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Analysis of Thermal Fatigue Failure in Material by using the Temperature Prediction Polynomial Regression Algorithm Employing Bolt Wi-Fi Module

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Abstract - *The failure caused by fatigue has a majority of share in the industries. The recent trends and studies have shown that 85 to 90 % components fail not due to static loading but due to cyclic loadings and fluctuating conditions around. The most common and prominent being the thermal fatigue failure. Due to uneven temperature conditions the components under cyclic loading tend to show a decreased fatigue life as compared to the ideal conditions thus their probability of failure is quite high and sometimes dangerous too. There are many techniques which are used to identify the failure signs and take proper action but all these techniques require a physical and non-destructive testing of the component which is time consuming and not suitable for critical operation components also the temperature factor is not considered although it being the major affecting factor. This paper presents an approach to do the online temperature analysis of the conditions and predict the further failure conditions by analysing the thermal stresses caused and preventing the potential sudden failure of the component by using polynomial regression algorithm to predict the temperature conditions based on the initial conditions and correlating it to the magnitude of thermal stress induced and analysing the failure possibility of the component.*

Key words: Fatigue failure; thermal fatigue failure; fatigue life variations; temperature prediction; temperature sensors; BOLT Wi-Fi module; Machine Learning; polynomial regression algorithm; Industrial Safety.

1) INTRODUCTION

In the modern structures the static loading failure are comparatively less as compared to the failure caused by cyclic loadings. In the present scenario the cyclic loading are considered critical for design criteria. For this reason, design analysts must properly analyse the effects of repeated loads, fluctuating loads, and rapidly applied loads along with changing temperature conditions. Such loading induces fluctuating or cyclic stresses that often result in failure of the structure by fatigue. The below graph shows the conventional S-N curve for 1045 Steel and 2024-T6 Aluminium.

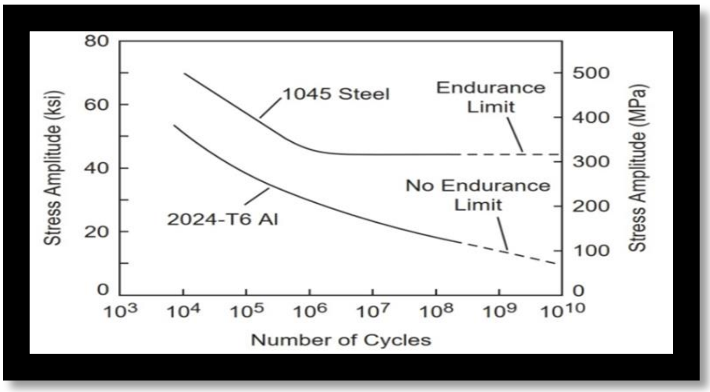

Fig .1 S-N curve for Aluminium and low Carbon Steel [7]

For most metals, failure by fatigue can occur at any temperature, below the melting point and the characteristic features of fatigue fractures, usually with little or no deformation, are apparent over the whole temperature range.. At high temperatures, the limiting factor in design is usually static strength, but resistance to fatigue is an important consideration in engine design, particularly when static and alternating stresses are combined. In addition, many service failures occur by thermal fatigue resulting from repeated thermal expansion and contraction [8].

Thermal stresses arise in materials when they are heated or cooled. Thermal stresses effect the operation of facilities, both because of the large components subject to stress and because they are effected by the way in which the plant is operated. On cooling, residual tensile stresses are produced if the metal is prevented from moving (contracting) freely. Fatigue cracks can initiate and grow as cycling continues. Stress concentrations can be reduced through appropriate design changes that take thermal expansion and contraction into account.

Although the primary cause of the phenomenon of fatigue failure is not well known, it apparently arises from the initial formation of a small crack resulting from a defect or microscopic slip in the metal grains. The crack propagates slowly at first and then more rapidly when the local stress is increased due to a decrease in the load-bearing cross section. The metal then fractures. Fatigue failure can be initiated by microscopic cracks and notches, and even by grinding and machining marks on the surface; therefore, such defects must be avoided in materials subjected to cyclic stresses (or strains).

