Fatigue Life Prediction of Aluminum Using Artificial Neural Network

Moises Jimenez-Martinez, *Member, IAENG,* and Mariel Alfaro-Ponce

***Abstract*—Lightweight materials are currently being more used in mechanical components due to their mechanical behaviour and lighter weight. To prevent failures on the service life is necessary to predict its fatigue life. To perform the life evaluation, the durability assessment is used to establish the damage applied by fatigue loads and the number of load cycles or spectrum repetitions versus material fatigue properties using its S-N curves to calculate the accumulated damage. This information is evaluated using a fatigue damage hypothesis. An artificial neural network (ANN) is proposed to predict the fatigue life based on material ultimate tensile strength (UTS). This is the first part of research to develop aluminum alloy through ANN based on the expected fatigue strength. The evaluation performed with results in literature with different types of aluminum: 5056, 2198-T851, 2024-T3 and 7050-T7451 has been proved that ANN can predict the fatigue life-improving its accuracy over traditional and modified damage rules.**

***Index Terms*—Lightweight; Aluminum; S-N curves; Artificial Neural Network; Durability.**

I. Introduction

ORIGINAL equipment manufacturers have been working on weight reduction. To achieve this target, the integration of lightweight materials has been applied to use alternative materials. The common lightweight materials used in body cars are Ultra High Strength Steels, Magnesium, Aluminum, and composites. The integration depends on its mechanical performance for crashworthiness and fatigue strength [1]. Fatigue improvements can be performed using thermal and mechanical treatment processes [2], [3]. Composite materials can be introduced to substitute metallic parts to reduce the body structure weight as well as manage impact load [4]. To improve its mechanical performance, static failure criteria have been proposed, and models for fatigue loading [5], [6].

One of the most used lightweight materials is aluminum, which, after iron, is the most used material in construction. This material can be customized through additive elements, like Mg and Mn, to improve mechanical strength and Cu and Zn to improve its machinability. Diverse alloys can be designed depending on the required characteristics[7], [8]. In a car's body, aluminum can be used to hang-on parts mainly of AlMgMn and AlMgSi alloys; it can also be applied to elements to manage crash energy as bumpers crash boxes [9], [10]. One of the limitations of introducing lightweight materials like aluminum is the high cost to characterize its mechanical performance. This work proposes an ANN to predict the fatigue life based on estimate $S-N$ curve parameters and UTS. It is introduced the ANNs in fatigue life prediction in section II, in this section is also generated the training parameters. In section III are reviewed the results for different alloys and are evaluated their performances. Also, the durability assessment using S-N curves is included with a scanning electron microscopy analysis to evaluate the alloying elements' contribution.

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M. Jimenez-Martinez is a Professor at the School of Engineering and Science, Tecnologico de Monterrey, Puebla, Mexico (corresponding author, e-mail: moisesjimenezmartinez@gmail.com).

M. Alfaro-Ponce is the Head of the BME program at the School of Engineering and Science, Tecnologico de Monterrey, CDMX, México (e-mail: mariel.alfaro@tec.mx).

II. Artificial Neural Networks

An ANN is a computational model that emulates a human brain [11] with diverse properties such as high parallelism, robustness, real-time adaptability, among others, making them suitable to been applied to different fields of engineering. Besides, there are many different topologies of ANNs, which reflects on how the neurons are connected; also, the selected topology will be a determining factor in the ANN function and learning [12]. By modifying the ANN topology, it can adapt to the complexity of highly specialized engineering problems, being mechanical engineering, not an exception [13]. This tool can be used as a design element to develop new concepts and analyze mechanical responses, as it can predict the damage evolution resulting from the manufacturing process,i.e., in forge [14].

As mentioned before, ANN in mechanical engineering had gain popularity in recent years, i.e. aluminum alloys have low weldability using traditional fusion processes; therefore, Shojaeefard et al.[15] proposed a friction process using ANN join cast and wrought aluminum alloys [16], which has the advantage to customize using data from experimental or physical processes. Although a mathematical model can be proposed, most of the times, physical behaviour includes a nonlinear response. In these cases, ANN improves its capability based on fine-tuning during the training process due to interconnected nodes updated through weights, generating dynamic feedback among the neurons [17], [18].

