Multivariable and Multiaxial Fatigue Life Assessment of Composite Materials using Neural Networks

Mas Irfan P. Hidayat

***Abstract*—In the present paper, multivariable and multiaxial fatigue life assessment of multidirectional composite laminates of polymeric-based composites was investigated using neural networks (NN) model. NN with non-linear auto-regressive exogenous inputs (NARX) structure was employed for the problem considered and the training algorithm of Levenberg-Marquardt with Bayesian regularization was chosen. The task of fatigue life assessment was accomplished in such a way that it was realized as one-step ahead prediction with respect to each stress level-*S* corresponding to stress ratio values-*R*. In addition, by sliding over one-step to one-step of the stress levels, the prediction dynamically covered all the corresponding spectrum loadings including multiaxial orientations examined. As a result, fatigue life assessment of the composite materials can be fashioned for a wide spectrum of loading in an efficient manner based upon solely the training data as the basis of the NARX regressor, thus developed multivariable and multiaxial fatigue analysis.**

***Index Terms*—composite materials, multiaxial and multivariable fatigue life assessment, NARX, neural networks**

I. Introduction

Modeling of composite fatigue life under complex and spectrum loading conditions remains a challenge to researchers in this field. Many considerations that must be taken into account, namely among others, fiber and matrix types, lay-up, anticipated failure modes, fatigue states governed by loading conditions of stress ratios-*R* or on-axis/off-axis orientations, making such a modeling task becomes complicated because so many factors should be included and anticipated in the model [1, 2]. On the other hand, the model development is frequently impeded by a large amount of fatigue testing data needed, which is thus very costly and time consuming.

Growing with the requirement for speeding up time frame from research stage to market place and also cutting down the associated cost, in recent years there has been increasingly interest in pursuing and utilizing alternative approach based upon soft-computing framework, in particular neural networks (NN), to develop efficient and robust predictive model for fatigue life assessment of composite materials.

Following Lee and Almond [3], Al-Assaf and El-Kadi [4], and El-Kadi and Al-Assaf [5] performed fatigue life assessment of unidirectional glass fiber/epoxy laminate using several NN paradigms, namely feed-forward (FF), modular (MN), radial basis function (RBF) and principal component analysis (PCA) networks. The works have presented comprehensive analysis and discussion about the utilization of different NN models in predicting fatigue life of unidirectional composite laminate. Freire Junior et al. [6, 7] noticed the potential of NN models of feed-forward and modular on building constant life diagrams (CLD) using only three *S-N* curves for predicting fatigue lives of multidirectional composite. Comparative study between NN models and conventional equations in the analysis of fatigue failure of GFRP has been also presented by the authors [8], where NN outperformed conventional equations in the analysis of fatigue failure of GFRP. Vassilopoulos et al. [9] showed that using only randomly selected 40 – 50 % of the experimental data were sufficient to produce reliable CLD using NN, emphasizing the NN convenience in performing fatigue life prediction of composite materials. Hidayat et al. [10] introduced the utilization of NN with non-linear auto-regressive exogenous inputs (NARX) structure and showed the robustness of the NN model for fatigue life prediction of composite materials under multivariable amplitude loading, based upon fatigue data from only two stress ratios. Improvements in term of mean squared error (MSE) values of NN prediction results were further obtained when the problem considered was examined by using RBFNN-NARX model [11].

In the previous papers, investigations were only focused on the utilization of NN for fatigue life assessment of composite materials under multivariable amplitude loading with respect to different stress ratio values-*R*. No further attempt, however, so far has been devoted to the utilization of NN for fatigue life assessment of composite materials under both multiaxial and multivariable loading conditions, in which factors of stress ratios and on-axis/off-axis orientations are taken into account and treated in simultaneously. With this respect, the corresponding fatigue life assessment is handled in such a way that fatigue lives of different stress ratio and on-axis/off-axis orientation values are predicted based upon fatigue data from, if possible just

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limited, particular stress ratio(s) and on-axis/off-axis orientation(s) which are utilized as basis training data. It has been shown in [10] that there was suitable NN model, namely NN-NARX model to implement the way for efficient fatigue life assessment of composite materials under multivariable amplitude loading based upon limited fatigue data.