Heat up and cooldown limitations, pressure limitations, and pump operating curves are all used to minimize cyclic stress.[1,3]

To use composite structures to their full potential, design strain levels will have to rise and a partial growth criteria needs to be adopted; if this is to happen, an accurate fatigue lifing methodology needs to be established.

Of the many papers written on fatigue–life prediction, including damage accumulation models, data manipulation models, and statistical accounts of monotonic and fatigue failure distributions by the use of Weibull functions, only a few are physically based.

It is essential that improved life–prediction methodologies are developed if polymer composites are to be used more widely at higher stresses and strains and the enormous benefits of these materials in performance and cost can be realized in structural applications. Key to this is the understanding of the effects of various damage mechanisms on fatigue life.

This paper also presents a supporting towards the prevention from thermal fatigue by using the polynomial regression algorithm to predict the temperature conditions based on the initial conditions and correlating it to the magnitude of thermal stress induced and analysing the failure possibility of the component.

Thermal fatigue, also known as thermomechanical fatigue, is a degradation mode, which involves simultaneous occurrence of both thermal and mechanical strain. Various combinations of mechanical strain (or stress) and temperature cycles are possible to generate thermal fatigue data .Unlike thermal fatigue, typical LCF testing is conducted with strain cycled at constant temperature. The most damaging cycle combination in thermal fatigue testing for coatings, which are brittle below the DBTT, is tensile strain at low temperature changing to compressive (or lower tensile) strain at high temperature. This is the traditional “out-of-phase” cycle, temperature being out of phase with tensile stress or strain. [5]

2) FATIGUE FAILURE INSPECTION METHODS

The best way to prevent failure due to thermal fatigue is to minimize thermal stresses and cycling in the design and operating of equipment. Reducing stress raisers, controlling temperature fluctuations (especially during shutdown and start-up), and reducing thermal gradients can help prevent thermal fatigue. Taking proactive measures to prevent cool liquid from touching hot boundary walls, e.g. installing liners or sleeves, can also prove effective. This event occurs as products travel downstream from one processing unit to the next where successive units may operate at various temperatures.

Unfortunately, thermal fatigue cannot always be prevented. As a result, there are several ways to inspect for and mitigate thermal fatigue, including:

- Visual inspection, liquid penetrant testing (PT), and magnetic particle testing (MPT) for inspection of equipment surfaces.
- Surface wave ultrasonic testing (SWUT) and other ultrasonics can be utilized as non-intrusive methods of testing for internal cracks.

2.1) Visual Inspection, or Visual Testing (VT), is the oldest and most basic method of inspection. It is the process of looking over a piece of equipment using the naked eye to look for flaws. It requires no equipment except the naked eye of a trained inspector.

Visual inspection can be used for internal and external surface inspection of a variety of equipment types, including storage tanks, pressure vessels, piping, and other equipment.

Visual inspection is simple and less technologically advanced compared to other methods. Despite this, it still has several advantages over more high-tech methods. Compared to other methods, it is far more cost effective. This is because there is no equipment that is required to perform it. For similar reasons it also one of the easiest inspection techniques to perform. It is also one of the most reliable techniques. A well-trained inspector can detect most signs of damage.

2.2) Liquid Penetrant Examination (LPE), also referred to as penetrant testing (PT), liquid penetrant testing (LP), and dye penetrant testing (DP), is a non-destructive examination (NDE) method that utilizes fluorescent dye to reveal surface flaws on parts and equipment which might not otherwise be visible. The technique works via the principle of "capillary action," a process where a liquid flows into a narrow space without help from gravity. Because it is one of the easiest and least expensive NDE techniques to perform, LPE is one of the most commonly used inspection techniques in many industries, including oil and gas.