Orbanić and Fajdiga [19] proposed an ANN to describe fretting fatigue. ANN had been used previously to estimate fatigue damage [20], [21], [22] and fault diagnosis [23]. Varol et al. [24] analyzed the mechanical behaviour of composites using ANN; depending on their expected predictions and input parameters [25]. Freitag et al.[26] have evaluated the lifetime of materials using ANNs, where the relationships in materials for chemical composition and their results in mechanical properties are nonlinear and depend on the microstructure of alloying elements in the processing variables [27], being ANNs a suitable solution for their modelling. Dini et al. [28] applied ANN to define the mechanical response of material inducing plasticity in Steel for TRIP and TWIP, and Sabhani and Mazahery analyzed mechanical properties through parameters as temperature gradient in cooling rate with ANNs to predict quasistatic response [29].

Even though ANNs have a certain level of complexity according to the problem they are addressing, in most of the previously mentioned cases, the authors report for their implementation normally three steps:

- Preparation of the information used as a database.
- Choosing of the ANN topology.
- Training and validations of the ANN.

During a supervised training process, the ANN weights are adjusted according to the presented data, and the desired output [30]. This is performed through an iterative process analyzing different weights. During the training process, it is important to prevent overfitting the ANN, which translate into a ANN that performs well with the training data but perform poor with new data. Different techniques can be applied to prevent overfitting; most of them rely on the number of samples employed for the training and validation process [31].

A. Artificial Neural Network to Predict the Fatigue Life of Aluminum Alloys

The specific parameters and topology of the ANN proposed to predict the fatigue life of aluminum alloys are addressed in this section; for the ANN training, synthetic data was used to predict the Wöhler S-N curve. The topology of the ANN employed is shown in Figure 1. A commonly used method for the training of ANNs is the Backpropagation (BP) algorithm, but this algorithm tries to overfit the data set rather than generalizing. Consequently, its performance decreases in the presence of noise in the input.

To avoid this problem, the Bayesian Regularization eq. (12) adds an additional term to the classical BP algorithm $F = E_D$. To obtain the objective regularization function [32]

$$F = \beta E_D + \alpha E_w, \quad E_w = \sum_{i=1}^{N} w_i^2 \tag{1}$$

where E_w is the sum of square errors of the ANN weights and α, and β are objective function parameters, N is the number of inputs employed as the training set, and w are the weights. It is important to remark that in the Bayesian Regularization, if $\beta >> \alpha$ overfitting occurs, but if $\alpha >> \beta$, training emphasizes weight reduction but tolerates higher errors.

Here the weights are considered random variables, and according to Baye's rules, they can be represented as

$$P(w|D, \alpha, \beta, M) = \frac{P(D, w, \beta, M)P(w|\alpha, M)}{P(D, \alpha, \beta, M)} \tag{2}$$

where w represents the vector of the network weights that will evolve due to learning of the input data, $P(w|\alpha, M)$ is the ANNs weights before the data set is given, the probability that the data will occur given the weights of the ANN is $P(D|w, \beta, M)$), and $P(D|\alpha, \beta, M))$ is the evidence of the model given the hyperparameters and determined by eq. (3)

$$P(D|\alpha, \beta, M) = \int P(D|w, \beta, M)P(w|\alpha, M)dw \tag{3}$$

[32] assume the noise is Gaussian in the training data set. Therefore, the previous distributions of their weights are also Gaussian.

$$P(D|w, \beta, M) = \frac{1}{Z_D(\beta)} \exp(-\beta E_D) \tag{4}$$

$$P(w, \alpha, M) = \frac{1}{Z_w(\alpha)} \exp(-\alpha E_w) \tag{5}$$

Here $Z_D(\beta) = (\frac{\pi}{\beta})^{\frac{n}{2}}$ and $Z_w(\alpha) = (\frac{pi}{\alpha})^{\frac{N}{2}}$. By replacing them in eq. (2)

$$P(w|D, \alpha, \beta, M) = \frac{1}{Z_F(\alpha, \beta)} \exp(-F(w)) \tag{6}$$

Once again by applying eq. (4) and substituting it in eq. (6), the following are obtained

$$P(D|\alpha, \beta, M) = \frac{\frac{1}{Z_D(\beta)} \exp(-\beta E_D) \frac{1}{Z_W(\alpha)} \exp(-\alpha E_w)}{\frac{1}{Z_F(\alpha,\beta)} \exp(-F(w))} \tag{7}$$

$$P(D|\alpha, \beta, M) = \frac{Z_F(\alpha, \beta)}{Z_D(\beta) Z_w(\alpha)} \tag{8}$$