In the present paper, multivariable and multiaxial fatigue life assessment is investigated and examined using NN model, which is the main motivation and objective in the present study. NN-NARX model was employed and two stress ratio values together with the corresponding on-axis/off-axis orientations served as a basis for training data employed for dynamically predicting fatigue lives of other stress ratios and orientations. It is important to note that the study is mainly related to the previous works of [9, 10].

The remainder of the paper is organized as follows: section II presents briefly the NN with NARX structure employed. Section III presents the materials examined and methods chosen for the NN configuration. Fatigue life assessment results using the NN configuration and related discussion are presented in section IV, followed by conclusion casted through the simulation study along with future research direction in section V.

II. Neural Networks with Narx Structure

NN with NARX structure has the signal vector applied to the NN input layer consisting of a data window made up by present and past values of *exogenous* (independent) inputs and by delayed values of the outputs. The NN model belongs to a class of recurrent neural networks (RNN) with one feed-back loop from the NN output layer to the input layer. Moreover, the presence of the feed-back loop has enabled such a configuration to acquire state representations. It also provides a unified representation for a wide class of discrete-time nonlinear systems [12, 13].

Mathematically, a NARX model can be represented as:

$$y(n+1) = \mathrm{f}[\mathbf{y}(n); \mathbf{u}(n)]$$
$$y(n+1) = \mathrm{f}[y(n),\ldots,y(n-d_y+1); u(n),u(n-1),\ldots,u(n-d_u+1)] \quad (1)$$

where $u(n)$ and $y(n)$, respectively, state the input and output of the model at discrete time n; $u(n), y(n) \in \Re$. Moreover, d_y and d_u are the output-memory and input-memory orders. d_y represents the number of lagged output values, which is often referred to as the order of the model, d_u represents the number of lagged input values (d_u, $d_y \geq 1$ and $d_u \leq d_y$). The vectors $\mathbf{y}(n)$ and $\mathbf{u}(n)$, therefore, form the output and input regressors, respectively.

The NARX model is commonly trained using two basic modes, namely:

1. Parallel (P) Mode

Using this mode, the output regressor utilized the estimated outputs which are fed back to the regressor.

$$\hat{y}(n+1) = \hat{f}[\hat{y}(n),\ldots,\hat{y}(n-d_y+1); u(n),u(n-1),\ldots,u(n-d_u+1)] \quad (2)$$

2. Series-Parallel (SP) Mode

Using this mode, the output regressor utilized the actual output values.

$$\hat{y}(n+1) = \hat{f}[y(n),\ldots,y(n-d_y+1); u(n),u(n-1),\ldots,u(n-d_u+1)] \quad (3)$$

It is worth to note that, although NARX with SP mode acts as one-step ahead predictor, standard feed-forward architecture trained with back-propagation (BP) technique can be used directly in the mode. In addition, various learning algorithms are also widely applicable. A form of regularization may also be employed because the additive measurement errors, ε_n, which are zero-mean Gaussian variables with Var[ε_n] = σ^2, can be also present in the model. Fig. 1 illustrates the NARX with input and output tapped delay lines, in parallel and series-parallel architectures [14].

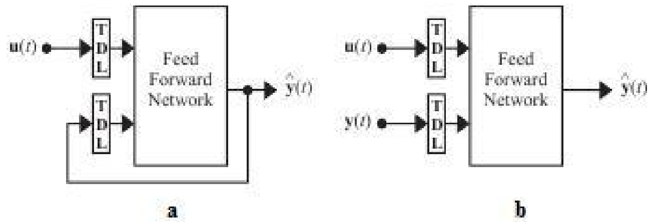

Fig. 1. The NARX architecture with tapped delay lines: (a) parallel architecture, and (b) series-parallel architecture

III. Material And Methods

A. Materials

The investigated materials were multidirectional laminates of E-glass/polyester and E-glass fabrics/epoxy, typical materials used in wind turbine blade applications [15, 16]. The corresponding lay-ups were $[0/(\pm45)_2/0]_T$ and $[\pm45/0_4/\pm45/]$, respectively. The materials were cut by diamond saw wheel at on-axis (0°) and off-axis orientations. For E-glass/polyester material, the corresponding off-axis orientations were 15°, 30°, 45°, 60°, 75° and 90° [15], while for E-glass fabrics/epoxy material, the only off-axis orientation was 90° [16].