While this method is effective due to its simplicity and accuracy, it does have its share of disadvantages as well. It can only detect flaws on the surface. So for subsurface flaws, a technique like magnetic particle testing (MPT) is more appropriate. It also only works on smooth surfaces, which can make it unsuitable for some parts.

2.3) Magnetic particle testing (MPT)

MPT is a fairly simple process with two variations: Wet Magnetic Particle Testing (WMPT) and Dry Magnetic Particle Testing (DMPT). In either one, the process begins by running a magnetic current through the component. Any cracks or defects in the material will interrupt the flow of current and will cause magnetism to spread out from them. This will create a "flux leakage field" at the site of the damage.

The second step involves spreading metal particles over the component. If there are any flaws on or near the surface, the flux leakage field will draw the particles to the damage site. This provides a visible indication of the approximate size and shape of the flaw. There are several benefits of MPT compared to other NDE methods. It is highly portable, generally inexpensive, and does not need a stringent pre-cleaning operation. MPT is also one of the best options for detecting fine, shallow surface cracks. It is fast, easy, and will work through thin coatings. Finally, there are few limitations regarding the size/shape of test specimens.

3) EFFECT OF TEMPERATURE VARIATION ON FATIGUE LIFE.

According to many case studies and experiments, the fatigue life of many specimens are tested and conclusive results were drawn out based on composition ,loading types such as static, cyclic and even combined. Although the surroundings in which the test is carried out is very important and should be taken into account in order to conclude the fatigue life behaviour as it is one of most influential parameter. In the cases where the components are subjected to different operating temperatures ranging from maximum to minimum, in those cases the thermal stresses are developed in the material and from the study carried out for the DIN 35 NiCrMoV 12 5 steel sample various conclusive results are drawn out [6], which can be seen in the figure 2 mentioned below.

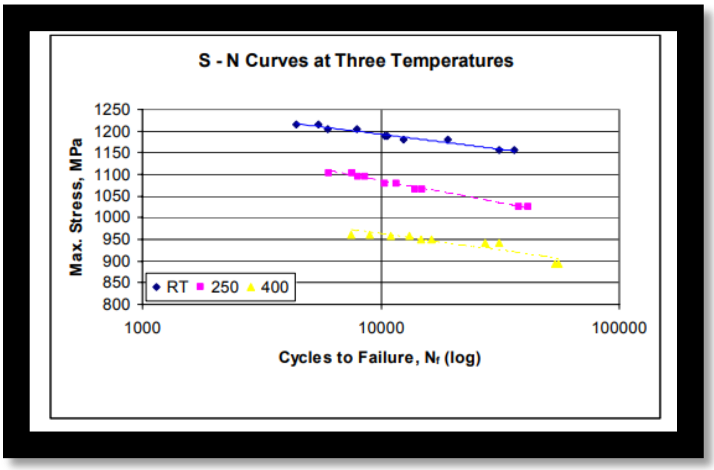

Fig.2 S-N curve for DIN 35 NiCrMoV 12 5 steel at three different temperatures.[6]

From the graph it can be concluded that there are adverse effects of changing temperature around the test component. The fatigue strength, the endurance limit has shown a significant decrease, which can be very dangerous if the component is employed in some industry and designed according to some maximum stress keeping the factor of safety aside, the component can fail at a loading very less than the designed due to thermal stresses and thus a proper monitoring must be carried out to identify the various temperature variations and how the material properties may behave during the operating phase. This indeed becomes very difficult as the dynamics are concerned but the polynomial regression method is capable to identify the various temperature conditions based on the history of the component and by using the machine learning algorithm accurate predictions can be made and the magnitude of thermal stress induced can be calculated and so as the various preventive measures.

