implantação de um programa de controle de qualidade de imagem em equipamentos de ultrassom modo-b, Campinas, Jun. 2003.

Author Profile

Tatiana Mallet Machado received the B.S. degree in Mechatronic Engineering from the University of Saarland in 2012 and is currently doing a M.S. in Production Engineering at the Campinas State University (UNICAMP). She also completed an MBA in strategic and economic project management at the Getúlio Vargas College (FGV) in 2016. She has 10 years of experience in research and development engineering projects through mechatronics and enabling technologies of the industry 4.0 (eg IoT) and hands-on experiments in academic, industrial, corporate and special environments (sterile room and hospitals). Her study emphasis is based on Automation, Mechatronic, Robotics, Product Development, Sustainability, Data Science, Machine Learning, Artificial Intelligence and Industry 4.0.

Francisco Ignácio Giocondo César received the B.S. degree in Mechanical Engineer from Paulista State University Júlio de Mesquita Filho (UNESP) in 1984. He also obtained the M.S. and Ph.D. in Production Engineering from the Methodist University of Piracicaba (UNIMEP) in 2007 and 2015, respectively and is currently doing a post-doc in Production Engineering at the Campinas State University (UNICAMP). He is a research associate professor at the State University of Campinas, Faculty of Applied Sciences (FCA-UNICAMP) since 2016 and professor at the Industrial Department of the Federal Institute of Education, Science and Technology of São Paulo (IFSP) since 2011. He is coordinator of the Sustainable Business Lab (SB-Lab), has 23 years of professional experience as International Project Manager at TRW and Caterpillar Brasil, is collaborator at the Collaborative Research Network on Supply Chain 4.0, is founding Member of SC4 (National Association for Research and Development of Innovative Companies) and is member of the Interaction Committee on Science and Technology. He has the Project Management (PMI) and Green Belt certifications and has a specialization course in Continuous Improvement from Japan International Cooperation Agency (JICA) in 2018. His study emphasis is based on Continuous Improvement, Lean Production, Six Sigma, Industry 4.0, Advanced Manufacturing, Industrial Internet of Things, Entrepreneurship, Business Canvas, Emerging Technologies, Disruptive Technologies.

Ieda Kanashiro Makiya is accredited professor at the State University of Campinas, Faculty of Applied Sciences (FCA-UNICAMP) in the Postgraduate Program of Administration (PPGA) and in the Postgraduate Program of Production and Manufacturing Engineering (PPGEPM) since 2010. She is the research group leader of SB-LAB (Sustainable Business Laboratory) at CNPq and member of the Agribusiness Laboratory (LAG), linked to the Center for Research in Administration (CEPAD), the Laboratory of Studies on Management of Sustainable Operations (LEGOS) and the Center for Research in Production Engineering (CENPRO). She received the B.S and M.S. degrees in Food Engineering from Paulista State University Júlio de Mesquita Filho (UNESP) in 1989 and Process Technology from State University of Campinas, Faculty of Food Engineering (FEA-UNICAMP) in 1996, respectively. She also obtained the Ph.D. and post-doc degrees in Quality Management from Production Engineering Department of the Polytechnic School of the University of São Paulo (EPUSP) in 2002 and in sustainability indicators from the Climate Change Laboratory (Agricultural and Biological Engineering) at the University of Florida in 2014, respectively. Her study emphasis is based on Sustainability, Quality & Productivity, Smart Cities, Industry 4.0 and Creative Economy.