In addition, the corresponding database containing fatigue data of various stress ratio values and the corresponding on-axis/off-axis orientations of ***R* = 0.1**: θ = 0°, 15°, 45°, 75° and 90°; ***R* = 0.5**: θ = 0° and 45°; ***R* = -1**: θ = 0°, 30°, 45°, 60° and 90°; and ***R* = 10**: θ = 0°, 30°, 45°, 60° and 90° for E-glass/polyester, and of ***R* = 0.1**: θ = 0° and 90°; ***R* = 0.5**: θ = 0° and 90°; ***R* = -0.5**: θ = 0° and 90°; ***R* = -1**: θ = 0° and 90°; ***R* = -2**: θ = 0° and 90°; and ***R* = 10**: θ = 0° and 90° for E-glass fabrics/epoxy. The database comprised, respectively, 85 and 96 fatigue data, making the database suitable for the study purpose. Note that number of stress levels in each stress ratio value employed were 5 and 8 for E-glass/polyester and E-glass fabrics/epoxy, respectively.

From the fatigue data, stress ratio (R), on-axis/off-axis orientation (θ) and maximum stress ($S_{\max}$) values were used as input set and the output was the corresponding fatigue cycles (log N) for the input set. For each particular R value, mean fatigue life values were used. Also, all the data were normalized in range of -1 to 1.

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Table 1 summarizes the materials examined together with the training and testing sets employed. Note that for the assessment task, stress ratio values-R were arranged in CCW direction according to the CLD, moving across from tensile-tensile sector to compressive-compressive sector. In addition, fatigue data as training set of R = 0.1 and 10 were chosen because the best relative positions of the R values in the CLD [10, 11]. The corresponding θ value chosen for both the stress ratios was 0°. With the training and testing data, the NN model will develop multivariable and multiaxial fatigue life assessment analysis.

TABLE I
MATERIALS EXAMINED TOGETHER WITH THE TRAINING AND TESTING SETS EMPLOYED

Material	Fatigue Data as Training Set: R and θ values	Fatigue Data as Testing Set: R and θ values
E-glass/polyester $[0/(\pm45)_2/0]_T$	R = 0.1: θ = 0° R = 10: θ = 0°	R = 0.5: θ = 0°
		R = -1: θ = 0°
		R = 0.1: θ = 15°
		R = -1: θ = 30°
		R = 10: θ = 30°
		R = 0.1: θ = 45°
		R = 0.5: θ = 45°
		R = -1: θ = 45°
		R = 10: θ = 45°
		R = -1: θ = 60°
		R = 10: θ = 60°
		R = 0.1: θ = 75°
		R = 0.1: θ = 90°
		R = -1: θ = 90°
		R = 10: θ = 90°
E-glass fabrics/epoxy $[\pm45/0_4/\pm45/]$	R = 0.1: θ = 0° R = 10: θ = 0°	R = 0.5: θ = 0°
		R = -0.5: θ = 0°
		R = -1: θ = 0°
		R = -2: θ = 0°
		R = 0.1: θ = 90°
		R = 0.5: θ = 90°
		R = -0.5: θ = 90°
		R = -1: θ = 90°
		R = -2: θ = 90°
		R = 10: θ = 90°

B. Methods

In the present study, the training algorithm of Levenberg-Marquardt was chosen and utilized to result in fast and efficient NN model [17]. Moreover, to accommodate the noise may be present in the target data in the model and also to deal with limited training data employed, that may lead to an ill-posed problem, Bayesian regularization technique was incorporated [18]. Utilizing the regularization, the objective function of NN, $E(\mathbf{w})$, was modified into:

$$E(\mathbf{w}) = \beta \sum_{q=1}^{Q}\left[t_q - \hat{f}\left(\mathbf{p}_q;\mathbf{w}\right)\right]^2 + \alpha\sum_{i=1}^{W} {w_i}^2 \qquad (4)$$

where: α is a weight decay parameter, β is an inverse noise variance parameter, t_q is the target data, the estimate $\hat{f}$ realized by the NN, $\mathbf{p}$ is the vector of input sets, $\mathbf{w}$ is the vector of weights (and biases), Q is the number of training examples and W is the total number of weights.

