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Advanced Predictive Maintenance with Machine Learning Failure Estimation in Industrial Packaging Robots

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***Abstract*— In production systems, the repeated breakdowns of the operation have to be taken into account with great importance. The continuation of long malfunctioning states as well as the temporary interventions involve excessive time and money costs. Industry 4.0 technologies extensively use real-time Big Data collected from the machinery, and this enables potential problems to be addressed and resolved before they become an avalanche for the company. Permanent solutions can be produced, and thereby production efficiency can be established. In this paper, utilizing the Mean Time to Failure (MTTF) values and the past breakdown history of the robot system of the production line an Artificial Neural Network (ANN) model is established for system failure prediction. The proposed model successfully manages predictive maintenance of the machinery without the use of Internet of Things (IoT) technology.**

Keywords—Industry 4.0, predictive maintenance, MTTF, machine learning, failure prediction,

I. INTRODUCTION

Recently major innovations in digital technologies such as IoT systems, predictive maintenance, big data, or a combination of such technologies namely Industry 4.0 increase productivity, safety, and quality while reducing expenses of production. The globalization of Industry 4.0 is gaining momentum and its scope of influence is increasing. The companies that cannot keep up with the trends cannot continue in the course of production in the market.

Unplanned downtimes, workforce occupied in periodic planned maintenance, machine maintenance costs, and planned stops in production are among the major factors impeding the production efficiency in factories. In unplanned stops long delays to supply required components to overcome a hardware failure induces excessive inefficiency in the production.

Accordingly, a critical data to be named as production line Overall Equipment Effectiveness (OEE) can be forged to monitor the underlying causes of the production downtime with the help of IoT technology governing the control of the processes and corresponding machinery. Big Data, as a great quantity of various information, can be collected in increasing volumes. Commonly it has been structured and analyzed employing artificial intelligent systems. However, the renovation of the machine and information technology infrastructure should be established to collect this data with the help of IoT.

In this study, a meaningful sub-set of Big Data has been created without the need for employing IoT technology. It consists essentially of the failure notifications collected from the production line. Enterprise Resource Planning (ERP) system which governs the operational machines and associated production conversion data is the source for this purpose. A methodology for predictive maintenance is presented from a different perspective. The nature of the system failures are comprehended by a Multilayer Perceptron (MLP) trained with the failure data. The trained MLP structure is then tested for predictive maintenance using the data of succeeding failures which are not used in the training stage. The main thrust of this study is the use of predictive maintenance to establish a system that can make failure estimations before the failure itself occurs. An analysis to quantify the predictions is also presented to illustrate the success of the model. Finally, the reliability analysis of the system was carried out on the robot of equipment based MTTF calculations of fault groups. Actual failure notifications, calculated MTTF values, and outputs of the ANN are presented.

The rest of the paper is organized as follows: Section II presents an overview of the most relevant concepts and different techniques associated with predictive maintenance.

Section III describes the architecture modules for our methods of predictive maintenance. The predictive maintenance tests are performed and a detailed comparison of calculated and real values is presented afterward in Section IV. Section V rounds up the paper with the conclusion.

II. Related Predictive Maintenance Studies

Many methods of Predictive Maintenance have been proposed in the literature. In these studies, commonly the sensor data is obtained with IoT Architecture and evaluated by machine learning, and deep learning models [1], [2]. A model of the overall system can be created based on the received sensor data as vibration, temperature, humidity, etc. By detecting abnormalities of Big Data obtained from the model, the system can be warned and more importantly maintained allowing intervention at the first stop the machine before a failure occurs. Thus, unplanned downtimes, labor, and maintenance costs are prevented with such planned interventions for the maintenance. In this way, production efficiency will increase.

In another study, the data was obtained with IoT Architecture governing low-cost sensors and evaluated by a machine learning model [3]. The data collection task with the help of IoT technology was launched conveniently with Azure IoT, and the data was kept in the cloud structure, and rendered for utilized ERP systems [4], [5]. The use of neural networks was reported to be providing fast and accurate predictions. A neural network structure is established by a feed-forward layer logic and Electro Migration (EM) significant reliability analysis was performed using integrated circuit packages [6]. MTTF characteristics of the system were computed and the nature of failure estimations are learned with such integrated circuit packages [7]. In a different application, the focus was the analysis of the Big Data created via Distributed Control System (DCS) and Industrial IoT (IIoT) with the development of industry 4.0 [8], [9]. In this context, the machinery data was structured and the failure estimations were established using the machine learning FB100 function package [10]. Maintenance and replacement tasks were performed conveniently regarding the estimates before the failure occurs [11].

