JJMIE

Volume 17, Number 1, March. 2023
ISSN 1995-6665
Pages 33 – 40

Jordan Journal of Mechanical and Industrial Engineering

Applying a Data Analytics Approach to Medical Equipment Maintenance Management to Improve the Mean Time Between Failure and Availability

Mohammad D. AL-Tahat[a,*], Farah Al-Rifa'e[b]

[a]*Professor of industrial engineering, Industrial engineering department, The University of Jordan, Amman, 11942, Jordan.*
[b]*Former graduate student, Industrial engineering department, The University of Jordan, Amman, 11942, Jordan.*

Received 21 Jul 2022 *Accepted 29 Jan 2023*

Abstract

Maintenance of medical devices has become a top priority around the world, this is due to the vital role of these devices in contributing to saving human lives. Maintenance engineering makes use of data analytics using statistical techniques to expose patterns to capture relationships among the different variables that affect the performance of medical devices. This research presents an attempt to discuss an efficient approach of data analytics for maintaining medical devices to enhance their reliability in terms of the mean time between failure and availability. Data analytics methodology is applied based on supervised machine learning techniques by training the classification models to improve reliability, availability. Raw data were collected from the cooling system of the Magnetic Resonance Imaging MRI magnet as a case study, then organized and cleaned to make it suitable to build and train classification models. A new representation of the data has been resampled using the Synthetic Minority Oversampling Technique (SMOTE). Six different classification models were trained and tested using Weka software, these are Logistic regression, K-nearest neighbors, J48 and Random Forest decision trees models, Support-vector machine SVM, and Naive Bayes. Based on the F-measure, K-nearest neighbor, Random Forest, and SVM were chosen to be the most significant classifiers, a comparison between these three classifiers was done based on evaluation metrics, the metrics are: Correctly classified instances, Incorrectly classified instances, Root mean squared error (RMSE), Recall, Precision, F-Measure, Area under ROC curve, and Accuracy, it was found that the random forest classifier has the best performance, highest accuracy, and the least error.

Maintenance performance in terms of MTBF and availability are estimated after applying the random forest model and compared with their values before to determine the efficiency of the classifier. It was found that the random forest model has caused an improvement in MTBF by 879%, and an improvement in the device availability by 11%. Data analytics plays a critical role in improving efficiency and generating understandings from the data generated by devices. Through this paper, data analytics was followed for maintenance planning to improve the mean time between failure and availability of the cooling system of the magnetic resonance imaging device, the results were positive and encouraging. The same methodology can be generalized to benefit from it in maintenance planning for other medical purposes.

Keywords: Maintenance Planning, Data analytics, Performance Improvement, Reliability, SMOTE.

1. Introduction

Data analytics is a term that is strictly connected with the word "Big Data". It is more comprehensive than the term data mining; data analytics is the art of investigating raw data to make conclusions. Any type of data can be subjected to data analytics to develop more efficient ideas for doing business as per the company's objective. Data analytics is categorized into four basic types, descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Data analytics may be characterized by: volume which represents the size of raw data, the velocity of data motion and generating new data, variety of data types and forms, veracity and trust under ambiguities, uncertainty, and inconsistency, the value that data can add to generate knowledge.

Data analytics is applied to several sectors, such as industry, travel, transportation, logistics and delivery, manufacturing, security, education, healthcare, military, fraud and risk detection, and many others.

A new progenitive computing technique related to big data analytics is proposed in [1], to improve the efficiency of health monitoring systems in providing a better living to people. Sujatha V. et al. [2] had analyzed a large-scale Diabetic data set to find the length of time taken for treatment of diabetes performing data analytics. As medicine is becoming an information science, data analytics was used to investigate the future of Cardiovascular medicine [3] where proficiency in big data

* Corresponding author e-mail: altahat@ju.edu.jo.

