Predictive Maintenance Algorithm of a Six-DoF Robotic Arm using Gradient Boosting Regression

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ABSTRACT

The objective of this study is to develop a predictive maintenance algorithm for the ABB IRB 4600, a 6-axis robotic arm, using digital simulations. A variety of tests were conducted using SolidWorks, including calculations pertaining to stress, strain, fatigue, and heat. The simulations included an analysis of the materials used in the construction of the robotic arm, which are gray cast iron and aluminum alloy. The robotic arm was tested in three positions—picking, raised, and placing—with loads of 100 kg, 200 kg, and 300 kg, respectively. The findings indicated that elevated stress, strain, and displacement levels diminish the robot's operational lifespan and accelerate its deterioration over time. The placing position was found to experience the greatest stress, displacement, and strain. The fatigue test also demonstrated that after 10 million cycles, the arm had accumulated damage. The gradient boosting regression algorithm was selected as the Machine Learning (ML) algorithm for the study following a comparison of the performance of various ML regression models. This finding underscores the significance of predictive maintenance in preventing breakdowns and extending the robot's lifespan.

Keywords-robotic arm; predictive algorithm; finite element analysis; gradient boosting regression; simulation

I. INTRODUCTION

The expansion of the automation sector has been markedly shaped by the advent of robotic arms. The technology is employed in a multitude of sectors, including logistics, manufacturing, and medicine [1, 2]. However, as with any other piece of machinery, the repetitive actions of the robotic arm can result in wear over time. It is essential to ensure that a robotic arm is properly maintained in order to increase its lifespan. To ensure optimal performance, a maintenance algorithm that incorporates analysis and control is essential. The maintenance of equipment is an effective means of enhancing the return on investment [3]. It is a common misconception that frequent maintenance of robotic arms increases productivity. However, this is not the case, as the additional downtime and the demand for extra time and resources result in a reduction in productivity, which is counterintuitive [4]. In scheduling maintenance for any type of equipment, including robotics, it is of the utmost importance that the benefits of maintaining the equipment far outweigh the drawbacks of the downtime that is brought about by the maintenance [5]. Wear and tear, or misalignment in joints or actuators, can introduce unpredictable disturbances into the system. In the absence of sufficient maintenance, these disturbances can compromise control algorithms, particularly those reliant on non-linear control laws. This can lead to increased errors, a decline in performance, and the potential for failure in precision tasks [6]. It is therefore crucial to plan maintenance schedules in an intelligent manner. Fortunately, the advent of advanced technology has led to the development of intelligent and efficient maintenance scheduling methods [7, 8]. At present, maintenance strategies can be classified into three principal categories: reactive maintenance, preventive maintenance, and predictive maintenance. In reactive maintenance, repairs are only undertaken when the asset in question has ceased to function correctly. As a result, the asset's usage is optimized. This strategy is beneficial only until the asset has failed [9]. Furthermore, the financial burden of repairing an asset after a failure has occurred is often greater due to the additional damage that can be caused to the machine as a result of the asset breaking down [10]. Consequently, the financial outlay required for repairs may exceed the value of the production output generated by operating an asset until it reaches the point of failure. In contrast, preventive maintenance, also known as planned maintenance, is a method of scheduling maintenance while the equipment is under normal conditions with the objective of preventing unexpected breakdowns. One disadvantage of this approach is that some useful periods of operation are lost due to premature maintenance. Finally, as previously stated [11], predictive maintenance places an emphasis on preventive measures with the objective of reducing costs and extending machine uptime. The objective of predictive maintenance is to forecast the point in time at which a system or component will cease to perform its intended function. This is achieved by the collection of data over time, which is then used to monitor the condition of an asset and identify patterns that can predict potential failures. The implementation of predictive maintenance techniques has the dual benefit of reducing equipment downtime and maximizing its operational lifespan.

