A Wireless Enabled IOT Nondestructive Fatigue Damage Sensor for Estimation of Remaining Useful Service (RUL) of Structures Through Artificial Intelligence-Machine Learning Algorithms

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ABSTRACT

In this study, a wireless enabled novel non-destructive evaluation (NDE) fatigue damage sensor for the structural fatigue health monitoring and prediction of fatigue life of structural members of large engineering structures is presented. The smart predictive IOT (Internet of Things) fatigue damage sensor has special designed smart breakable sacrificial sensor beams for early fatigue damage detection and prediction of fatigue sensitive structural and mechanical parts of fatigue sensitive structures. The IOT non-destructive fatigue damage sensor can measure directly the state of fatigue damage accumulation levels and predict the remaining useful life (RUL) of structural components or locations for the life cycle management and predictive maintenance of structures without using any fatigue damage algorithm. The non-destructive evaluation (NDE) fatigue sensor consists of mechanical and electronic units. The mechanical part of the fatigue damage sensor has special designed smart and predictive sacrificial beams with different levels of lifetimes (10% *N*, 20% *N*, 30% *N*, 40% *N*, 50% *N*, 60% *N*, 70% *N*, 80% N, 90% *N,* 95-100% N) normalized to the total lifetime of a real structure. The mechanical sensor beams designed with special geometry using stress magnifying effects to measure the fatigue damage accumulating level and early fatigue damage detection and fatigue state health monitoring of structures. The smart fatigue damage sensors attached onto the surface on a real structure is expected to have the same cyclic stress-strain loading behaviour and the same cyclic stress-strain history for during the operational service life. The sensor having multiple parallel oriented and mini-micro non-destructive fatigue damage measurement sensing beams are designed to fail earlier than a real structure in the different predetermined fatigue lifetimes like a mechanical fatigue fusing system. Due to its predictive feature the fatigue sensor will extent not only the service life of fatigue sensitive mechanical components but also increase the safety and reliability of structures. Since the wireless enabled fatigue damage sensor network through Internet of Things (IOT) technologies collect the real operational fatigue data remotely, the statistical fatigue damage sensor network data can be used for the prediction of lifetimes of structural or mechanical members by using Artificial Intelligence (AI) Machine Learning (ML) Algorithms. The distributed fatigue sensor network also provides a real operational-experimental statistical data for condition based predictive maintenance, maintenance management, end of service life indicator (ESLI) and development of new fatigue design tools for fatigue sensitive parts or locations of fatigue critic metallic and composite structures.

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INTRODUCTION

Fatigue Damage and Life have a critical role in the design of fatigue critic structural and mechanical components. There are several different types of fatigue design methods are commonly used for the fatigue design of fatigue sensitive mechanical components or structures. All these techniques are based on some estimations and load assumptions. Any fatigue failure of one of the structural members of the system may lead to a devastating failure with serious consequences that cost life and properties. Therefore, the health conditions of the structural and mechanical elements suffering from cyclic dynamic stresses should be constantly monitored and the fatigue damaged parts should be replaced before the fatigue failure limit is reached. Steel bridges, ships, oil platforms, planes, helicopters, wind turbines, mega cranes, military portable bridges, railway structures, and marine ships are particularly considered vulnerable systems to this type of fatigue damage. The nondestructive IoT predictive fatigue damage sensor seen in Figure 1 is proposed for structural fatigue damage monitoring and prediciton of remaining uselful life of structures. The sensor directly measures the fatigue damage accumulation levels and the remaining service lifetime of fatigue sensitive metallic, additively manufactured and composite structures through the special designed direct fatigue damage measurement sensor beams from critical points of the structure without using any algorithm. The fatigue sensor is wirelessly activated and does not require any power connection. The electronic part can be combined with the sensor to become really small but can also stay a separate box with the sensor element connected by short cables. These features together make it possible to install the sensor in hard-to-reach places of fatigue monitoring structures. The smart structures instrumented with the NDE fatigue damage for structural health monitoring (SHM) can provide real-time critical predictive and statistical information on the status of the monitored real structure. Due to the nondestructive and direct fatigue damage measurement nature of the sacrificial-breakable mini or micro electro mechanic (MEMS) sensing beams, the sensor provides real operational and progressive statistical fatigue life data. The collected fatigue sensor data through the distributed sensor network is quantitative and easy to interpret and understand without any further mathematical analysis through Artificial Intelligance AI-Machine Learning (ML) Methods [1-9]. The proposed Novel Smart Fatigue Sensor in Figure-1 is a lightweight, reliable and direct measurement sensor which enables monitoring health state of the structure whether it is an aircraft, helicopter, ship, tanker, offshore wind turbine or offshore oil platforms etc.