is an invaluable asset for cardiovascular disease investigators, which contributes positively to the treatment of cardiovascular disease. Methods, practices of data analytics are examined and explored in [4], big data analytics approaches applied for logistics and supply chain management invariant dimensions like; technology-driven tracking strategies, and financial performance relations, an interesting literature review on data analytics for the period from 2012 to 14 March 2018 is presented [4]. Anjaneyulu and Mohan [5] tackled some problems in Intelligent Transportation System (ITS) with the use of data analytics and presented a thorough review of the literature associated with data analytics in ITS. They addressed various ITS data analytics programs, along with traffic crowding forecasting, route optimization, massive transit management, crash investigation, and transportation infrastructure organization. Manufacturing now can gather large quantities of data, coming from several production activities, such as product design, operations, assembly, planning and scheduling, quality engineering, maintenance management, error detection, and many other activities along with the product life cycle. The importance of terms that are now frequently applied in the context of data analytics is presented and clarified in [6] by Laura et al., who provided a summary of the data analytics tools that could be applied to acquire knowledge from row data along the production process. An efficient approach of data analytics to optimize asset performance and enhance the manufacturing process was discussed in [7], historical data that is coming from different stages of manufacturing was processed and tackled by data analytics, results were used by the production management to take decision-related manufacturing process. In [8] Animesh et al. presented an approach for predictive big data analytics for service needs to discover patterns about service needs and forecast the future demands for these services. The results of their work may provide decision-makers deeper understanding of the data and demand of services, accordingly a proper action could take place.

In the health sector, under recent health circumstances around the world, medical devices are becoming more important in playing a vital role in saving people's lives and helping them to get over their health problems. Maintaining medical devices and avoiding their failures have a significant role in improving patients' medical conditions because failures in medical devices can be risky as they affect the procedure of treating and/or diagnosing, and, in some cases, they can be a matter of life and death.

Maintenance is a very important task applied by medical engineers in the medical sector, some failures of medical devices cannot be avoided by performing it [9]. In addition, maintenance engineering does not help in analyzing the performance of medical devices, and how and when some failures occur to understand the behavior of the device to avoid failures or malfunctions [10]. In general, maintenance engineering makes use of data analytics using statistical techniques to expose patterns that are not clear or visible to capture relationships among the different variables that affect the performance of medical devices [11].

Performance enhancement plays a critical role in the survival and permanence of systems. For example, a lean methodology as an improvement for workforce management in manufacturing firms is presented in [12], window analysis, and Malmquist index for assessing efficiency in a pharmaceutical industry was investigated by [13]. On the other hand, performance evaluation and analysis of a JIT–Kanban production system with sampling inspection was examined in [14], a multiple criteria decision making (MCDM) for performance improvement of a pharmaceutical system was developed in [15]. Ordinal logistic regression model for the improvement of pharmaceutical tablet production was developed in [16]. A model for improving cost estimation for a steel foundry was explained in [17]. An improvement approach for performance measures of maintenance effectiveness is developed in [18]. Computing-based dynamics model, Kansei tool and data mining, Data Envelopment Analysis (DEA), fuzzy reasoning, neural network, and agent-based fuzzy are all used as data analysis tools for performance improvements, following are examples of these applications. A parallel computing-based dynamics model is followed as a data analytic tool to solve the problem of low tracking accuracy of tennis ball trajectory is proposed by Yugang Cui [19], the results show that the coordinates of the highest point of the tennis ball trajectory in the three-dimensional coordinate system is consistent with the coordinates of the highest point of the actual motion path and has high robustness to external disturbances. Data Mining, data mining is the process of analyzing massive datasets to discover the unsuspected relationship and review data more logically, Kansei Engineering is one of the technology of data mining that been applied for Eyewear Industry in Jakarta [20], where a random tree algorithm with ten cross-validations was employed in a decision tree to form a classification model in a tree shape that can be translated into a combination of eyeglasses design attributes satisfying the affective needs of teen girls in Jakarta. Data envelopment analysis (DEA) is a nonparametric operations research method that can be used for the estimation of production frontiers, for example, DEA is used to assess the efficiency of production processes in the plastics industry [21]. A neuro-fuzzy reasoning scheme for mobile robot navigation has been presented in [22] based on decomposing a multidimensional fuzzy system into a set of simple parallel neural networks. The scheme relies upon finding quantifiable means to represent the expert's experience and determines a mapping from current state of a system to the fuzzy measures with which the expert's knowledge is quantified. Artificial networks used for predictive modeling, and applications where they can be trained via a dataset. Self-learning resulting from experience can occur within networks, which can derive conclusions from a complex and seemingly unrelated set of information. A "Fuzzy ARTMAP" neural network model is presented [23] for a power station in Al-Daura Refinery for the multiagent process to improve the process real-time performance. A neural network model for turning process identification to track a desired vibration level of the turning machine is presented in [24] as an example of using the neural network for manufacturing process control. Another Application of Neural Net Modeling and Inverse Control to the Desulphurization of Hot Metal Process is presented in [25].