In another industrial practice, Big Data was created using IoT technology governing the machinery; and subsequently the information about operator failure notifications and interventions for failures were extracted out [12], [13]. Such data was analyzed using an advanced data analytics tool called Maintenance 4.0 consists of data mining, machine learning, and cloud technology [14]. As a result of the analysis, the system is monitored dynamically and a predictive maintenance application was automatically activated in the work schedule of the maintenance technician [15].

Our study differs from the mentioned studies in that sub-set of Big Data is created by utilizing the past failure notifications produced by just the ERP system and the use of IoT sensor technology as well as extra equipment installation is not considered. This study is the prediction of the failures with a machine learning algorithm before the failure itself may occur.

III. Proposed Approach

In this study, downtime records of the facility from the last 3 years have been investigated towards the prediction of the downtimes that occurred in the production lines. Unplanned downtimes are essentially due to environmental and hardware issues. As a result of expert examinations, some similarities have been determined in the stances of the industrial packaging robots that are shown in Fig. 1, in terms of working times, seasonal factors, downtimes, conversions, etc. Considering the expert knowledge based on these similarities, a training structure is established in which an artificial intelligence structure can cope with downtime and conversion data obtained from the system within working hours of ERP systems.

In the training structure the expert knowledge is conveyed on the artificial neural network by evaluating the failure data. A grouping strategy is employed for the data to be presented to the network. Through the process of weight updates involving iterations using the training samples, the system consequently reaches a state at which the failure predictions can ensure planned maintenance [16].

The study is conducted also on the reliability analysis of the components in the hardware of the system. Considering the current system downtimes MTTF values are computed for each component. The theoretical and practical tests are performed introducing the available data to the ANN and the reliability analysis.

Fig. 1. Packaging robot.

A. Data Collection and Optimization

After some examinations, we have figured out that the production lines occupied for two specific products host most of the faults in the factory. These two lines consist of regional work stations as the buffer, the packaging robots, and the cartooning robots. We focused basically on the packaging robots of the production line, the incoming failure notifications considering these robots are structured.

Our Big Data consists of 157 failure notifications associated with packaging robots of the production line produced between the years 2017 and 2019. In addition to these failure notifications an accompanying set of data about the machine working hours between successive failures for the similar groups of the machines, the product at the time of failure, and the production conversion quantity via ERP system were collected. This complementary data is used to elevate the success of the ANN. Necessary arrangements have been made for the data. From Table I, we can see that analog data presented to the artificial neural network is normalized to be in the range of [0,1] employing the log-sigmoid transfer function.

TABLE I. OPTIMIZED ROBOT FAULT NOTIFICATIONS

SEASON (t-1)/3	WORKSHOP (Code)/2	MACHINE (Code)	FAILURE AREA (Code)/2	OPERATION TIME (min/518400*3)	DOWNTIME (min/540)	PRODUCTION AT FAILURE (Code)/4	CONVERSION (pieces)/40
1.0000	0.00	1	0.0000	0.1247	0.1111	0.25	0.2750
1.0000	0.00	1	0.5000	0.1597	0.0556	0.75	0.5500
1.0000	0.50	1	0.0000	0.1540	0.0556	0.50	0.5750
1.0000	1.00	0	1.0000	0.1932	0.2222	0.50	0.6750
1.0000	1.00	1	0.5000	0.0341	0.1667	0.50	0.1000
1.0000	0.00	0	0.5000	0.0203	0.1111	0.25	0.1000
0.0000	0.50	0	0.0000	0.0122	0.0556	0.25	0.0250
0.0000	0.50	1	0.0000	0.0119	0.0556	0.25	0.1750

B. *Artificial Neural Network Approach*

Artificial intelligence is defined as the ability of a computer or a machine to perform human-like tasks such as reasoning, prediction. For such task learning mechanisms should be utilized. Here in this study an MLP structure is used as an ANN. Each connection between artificial neurons can transfer a signal from one to another. Often, the signal is represented with real values, and the output of each artificial neuron is calculated by a non-linear function of the sum of its inputs. The backpropagation algorithm learns the weights for a multilayer network, given a network with a fixed set of units and interconnections. The attributes of the data mentioned in the previous chapter is briefly stated in Table II. The inputs hold the values associated with the current downtime instances. The outputs indicate the prediction in the next downtime. Fig. 2 illustrates the parameters of the MLP model; 8 input nodes, 20 hidden layer nodes, and 4 output nodes are employed.