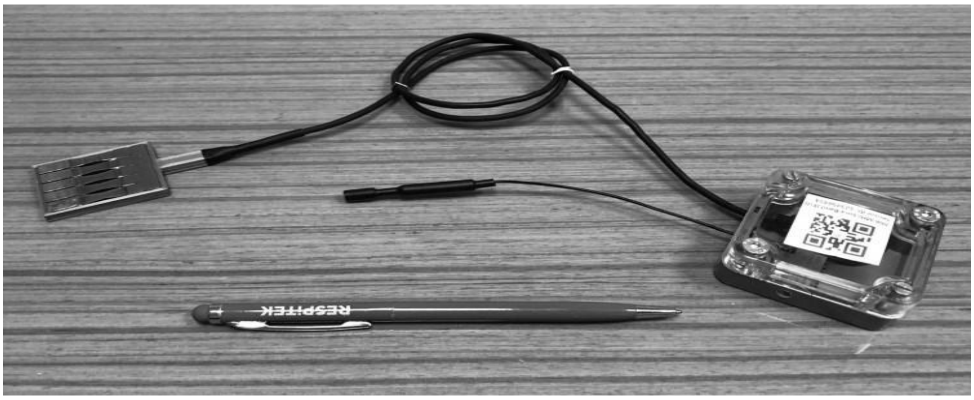

Figure 1. A general view of the Active(With Battery) Fatigue Sensor (US 8,746,077 B2) [12]

IOT PREDICTIVE SMART IOT FATIGUE DAMAGE SENSOR SYSTEM MODEL

The smart fatigue sensor system is designed with multiple parallel beams, each sensitive to different levels of fatigue damage(%D) levels and fatigue lifetimes(%N Total Lifetime). The mini-micro beams of the sensor are designed to be sacrificed and the sensor is designed to fail early but gradually while passing through the same fatigue cycles as the structural member to which it is attached. The sensor beams with “Stress Magnified U Type Notches” have the special geomerical design parameters, the length(L), radious(R) and thickness(t) designed to fail after passing through the fatigue load cycles. The fatigue sensor has two versions, one battery version and the other powered by RF power. The system with the battery uses Zigbee or similar low-power sensor network to check the sensor about the condition of breakable fingers. Sensor nodes transmit information from one node to another to communicate with the master node. This type is shown in Figure 1. Zigbee is a well-known low-power communication network used for sensor communication. As seen, in Figure 1, the sensor system has multiple U type mini beams that represent the different incremental fatigue lifetimes (10% N, 20% N, 30% N, 40% N, 50% N, 60% N, 70% N, 80% N, 90% N, 95-100% N) and the levels of fatigue damage. In any case, the fatigue strength limit of the fatigue sensor life should be designed to be lower than the fatigue life of the fatigue critic component of a real structure.

The battery-free sensor is shown in Figure 3. This type works with RF power emitted by the interrogation bar. The interrogation distance of RFID devices depends on both the transmitter power and the coil size of the receiver. This application requires high-power transmitters as metal surfaces protect and reduce the power received by the receiver. Such sensors need to be questioned (periodically) from time to time; for example, the aircraft enters the service hangar for regular maintenance intervals.In both versions, the sensor node weighs only a few grams, and the size varies from postage stamp to postcard, depending on the location of the application.When a certain beam of the sensor exceeds the number of designed fatigue cycles, the beam fails, and sensor electronics detect this malfunction and transmit this information wirelessly. Having a large number of beams designed to fail after a definite number of fatigue cycles allows the health status of the structural member to be monitored. It gives a broad warning about the health of the component so that the necessary predictive maintenance measures can be taken.