We evaluate $Z_F(\alpha, \beta)$ using Taylor series expansion, and obtain the normalization constant by

$$Z_F = (2\pi)^{\frac{N}{2}} (\det((H^{MP})^{-1}))^{\frac{1}{2}} \exp(-F(w^{MP})) \tag{9}$$

where the Hessian matrix of the objective function is represented by H. To optimize the regularization parameters α and β, it is necessary to solve H at the minimum point w^{MP} obtaining

$$\alpha^{MP} = \frac{\gamma}{2E_w(w^{MP})} \tag{10}$$

$$\beta^{MP} = \frac{n - \gamma}{2E_D(w^{MP})} \tag{11}$$

Here $\gamma = N - 2\alpha^{MP} tr(H^{MP})^{-1}$ represent the numbers of parameters in the ANN.

The activation function influences the training process, which is the transfer function between the parameters. The most commonly used activation functions are linear, threshold, gaussian, sigmoid and hyperbolic tangent sigmoid. A sigmoidal activation function was employed, as it combines different behaviours as linear, curvilinear and near-constant, as expressed in eq. 12.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

Where x is the weighted sum of input.

The data were split into random subsets: 70% for the training, 15% for the correlation and 15% for the test, and the convergence was achieved in 1000 iterations. The weights were obtained from the toolkit of MATLAB as a result of the supervised learning process. A two-layer feed-forward network was used, and the number of hidden neurons were 40 and 44 using the fitnet tool. The training was performed using Bayesian Regularization (trainbr). It has performed using one pass through training set (1 epoch), the weights and biases of the network are assumed to be random variables. The novelty of this paper deals with the introduction of parameters to estimate S-N curve as input.

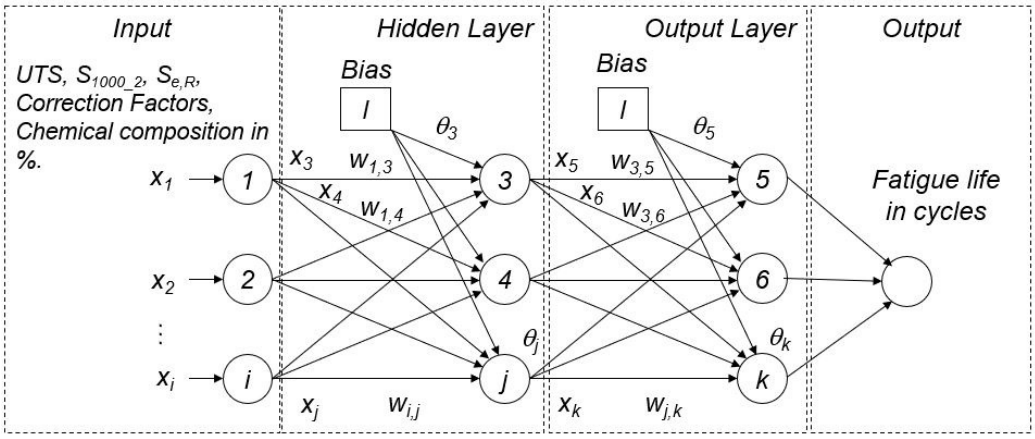

Fig. 1. Topology of the proposed ANN

TABLE I
CHEMICAL COMPOSITION IN %.