In light of the technological advancements that have occurred in recent times, it is imperative that outdated and ineffective procedures be modernized. The high costs associated with reactive maintenance and the impracticality of preventive maintenance should now be replaced by methods that make use of cutting-edge technology, including the utilization of predictive maintenance [12]. The objective of this research is to develop and train a predictive maintenance algorithm for a 6-DoF robotic arm that uses digital simulation-based data. The objective of this project is to predict the damage that is most likely to occur in the structure of the robotic arm and thereby reduce machine downtime. This is achieved through the utilization of contemporary innovations, namely digital simulations [13], particularly finite element analysis, and ML, which facilitate the generation of actual and potential damage. The issue addressed in this study concerns the occurrence of unanticipated anomalies in robotic arms within the manufacturing sector. This study focuses on the ABB IRB 4600 robotic arm in particular. At present, techniques are being employed to address the issue. The goal of preventive maintenance is to forestall the complete deterioration of an asset by implementing a scheduled maintenance program. However, this approach does not fully leverage the machine's total useful life before failure [14]. Fortunately, predictive maintenance can reduce a machine's downtime by anticipating the damage that is likely to occur. To achieve this, the system generates predictions by examining the data sets acquired in the simulation environment. This study focuses on the application of ML for the predictive maintenance of a 6-DoF robotic arm using digital simulation data [15]. The research will involve the implementation of algorithms for predictive maintenance using data collected from the digital simulation of the robotic arm [16]. Additionally, the study will employ finite element analysis using software for the purpose of data acquisition and conducting simulations. It should be noted that the present study is limited to the predictive maintenance of the ABB IRB 4600 robotic arm's structure. Consequently, the findings may not be directly applicable to other components of the robotic arm or to other types of robotic systems. Furthermore, the predictive maintenance algorithm's capabilities are limited in terms of predicting damage to the robotic arm and identifying the location of damage.

II. METHODOLOGY

In developing the finite element analysis, a number of simulation software programs were used. In conducting this study, SolidWorks was selected as the software for the simulation and that was based on its integrated suite of tools that facilitate the streamlining of complex modeling processes, including fatigue, thermal, and strain analyses. The software is useful for achieving the study's objective of setting up a simulation environment and is also capable of performing finite element analysis [17]. Specifically, the software is capable of performing stress and strain analysis, fatigue analysis, and thermal analysis [18]. The Computer-Aided Design (CAD) model of the ABB IRB 4600 robotic arm was imported and assembled within the software for finite element analysis. Furthermore, the configuration of the robotic arm manipulator is also considered in this study with regard to its kinematics [19]. This study examined three pivotal positions for the robotic arm: the picking position, the elevated position, and the placing position. The joint angles used to establish the key positions for the simulation were derived from the data sheet provided by the manufacturer [20]. In order to conduct a stress and strain analysis, it is first necessary to set the simulation parameters, which include the meshing, fixtures, applied load, and material [21]. A mesh was applied with the intention of simplifying the simulation calculations. However, it became evident that certain parts were not meshing properly. As a result, different mesh control configurations were required to ensure successful meshing [22]. A fixture was then applied at the base of the ABB IRB 4600 in order to ensure that the model was fixed at that specific point. The load applications were varied, with values of 100 kg, 200 kg, and 300 kg applied in different positions, and linked to six components of the robotic arm. Finally, the material properties from the datasheet were incorporated into the robotic arm components, and the simulation was executed. In the current study, the fatigue analysis cycle is set to 10,000,000 cycles. Moreover, the appropriate S-N curve for the materials has been applied, which can be accessed and loaded via the SolidWorks simulation.

A. *Generating the Finite Element Analysis Dataset*

The data collection process for the 6-DoF robotic arm simulation was conducted in SolidWorks and comprised several steps to obtain the following data: stress and strain analysis, fatigue analysis, and thermal analysis [23]. The results of the stress and strain analysis, fatigue analysis, and thermal analysis were exported from SolidWorks and subsequently tabulated in order to create a finite element analysis dataset. Initially, a series of ML algorithms were evaluated to identify the most appropriate algorithm for the generated dataset [24, 25]. Subsequently, the datasets underwent pre-processing, including standardization, the identification and removal of any missing values, and the application of a feature selection algorithm. The model was trained to predict the damage value using the aforementioned dataset, and its performance was subjected to a series of tests. Ultimately, the trained model was saved in order to facilitate the prediction of new datasets [26, 27].