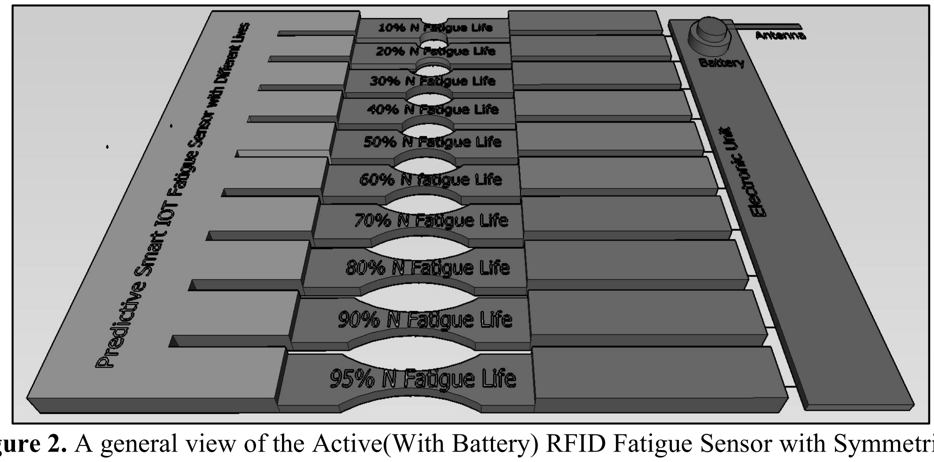

Figure 2. A general view of the Active(With Battery) RFID Fatigue Sensor with Symmetric U notched sensing beams with different Progressive Fatigue Lifetimes (10% *N*, 20% *N*, 30% *N*, 40% *N*, 50% *N*, 60% *N*, 70% *N*, 80% N, 90% *N,* 95-100% N)

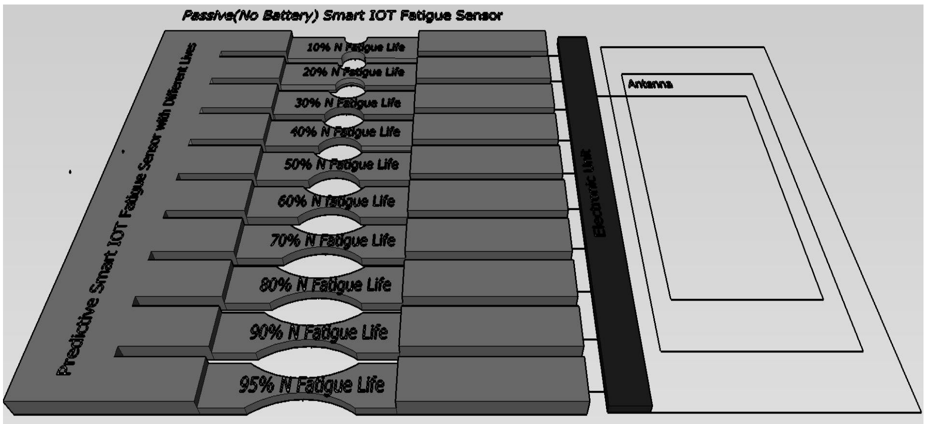

Figure 3. The scheme of the passive(Without Battery) symmetric U type notched fatigue sensor with different Fatigue Lifetimes (US 8,746,077 B2) [12]

The sensor is very lightweight and weighs only a few grams and is slightly bigger than a small postage stamp. The sensor needs to be customized for the specific base metal of the structure. It is usually produced using non-traditional manufacturing methods. The sensor is wireless and does not require any power connection. These features together make it possible to install the sensor in hard-to-reach places of fatigue life monitoring structures.