TABLE II. INPUT AND OUTPUT ATTRIBUTES OF FAILURE DATA

INPUTs
Season
Workshop
Machine
Failure Area
Operation Time
Downtime
Production at Failure
Conversion

OUTPUTs
Workshop
Machine
Failure Area
Operation Time

After the MLP structure and backpropagation learning algorithm is designed 146 of the 157 physical failure notifications are used in the training stages and 11 of them are kept unknown for the network to be tested later.

The learning algorithm employs essentially gradient descent to minimize the squared error between the network output values and the target values. In the training stage 2000 iterations are used, and it was ensured that the training error was minimized.

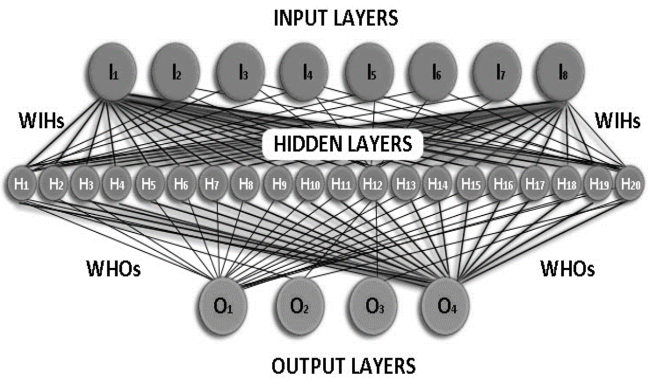

Fig. 2. MLP structure with machine learning application

C. *MTTF Values Computation for Machine Components*

In this context, the study was started by ensuring that the components used on the machine are determined locally. From Table III we can see that 13 failure zones on the robot are considered.

TABLE III. FAILURE ZONEs AND GROUPs ON THE ROBOT

FAILURE AREA		
0-GROUP SYSTEM	***1-GROUP SYSTEM***	***2-GROUP SYSTEM***
CLOSER SYSTEM	SAFETY SYSTEM	ENTER BAND SYSTEM
ERECTOR SYSTEM	HOT MELT SYSTEM	CELL SYSTEM
FILLER SYSTEM	DATE CODING SYSTEM	TRANSPORTER SYSTEM
MAGAZINE SYSTEM	VACUUM SYSTEM	
MODULE SYSTEM		
TRANSFER SYSTEM		

MTTF determination study is carried out for the detected equipment/sub-systems. For this purpose, NPRD-95 mechanical standards and ground-benign cellular structures at 25 C° are taken as the base conditions. Following the equipment listed regionally, all independent zones of the robots were drawn using the Fault Tree Diagram (FTD). Fig. 3 shows the transporter system FTD of the packaging robot.

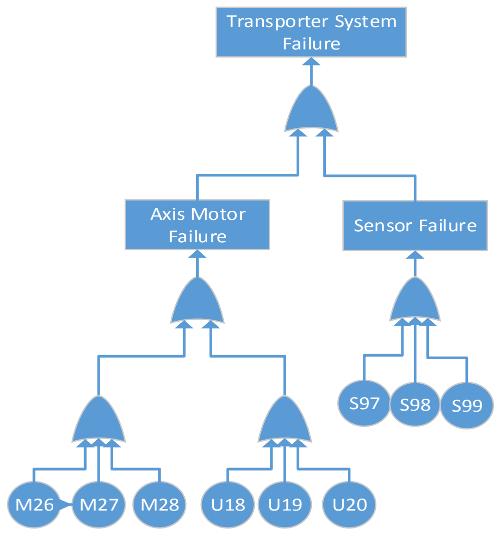

Fig. 3. Drawing transporter system with fault tree diagram

By adhering to the diagrams, it is provided to formulate the equipment over the table of 1oo1, 1oo2, or 1oo4 Fault Tree Diagram. In this structure of the formula, it is divided into 16 different periods between 1 day and 5 years. The reliability function $R(t)$, the failure function $F(t)$, and is the failure rate function $\lambda(t)$ can be calculated as follows:

$$R(t) = e^{-\int_0^t \lambda(u)du} \tag{1}$$

$$F(t) = 1 - R(t) \tag{2}$$

$$\lambda(t) = -\frac{d}{dt}\ln R(t) \tag{3}$$

where t is the time to failure.