3.1) Influence Of Temperature on Fatigue Crack Propagation

The basic process of fatigue failure in metals at ambient temperature is the relatively rapid nucleation of small surface cracks followed by the steady slow growth of one or more of these cracks until material separation occurs, or the crack achieves a critical size for fast fracture [9]. At elevated temperatures, although this process persists as the dominant one, secondary effects are observed which can particularly influence the rate of crack growth. Such effects include the weakening of grain boundaries, the development of internal grain boundary cracks or cavities, and an enhanced rate of oxidation of freshly exposed fracture surfaces. [6]

3.2) Effect of Coefficient of thermal expansion with the temperature variation for analyzing the induced thermal stresses

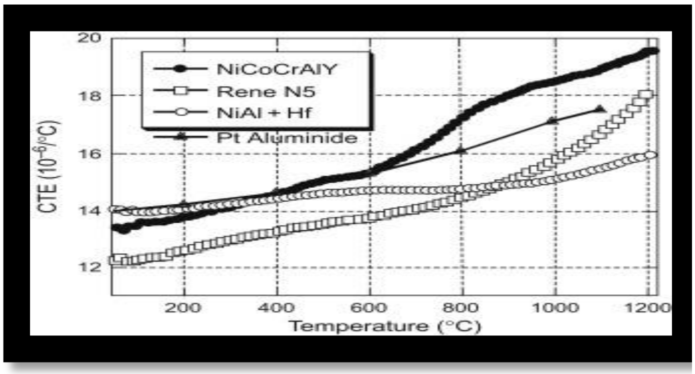

Fig.3 Coefficient of thermal expansion of nickel base superalloy single crystal, nickel aluminide, and NiCoCrAlY.[10]

The above graph projects the effect of temperature variation on the coefficient of thermal expansion. But in the later analysis of stress induced this parameter is taken as a constant and assumed to be of same value throughout the prismatic steel bar. However a further analysis can also be done by varying this parameter as well.

We know that according to theory,

$$\sigma_T = E\,(\alpha\,\Delta T) \qquad (1)$$

$\Delta T = T_f - T_i$,where $T_f > T_i$ or $T_f < T_i$

Where σ_T is the induced thermal stress, E is the Young's Modulus, (α ΔT) is the thermal Strain. A being the coefficient of thermal expansion and T_i is the steady temperature of performance but subjected to temperature fluctuation of magnitude ΔT.

Thus from Equation (1) we can conclude that, if the component is not allowed to expand freely and contract freely as we have imposed some restrictions and then the component is subjected to dynamic loading and subjected to temperature difference, the magnitude of thermal stress is directly proportional to the temperature difference given that the material has a constant Young's modulus (E).

Building on this work, the BOLT Wi-Fi module was employed to predict the future temperature limits by using the polynomial regression algorithm using a temperature sensor for a sample and it was subjected to different temperature limits over time and the corresponding stress induced was recorded .Thus this was in the initial phase, which served as a database for the machine learning algorithm to predict the future fluctuation in temperature to indicate any sudden increase in thermal stress over a particular period of time by using the graphical depiction of real time operation and accordingly the safety measures may be taken if any parameter crosses the set limits.

4) PRACTICAL SET UP AND ANALYSIS OF THE ACCURACY OF PREDICTION BY BOLT.

BOLT - It's a IoT platform which enables us to control the things through internet .Connect the sensors, actuators etc. to bolt, write a short code and it's good to go. It collects, monitors and visualise the data through the sensors embedded. [13]

CLOUD - the bolt cloud enables the microcontroller to be configured even when the device is not directly connected to the initial setup. The data collected is saved in this and further analysed by using the technique of data visualization.

4.1) Hardware required

This analysis requires a very simple setup, a system having a temperature controlling unit, a programmable Bolt Wi-Fi module along with a temperature sensor (LM35) with a sample of steel rod mounted on bearing having single degree of freedom i.e. rotation about the major axis. The same can be seen in the figures below.