DESIGN OF THE FATIGUE DAMAGE SENSORS FOR PREDICTION OF REMANING USEFUL LIFE(RUL) OF STRUCTURES AND PREDICTIVE MAINTENANCE

In the proposed sensor system, the symmetric U type notched flat beam system model is used as the stress magnifying-concentration (K_{tn}) factor for the design of the sensor. The stress concentration design parameters of the symmetric U notched flat beam system model (Figure 4) and the geometric design parameters of the ten(10) different shaped sensor beams of the predictive fatigue damage sensor model are shown in Figure 4;

The main design parameters of the symmetric U notched flat beam system model are:

the lengths of the beams $(L_A = L_B = L_C = L_D = L_E = L_F = L_G = L_R = L)$,

the thicknesses of the beams $(t_{A.B,C,D,E,F,G} = t)$,

the depth of notches $(h = h_{A.B,C,D,E,F,G,})$,

the witdth of the beams $W_2 = W_{2A.B,C,D,E,F,G,H,I,R}$,

the radius of beam notches $(R)_{\%100-95}, (R)_{\%90}, (R)_{\%80}, (R)_{\%70}, (R)_{\%60}, (R)_{\%50}, (R)_{\%40}, (R)_{\%30},$

$(R)_{\%20}, (R)_{\%10}$.

The notch stress concentration factors $(K_{tnG}), (K_{tnF}), (K_{tnE}), (K_{tnD}), (K_{tnC}), (K_{tnB}), (K_{tnA})$ in the critical sections of the mini sensor beams will be the key geometric design parameter to predict the fatigue life time of sensing beams in the different stress levels.

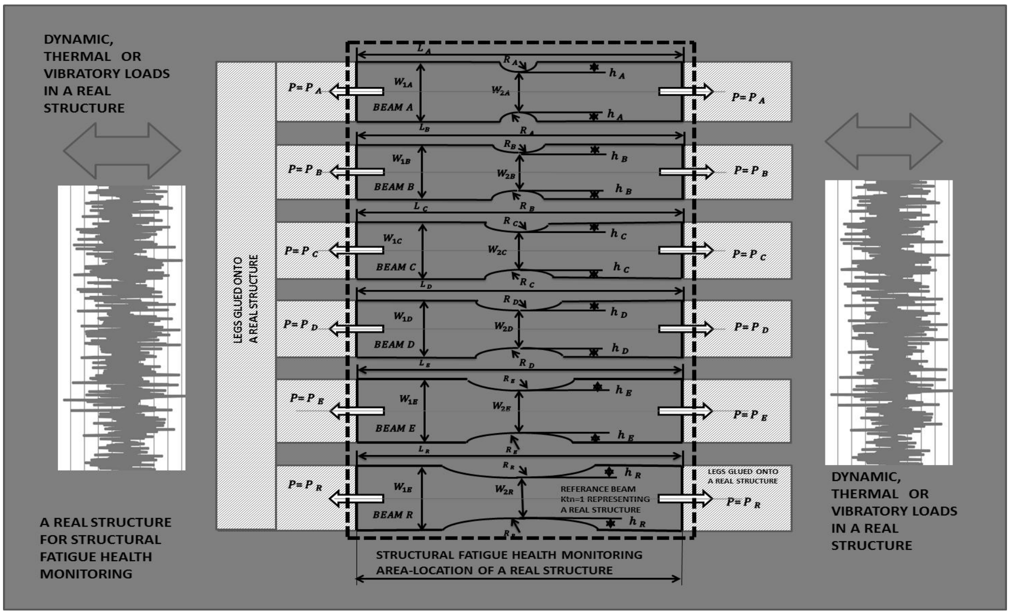

Figure 4. The Stress Based Predictive Smart Fatigue Damage Sensor Model with Different Fatigue Lifetimes

