International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

December 2023	Issue 57	Volume 15	Number 4	Pages 410-419

MAINTENANCE MANAGEMENT BASED ON RELIABILITY ANALYSIS OF WELDING ROBOTSUSING SVM

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Abstract- As more repetitive operations (such as riveting and welding) are performed by robots in the automotive industry, it is important to evaluate their reliability to adopt an appropriate maintenance management strategy. With Industry 4.0, businesses are moving toward complete process automation and the use of intelligent sensors to collect data, evaluate it, and predict robot behavior and potential issues using artificial intelligence methods like Support Vector Machine (SVM). In this research, six welding robots were followed and data was collected during a year of operation. After the analysis of data related to actual failures, Weibull's law, and Support Vector Regression (SVR) techniques were used to calculate the reliability functions. Several MATLAB programs were used to determine the parameters for the prediction laws and the graphics. To properly manage the maintenance of these robots, we then suggested a methodology that should be followed.

Keywords: Robotics, Reliability, Maintenance, SVM, SVR, Prediction.

1. INTRODUCTION

The reliability functions of robots can be identified, which allows the definition of the proper maintenance management [1], observation of degradation, and the planning of predicted dates for replacement or renovation [2, 3]. A novel kind of maintenance is starting to adapt to the present industrial revolution, known as Industry 4.0, which uses new technologies [4], particularly artificial intelligence, inside industrial production structures. This new type of maintenance has been developed to match Industry 4.0 and become more reactive and efficient. This is called maintenance 4.0 or predictive maintenance [5].

To evaluate data and identify defects early on, maintenance 4.0 employs the analytical tools of artificial intelligence, particularly machine learning [6]. Statistical methods like the Weibull probability law are used to examine system reliability, it is the most frequently applied law in reliability. It describes how a system performs at a specific moment. Various techniques can be employed to define the Weibull distribution's parameters. The support vector machines (SVM) have been selected. This technique will be detailed later in this paper.

In the present research, we analyze six welding robots' reliability of the assembly line in an automotive manufacturing implemented in Morocco. Over a period of a year of use, we gathered failure information from the six robots. The life cycle phases and reliability functions of the robots are determined using this data. For this reason, MATLAB scripts have been created [7]. We first introduce the reliability and several sorts of maintenance in the first part, then we review SVM and Weibull's law. The technical information about the robots is described and an analysis of the results is provided in the fourth part. Finally, an appropriate maintenance management approach is suggested.

2. RELIABILITY AND MAINTENANCE

When an entity is performing its task at its starting point, reliability is the probability $R(t)$ that the entity will continue to carry out the needed function under the circumstances specified at some later time $(0, t)$ [8]. The main concern of reliability is to predict the probability of a system failure by establishing a reliability law. The curve "bathtub", as it's known, presented in Figure 1 is frequently used to describe the failure rate $\lambda(t)$ of equipment [9]. It illustrates three stages in a product's life cycle and describes how the failure rate has changed over time:

- The youth stage, which has a decreasing failure rate, is concerned with initial failures resulting from problems with the design or production process.
- A service lifetime with a consistent breakdown rate is a sign of unexpected breakdowns.
- Ageing phase with increasing breakdown rate: this time is concerned with breakdowns carried on by aging.

Due to deterioration in mechanical systems, the curve has no flat component (λ=constant) and rises once the running-in time is over.

Numerous statistical approaches can be used to identify reliability functions, Weibull's law will be applied in this paper. According to international standards, maintenance is a series of operations meant to keep an asset in a particular state or enable it to perform a specific service.

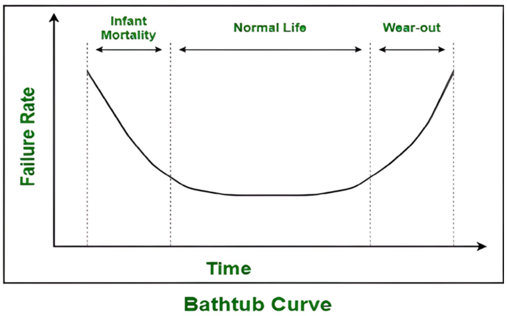


Figure 1. Bathtub curve

There are various forms of maintenance [2]:
- Corrective maintenance, sometimes referred to as curative or reactive maintenance, includes engaging with the equipment after a breakdown has occurred [10].
- Preventive maintenance involves replacing components that could result in a service interruption or unexpected expenses that are considered crucial for the business [11]. It depends on the following principles to prevent and reduce the probability of system failure:

- Systematic maintenance means frequently replacing components that are too crucial for the operation of the unit, in accordance with a predetermined schedule.
- Conditional maintenance: this type of maintenance is preventive and calls for a diagnosis before a component is replaced.
- Predictive maintenance, also known as maintenance 4.0 [12]is a new type that was created with Industry 4.0. It involves predicting breakdowns as soon as pre-signs are detected on the machine, allowing the necessary parts to be changed at the right time and reducing the expenses of changing other parts unnecessarily.