	Al	Cr	Cu	Fe	Li	Mg	Mn	Si	Ag	Ti	Zn	Zr
5026	93.80	0.12	0.10	0.40	0.00	5.05	0.12	0.30	0.00	0.00	0.10	0.00
2198-T851	93.83	0.05	3.20	0.10	0.95	0.52	0.50	0.08	0.30	0.00	0.35	0.11
2024-T3	92.05	0.10	4.35	0.50	0.00	1.50	0.60	0.50	0.00	0.15	0.25	0.00

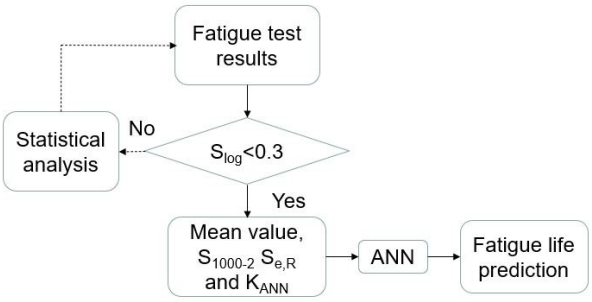

Fig. 2. Fatigue life prediction methodology

The inputs used are the chemical composition shown in table I, mechanical properties, estimated S-N curves and correction factor. Although [31], proposed normalization of the parameters, the process has been designed to use the raw data in the inputs as well as the forecast output.

The last parameter used is the relationship between the UTS represented as S_u and the applied load expressed as:

$$K_{ANN} = \frac{S_u}{S_i} \tag{13}$$

Where S_i is the amplitude at the i_{th} load level.

The fatigue life prediction methodology is shown in Figure 2. Statistical analysis is necessary to train the network to know the scatter (s_{log}). The formula for standard deviation is given as:

$$s_{log} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{14}$$

where μ is the mean value at i_{th} load level, x_i is the sample and N is the sample number.

B. Estimated S-N Curve Parameters for Aluminum

The relationship to estimate the S-N curve will be used to generate parameters for evaluating aluminium and train the ANN. The endurance limit S_{be} is evaluated for 5x10^8 cycles [33] and is described in eq. 15 for UTS below 336 MPa, otherwise S_{be}=130 MPa:

$$S_{be} = 0.4 \times S_u \tag{15}$$

During fatigue assessment, it is necessary to consider different factors that reduce the endurance limit. For a probability of failure of 50% with a surface finish polished, the relationship is expressed in eq. 16.

$$S_{e,R} = S_{be} \times C_L \times C_D \tag{16}$$

Where C_L is the load factor and C_D is the size factor. The size coefficient is defined by eq. 17:

$$C_D = 1.189 \times d^{-0.097} \tag{17}$$

The fatigue strength at 10^3 cycles (S_{1000}) depends on the type of loading, for a reliability of 50% is defined to estimate (S_{1000-2}) as shown in eq. 18:

$$S_{1000-2} = S_u - \frac{1}{2}S_u \times ln\frac{1}{K} \tag{18}$$

Where K is the factor that depends on the type of loading for torsion K=0.63, for bending is K=0.9, and for axial load K=0.75.

The first results are shown in figure 3 and have been reported by Kikuchi et al. [34]. The UTS (S_u) is 310 MPa, the yield strength (Ys)= 152MPa and the specimen has a radius of 27 mm (C_D=0.807), load is bending C_L=1; with eq. 4 and 5, $S_{e,R}$=100.12 MPa is obtained. Using eq. 7, (S_{1000-2})=293.67 MPa.

The next results are for 2198-T851 and 2014-T3 reported by Alexopoulos et al. [35] with an UTS of 484 MPa and 500 MPa respectively, yield stress = 432 and 391MPa respectively. The specimens have a radius of 130mm, obtaining C_D=0.693. For its UTS S_{be} =130 MPa for both cases, the load is axial (C_L=0.7) and modifying it by the coefficient factors, using equation 4 is obtained $S_{e,R}$= 63.09 MPa. With equation 6, we have (S_{1000-2})=414.38 MPa for 2198-T851 and (S_{1000-2})=428.07 MPa for 2024-T3. The results are shown in figure 4.

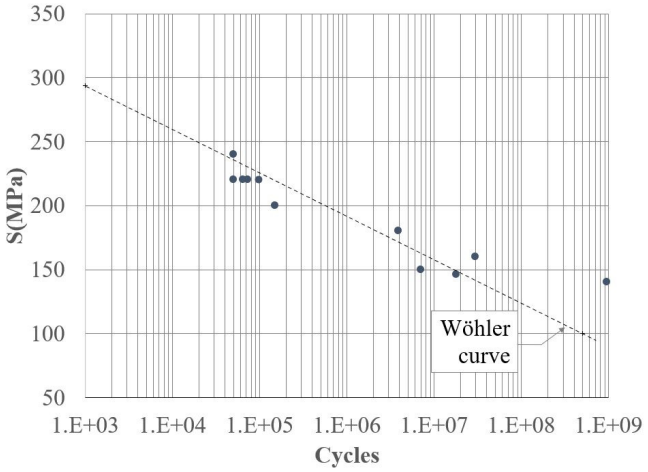

Fig. 3. Fatigue aluminum 5056 adapted from [34]