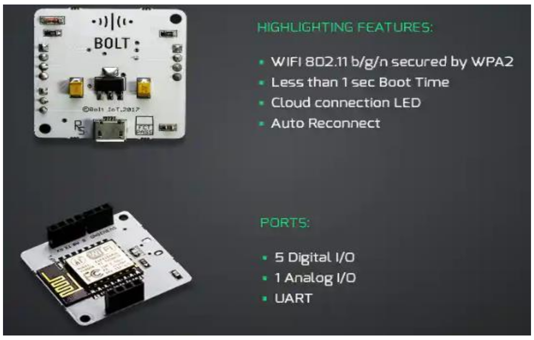

Fig.4 BOLT Wi-Fi Module [13]

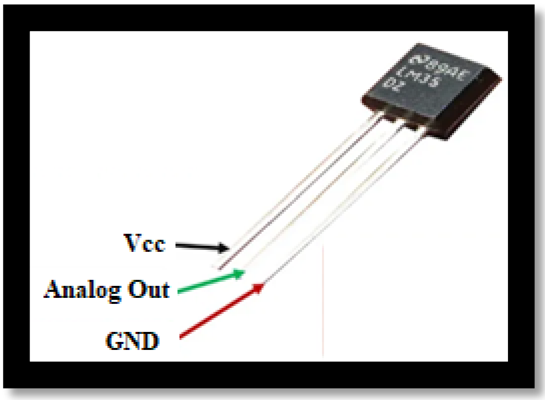

Fig.5 LM35 (Temperature sensor) [12]

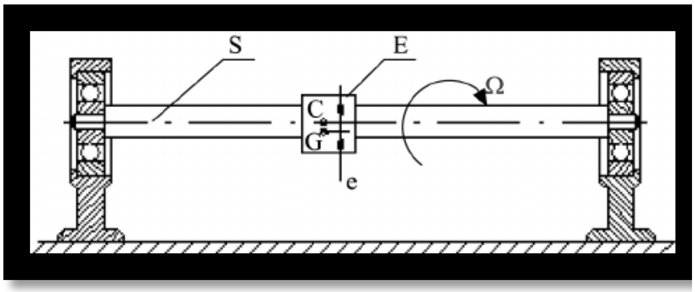

Fig.6 Schematic set of a shaft of suitable material fixed from ends but free to rotate. [11]

4.2) Hardware Connections

- For the LM35 connections, the LM35 has 3 pins namely the VCC, Output and Gnd. The VCC pin of the LM35 connects to 5v of the Bolt Wi-Fi module. Output pin of the LM35 connects to A0 of the Bolt Wi-Fi module and Gnd pin of the LM35 connects to the GND.
- After the connections are done power the Bolt Wi-Fi Module to laptop via the USB cable.

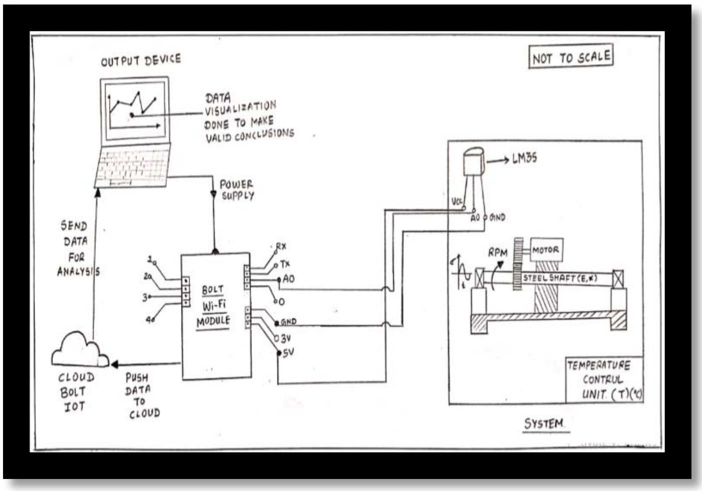

Fig.7 Schematic diagram of the practical setup to analuyse the effect of temperature vaiation and prediction and the thermal stresses induced.(Not to scale)

The above set up shows the schematic set of the arrangements which are made for the real time temperature analysis and the corresponding thermal stresses induced. The connections and the flow diagram can be properly seen from the above figure.7.