The selection of an appropriate ML algorithm necessitates an in-depth examination of the datasets that have undergone ML [22, 28]. In the current study, the generated dataset features include node, stress, displacement, strain, fatigue damage percentage, fatigue life, and thermal stress of the component [29]. The dataset does not include time as a feature, and thus time-series-based ML algorithms,, such as the Autoregressive Integrated Moving Average (ARIMA) model, Exponential Smoothing Methods, and Long Short-Term Memory (LSTM) networks, are not applicable to this ML problem. There are several potential ML algorithms that could be employed for the purpose of predictive maintenance of the ABB IRB 4600 Robotic Arm. These include linear regression, K-Nearest Neighbor regression (KNN), decision tree regression, random forest regression, and gradient boosting regression [11, 30]. The basic codes for each ML algorithm previously mentioned were generated using the picking position with 100 kg applied load dataset. The results will be summarized and evaluated to determine the most appropriate ML algorithm for the study.

B. *Evaluating the Model Using the Criteria for ML*

The initial process is to scale the data using a standard statistical method. Subsequently, a variety of feature selection techniques are employed, including ranking the feature importance of each feature. This was done in order to ascertain which features are necessary for predicting the damage [26]. Finally, a grid search technique was deployed in order to identify the hyperparameters that best suit the ML algorithm. The Mean Absolute Error (MAE) is a measurement of the average size of errors in a set of predictions without accounting for the direction, whether positive or negative. The equation for solving the MAE is:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (1)$$

where N is the number of predictions, y_i is the true value, and $\hat{y}_i$ is the predicted value [31]. The Mean Squared Error (MSE) is a statistical measure that assesses the degree of fit between a regression line and a set of data points. It is a risk function that represents the expected squared error loss [32]:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (2)$$

The Root Mean Square Error (RMSE) is defined as the standard deviation of the residuals, which are the prediction errors. The residuals represent the distance between the data points and the regression line. The RMSE is a measure of the spread of these residuals. In other words, it indicates the degree of concentration of the data points along the line of best fit [33, 34]:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (3)$$

The coefficient of determination (R^2) is a statistical measure that quantifies the goodness of fit of a model. In the context of regression analysis, it is a statistical measure of how well the regression line correlates with the actual data set. The sum of squared regressions represents the sum of residuals squared, while the total sum of squares is the sum of the squared distances between the data points and the mean. The calculation of R^2 in regression analysis is:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y_i})^2}{\sum(y_i - \overline{y_i})^2} \quad (4)$$

where $\sum(y_i - \hat{y_i})^2$ is the Sum Squared Regression (SSR), and $\sum(y_i - \overline{y_i})^2$ is the Total Sum of Squares (SST).

III. RESULTS

In order to establish a simulation environment for the 6 DoF robotic arm, SolidWorks was selected as the appropriate software due to its robust features and versatility. A variety of properties must be adjusted and considered at the outset of the simulation, including joint positions, meshing, fixtures, load selection, and material application. Figure 1 presents the specific model of a 6-DoF robotic arm employed throughout the simulation. The ABB IRB 4600 robotic arm model is used as a representation of the robotic arm employed throughout the research simulations.

The manipulation of joint positions as a means of exerting control over the robot's orientation is presented, providing the particular joints, types of motion, and angles pertinent to the picking position, raised position, and placing position. The joint angles of the ABB IRB 4600 model in the picking position, as shown in Figure 2(b) of the ABB IRB 4600 robotic arm, are: for joint 1, the angle is set to 180°, for joint 2, it is set to -60°, for joint 3, it is set to -40°, and for joint 4, it is set to 0°. Figure 2(b) displays the kinematic diagram of the ABB IRB 4600 in a raised position. The joint angles of the ABB IRB 4600 model under placing position are: for joint 1, the angle is set to -180°, for Joint 2, it is set to -30°, for joint 3, it is set to -30°, and both joint 4 and joint 5 are set to 0°. These values provide insights into the robot's axis, type of motion, and angles of the robotic arm while it is in the process of placing position. Figure 3(a) demonstrates the displacement behavior of the apparatus in its raised position with a 100 kg load. The maximum displacement was observed at the end effector of the robotic arm, with a value of 27.31 mm. Conversely, the minimum displacement was recorded at 1.000e-30 mm, as determined through displacement analysis. Figure 3(b) presents the displacement behavior of the system in the placing position with a 100kg load. The maximum displacement was 19.77 mm, occurring at the end effector of the robotic arm, with a minimum displacement of 1.000e-30 mm. Figure 3(c) shows the displacement behavior when the system is in the process of picking with a 300 kg load. The maximum displacement of 52.57 mm is located at the end effector of the robotic arm, while the minimum displacement is 1.000e-30 mm.