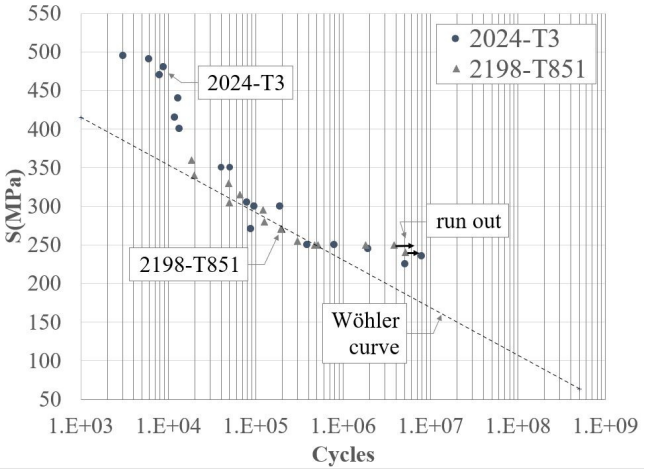

Fig. 4. Results adapted from [35]

III. Results and Discussion

In this work, different topologies were analyzed to reduce the error; also, diverse training information was taken into account. In the first neural networks, the chemical composition, hardness, Youngs' modulus, yield stress, and UTS were used as an input, and the term (S_{1000-2}), Se_R, the factors C_D and C_L, the amplitude of load and a relationship between the UTS and the load (eq.13) have been used to describe the fatigue strength. To evaluate the capability of prediction, the percentage error e is analyzed:

$$e = ABS\left(100 - \frac{ANN_{i\times 100}}{\mu_i}\right) \tag{19}$$

where ANN_i is the fatigue life prediction and μ_i is the mean experimental value at i_{th} load level.

With all the input parameters and using eq.8, the $ANN1$ has an average error of 22.11% using 40 hidden neurons. Some alloying elements are not present among the alloys analyzed, and it was registered as a null per cent. In the second network $ANN2$, the next elements were eliminated: Li, Ti, Ag and Zr, improving the prediction reaching an average error of 15.26%. To evaluate the chemical composition and tic strength influence on the forecasting of the ANN, the next elements were eliminated: chemical composition, Youngs' modulus, hardness and yield stress, only are take into account the parameters that represent the fatigue strength of the material, reducing the error to 10.72% using 44 hidden neurons ($ANN3$). Eliminating the parameter that relates the UTS with the applied load (S), the average error reaches a value of 37.98% ($ANN4$). The best architecture and input parameters are at $ANN3$.

TABLE II
Experimental results and fatigue life prediction.

Material	Amplitude (MPa)	Mean Cycles	N_2 Cycles	%	N_2ANN Cycles	%
5056	220	69,600	33,865	48.65	69,595	99.99
2198	270	196,750	19,815	10.07	187,050	95.07
-T851	255	295,000	29,517	10.01	307,537	104.25
	250	923,333	33,887	3.68	361,446	39.15
2024-	350	45,500	3,975	8.74	44,771	98.40
-T3	300	142,500	11,433	8.02	145,947	102.42
	250	590,000	39,888	6.76	584,315	99.04

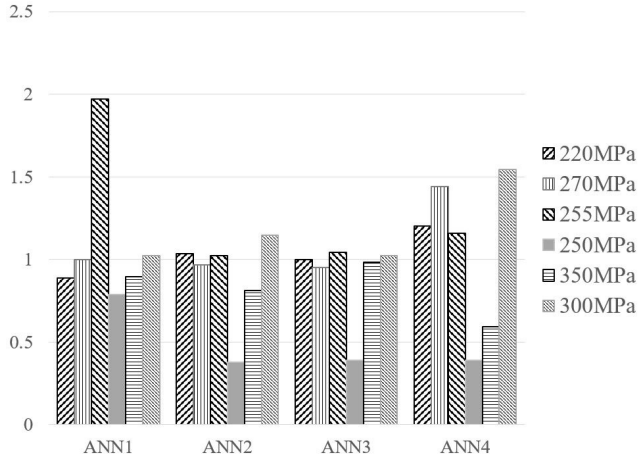

Fig. 5. Normalized prediction

To compare the prediction of load level, the normalized prediction was evaluated using equation 20, which is shown in figure 5:

$$normalized\ prediction = \frac{\sum_{i=1}^{n} x_i}{n_i \times ANN_i} \tag{20}$$

where x_i are the cycles and n_i the samples at the i_{th} load level. ANN_i is the fatigue life prediction at the i_{th} load level.

It can be expected that the best prediction is around 1; on the other hand, the dispersion is taken into account as shown in figure 5, completing the average value as well as the normalized prediction. The best architecture and input parameters are at $ANN3$. The prediction value per alloy and the prediction with damage rule (N_2) are summarized in Table II.

After validating the proposal, fatigue life prediction has been performed to aluminum alloy 7050-T7451 [36], and aluminum alloy with UTS=179.24MPa only with ANN. Experimental results are shown in figure 6 and 7, respectively.

The results for torsional as well as axial test are shown in table III, it has an average error of 1.683 %.

The last set of results are summarized in table IV, it has an average error of 5.66 %.

To evaluate if this proposal can be applied to other aluminum alloys, Scanning Electron Microscopy (SEM) was used to evaluate if the crack is on a specific component.

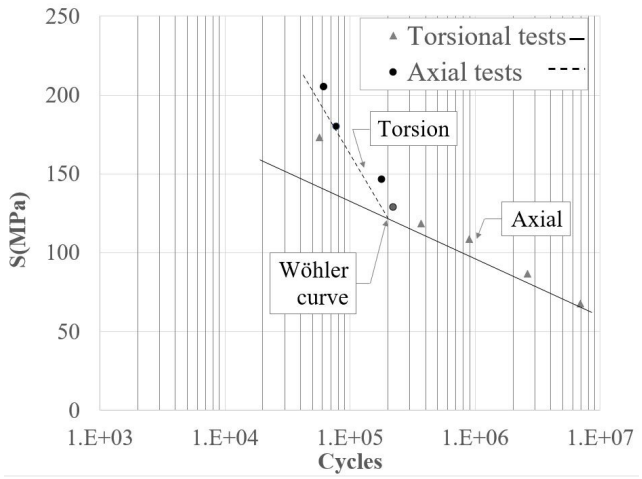

Fig. 6. Results adapted from [36]

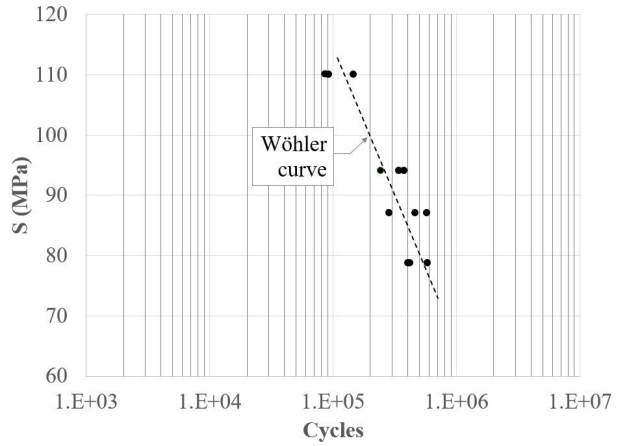

Fig. 7. Experimental results

TABLE III
FATIGUE LIFE PREDICTION 7050-T7451.

Load	Amplitude (MPa)	Mean cycles	N_{2ANN} cycles	e %
Torsion	173.2	57,067	57,064	0.004
Torsion	118.4	368,000	367,947	0.014
Torsion	108.6	895,000	894,972	0.003
Torsion	86.6	2,622,500	2,925,957	11.571
Torsion	67.7	6,936,667	6,936,724	0.000
Axial	205	61,900	61,900	0.000
Axial	180	77,340	77,340	0.000
Axial	146	179,000	172,630	3.558
Axial	129	223,500	223,500	1.918

TABLE IV
FATIGUE LIFE PREDICTION WITH ANN.