4.3) WORKING

4.3.1) ML Polynomial Regression [14]

Polynomial Regression is a regression algorithm that models the relationship between a dependent(y) and independent variable(x) as nth degree polynomial. The Polynomial Regression equation is given below:

$y = b_0 + b_1x + b_2x^2 + b_3x^3 + \ldots\ldots b_nx^n$

a) Need for Polynomial Regression

1) If we apply a linear model on a linear dataset, then it provides us a good result as we have seen in Simple Linear Regression, but if we apply the same model without any modification on a non-linear dataset, then it will produce a drastic output. Due to which loss function will increase, the error rate will be high, and accuracy will be decreased.

2) So for such cases, where data points are arranged in a non-linear fashion, we need the Polynomial Regression model. We can understand it in a better way using the below comparison diagram of the linear dataset and non-linear dataset.

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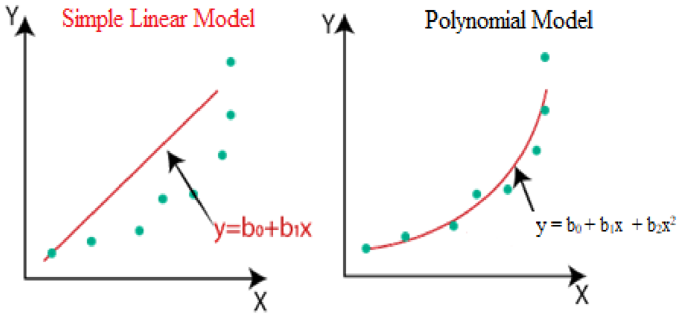

Fig.8 Simple linear mode and polynomial mode.

3) In the above image, we have taken a dataset which is arranged non-linearly. So if we try to cover it with a linear model, then we can clearly see that it hardly covers any data point. On the other hand, a curve is suitable to cover most of the data points, which is of the Polynomial model.

4) Hence, *if the datasets are arranged in a non-linear fashion, then we should use the Polynomial Regression model instead of Simple Linear Regression*

b) The main steps involved in Polynomial Regression are given below:

- Data Pre-processing
- Build a Linear Regression model and fit it to the dataset
- Build a Polynomial Regression model and fit it to the dataset
- Visualize the result for Linear Regression and Polynomial Regression model.
- Predicting the output.

4.3.2) Applying the Polynomial Regression algorithm for the temperature monitoring and induced thermal stress calculation.

The temperature conditions in the system are varied and the variations in a pictorial format are observed on the respective output device. The machine learning requires some of the initial data to predict the further conditions so keeping that in mind, some reading of temperature were influenced by the temperature control unit for the system and the results can be seen clearly in the below figure.9. After a specific time period the temperature data is pushed to the cloud and through google chart library the graph can be plotted toward data visualization.

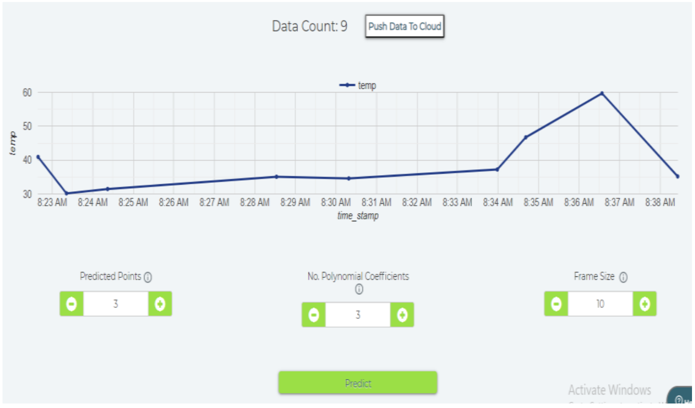

Fig.9 Initial readings to serve as a feed to the ML algorithm to assist prediction.