(a)

(b)

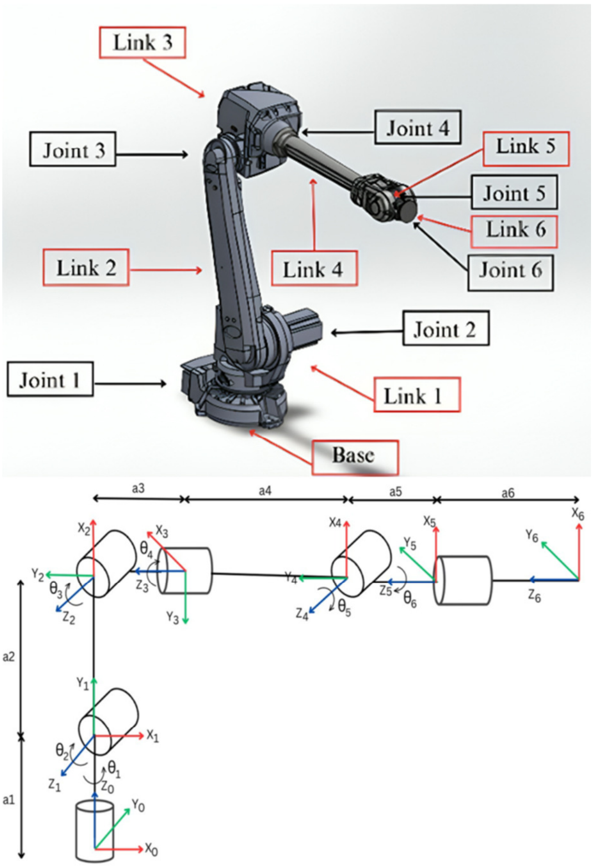


Fig. 1. ABB IRB 4600 robotic arm (a) 3D CAD model, (b) kinematic diagram.

Figure 4 depicts the discrepancy between the predicted and actual damage values of the ML model across diverse datasets. A comparison of the predicted damage values with the actual damage values in the figures reveals that the predictions made by the trained ML model using multiple datasets are similar to the actual damage that occurred in the simulation of the robotic arm. Therefore, this suggests that the trained ML algorithm is performing well.

IV. DISCUSSION

The finite element analysis of the ABB IRB 4600 robotic arm was conducted using SolidWorks as the simulation environment. The capabilities of SolidWorks include the ability to perform calculations related to stress, strain, fatigue, and thermal effects, which are essential for conducting the requisite simulations for the study. The materials used for the construction of the robotic arm's links and joints predominantly consisted of gray cast iron and aluminum alloy, as documented in the manufacturer's datasheet. The algorithms subjected to examination in the course of this study were: linear regression, KNN, decision tree regression, random forest regression, and gradient boosting regression, as portrayed in Table I. The gradient boosting regression algorithm demonstrated the most impressive performance among the tested algorithms, exhibiting an exceptional capacity to predict damage with an MAE of 1.3446×10^{-4} and an R^2 value of 0.9999. In contrast, the linear regression algorithm exhibited the least effective performance in predicting damage. The concentrated damage checker algorithm was able to identify areas with a high concentration of damage values, specifically at links 1, 2, 3, and 4. The gradient boosting algorithm demonstrated satisfactory performance across a range of datasets. The lowest recorded RMSE was 7.8819, while the highest RMSE was 1.2389.

(a)

(b)

(c)