Predictive maintenance analyzes data and detects defects early on using the analytical tools of artificial intelligence, especially machine learning. With this type of maintenance, the machine may be evaluated with information from implanted sensors, allowing for real-time monitoring of the situation and the performing of the required maintenance. Unlike preventative maintenance, which plans to do regular checks on the equipment over its estimated life cycle.

3. WEIBULL'S LAW

The most well-known continuous probability law is Weibull's law. It is used in reliability [13], especially for determining the reliability prediction of systems [14]. In 1951, Waloddi Weibull's name was added to this law. It is used to describe how a system performs during its life cycle [15]. The Weibull distribution employed in this article is a continuous distribution with three parameters [8]:

$$R(t) = e^{-(\frac{t-\gamma}{\eta})^{\beta}} \tag{1}$$

where, γ is the position or lag parameter, which is frequently set to 0. It shows the possible gap between the start of observation (the day we start observing a sample) and the start of the process we are studying (the day the observed process first showed symptoms).

The η is the scaling parameter that indicates the duration of the average lifetime and β is the form parameter linked to the dynamics of the observed activity.

3.1. Reliability Function

The likelihood of success overall as a function of time is called the reliability:

$$R(t) = 1 - F(t) = e^{-(\frac{t-\gamma}{\eta})^{\beta}} \quad , \quad t \geq \gamma \tag{2}$$

3.2. Unreliability Function

Unreliability function indicates the total probability of failure between 0 and t:

$$F(t) = 1 - e^{-(\frac{t-\gamma}{\eta})^{\beta}} \quad , \quad t \geq \gamma \tag{3}$$

3.3. Failure Rate

Failure rate is the instantaneous likelihood of a failure at time (t+Δt) when it is known the equipment is functioning well at time t:

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1-F(t)} = \frac{\beta}{n}(\frac{t-\gamma}{\eta})^{\beta-1} \quad , \quad t \geq \gamma \tag{4}$$

There are many ways to estimate the variables of a function that is known, or to relate an equation to a fog of points, that can be used to determine the Weibull distribution's parameters. The approaches most frequently employed are:

- Graphical estimating (Weibull paper): a quick method with poor accuracy.
- The least squares method: which is simple and time-tested.
- The Maximum Likelihood Estimation (MLE) has interesting asymptotic characteristics.

The SVM methodology, that we employed in this study and will be detailed in the next section.

4. SVM AND SVR METHOD

4.1. SVM and SVR Definition

Support vector machines are algorithms used in machine learning for managing classification, regression, or anomaly detection problems [16]. SVMs were developed in the 1990s based on the Vapnik-Chervonenkis theory, a statistical learning theory created by Russian computer scientists Vladimir Vapnik and Alexey Chervonenkis [17]. Due to this model's efficiency with massive amounts of data, theoretical warranties, and successful practical application, it was adopted immediately [18]. SVMs are liked for their simplicity of usage because they only need a few parameters.

In 1996, Vladimir Vapnik presented a technique for employing SVMs to address regression issues [19]. He worked with other mathematicians Harris Druckerand Alex Smola on the project. By utilizing the kernel method, which is popular in machine learning since it enables the use of linear classifiers to address non-linear problems, this is made achievable. Support Vector Regression (SVR) is the name given to the regression variant of SVM.

The SVM research the issue of categorizing a corpus of instances into two classes based on whether they have labels of +1 or -1. In regression, labels with any real value are considered, and samples from the data set are used to try to infer the function that links the label to the vector [19]. Again, we have investigated the situation of linear regression, which is generalizable to other regressions by utilizing distributions as rather than scalar products [20]. The provided regression presupposes a linear separator of the form;

$$f(x) = \langle w, x_i \rangle + b \tag{5}$$

where, $\langle w, x_i \rangle$ is the scalar product.

In case of the data training is precisely expresses by the separator, a $\varepsilon > 0$ approximately the error, to accomplish this goal, it is important to reduce the vector norm w to

$$\frac{1}{2}\|W\|^2 \text{ subject to } \forall_i, \left|\langle w, x_i \rangle + b - y_i\right| \le \varepsilon \tag{6}$$

In reality, it is challenging to maintain all the instances in a hyper-tube that is 2ε wide. We will define an optimization function that allows some samples to deviate from this restriction. Two relaxation variables (Slack variables), ξ_i and $\xi_i^{'}$, were added to the problem formulation to penalize the incorrectly categorized data. A cost parameter C>0 creates an agreement among the amount of misclassified samples and the margin width, which plays a role of regularizing. The term "soft margin" refers to this novel perspective on the issue. Figure 2 serves as an example of this point. Regression optimization involves playing with w, b, ξ and $\xi^{'}$ to minimize.