D. Grouping of Machine Zones and Reliability Analysis

After performing post-regional calculations, the regions were divided into three main groups according to the similar equipment and the similar functionality. Fault and reliability values of the groups are calculated. Finally, using this data, calculations (4-8) are made in 16 different periods of the robot. After the calculation, the failure rate and MTTF values of all regional groups and systems are obtained These values are displayed in Table IV.

TABLE IV. FAULT AND RELIABILITY ANALYSIS ON THE ROBOT

	0.GROUP FAIL SAFE	1.GROUP FAIL SAFE	2.GROUP FAIL SAFE
F(1st.day)	0.023289	0.011182	0.003441
F(2nd.day)	0.046036	0.022239	0.006870
F(4th.day)	0.089953	0.043984	0.013693
F(1st.week)	0.162000	0.080880	0.025520
F(2nd.week)	0.297760	0.155218	0.050388
F(1st.month)	0.506873	0.286344	0.098237
F(2nd.month)	0.756853	0.490695	0.186824
F(3rd.month)	0.880125	0.636531	0.266708
F(4th.month)	0.940906	0.740608	0.338745
F(6th.month)	0.985644	0.867891	0.462283
F(9th.month)	0.998282	0.951982	0.605696
F(1st.year)	0.999795	0.982547	0.710860
F(2nd.year)	1.000000	0.999695	0.916398
F(3rd.year)	1.000000	0.999995	0.975827
F(4th.year)	1.000000	1.000000	0.993011
F(5th.year)	1.000000	1.000000	0.997979

ROBOT RELIABILITY	
R(1st.day)	0.962466
R(2nd.day)	0.926341
R(4th.day)	0.858107
R(1st.week)	0.750567
R(2nd.week)	0.563347
R(1st.month)	0.317351
R(2nd.month)	0.100700
R(3rd.month)	0.031950
R(4th.month)	0.010136
R(6th.month)	0.001020
R(9th.month)	0.000033
R(1st.year)	0.000001
R(2nd.year)	0.000000
R(3rd.year)	0.000000
R(4th.year)	0.000000
R(5th.year)	0.000000
F. RATE(λ)	0.0383
MTTF(DAY)	26.14

$$MTTF(t) = \frac{1}{\lambda(t)} \tag{4}$$

for a year;

$$\lambda(1year) = -\ln(1.03602E - 0.6) \tag{5}$$

$$\lambda(1year) = 13.78 \tag{6}$$

$$MTTF(day) = \frac{1}{\lambda(1year)} * 360 \tag{7}$$

$$MTTF(day) = 26.12 \tag{8}$$

where $MTTF(t)$ is the meantime to failure, E is the Euler's number of mathematical constants.

E. Spare Parts Analysis with Poisson Distribution

After calculating the time based on the quantity and MTTF values of the components on the packaging robots, the system can operate with 85% efficiency. To ensure efficiency, in the case of downtime, the relevant equipment must be available and can be replaced quickly. In this way, it is aimed to increase production efficiency by minimizing the downtime occurrences of the machine.

Poisson distribution can be used to determine machine spare parts stocks:

$$\lambda t = \frac{A.N.M.T}{MTTF} \tag{9}$$

where λt is the average number of events per interval, A is the number of equipment, N is the number of subsystems, M is the working year, and T is the time to period.

$$P \le \sum_{x=0}^{n} \frac{(\lambda t)^x}{x!} e^{-\lambda t} = e^{-\lambda t}\left[1 + \lambda t + ... + \frac{(\lambda t)^n}{n!}\right] \tag{10}$$

where P is the probability of events for a Poisson distribution, x is the values (0,1, 2, …), $x!$ is the factorial of x, n is the spare of equipment, and e is the Euler's number.

For 85% System Reliability with two spares on PCB card can be calculated as follows;

$$P \le \sum_{x=0}^{2} \frac{(\lambda t)^x}{x!} e^{-\lambda t} \tag{11}$$

$$P \le e^{-0.96}\left[1 + 0.96 + \frac{(0.96)^2}{2!}\right] \tag{12}$$

$$P_{PCBcardfor2spares} \ge 92.7\% \tag{13}$$

Spare parts analysis with Poisson distribution is revealed in Table V. In spare parts analysis calculated with Poisson Distribution, keeping two spare parts for PCB Control Card as an example will ensure that the efficiency of the system remains at 92.7%.