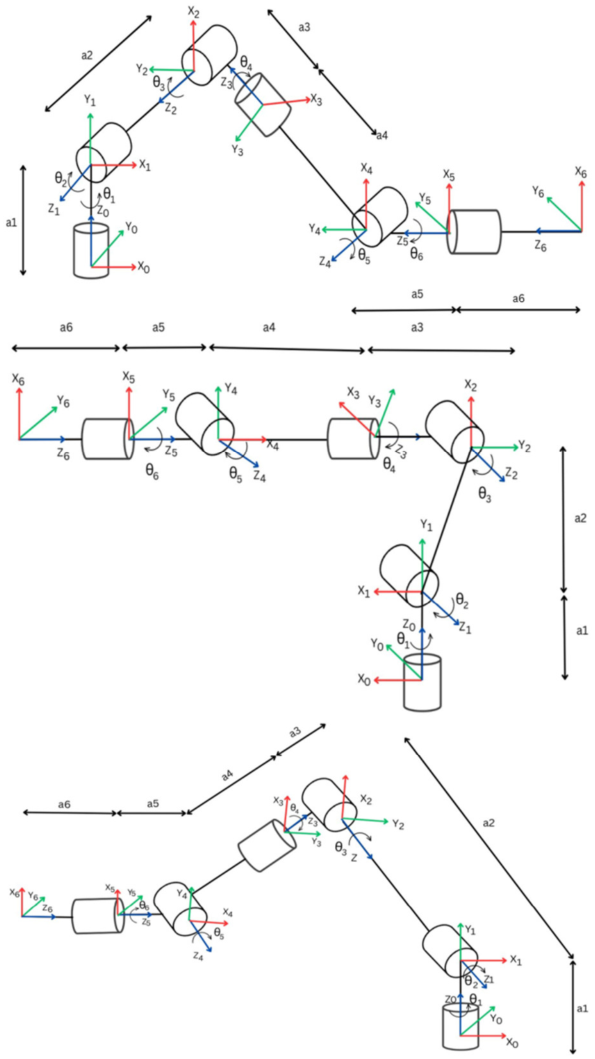


Fig. 2. ABB IRB 4600 robotic arm kinematic diagram (a) picking, (b) raised, (c) placing 3D CAD model.

At the picking position, the load with a mass of 300 kg resulted in the highest stress value, 6.75E+08 Von Mises Stress, the highest displacement, 52.6 mm, and the highest strain value, 8.63E-03 ESTRN. In contrast, the peak stress value for the raised position was 8.62E+08 Von Mises Stress, the displacement reached a peak of 81.94 mm, and the peak strain value was 1.106E-02 ESTRN under a 300 kg load. The final position, designated as the "placing position," exhibited the highest levels of stress, displacement, and strain when subjected to an applied load of 300 kg.

(a)
(b)
(c)