2. Problem statement and objectives

The main purpose of maintenance models is to reduce the unexpected downtime of a machine or a piece of equipment to keep the production line working with the least interruptions and minimum maintenance cost. Medical devices are devices that diagnose, treat, monitor, and prevent different diseases. Any malfunction or deviation in the performance would give faulty results that lead to the wrong diagnosis and therefore, wrong treatment. It is essential to keep the medical devices working efficiently over time with the highest performance. This paper is focused on medical imaging devices that are used in most hospitals. Medical imaging devices are classified as diagnostic devices in the medical sector. Imaging devices can be defined as the devices that use different technologies to expose the internal organs in the human body that are hidden by bones and skin to monitor, diagnose and/or treat some medical conditions. There are several types of medical imaging devices, each type uses different technology based on the targeted organ and the information that is needed to be provided. Magnetic Resonance Imaging (MRI) that uses radiology to produce images of the internal body organs used in one hospital in Jordan will be recruited as a case to conduct this research, see Fig. 1.

The procedure of producing images by the MRI uses a magnetic field gradient, a very strong magnetic field, and radio waves. During the MRI examination, the electric current passes through coiled wires to generate a temporary magnetic field in the body. A transmitter sends radio waves, and they are received by a receiver in the device to produce a digital image of the targeted body part.

The cooling system targeted in this research has three main sensors: the Helium level sensor, the Helium boil-off sensor, and the pressure sensor. These sensors have been collecting readings since 12 December 2014, the time of installation of the device. As scanning consumes energy in a very large amount, it raises the heat inside the magnet. The temperature and the pressure of the MRI device must be within a specified limit to prevent overheating which in turn leads to a breakdown or a failure. The temperature of the 10K MRI device must be approximately -270 C° (-450 F°) a cryogenic temperature. MRI cooling systems are one of the most important components in the MRI machine to keep the machine working properly. In the present system, heating, ventilation, and air conditioning (HVAC) systems were installed, but cannot provide the cold temperatures needed. The cold head is located inside the MRI device which aims to cool down the magnet by condensing helium gas into its liquid state. The consumption of helium varies greatly depending on the magnet type, MRI scanner type, number of images produced daily, and maintenance type of the system. While big data provides new knowledge and information, it supports a better or new understanding of the issues and thereby it reshapes and challenges theories based on the traditional data that are basic (Yu, et al., 2019).

Machine learning (ML) has several approaches that depend on the available signal or feedback in the learning system. The first approach is the supervised learning algorithm that builds a model based on a dataset that contains inputs and outputs data (Russell and Norvig, 2010). The data set is called the training data which is used to train the model by having several training examples. Each one of the training examples has one input or more and has an output. Through iterative optimization, supervised learning algorithms can learn a function that will predict the output associated with new, different inputs [26]. Supervised learning can further be divided into regression, classification, and active learning [27]. Classification ML algorithms can be used when the outputs are nominal while regression ML algorithms can be used when the outputs are numerical value. Similarity learning is somehow related to classification and regression. Similarity learning aims to learn from existing examples by using a similarity function. The similarity function measures how related or similar two (or more) objects are. The second approach of ML is unsupervised learning. The unsupervised learning algorithms deal with the dataset that has only inputs to group or cluster the dataset. The algorithms learn from the dataset that does not have labels, categories, or classes. Clustering analysis is a process in which data points are grouped in such a way that points in the same group or the same cluster are like each other but dissimilar to points in other groups or clusters. Semi-supervised learning falls between supervised learning and unsupervised learning as some training examples have missed classes or labels.

This research presents an attempt to discuss an efficient approach of data analytics for maintaining medical devices to enhance their reliability in terms of mean time between failure and availability.

Figure 1. The magnetic resonance imaging (MRI) device that used for the case study.