TABLE V. SPARE PARTS ANALYSIS WITH POISSON DISTRIBUTION

	PCB Control Card	Servo Module Power Card	Date Coding
MTTF	16.7	15.5	16.5
A (piece)	8	3	1
N (system)	2.00	2.00	2.00
M(time)	1.00	1.00	1.00
T (period)	1.00	1.00	1.00
λt	0.96	0.39	0.12
Spare 0	38.4	67.9	88.6
Spare 1	75.2	94.2	99.3
Spare 2	92.7	99.3	100.0
Spare 3	98.3	99.9	100.0

IV. Performance Test And Evulation

A. *Comparison of Calculated and Real MTTF Values*

The reliability and fault analysis for the robot system is shown in Fig. 4. it can be seen from the plots the robot's reliability drops to 75% around one week after the last failure intervention.

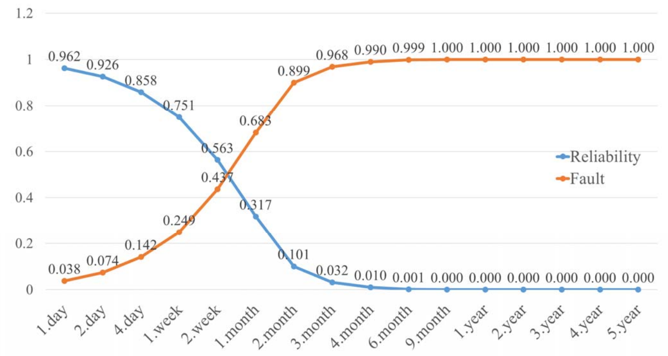

Fig. 4. Reliability and fault analysis chart of robot system

To be more precise considering the real failure notifications in the robot system groups, possible system failure may occur after 6.79 days and the reliability of the system has decreased to around 75%.

MTTF value of the robot system is calculated as 26.12 days regarding the reliability analysis. When a detailed examination of the fault zones in the robot takes place, it is determined zone-based faults occur between 18 and 23 days. The results are shown in Fig. 5.

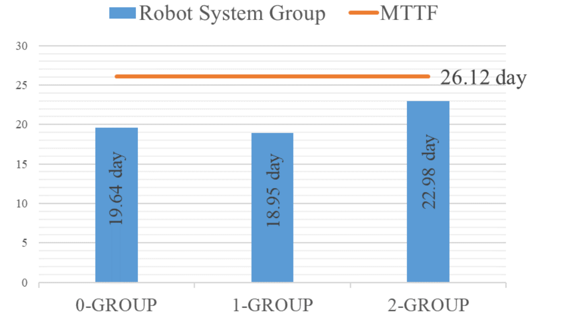

Fig.5. Calculated MTTF and failure frequency comparison in fault regions

B. *Testing the Data with MLP Model*

Neural networks can store experiential knowledge and make it available for use in advance. The weight update is performed in the learning phase using the training samples, and the network. For the test phase we introduced 11 test samples which are the cases not experienced by the network. We expect that the system can predict the failure within a period of 0 to 22 days before the real occurrence. The results regarding the prediction of operating time after introducing the test samples are displayed in Fig. 6.

A 91% prediction success rate is achieved with a σ=7.25 standard deviation between real failures and predicted test data in Fig. 7. The calculated value of the system's average of estimating failure is 5.24 days, and this was 6.79 days in real situation. 75% reliability was determined after 5-7 days in the reliability analysis of the robot system.