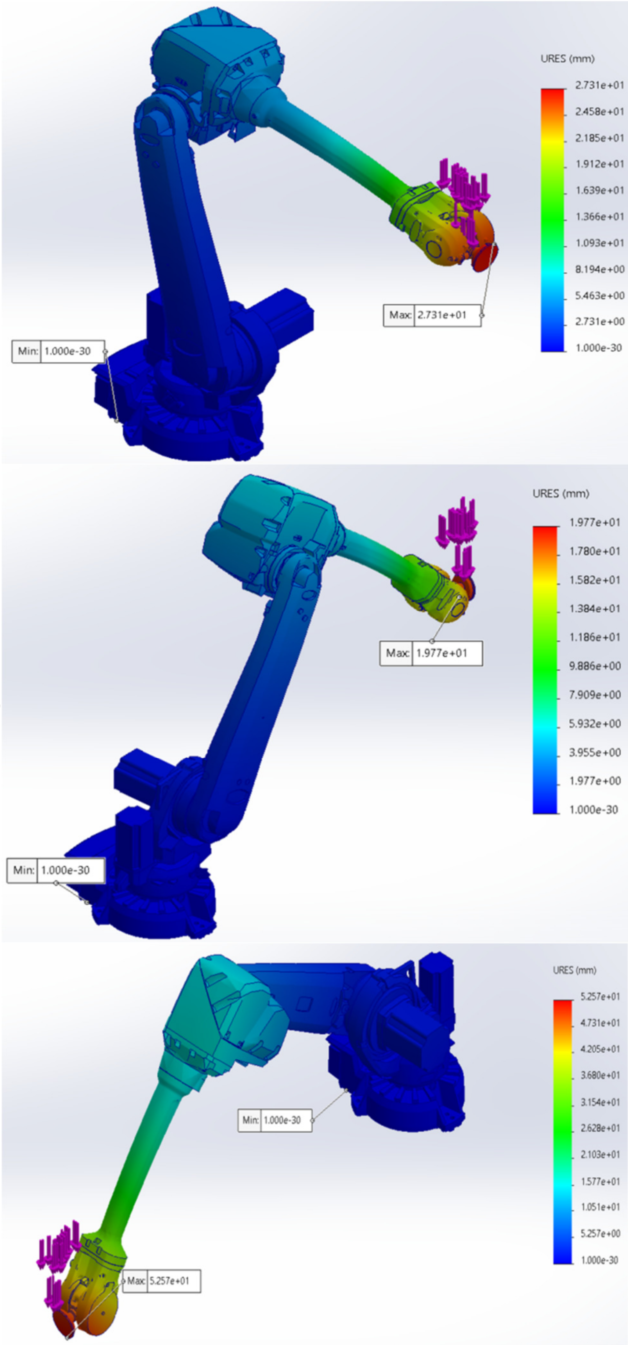
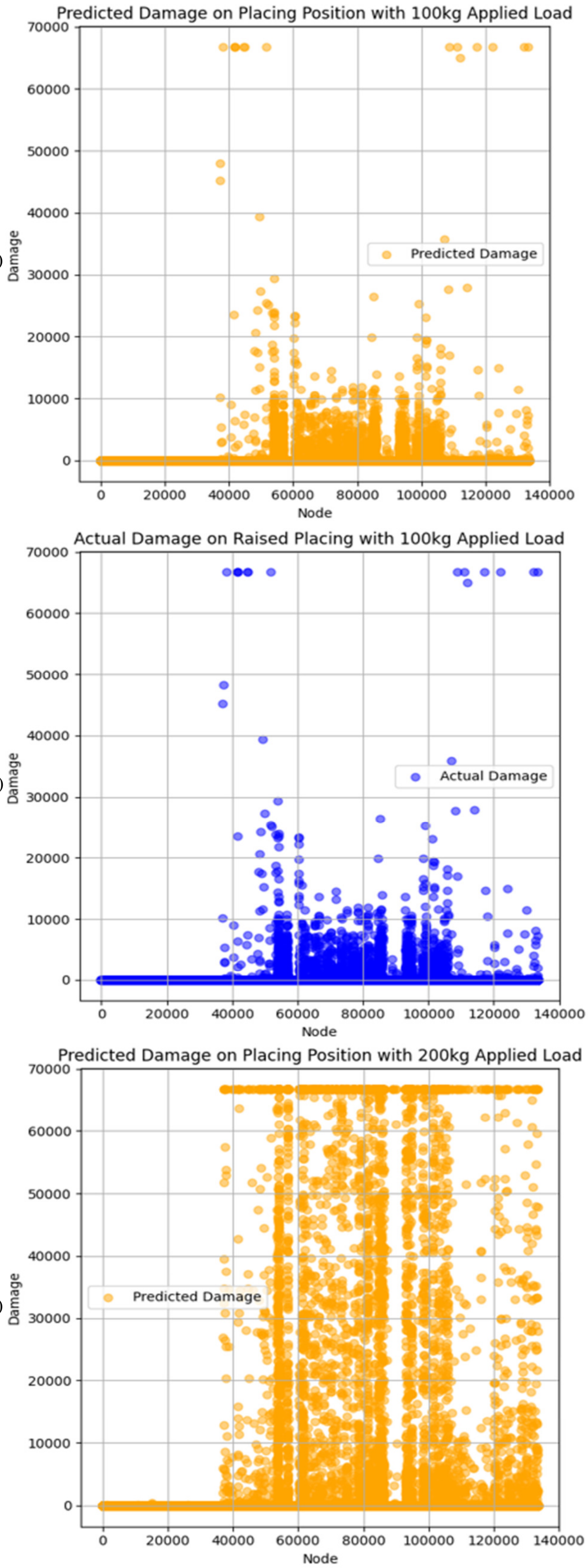


Fig. 3. (a) Raised position displacement results, (b) placing position stress results, (c) picking position displacement results.

(a)
(b)
(c)



The values of Von Mises Stress, displacement, and ESTRN are 6.05E+08, 59.3 mm, and 7.74E-03, respectively. The fatigue analysis yielded a maximum damage percentage of 6.67E+04 and a minimum damage percentage of 10 at 10,000,000 cycles, with a minimum life cycle of 15,000 across all positions and load applications. Furthermore, elevated levels of stress, displacement, and strain resulted in diminished life cycles and augmented damage accumulation. All results are presented in Tables II - IV.