The stress based fatigue life equations of the fatigue sensing beams with a special designed geometry (symmetric U notch) stress concentration-notch (K_{tn}) can be written as,

$$K_{tn} = C_1 + C_2\left(\frac{2h}{W_1}\right) + C_3\left(\frac{2h}{W_1}\right)^2 \tag{1}$$

$$C_1 = 0.756889 + 2.92489\left(\sqrt{\frac{h}{R}}\right) + 0.0558271\frac{h}{R} \tag{2}$$

$$C_2 =- 1.39662 - 5.2069\left(\sqrt{\frac{h}{R}}\right) - 0.233781\frac{h}{R} \tag{3}$$

$$C_3 = 1.66327 + 3.3296\left(\sqrt{\frac{h}{R}}\right) + 0.28635\frac{h}{R} \tag{4}$$

$C_1, C_2\ and\ C_3$ are the equation constants., $(h = h_{A.B,C,D,E,F,G})$, are the depth of the beam notches and $(R)_{\%90} > (R)_{\%70} > (R)_{\%50} > (R)_{\%40} > (R)_{\%30} > (R)_{\%20} > (R)_{\%10}$ are the radius of symmetric U notched beams. In the Fatigue Sensor System Model (Figure-4), the stresses $(\sigma_{nG}), (\sigma_{nF}), (\sigma_{nE}), (\sigma_{nD}), (\sigma_{nC}), (\sigma_{nB}), (\sigma_{nA})$ as a function of the U notch stress concentration factors $(K_{tnG}), (K_{tnF}), (K_{tnE}), (K_{tnD}), (K_{tnC}), (K_{tnB}), (K_{tnA})$ in fatigue critic notched sections of mini beams will be used for design of sensing beams as a function of the fatigue lifetimes of the sensor beams normalized to the real structure total fatigue lifetime (N). The stresses of the sensor beams in the U notched sections,

$$(\sigma_{nG})_{\%90} \leq (\sigma_{nF})_{\%70} \leq (\sigma_{nE})_{\%50} \leq (\sigma_{nD})_{\%40} \leq (\sigma_{nC})_{\%30} \leq (\sigma_{nB})_{\%20} \leq (\sigma_{nA})_{\%10} \tag{5}$$

$$(K_{tnG})_{\%90} \leq (K_{tnF})_{\%70} \leq (K_{tnE})_{\%50} \leq (K_{tnD})_{\%40} \leq (K_{tnC})_{\%30} \leq (K_{tnB})_{\%20} \leq (K_{tnA})_{\%10} \tag{6}$$

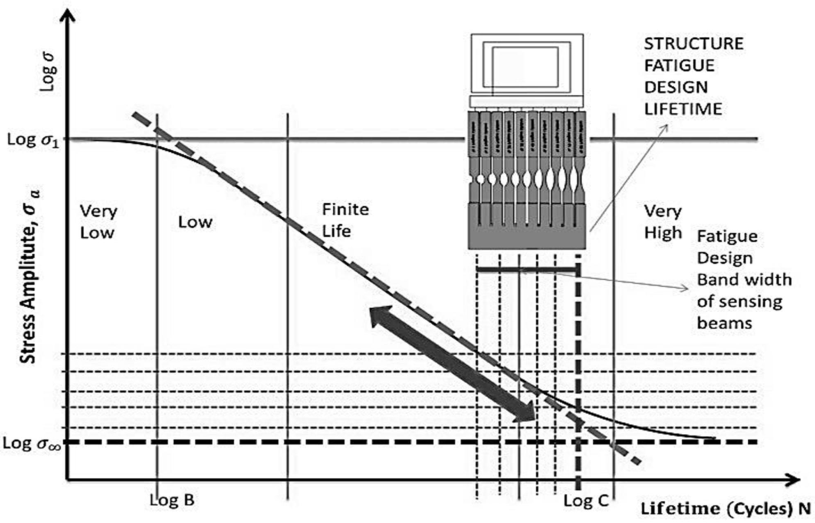

Figure 5. The Stress-Life(S-N) Fatigue Curve and Design of Fatigue Sensor

For the design of the Predictive Fatigue Damage Sensor, the stress life curve will be used for different fatigue lifetimes of the sensor beams. The Stress-Life fatigue equation is represented by low, finite life and high cyclic stress conditions of the Fatigue S-N curve as shown in Figure-5. The finite Stress-Lifetime Fatigue Curve (S-N) of materials is used for the fatigue life of sacrificial sensing beams for different stress levels as seen in Figure 5.