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^{'}) \tag{7}$$

Subject to;

$$\begin{cases} -\langle w, x_i \rangle - b + y_i \le \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \le \varepsilon + \xi_i^{'} \\ \xi_i * \xi_i^{'} \ge 0 \end{cases} \tag{8}$$

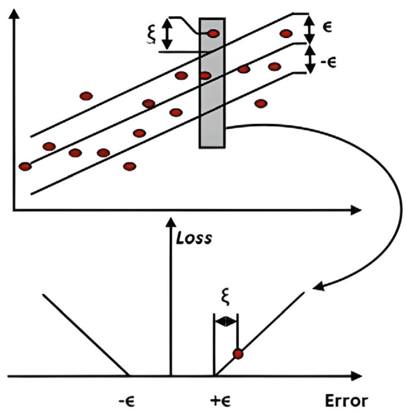


Figure 2. Error function [20]

4.2. Weibull Distribution Parameter Estimation Using SVR

From the reliability law (2), we are able to type:

$$\ln(1 - F(t)) = -\left(\frac{t-\gamma}{\eta}\right)^{\beta} \tag{9}$$

$$\ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right) = \beta * \ln\left(\frac{t-\gamma}{\eta}\right) \tag{10}$$

$$\ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right) = \beta * \ln(t-\gamma) - \beta * \ln(\eta) \tag{11}$$

As $y = \beta x + b$ (12)

So, the Equations (13) and (14) are used

$$y = \ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right) \tag{13}$$

$$x = \ln(t-\gamma) \text{ and } b = -\beta\ln(\eta) \tag{14}$$

The maintenance staff keeps careful surveillance on the robots because they are important equipment's in the vehicle assembly facility. Since we expect that γ to be zero, the law takes the following linear form:

$$y = \beta x + b \tag{15}$$

The SVR equation's identification method is used to estimate the coefficients β and b.

$$\beta^* = w^* \tag{16}$$

$$\eta^* = e^{-\frac{b^*}{\beta^*}} \tag{17}$$

5.WELDING ROBOTS FAILURES ANALYSIS

5.1. Context

The present research centered on industrial robots' deployment in a factory implemented in Morocco which produce vehicles for both the home market and export abroad. The robots employed to ensure the welding in the sheet metal industry are the subject of this study. Manufacturing robots are computer-controlled devices that are capable to perform a variety of tasks [21], such as the welding in this instance. They include the following elements [22]:

- A mechanical element like axis, articulation.
- An electrical element, like wires, motors.
- An electronic part, like sensor, card, or control system.
- A form of computer science that enables dialogue between humans and robots.

Robots assemble the stamped parts that make up the vehicle bodywork in our study scenario [23]. Numerous welding techniques, such as ultraviolet welding, flow of gas welding, welding by spot, and riveting, are employed during the assembly. Over 5000 automated welding points are used during the assembly of the bodywork. The sheet metal lines employ more than 200 robots from a variety of multinational brands. Figure 3 shows a picture of a welding robots.

Figure 3. Welding line

5.2. Robots' Technical Data

Six robots that perform welding operations above the side doors and at the wheel arch of body serve as subjects of our study. These robots have six axes as shown in Figure 4 and handling capacity ranging from 150 to 500 kg.

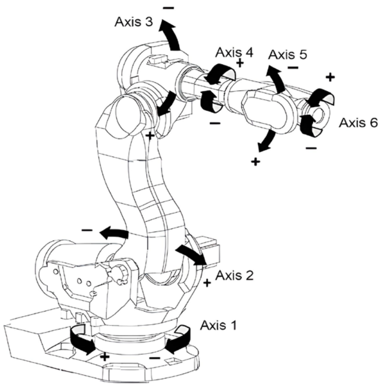


Figure 4. Robot with 6 axes

Spot-welding tongs are an element of the robots, as shown in Figure 5. Depending on the geometry of the body, each robot has the proper welding tongs that allow accessibility to the welding areas. The use of spot-welding tongs, a piece of industrial the use of spot-welding tongs, a piece of industrial equipment, eliminates the need for additional material during the welding operation. A summary of the robots' properties is given in Table 1.

Figure 5. Robot equipped by spot-welding tong

Table 1. Robots' properties

	A1	A2	A3	A4	A5	A6
Number of welded spots	21	15	16	15	21	16
Welding clamps type	RXE	RXA	RJG	RXA	RXE	RJG
Maximum of electrode forces (DaN)	450	630	425	630	450	425
Clamp Weight (Kg)	193	98	161	98	193	161

5.3. Breakdowns Data Analysis

Throughout the robots' usage of a year, breakdown information has been collected, we are particularly interested in the following data from the numerous records:

- Date of failure;
- Duration of failure (in hours, minutes, and seconds);
- Failure type.

5.3.1. Data Analysis by Number of Failures

The robots have sensors that monitor each action, including error messages that are shown as alerts and the number of welds that are not finished within the predetermined cycle time. In this study, we only keep the data that are considered as failures and need the intervention of the maintenance staff to be corrected. Robots are always in use, and any breakdown can be repaired. The information is immediately recorded. Failures have been arranged by months as shown in Table 2 for simplicity of use.