3. Research methodology and design

The design of this research consists of collecting big data from the cooling system of the MRI magnet, defining failures in the data gathered, pre-processing the data, applying supervised machine learning techniques by training the classification models to predict the status of the device based on the data and examining the classification models, choosing the model with the best performance, then evaluate the resultant mean time between failures MTBF, and availability and comparing them to their values before applying the model to analysis improvement. The classification type supervised machine learning method is followed, it aims to predict the status of the device (Passed/Failed), as shown in Fig. 2, and to achieve this objective, the following steps have been conducted.

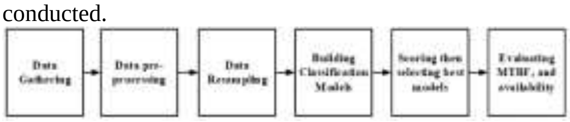

Figure 2. Flowchart for the research model.

3.1. Data Gathering

Data gathering was done by extracting data from sensors located in the cooling system of the MRI magnet which are the Helium sensor, the Helium boil-off sensor, and the pressure sensor. The data recorded were extracted from the system for the period of 12/19/2014 to 2/21/2020 as symbolized in Appendix, then saved in an excel format. To keep the device working and producing detailed, high-quality images, Helium level must not be lower than % 49. Any reading below this level would be considered a failure as many malfunctions would happen to the magnet. The pressure level must be around 70 hPa, if the pressure level dramatically drops down, this indicates that the MRI is experiencing some type of quenching. Fig. 3 shows the representation of the Helium boil-off values in the x-axis and the instances number in the y-axis. The Helium boil-off values in the MRI device are ranging from 0.01 to 0.5. The Helium boil-off represents the rate of liquid helium evaporation in the superconducting magnet; it is usually measured in liquid Pound per hour.

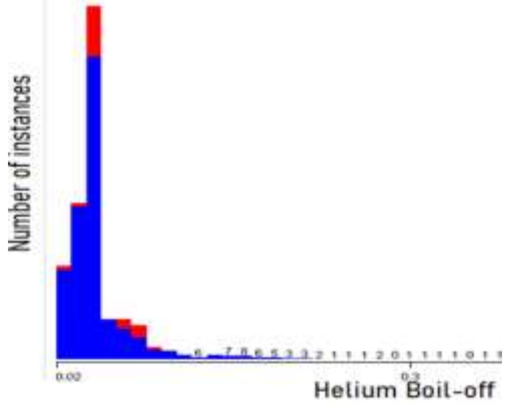

Figure 3. Distribution of the sensor data (Helium Boil-off).

Fig. 4 shows the percentage of Helium level. The x-axis represents the Helium level percentage, and the y-axis represents the number of instances (days), where the blue color represents the "Passed" class and red represents the "Failed" class. As it is shown, most of the readings are in the "Passed" class (the normal state of the device) but there are many instances with the "Failed" class that should not be underestimated.

The x-axis in Fig. 5 represents the pressure level and the y-axis represents the number of instances recorded (days). The magnet is considered in good form when the pressure level is around 70 hPa, as shown by the blue color.

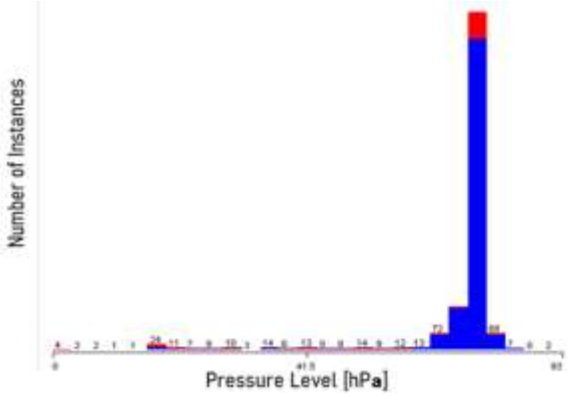

Figure 5. Distribution of the Pressure Level (hPa).

Fig. 6 shows the representation of the classes "Passed/Failed" in the last period, the red color represents the 'Failed" class and the blue color represents the "Passed" class. It shows that the cooling system of the magnet of the MRI device was working well, and the magnet was efficient in 1672 days since the installation of the device (December 2014) while in 219 days, the magnet's cooling system was down due to Helium consumption and the imaging process was stopped.