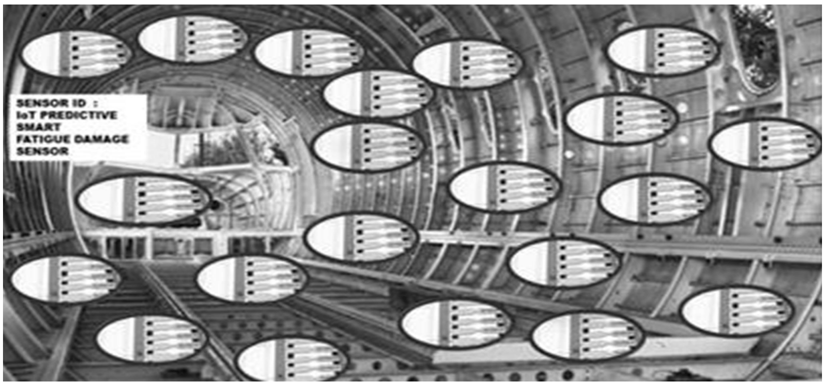

Figure 6. The Application of the Wireless IoT Fatigue Sensor and A Distributed Sensor Network System on Large Fatigue Critic Aircraft Structures for IoT Structural Fatigue Health Monitoring

THE SMART IOT FATIGUE DAMAGE SENSOR FOR PREDICTION OF REMANING USEFUL LIFE(RUL) THROUGH ARTIFICIAL INTELLIGENCE (AI)-MACHINE LEARNING(ML) METHODS

The linear regression method is one of the most common machine learning algorithms used in Engineering. It is a mathematical and statistical method used for predictive analysis. Machine Learning [1,6] as a subdivision of Artificial intelligence learns from algorithms and statistical models in order to make predictions on data. The Artificial Intelligence (AI) Machine Learning Algorithms can be used to predict remaining useful life (RUL) of fatigue critic structures using the predicted(simulated) and the measured IoT Fatigue Sensor network data. The predicted and collected operational(experimental) actual-measured fatigue damage sensor network data is predictive, statistical and easy for modeling, analysis and interpret. The actual fatigue sensor dataset collected by the distributed sensor network is statistical quantitative data for mathematical analysis through Machine Learning (ML) Linear Regression Methods to estimate Remaining Useful Fatigue Lifetime of structures as seen in Figure-7.

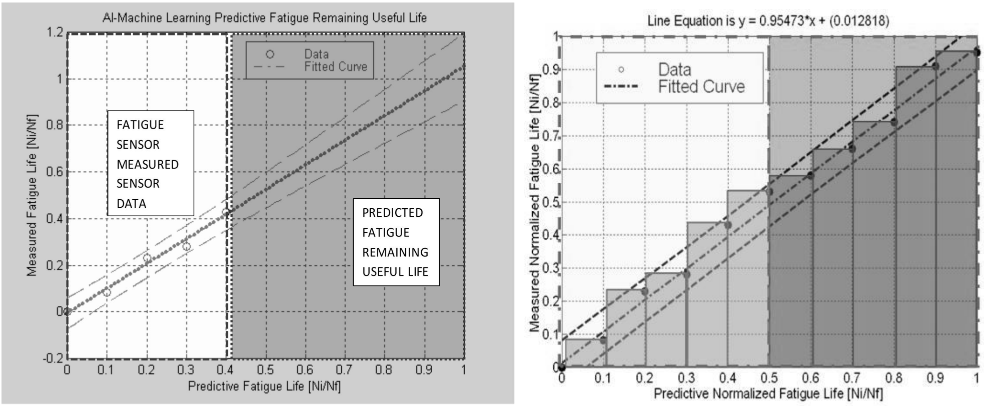

Figure 7. Sensor (ID-1and 2) Progressive Fatigue Sensor Simulated and Measured Data and Prediction of Remaining Useful Fatigue Life (RUL) through Machine Learning Regression Analysis.