(d)

(e)

(f)

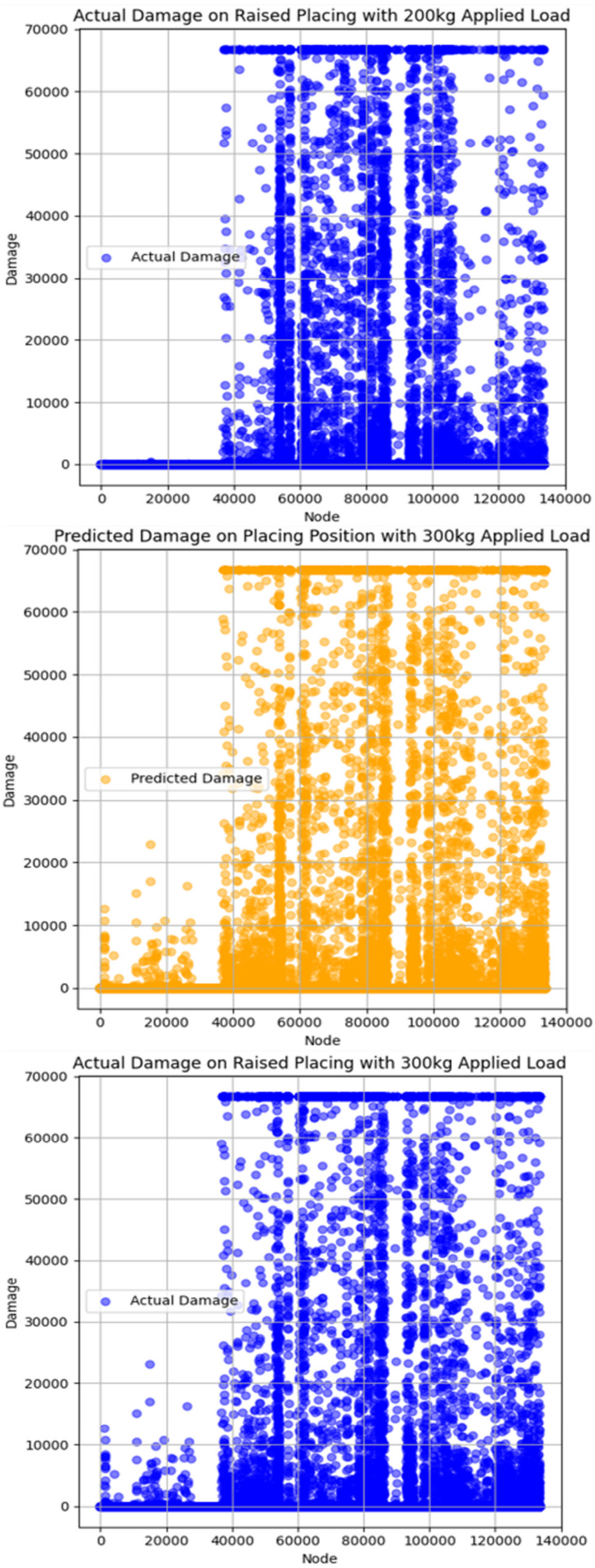


Fig. 4. Damage value for an applied load of: 100kg (a) predicted, (b) actual, 200kg (c) predicted, (d) actual, 300kg (e) predicted, (f) actual.

TABLE I. ML ALGORITHM SELECTION

Dataset	MAE	MSE	RMSE	R^2
Linear Regression	1,508.12595	12,176,674.9	3,489.509274	0.4967982977
K-Nearest Neighbour Regression	22.1274967	100,411.6029	316.8778991	0.9958504855
Decision Tree Regression	2.76332035	33,942.84707	184.2358463	0.9219902694
Random Forest Regression	0.32913652	15.89124245	3.986382125	0.9999993433
Gradient Boosting Regression	1.3446×10^{-4}	1.9815×10^{-4}	1.4077×10^{-2}	0.9999

TABLE II. PICKING POSITION TRAINING GRADIENT BOOSTING REGRESSION ALGORITHM EXCERPT RESULTS

Training Dataset	MAE	MSE	RMSE	R^2
Picking Position 100 kg	1.3446×10^{-4}	1.9815×10^{-4}	1.4077×10^{-2}	0.99999999
Picking Position 200 kg	0.3849	27.688	5.2620	0.99999886
Picking Position 300 kg	0.5945	0.4461	6.6791	0.99999952