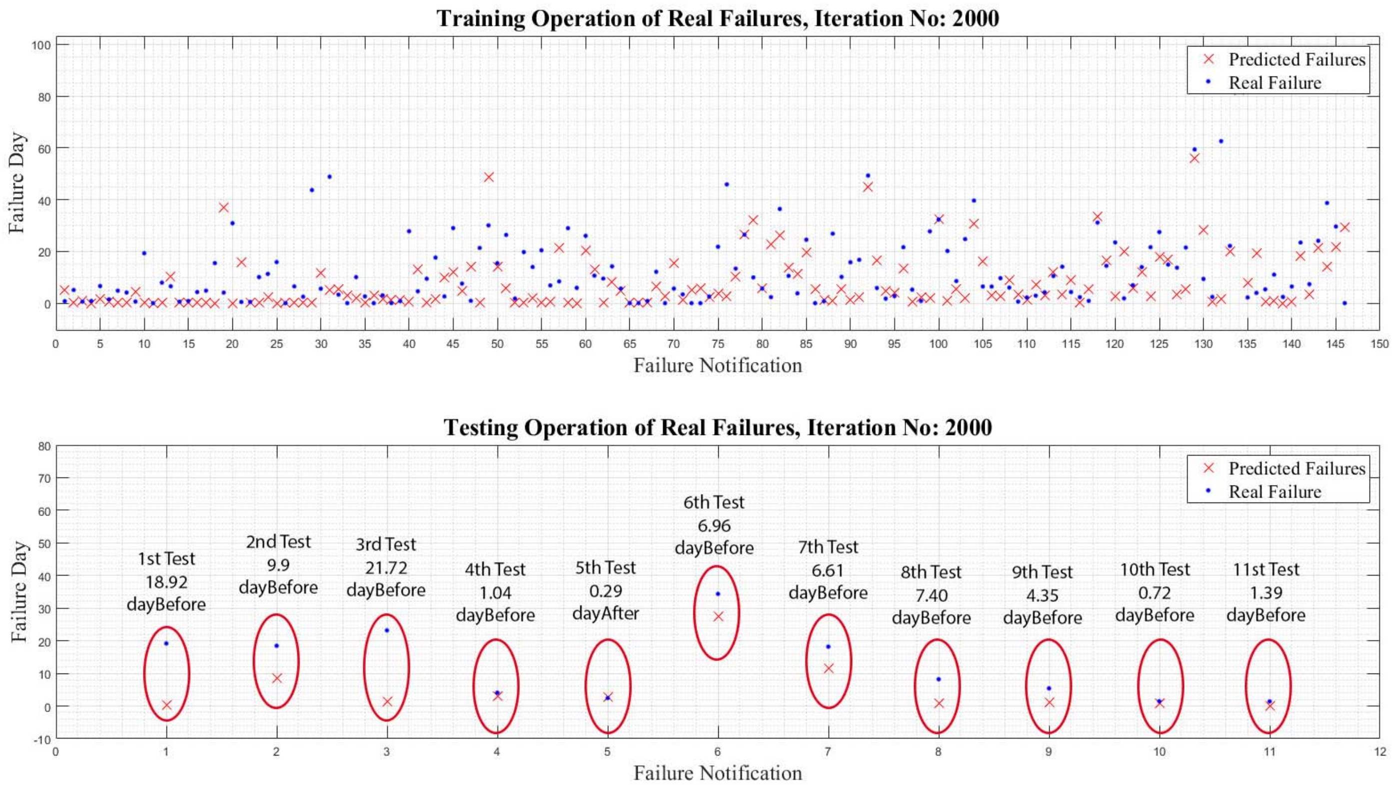

Fig. 6. Training and testing phases of the neural network

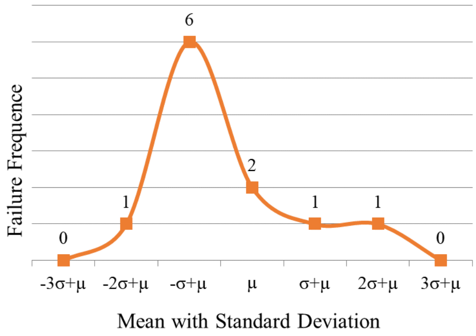

Fig. 7. Prediction test results with σ=7.25 standard deviation

V. Summary And Conclusions

In this study, a robot system is analyzed for predictive maintenance purposes for the scenarios of not having IoT technology that usually governs the Big Data of a facility. In our case the past failure notifications were collected with the help of the ERP system. The theoretical and practical tests are performed introducing the available data to the ANN and the reliability analysis tools that we designed. The results illustrated that the MLP structure can cope with unplanned downtime occurrences. Such a prediction will increase production efficiency by producing scheduled maintenances to several days before the actual failure occurs. In other words, it can reduce the unplanned production downtime costs immensely.

Besides, with the component-based reliability analysis made; both theoretical and practical comparison of the failures in the system has been provided. It has been ensured that our predictions made with machine learning-based predictive maintenance implementation is compatible with the findings of MTTF calculations. With the analysis of the spare parts employing Poisson distribution, we assure a material requirement list was created for the system to be able to operate at high production efficiencies of 85%. Thus, intervention times due to the insufficiency of material will be minimized during predictive maintenance applications.

Enlarging the size of the Big Data (157 physical failure notifications are used in this study) will allow us to make more precise predictions in the future. Currently, the system offline errors are collected manually. In the following process, the prediction system can be utilized with an online HMI interface that communicates with the facility ERP system.

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