Pre-processing is a very important step as it helps in enhancing the data quality to get meaningful insights from raw data. In machine learning data, pre-processing means organizing and cleaning the raw data to make it suitable to build and train models. In this research, data pre-processing being handled as follow:

1. *Cleaning*: Removing missing data and duplicated values are performed to the dataset because in data analysis, missing data and/or having duplicated values make "poor" data which may distort findings and insights that cannot be true.
2. *Attribute Selection*: this is a process that chooses relevant attributes to the problem that needs to be solved to build an efficient model and reduce the time taken to build the predictive model. To build an efficient PdM model, the attribute reduction method was used to eliminate irrelevant information from the dataset.

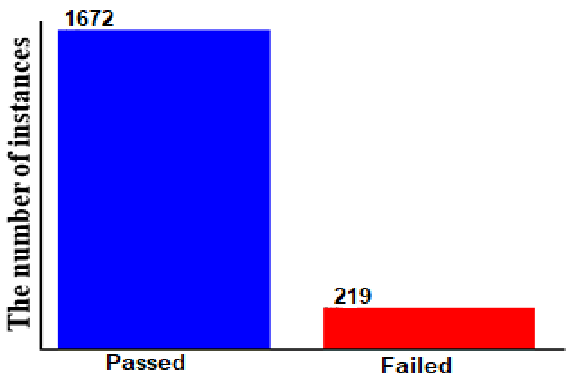

Figure 6. Representation of the classes (Passed, Failed).

3.2. Data Resampling

Resampling data is a technique that is used when there is an unequal distribution of classes in the dataset. In other words, when the number of data points in the negative class (majority class) is very large compared to the number of the positive class (minority class),this will push the model to focus on the majority class but in general, the minority class is the class of interest as it indicates failures. If imbalanced data was not treated before building the model, the model will lack accuracy and the performance will be degraded.

There are two methods for data resampling; the under-sampling method and the oversampling method (Galar, et al., 2012). The Synthetic Minority Oversampling Technique (SMOTE), which is a very popular technique in oversampling method, aims to make the minority class equal to or approximately equal to the majority class by identifying its k nearest neighbors and selecting a set of neighbors at random that used in the generation process. Fig. 7 and figure 8 show the new representation of the data after applying the SMOTE algorithm.

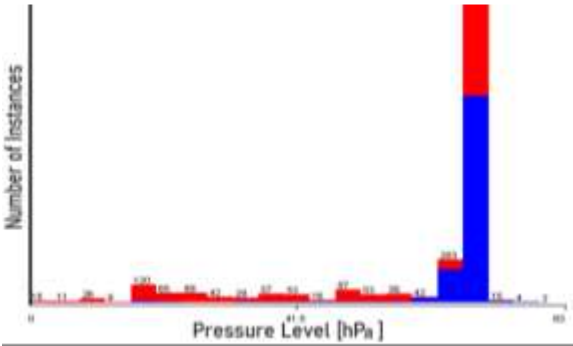

Figure 7. Distribution of Pressure Level (hPa) after SMOT

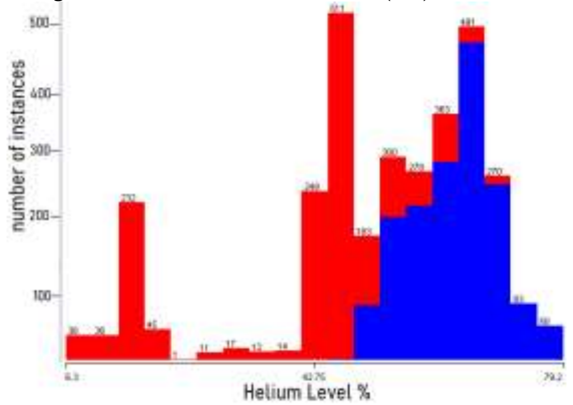

Figure 8. Distribution of the sensor data after SMOTE (Helium Level)

Fig. 9 shows the new representation of the two classes after applying the SMOTE algorithm. The majority class, which is colored with blue, had no changes but the minatory class (colored with red) increased in a way that became approximately equal to the majority class. After applying the SMOTE algorithm, the data is ready to be used to build classification models and test them later.

3.3. Building Classification Models

Classification is a supervised technique in ML algorithms that aims to learn how to label a class to examples in the problem domain. The bigger the data set, the higher the accuracy becomes. There is no such theory on how to map algorithms depending on problem types. The best way to do so is to use controlled experiments to discover which is the most appropriate algorithm results with the best performance and least errors for a given classification task. The evaluation of classification predictive modeling is based on results.