Furthermore, fatigue life assessment of the materials is performed and realized as one-step ahead prediction with respect to each stress level-S corresponding to stress ratio values-R, which is arranged in such a way that transition took place from a fatigue region to another one in the CLD as previously mentioned. It is then clear that the NARX-SP architecture is being currently employed and sliding over one-step to one-step of stress level, the prediction will be dynamically covering all the spectrum loadings of the testing sets including multiaxial orientations examined. As a result, material lifetime assessment can be fashioned for a wide spectrum of loading with multiaxial orientations in an efficient manner based upon solely the training data as the basis of the NARX regressor, thus developed multivariable and multiaxial fatigue analysis.

Fig. 2 describes the lifetime assessment process in the study using the NN-NARX model.

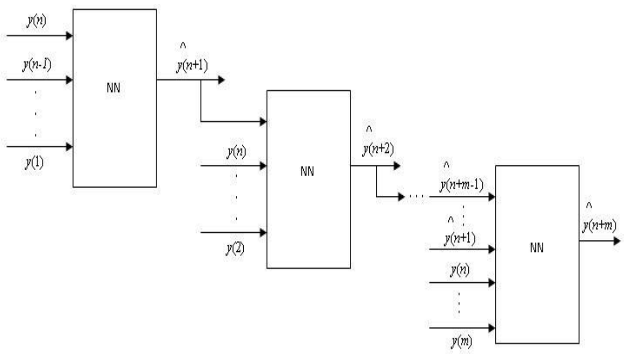

Fig. 2. Multivariable fatigue life prediction made up by one-step ahead prediction using NN with NARX-SP structure

IV. SIMULATION RESULTS AND DISCUSSION

Using the methods described previously, all simulation results of fatigue life assessment of the materials considered are presented in this section. It is important to note also that the number of hidden nodes employed for the NN with NARX model was 10. Also, as shown in Table I, there were 15 and 10 testing sets to be predicted for E-glass/polyester and E-glass fabrics/epoxy, respectively. Note that the arrangement of fatigue data as training set and fatigue data as testing set, in particular those of R and θ values in Table I. The NN simulation results and the related discussion will be referred to what Table I has been describing.

Figs. 3 and 4 present respectively multivariable and multiaxial fatigue life predictions of E-glass/polyester and E-glass fabrics/epoxy materials at the testing sets examined.

In general, it can be seen that the NN-NARX model prediction results were consistent with the experimental data, thus showing the applicability of the NN model to the problem considered in this study. The NN model also shows its ability to dynamically predict the fatigue lives from the testing sets examined by sliding over each stress level in a fashion of spectrum loading and multiaxial orientations, made up by several R and θ values.

In addition, it is important to note again that only one information value of axial orientation-θ was utilized in the

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training set employed, while two values of stress ratio-*R* were employed. It was shown in Figs. 3 and 4 that with such a selection of training set, the NN simulation results were adequately agree with the experimental data.

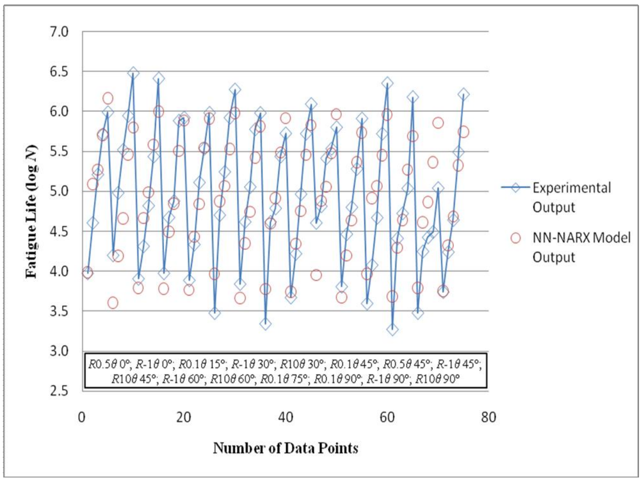

Fig. 3. Multivariable and multiaxial fatigue life prediction of the NN-NARX model for several *R* and θ values of the testing sets examined of E-glass/polyester (left to right sequence)