Table 2. Number of failures by month

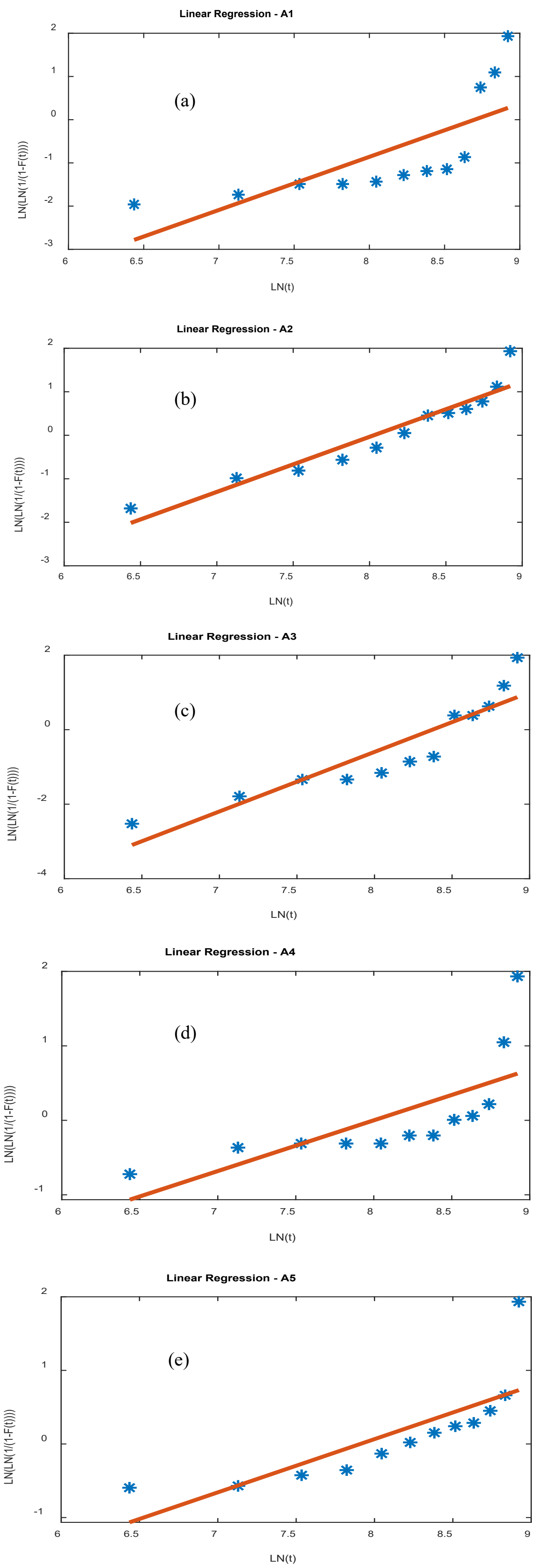
	Number of failures by Robot					
Month	A1	A2	A3	A4	A5	A6
January	13	18	2	20	53	10
February	3	15	2	6	1	7
March	4	5	2	1	6	25
April	0	8	0	0	3	18
May	1	10	1	0	10	13
June	3	13	2	2	7	25
July	2	15	1	0	6	27
August	1	2	10	4	4	43
September	7	3	0	1	2	2
October	53	5	2	3	7	12
November	7	7	3	12	8	23
December	5	5	1	3	18	20

5.3.2. Results and Discussion

We determine the distribution function $F(t)$, which is the reciprocal of $R(t)$. At time t_i, there are n_j failures taking place in the intervals $[t_j–1; t_j]$. Then, we have;

$$F_i = \frac{\sum_{j=1}^{i} n_j}{N} \tag{18}$$

For every robot, F_i is determined monthly. Actual data were linked to straight lines using SVR algorithms. With 95% confidence level, the Weibull distribution coefficients were identified. The SVR lines for the six robots are shown in Figures 6a to 6f.