Classification models that were trained/tested in this research are Logistic regression, K-nearest neighbors, Decision Trees models (J48 and Random Forest), Support-vector machine (SVM), and Naive Bayes.

4. Results and discussions

4.1. Using F-Measure

The F-measure –sometimes, called the F-score - is a measure that tests the accuracy of a test. It is based on the calculation of the recall and the precision. The recall, which is known as the sensitivity, is the number of True Positive (TP) results divided by all samples number that should have been identified as positive. F-measure is used to compare between classification models to choose the most significant model/models.

The models were tested by the F-measure to evaluate the performance of each model. As presented in Table 1, results provided by Weka software, showed that models that have statistically significant performances are the K-nearest neighbor model, random forest model, and SVM model. On the other hand, the J48 model and the naïve Bayes model marked with an asterisk are statistically insignificant, therefore these models are excluded from further analysis.

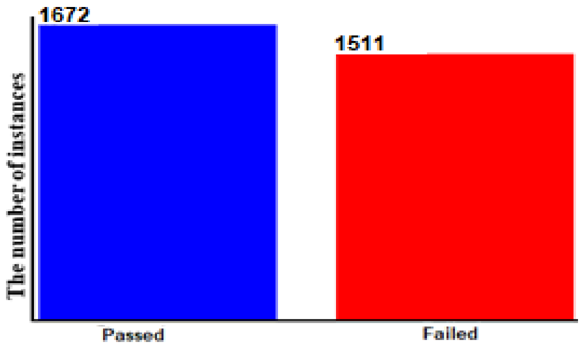

Figure 9. Representation of the classes after SMOTE (Passed, Failed).

Table 1. The F-measure score for Classification models using WEKA software.

Classifier	Logistic Regression	K-nearest neighbor	J48	Random Forest	SVM	Naïve Bayes
F-score	0.96	0.96 v	0.93 *	0.99 v	0.99 v	0.92 *

v: means have statistically significant performances (victory).

*: means cell loss.

4.2. Classifiers Comparison Using Detailed Accuracy

Each model among the significant models comes with evaluation metrics that represent its performance, the metrics are correctly classified instances, incorrectly classified instances, root mean squared error (RMSE), recall, precision, F-measure, area under ROC curve, and accuracy, the evaluation metrics refer to the test split (20% of the entire dataset) are presented in table 2.A comparison between these three classifiers was done based on metrics' values in Table 2, it was found that the random forest classifier has the best performance, highest accuracy, and the least error, there for the random forest classifier will be followed for maintenance improvement of the device.

4.3. Comparing Before with After scenarios

To compare the maintenance performance based on the original dataset with the expected maintenance performance based on the resampling data after applying the random forest model, MTBF, based on the equation (1) and equation (2) and availability are calculated for the two scenarios, results are presented in Table 3.

$$\text{Availability} = \frac{\text{MTBF}}{\text{MTBF+MTTR}} \quad (1)$$

When:

$$MTBF = \frac{\text{number of operational hours}}{(\text{number of failures})} \quad (2)$$

and

$$MTTR = \frac{\text{Total maintenance time}}{\text{Number of repairs}} \quad (3)$$

Table 2. Evaluation metrics of the three classification models

Evaluation Metrics/Model	K-nearest neighbor	Random Forest	SVM
Correctly classified (out of 637)	612	615	569
Incorrectly classified (out of 637)	25	22	68
Root Mean Squared Error	0.1966	0.1732	0.3267
Recall	0.961	0.965	0.893
Precision	0.961	0.966	0.895
F-measure	0.961	0.965	0.893
Area under ROC curve	0.973	0.990	0.892
Accuracy	96.0754%	96.5463%	89.325 %

Table 3. Maintenance performance of the two scenarios before and after

Scenario	MTBF	Availability
Based on the original dataset	183 hours	88%
Based on the resampling data	1791 hours	98%,
Improvement Percentage	879%	11%

If the PdM model was applied and the maintenance staff did know when the machine was going to fail, this means they would perform the needed maintenance activities at the right time to avoid the failure of the machine. But because the prediction model has FN instances, which means that 24 instances are actually "Failed" but classified as "passed", failures in these cases would not be avoided.