Now once the initial temperature conditions are stated, which also represent the working conditions of the component, we can start the prediction by the polynomial regression algorithm by setting the number of polynomial coefficient and the predicted points within a specified time frame. The number of polynomial coefficients decide the degree of polynomial used as regressor. The degree of a polynomial is the largest power of the dependent variable.

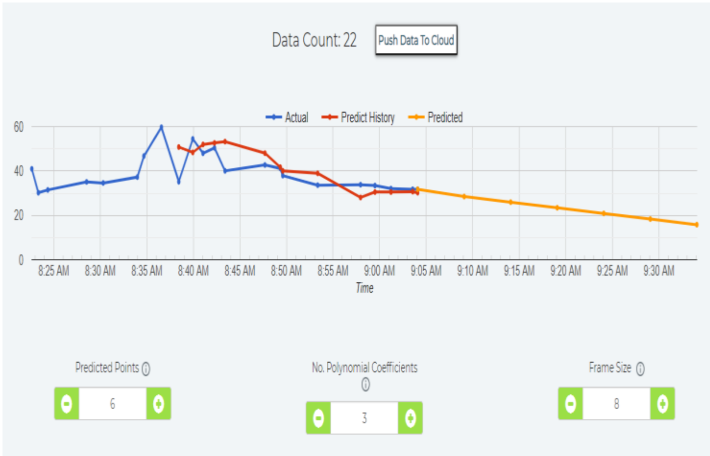

Fig. 10 Real time temperature monitoring with specific time duration.

In Fig.10, The red line shows the predicted points and from that it is quite evident that the actual conditions show a slight deviation and thus using that change in temperature the induced thermal stress can be calculated by using Eq.1 as the temperature difference is the only variable parameter to calculate the induced thermal stress also a proper matrix of stresses can be formed so that the nature and magnitude of stress induced can be monitored and any change exceeding the design parameters can be predicted beforehand and proper actions can be planned. So the real time temperature and thermal stress analysis serves as a add on to the existing methods towards industrial safety.

Further the accuracy is tested and the temperature limits were not fluctuated and a constant temperature was set and the limits were defined and the predictions were made and from the Fig.11 so as to test the magnitude of the stress induced, whether it is within the limits or exceeds the predefined limits but the results were as predicted as per the algorithm formulated, it is also clear that this method also employs high accuracy and good prediction capability once proper initial data is feed to the machine learning algorithm.

Fig.11 Output for the predicted temperatures and a comparative analysis of actual and predicted.

The output so predicted largely depends upon the initial conditions provided as it is clear from the Fig.11, the nature of the temperature predicted depends upon the past trends. So if there is any undesirable fluctuation caused the polynomial regression algorithm will predict the occurrence of the same over a period of time and predict accordingly.

5) CONCLUSIONS

Thermal fatigue failure is quite a big issue for the components subjected to cyclic loading along with fluctuating temperature conditions. Thus there was an alarming need for the online temperature monitoring system, which can analyse and predict the nature and magnitude of thermal stress induced. By Machine learning, using the Polynomial regression it is very clear that this is an effective arrangement and fairly accurate as well. The real time thermal stress induced can be calculated and by using a suitable software a separate visualization can also be formulated by setting the threshold stress limits as it will show the variation of stresses induced due to different temperature conditions thus will also serve as an indicator to schedule the inspection and maintenance of the mechanical components by analysing the number of times the induced stress crossed the safety level and in the long run such installations can also improve the working life of the components by a significant amount. Also it will save the components which are directly connected to the component being monitored as if it will fail it will also affect the performance of the other components thus it will be very beneficial as far as the assembly is taken into account.

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