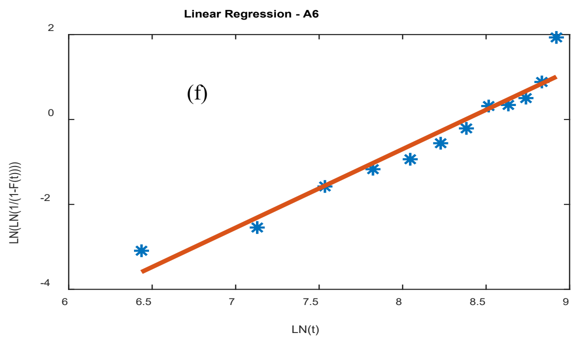
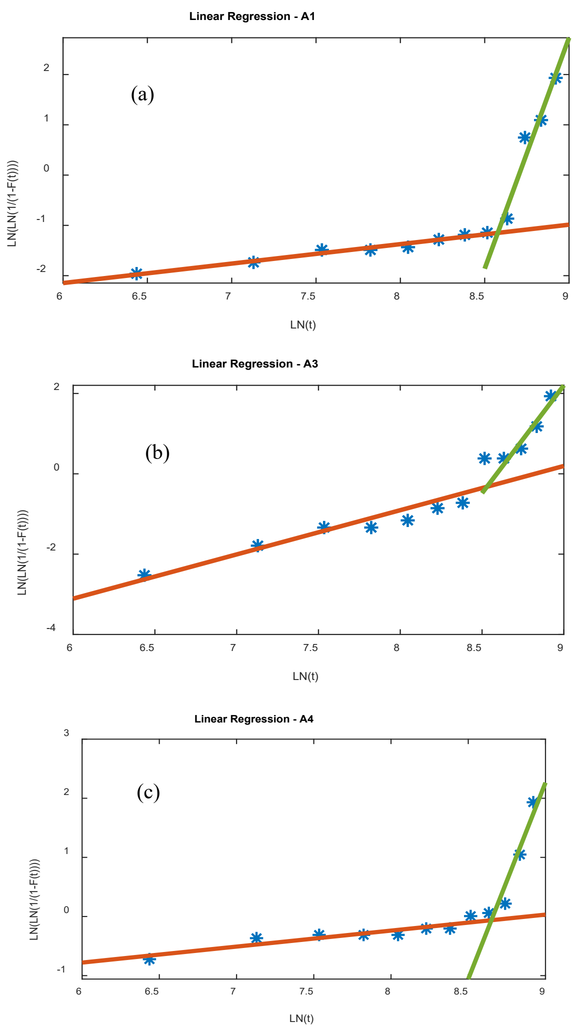


Figure 6. a) The simple regression SVR of A1 robot, b) The simple regression SVR of A2 robot, c) The simple regression SVR of A3 robot, d) The simple regression SVR of A4 robot, e) The simple regression SVR of A5 robot, f) The simple regression SVR of A6 robot

According to the findings, robots A1, A3, A4, and A5 did not achieve their goal. To solve the problem, we divide the scatter plot into two subsets. This case presents a situation in which two distinct failure modes overlap. The double regression of these four robots is shown in Figures 7a to 7d. The first phase runs from January to August, while the second runs from September to December.



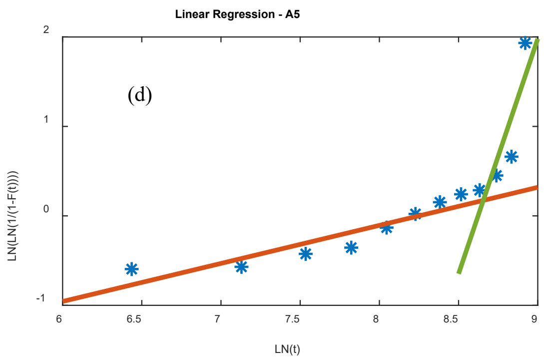


Figure 7. a) The double regression SVR of A1 robot, b) The double regression SVR of A3 robot, c) The double regression SVR of A4 robot, d) The double regression SVR of A5 robot

The values of β and η are grouped in Table 3.

Table 3. β and η values

Robot	Single regression		Double regression			
	β	η	β_1	η_1	β_2	η_2
A1	1.2293	5998.4	0.3868	103700	9.1859	6019
A2	1.2662	3066.1				
A3	1.5981	4333.3	1.1011	6786.3	5.3692	5376.6
A4	0.6814	2980.4	0.2705	7200.5	6.6457	5763.2
A5	0.7233	2722.1	0.4253	3826.4	5.2542	5559.5
A6	1.8509	4344.6				

5.3.3. Acceptance Test

The selected Weibull distribution is compared to the experimental points with a 5% error to check if it matches. We calculate the resulting error using the Kolmogorov-Smirnov approach [24]. Table 4 resume values of reach robot.

$$\varepsilon_j = \max_{i=1,\dots,N}(|\varepsilon_i|) \quad \text{with} \quad \varepsilon_i = F(t_i) - F_{th}(t_i) \tag{19}$$

Table 4. ε_j values

Robot	Single regression	Double regression
	ε_j	ε_j
A1	0.277	0.127
A2	0.112	
A3	0.252	0.259
A4	0.169	0.105
A5	0.133	0.096
A6	0.096	

We compare the biggest variation, labeled $D=\varepsilon_j$, with the value of D (N=12, α=0.05) = 0.375. We conclude that the test is acceptable as $D<D_{N,\alpha}$.

5.3.4. Root Mean Square Error Calculation

The mean square difference between values that a model predicts and observed or actual values is known as root mean square error (RMSE) [25]. In general, a lower RMSE number indicates greater precision. We have calculated the RMSE as indicated in Table 5, in the both cases with a single regression line and with a double regression.