For the prediction of the remaining useful fatigue life of structures using the IOT Fatigue Damage Sensor data through Machine Learning Linear Regression Methods, a generic linear regression model can be written as,

$$y = \theta_0 + \theta_1 X_1 + \theta_2 X_2 + \cdots + \theta_n X_n + \varepsilon \qquad (7)$$

Where, y is the dependent output variable, $X_1, X_2, \cdots X_n$ are the independent variables and $\theta_0, \theta_1, \theta_2 \cdots \theta_n$ are the regression coefficients defining the relationship between the predicted(simulated) and the actual (measured) values of the fatigue sensor data. 'ε' is the error term defining the difference between the predicted and the measured values of the sensor data. The error 'ε' should be minimum to get a highly accurate regression model. Different mathematical methods can be used to minimize the error. Among these techniques, the most common method is RMSE defined as the root of squares of difference between predicted and actual values of a ML model. This technique has been adopted for the analysis and prediction of the remaining useful fatigue life of structures using the IOT Fatigue Damage Sensor data through Machine Learning Linear Regression Methods in this paper. The term 'n' is the number of operational actual fatigue sensor data measured from the critical element of a structure to calculate error. $Y_{predict}$ is the predicted(simulated) values of dependent values and Y_{actual} is the actual(experimental) measured values of the fatigue sensor. If the fatigue life estimations are made with a single one variable (X), the equation becomes the simple linear regression algorithm,

$$y = \theta_0 + \theta_1 X + \varepsilon \qquad (8)$$

The simple linear regression algorithm aims to estimate the regression coefficients (θ_0, θ_1) for the best linear fit line using the progressive incremental predicted and measured actual fatigue sensor data in different fatigue lifetime periods (10% N, 20% N, 30% N, 40% N, 50% N, 60% N, 70% N, 80% N, 90% N, 95-100% N). This estimation in general is done by using the Ordinary Least Squares method to minimize the sum of the squared the differences between the actual values and the predicted values. For the precision performance analysis of the ML linear regression models [7,8], R-Squared (R^2) (the coefficient of determination) and Root Mean Squared Error (RMSE) are the two main indicators. RMSE is a performance indicator in Machine Learning to evaluate the overall accuracy of the prediction model. RSME measures the average magnitude of the errors between predicted values and actual-real operational values. As seen from Figure-7, the trend between the actual and predictive fatigue lifetimes is linear and there is a good agreement between the operational actual fatigue lifetime and the predicted fatigue lifetime values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{predict} - y_{actual})^2}{n}} \tag{9}$$

R-squared, the coefficient of determination, is a statistical measure used in machine learning to evaluate the quality of a regression model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{predict,i} - y_{actual,i})^2}{\sum_{i=1}^{n} (y_{predict,i} - \bar{y}_{predict})^2}\ ,\ \bar{y}_{predict} = \frac{1}{n}\sum_{i=1}^{n} y_{predict,i} \tag{10}$$

CONCLUSION

A novel wireless smart predictive and nondestructive IoT fatigue sensor has been developed to monitor and predict the remaining useful life(RUL) of fatigue critic structures through Machine Learning Methods. The proposed sensor has multiple fatigue sensor beams designed with different levels of fatigue lifetimes attached on the fatigue sensitive welded, pinned, bolted and higher load locations of fatigue critic structures. The predicted and collected measured real fatigue sensor data via the distributed sensor network are used for the estimation of the remaining useful fatigue lifetimes of structures through Artificial Intelligence (AI)-Machine Learning (ML) Algorithms such as Regression, ANN, RF. The mathematical and statistical analysis of the predicted and collected operational actual sensor network data through Machine Learning Methods can be used for the improvement and checking the fatigue design life of a structure, a development of a decision support system(DSS), Predictive Maintenance Management System(PdMM), Retirement and Limit of Validity(LOV) System for fatigue critic structures including aircrafts.

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