5. Conclusions

This paper came as a continuation of the approach of researchers and scientists, where data analytics was employed to manage performance measurement in the field of health care. Data analytics tools and concepts are highly desired also in the maintenance engineering field, it is a good choice for maintenance management of medical devices. Data analytics plays a critical role in improving efficiency and generating understandings from the data generated by medical devices.

There was a noticeable increase in the estimated values of MTBF and the availability after applying the Random Forest classifier. Following this model, the Helium refilling procedure will be regulated in a way that minimizes the shutting down resulting from Helium consumption and, therefore, increases the availability of the device and keeps the workflow of the hospital flowing.

Through this paper, a methodology of improving mean time between failure and availability of a specific medical device by data analytics was discussed for maintenance planning purposes, with the same methodology, the application of data analytics can be generalized in future research to benefit from it in maintenance planning for other medical devices and to other systems such as production systems, forecasting systems, and so.

References

[1] M. Srivathsan, A. K. Yogesh, “Health Monitoring System by Prognotive Computing using Big Data Analytics”. Procedia Comput. Sci., Vol. 50, 2015, 602 – 609.

[2] V. Sujatha, D. S. Prasanna, K. S. Vinu, S. Manivannan. “Bigdata Analytics on Diabetic Retinopathy Study (DRS) on Real-time Data Set Identifying Survival Time and Length of Stay”. Procedia Comput. Sci., 2016, 227-232.

[3] J. Kim, “Big Data, Health Informatics, and the Future of Cardiovascular Medicine”., J. Am. Coll. Cardiol, , Vol. 69, No. 7, 2017, 899-902.

[4] K. Govindan, T.C.E. Cheng, N. Mishra, N. Shukla, “Big data analytics and application for logistics and supply chain management”, Transp. Res. E: Logist. Transp. Rev., Vol. 114, 2018, 343-349.

[5] A. Mohandu, M. Kubendiran, “Survey on Big Data Techniques in Intelligent Transportation System (ITS)”, Mater. Today: Proc., Vol. 47, No. 1, 2021, 8-17.

[6] L. Cattaneo, L.Fumagalli, M. Macchi, E. Negri, “Clarifying Data Analytics Concepts for Industrial Engineering”, IFAC-Papers Online, Vol, 51, No, 1, 2018, 820-825.

[7[D. K. Mishra, A. K. Upadhyay, S. Sharma, “An efficient approach for manufacturing process using Big data analytics”, Mater. Today: Proc., Vol. 47, Part 1, 2021, 6864-6866.

[8] A. S. Chauhan, A. Cuzzocrea, L. Fan, J. D. Harvey, C. K. Leung, A. G.M. Pazdor, T.Wan,, “Predictive Big Data Analytics for Service Requests: A Framework”, Procedia Comput. Sci., Vol. 198, 2022, 102–111.

[9] L., C. Cao, Y. N., Kam, “Big Data Analytics for Predictive Maintenance Strategies”, Supply Chain Management in the Big Data Era.,2017, 978-956.

[10] C. J. López, D. A. Martos, I. G.Gil, D. Markova, I. G. Barzana, M. A. Rodil, M. Luengoa, J. F. Herrera, “Anomaly detection in Predictive Maintenance: A new evaluation framework for temporal unsupervised anomaly detection algorithms”. Neurocomputing, 2021, 462, 440-452.

[11] A. Gandomi, M Haider, “Beyond the hype: Big data concepts, methods, and analytics”, Int. J. Inf. Manage., Vol. 35, 2015, 137-144.

[12] Mohri M, Rostamizadeh A, Talwalkar A. Foundations of machine learning. New York: MIT Press; 2012.

[13] A. Al-Refaie, R. Najdawi, M. D. AL-Tahat, N. Bata,” Window analysis and Malmquist index for assessing efficiency in a pharmaceutical industry”. WCE, 1, London, U.K. 2015.

[14] M. D. AL-Tahat, A. Al-Refaie, A. Al-Dwairi, “Performance evaluation and analysis of a JIT–Kanban production system with sampling inspection”. Int. J. Ind. Syst. Eng., Vol. 11, No. 3, 2012, 225-249.