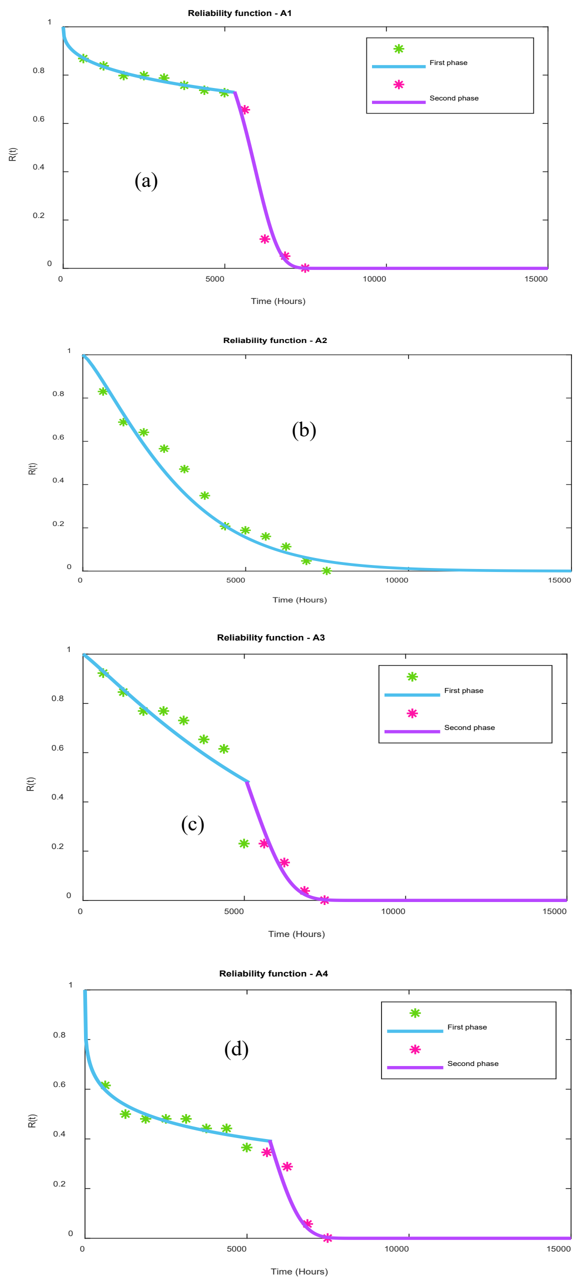
Double regression provided us with better predicted accuracy for the four robots (A1, A3, A4, and A5) since we observed that the RMSE value is lower in the case of double regression than in the case of a single straight line.

Table 5. RMSE values

Robot	Single regression	Double regression
	RMSE	*RMSE*
A1	0.1951	0.0423
A2	0.0585	
A3	0.1182	0.0868
A4	0.1150	0.0445
A5	0.0803	0.0515
A6	0.0543	

5.3.5. Reliability and Failure Functions

The reliability curves are presented in Figures 8a to 8f.



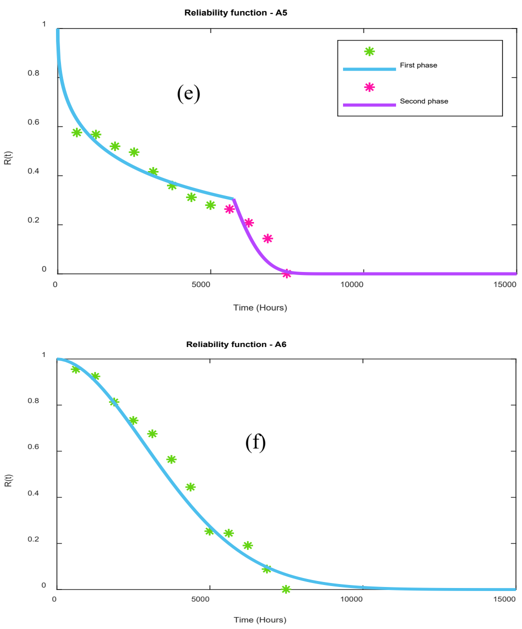


Figure 8. a) A1 Robot reliability function, b) A2 Robot reliability function, c) A3 Robot reliability function, d) A4 Robot reliability function, e) A5 Robot reliability function, f) A6 Robot reliability function

The system's reliability evolves normally in the first part of the curve, then deteriorates sharply. This confirms our earlier observation that robots experience two different life cycles during the observation period. The results for the β shape parameter for all robots are summarized in the Table 6.

Table 6. β shape parameter values

Robot	*Β* Value	Life cycle phase
A1	$\beta_1 = 0.3868$ $\beta_2 = 9.1859$	The robot passes from the youth phase to the aging phase (wear and tear)
A2	$\beta = 1.2662$	The robot is relatively in its useful life end and is beginning to age
A3	$\beta_1 = 1.1011$ $\beta_2 = 5.3692$	The robot moves from the useful life phase to aging phase (wear and tear)
A4	$\beta_1 = 0.2705$ $\beta_2 = 6.6457$	The robot passes from the youth phase to the aging phase (wear and tear)
A5	$\beta_1 = 0.4253$ $\beta_2 = 5.2542$	The robot passes from the youth phase to the aging phase (wear and tear)
A6	$\beta = 1.8509$	The robot is relatively in its useful life end and is beginning to age

Figures 9a to 9f presents the evolution of the failure rate for the different robots.