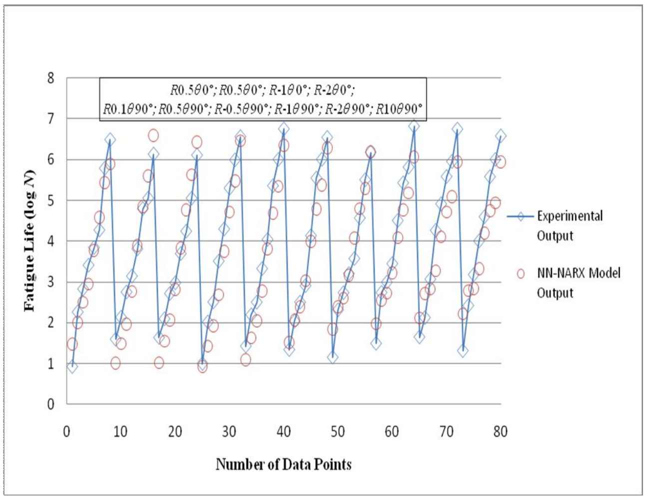

Fig. 4. Multivariable and multiaxial fatigue life prediction of the NN-NARX model for several *R* and θ values of the testing sets examined of E-glass fabrics/epoxy (left to right sequence)

The accuracy of the NN-NARX model prediction can be also checked by noting the produced mean squared errors (MSE) of 0.123 and 0.27 for E-glass/polyester and E-glass fabrics/epoxy, respectively. Note that the training sets employed were a very small number of fatigue data.

It should be pointed out, however, that large enough or noticeable discrepancies between fatigue lives predicted by the NN-NARX model and those of experimental data were also observed. For E-glass/polyester, such discrepancies, in particular, belong to R = -1, namely fatigue lives of R = -1: θ = 0°, 60° and 90°, respectively. For E-glass fabrics/epoxy, the noticeable discrepancies belong to R = -2: θ = 90°. The largest discrepancies will also later be shown in the related *S-N* curves.

To further measure the closeness between fatigue lives predicted by the NN-NARX model and those of experimental data, the NN simulation results were also presented in the corresponding *S-N* curves, with the corresponding coefficient of determination (R^2) between the NN fatigue life prediction results and the experimental data.

Figs. 5 and 6 show the *S-N* curves of E-glass/polyester obtained by the NN-NARX model and the experimental data for stress ratios R = -1: θ = 90° and R = 10: θ = 30°, respectively. Furthermore, Figs. 7 and 8 show the *S-N* curves of E-glass fabrics/epoxy obtained by the NN-NARX model and the experimental data for stress ratios R = -2: θ = 90° and R = 0.5: θ = 90°, respectively. Note that the NN simulation results were selected and presented because the results respectively corresponded to the lowest and the highest of R^2 values produced, representing the "goodness" of the NN-NARX model in modeling fatigue lives for the problem considered.

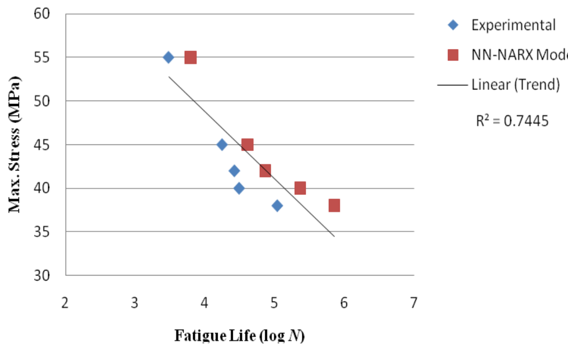

Fig. 5. *S-N* curves obtained by the NN-NARX model and the experimental data for R = -1: θ = 90°

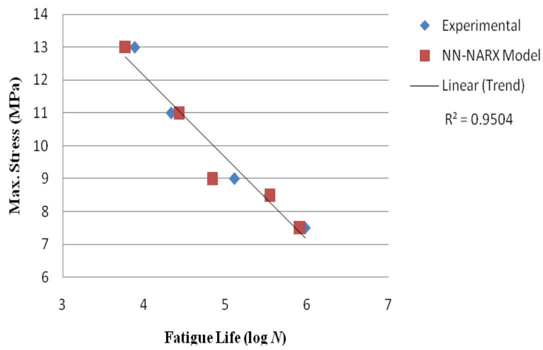

Fig. 6. *S-N* curves obtained by the NN-NARX model and the experimental data for R = 10: θ = 30°