[15] D. Dalalah, M. D. AL-Tahat, K. Bataineh, “Mutually Dependent Multi-criteria Decision Making”. Fuzzy Inf. Eng., Vo, 4, No. 2, 2012, 195–216.

[16] M. D. AL-Tahat, A.K.M. Abdul Jawwad, Y.L. Abu Nahleh, “Ordinal Logistic Regression Model of Failure Mode and Effects Analysis (FMEA) in Pharmaceutical Tabletting Tools”. Eng. Fail. Anal., Vol. 27, 2013, 322–332.

[17] M. D. AL-Tahat, A. Al-Refaie, “Activity-based cost estimation model for foundry systems producing steel castings”. Jordan Journal of Mechanical and Industrial Engineering, Vol, 6, No. 1, 2012, 75–86.

[18] K. .R. Al-Momani, M.D. AL-Tahat, E. Jarada, “Performance measures for improvement of maintenance effectiveness,” in Proceedings - ICSSSM’06: International Conference on Service Systems and Service Management, , 632–637, 2006

[19] Y. Cui, “Parallel Computing-Based Dynamics Model for Tracking Moving Targets”. Jordan Journal of Mechanical and Industrial Engineering, Vol. 16, No. 1, 2022, 79 - 86.

[20] Y. T. Jou, R. Sukwadi, R. M. Silitonga, Roselly, "Application of Kansei Engineering and Data Mining for the Eyewear Industry in Jakarta". Jordan Journal of Mechanical and Industrial Engineering, Vol. 16, No. 2, 2022, 175 - 183.

[21] A. Al-Refaie, R. Najdawi, E. Sy, "Using DEA Window Analysis to Measure the Efficiencies of Blowing Machines in Plastics Industry". Jordan Journal of Mechanical and Industrial Engineering, Vol. 10, No. 1, 2016, 27- 38.

[22] K. K. Tahboub, M. S. N. Al-Din, "A Neuro-Fuzzy Reasoning System for Mobile Robot Navigation". Jordan Journal of Mechanical and Industrial Engineering, Vol. 3, No. 1, 2009, 77 - 88.

[23] Q. M. Doos,, Z. Al-Daoud, S. M. Al-Thraa, "Agent Based Fuzzy ARTMAP Neural Network for Classifying the Power Plant Performance". Jordan Journal of Mechanical and Industrial Engineering, Vol. 2, No. 3, 2008, 123 - 129.

[24] B. I. Kazem a, N. F. H. Zangana, "A Neural Network Based Real Time Controller for Turning Process". Jordan Journal of Mechanical and Industrial Engineering, Vol. 1, No. 1, 2007, 43 - 55.

[25] M. S. Ashhab, "Application of Neural Net Modeling and Inverse Control to the Desulphurization of Hot Metal Process". Jordan Journal of Mechanical and Industrial Engineering, Vol. 1, No. 2, 2007, 79 - 84.

[26] Alpaydin E. Introduction to machine learning. New York: MIT Press; 2010.

[27] M. D. AL-Tahat, O. Bwaliez, "Lean-based workforce management in Jordanian manufacturing firms". Int. J. Lean Enterp. Res., Vol. 1, No. 3, 2015, 284-316.

Appendix A

A sample of sensor's readings for the /cooling system

	Sensor			Date
	Pressure Level HectoPascal (hPa)	Helium Boil Off Liquid Pound per Hour (LPH)	Helium %	
. . .	. . .	. . .	. . .	12/19/2014 . .
Passed	71	0.077035	49.9	5/1/2016
Passed	69	0.077272	49.6	5/2/2016
Passed	69	0.077499	49.5	5/3/2016
Passed	68	0.077716	49.4	5/4/2016
Passed	68	0.077909	49.4	5/5/2016
Passed	68	0.078137	49.0	5/6/2016
Failed	70	0.078356	48.9	5/7/2016
Failed	69	0.078565	48.8	5/8/2016
. . .	. . .	. . .	. . .	. . .
Passed	67	0.182756	54.5	2/15/2020
Passed	69	0.175236	54.5	2/16/2020
Passed	70	0.167974	54.4	2/17/2020
Passed	70	0.161475	54.1	2/18/2020
Passed	68	0.155634	54.1	2/19/2020
Passed	69	0.149561	54	2/20/2020
Passed	69	0.144888	54.1	2/21/2020