Our research has shown that each robot has a unique failure rate, which must be considered while managing maintenance. In the current maintenance management system, corrective measures are still conducted as soon as a breakdown occurs, and preventive actions are scheduled twice during the plant's annual shutdowns (August and December). We suggest modifying the preventive maintenance schedule to prioritize robots based on life-cycle phase and failure rates (β values) with more moderated frequencies.

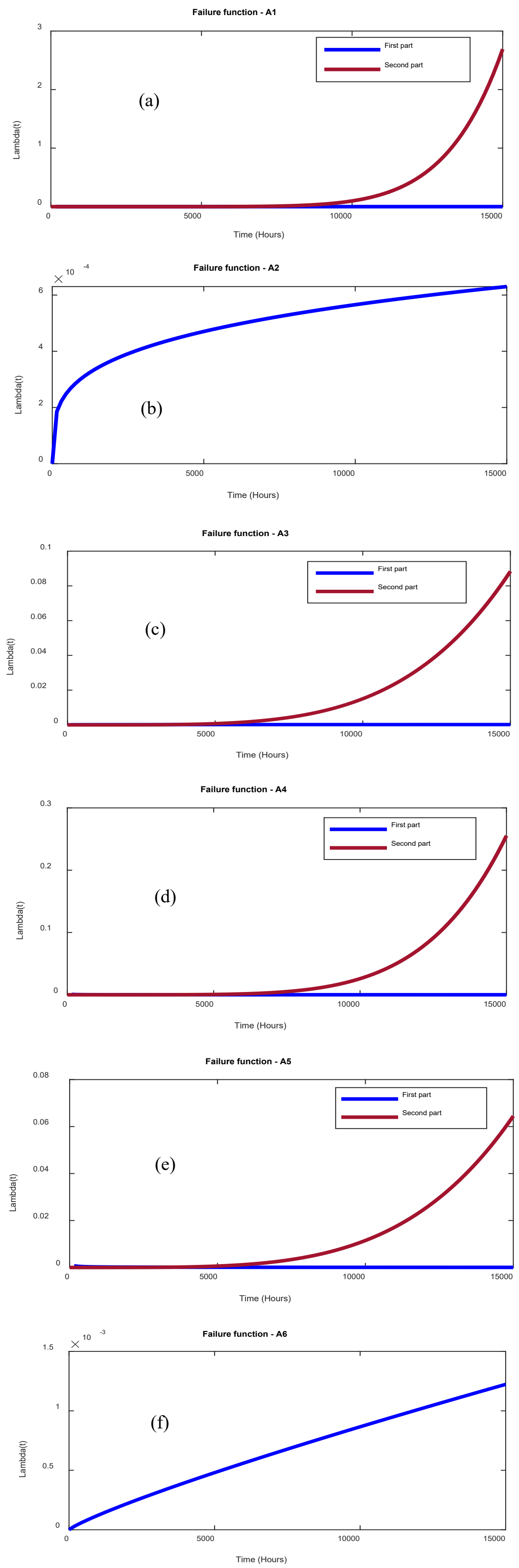


Figure 9. a) A1 Robot failure function, b) A2 Robot failure function, c) A3 Robot failure function, d) A4 Robot failure function, e) A5 Robot failure function, f) A6 Robot failure function

In this situation and using the available information, maintenance intervention should be carried out in the following priority order: A1 - A4 - A3 - A5, followed by A6 and A2. Due to the welding guns that these robots are equipped with, the reliability of the entire system is based on the reliability of the guns and the robot reliability. Wear phenomena affect the robots A1, A4, A3, and A5, and we examine the sorts of failure to identify which robot entity is impacted (the robot or the related clamp).

5.3.6. Failure Type Analysis

We divided failures into two families: number of failures involving clamps and failures involving just robots as shown in Table 7. Figure 10 presents the failure percent of each part: clamp and robot.

Table 7. Number of failures by family

Robot	A1	A2	A3	A4	A5	A6
Clamp failure	80	80	11	14	68	113
Robot failure	19	26	15	38	57	112

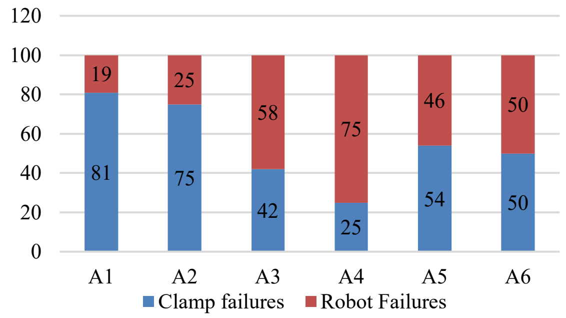


Figure 10. Failure-type repartition

We note three categories:
- Clamp Failures > robot failure: Robots A1 and A2.
- Clamp Failures < robot failure: Robots A3 and A4.
- Clamp Failures ≈ robot failure: Robots A5 and A6.