Amplitude (MPa)	Mean cycles	N_{2ANN} cycles	e %
110.0	109,056	109,056	0.0
94.0	322,703	322,703	0.0
87.0	442,667	442,667	0.0
78.7	470,574	577,148	22.647

Figure 8 shows the crack, and in figure 9 is shown the composition.

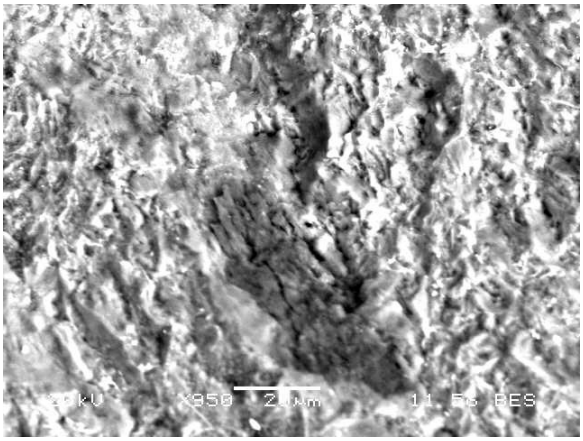

Fig. 8. SEM analysis

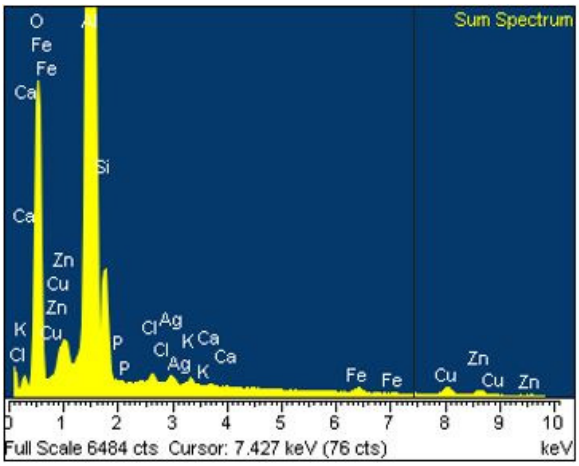

Fig. 9. Composition analysis

The inclusion is of alumina (Fig.9). The crack is not nucleated on other components of the alloy. Based on this analysis, to predict fatigue life using ANN, it is unnecessary to include the chemical composition in the ANN structure.

IV. CONCLUSION

For the aluminum 5056 the prediction has been improved 51.34% using ANN. The prediction for results of [35] in 2024-T3 has been improved 71.57% for the three load levels, and for 2198-T851 the prediction has been improved in an average of 92.11% for the three load levels. Based on these results, it is believed that the relationship (eq. 6) can be used to estimate parameters for aluminum as an input of ANN. The average prediction using ANNs for the three aluminum alloys is 89.28%.

It is possible to predict the fatigue life of a set of samples foretelling its mean value as in experimental fatigue life analysis; however, depending on the test conditions and material parameters, it is necessary to evaluate the ANNs results under supervised training.

The topology of the network depends on the nature of the investigated problem. As well as in the inputs, it was necessary to adjust it to get the best correlation. Due to the minor number of training inputs in the last networks, it was necessary to increase the hidden neurons to generate through the ANNs internal parameters correlation.

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M. Jimenez-Martinez was born in México in 1979. He received his PhD in Mechanical Engineering from IPN in 2015. He became a Member (M) of IAENG in 2020. His current research interests include Artificial Neural Network in Mechanical design. Finite Element Analysis and Nonlinear Analysis.

Dr. Jimenez is member of the Canadian Society of Mechanical Engineering(CSME) and is member of the Mexican National System Research (SNI).

M. Alfaro-Ponce received the B.S. degree in biomedical engineering, M.S. degree in microelectronics and a PhD in Computer Science from the Instituto Politecnico Nacional, Mexico. She is currently a Faculty Researcher and the Head of the Biomedical Engineering Program at Tecnologico de Monterrey Campus Ciudad de Mexico. Belonging to the National System of Researchers (SNI) Level 1 since 2020. Her current research interests include neural networks, rehabilitation devices and intelligent bioinstrumentation.