TABLE III. PICKING POSITION TESTING GRADIENT BOOSTING REGRESSION ALGORITHM EXCERPT RESULTS

Testing Dataset	MAE	MSE	RMSE	R^2
Picking Position 100 kg	0.1874	18.813×10^{-2}	0.1372	0.99757443
Picking Position 200 kg	0.6459	0.6040	7.7718	0.99999755
Picking Position 300 kg	0.9148	0.8712	9.3337	0.99999907

TABLE IV. RAISED AND PLACING POSITION TRAINING GRADIENT BOOSTING REGRESSION ALGORITHM EXCERPT RESULTS

Dataset	MAE	MSE	RMSE	R^2
Raised Position 100 kg	0.5459	42.9434	6.5531	0.99999839
Raised Position 200 kg	0.6859	59.5029	7.7138	0.99999959
Raised Position 300 kg	0.611	49.2159	7.0154	0.99999976
Placing Position 100 kg	0.0564	1.5348	1.2389	0.99999824
Placing Position 200 kg	0.711	62.1238	7.8819	0.99999991
Placing Position 300 kg	0.652	53.3013	7.3008	0.99999962

V. CONCLUSIONS

This research presents a novel study that incorporates the gradient boosting regression algorithm for the predictive maintenance of a 6-DoF robotic arm. The significance of this study lies in its ability to schedule and create a plan for industrial applications that have the same configuration. Previous studies have employed data-based Machine Learning (ML) algorithms to create models for preventive maintenance in a variety of fields, including automotive, food manufacturing, medical devices, and many more. These models have been successfully applied to the robotics field. The study employed the use of SolidWorks, a Computer-Aided Design (CAD) software, to illustrate the simulation environment. Three key positions were established for the simulation of a pick-and-place application of the ABB IRB 4600 robotic arm: the picking position, the raised position, and the placing position. The model was simplified for the purpose of facilitating the finite element analysis calculation through the process of meshing. Mesh controls were adjusted by increasing density and decreasing size, thereby enhancing the accuracy of the model and facilitating the capture of the desired geometric entities. Fixtures are set in standard fixed geometry by selecting the face under the base of the model to provide additional support and enhance stability throughout the simulations. The load applications were set to 100 kg, 200 kg, and 300 kg for each joint, allowing for the collection of a wide range of data and the generation of more accurate results. The selection of materials for each component was based on the data provided in the manufacturer's datasheet. The base, links 1, 2, 4, and 5 were constructed from gray cast iron, while links 3 and 6 were made from aluminum 6061 alloy. Once the properties were defined, the simulation environment was created.

The study yielded finite element analysis data for stress and strain, fatigue, and thermal analysis. The results of the stress and strain analysis indicate that, with regard to the picking position and placing action, across all load applications, the peak stress and strain were identified at link 1 of the robotic arm. In contrast, when the robotic arm was in a raised position, the highest levels of stress and strain were observed at link 2. In terms of fatigue analysis, at 10,000,000 cycles, the highest damage percentage is 6.67E+04, while the lowest calculated lifespan is 15,000 cycles across all datasets. The gradient boosting regression algorithm was selected as the ML algorithm for the study, following a comparison of the performance of various ML regression models. The data were subjected to standard scaling in order to ensure uniformity. The fatigue life data were assigned the highest importance ranking for feature selection, with a score of 0.7304. In contrast, the thermal data were assigned the lowest ranking and are therefore irrelevant in predicting damage. The optimal hyperparameter combination, as determined through grid search, is composed of estimators 500, a learning rate of 0.01, and a maximum depth of 9. Upon training the individual datasets, the model demonstrated a high degree of accuracy, with points largely aligned with the perfect prediction line. In conclusion, the ML algorithm trained using multiple datasets demonstrated the capacity to predict damage values with a minimal degree of error. It is recommended that the robot arm be redesigned according to the damage sustained, taking into account the position of the arm. The damage concentration algorithm was able to identify the specific nodes and components where damage was concentrated. The evaluation metric for the training and testing datasets demonstrated that the gradient boosting regression algorithm exhibited robust performance across a diverse range of datasets. The algorithm demonstrated remarkable efficacy in predicting damage values at the placing position with a 100-kilogram applied load, exhibiting a Root Mean Square Error (RMSE) score of 1.2389. Conversely, it exhibited suboptimal performance in the same context with a 200-kilogram applied load, with an RMSE score of 7.8819. In general, the predictive maintenance algorithm demonstrated satisfactory performance.

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