During Preventive Maintenance, the same checklist is applied to all robots without taking the different types of failure in consideration. Our suggestion is to:

➢ Create special checklists based on the component that affects system reliability most significantly, with particular focus on the robot or gripper.

➢ Plan periodic, quarterly, or monthly inspections based on the severity and occurrence of breakdowns.

5.3.7. Preventive Maintenance Efficiency

As part of our ongoing failure analysis, we compared the average number of breakdowns per month before and after the preventative maintenance work done in August in Table 8 and Figure 11.

Table 8. Average number of failures

	A1	A2	A3	A4	A5	A6
Welding clamp failure- Before	1.37	7.75	0.75	0.75	5.5	8.62
Welding clamp failure- After	17.25	4.5	1.25	1.75	6	11
Robot failure - Before	2	3	1.75	3.37	5.75	12.37
Robot failure - After	0.75	0.5	0.25	3	2.75	3.25

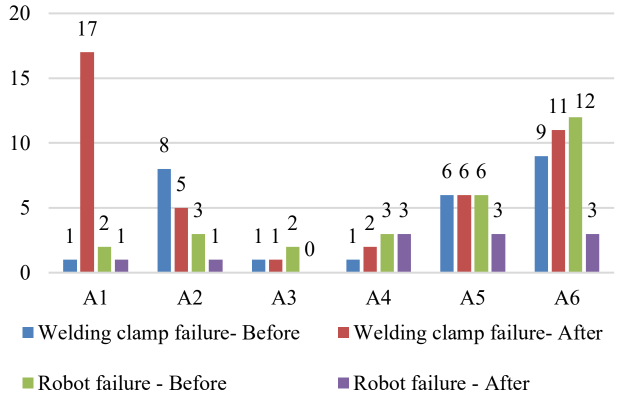


Figure 11. Average number of failures

The average frequency of robot failures has decreased for all robots, indicating the effectiveness of the preventive maintenance. For all robots, except robot A2, we noticed an increase in the average number of welding clamp failures. So, for this reason, we suggest replacing the welding clamps spare parts, or the welding clamps themselves if the spare parts were changed during the preventive maintenance previous. In conclusion, we recommend the model presented in Figure 12 for improved robot system management.

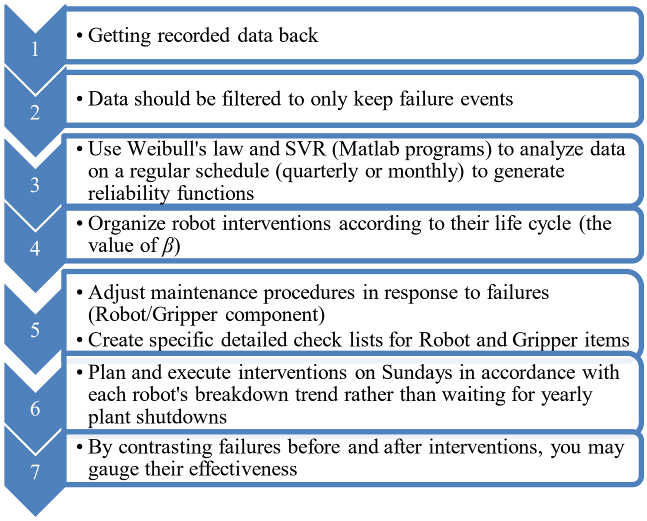


Figure 12. Maintenance management model

6. CONCLUSION

This work focused on optimizing the Maintenance of welding robots through reliability in the context of automobile manufacturer, Weibull's law and SVR algorithms were used in MATLAB to determine reliability functions by evaluating failure data gathered over the course of a year. The employed prediction law's acceptance test passes with minimal RMSE error levels. The values of β allowed us to decide which robots should receive priority maintenance. In order to concentrate maintenance efforts at the component that has an impact on system reliability, we examined the type of failure. The transition of existing maintenance from preventive to predictive, or maintenance "4.0", is suggested using an elaborate model.

The challenging part of the research was determining how to use the defect data, identify the information to be used, and filter it using internal standards. The choice of formulas, statistical rules, and regression tools to be employed was equally complicated, especially because the robots are still in service and any breakdown could be repaired. Our study was carried out on 6 robots, but the method followed is applicable to all welding robots used in the automotive industry. The reliability of robots can also be examined using various artificial intelligence technologies.

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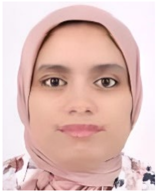

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