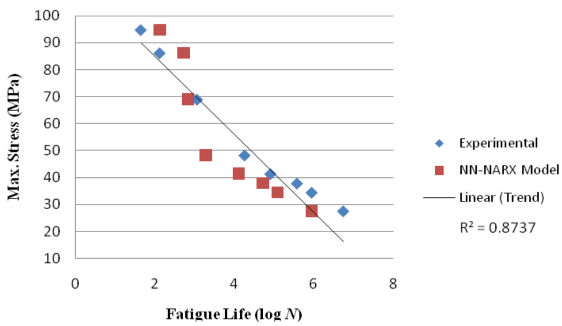

Fig. 7. *S-N* curves obtained by the NN-NARX model and the experimental data for R = -2: θ = 90°

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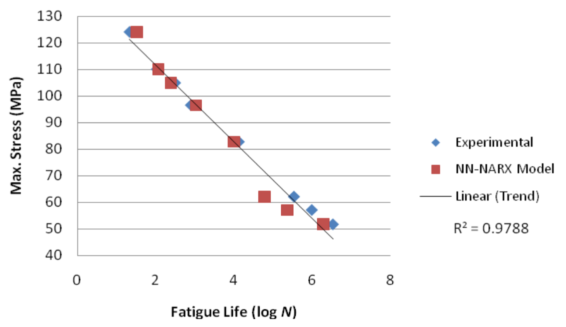

Fig. 8. *S-N* curves obtained by the NN-NARX model and the experimental data for $R = 0.5$: $\theta = 90°$

In the form of *S-N* curves, in general it can be seen again that for the discrepancies observed, fatigue lives predicted by the NN-NARX model were not excessively far from those of experimental data. Thus, the coefficient of determination (R^2) of fatigue life prediction produced can be considered high for the materials examined with the NN-NARX model. The values of R^2 ranged from 0.7445 to 0.9504 for E-glass/polyester material, while those of E-glass fabrics/epoxy ranged from 0.8737 to 0.9788. Moreover, it can be also seen that the highest R^2 values for the materials examined were coming from fatigue data of the non-on-axis orientations, namely $\theta = 30°$ and $\theta = 90°$ for E-glass/polyester and E-glass fabrics/epoxy, respectively. This emphasized again the applicability and the feasibility of the NN-NARX model and the procedure developed in the study for multivariable and multiaxial fatigue life assessment of the composite materials.

V. Further Discussions

The idea for analyzing multivariable and multiaxial fatigue life assessment using NN, in particular NN-NARX model came while the present author was accomplishing the research works of multivariable fatigue life assessment with NN-NARX models [10, 11]. With the utilization of the NN models, several interesting and relevant discussions thus emerge.

Firstly, because fatigue life assessment is realized as one-step ahead prediction with respect to each stress level-*S* corresponding to the related *R* and θ values, thus the accuracy of the NN prediction results will depend on the accuracy of the NN prediction result on each stress level-*S* examined. The obtained NN fatigue life prediction for a stress level will affect that of the next stress level. With respect to this matter, two aspects may be considered that the change in the selection of training fatigue data will also change the NN fatigue life prediction results. Also, the sequence of fatigue data of the testing sets examined can affect the NN fatigue life prediction results obtained. To be consistent, in the present study, stress ratio-*R* values were arranged according to their positions and transitions in the CLD, while on-axis/off-axis orientation-θ values were arranged based on the magnitude value from longitudinal to transverse direction, as shown in Table I.

Secondly, only one value of θ was employed in the training set, namely $\theta = 0°$, as previously pointed out. It is intended to employ such a selection to examine the feasibility of the approach offered and used in this study. Looking at the NN prediction results obtained, it appears that the NN-NARX model was able to perform the fatigue life prediction of the material fairly well using the starting point of training fatigue data. Moreover, different values of θ, say $\theta = 0°$ and 90°, can be of course selected and employed in the training set, thus the training set could consist of, for example, fatigue data from $R = 0.1$: $\theta = 0°$ and $R = 10$: $\theta = 90°$. Using the selection, the training data will be based upon two different values of *R* and θ. It is clear that multivariable and multiaxial aspects are emphasized.

Thirdly, the discrepancies observed between fatigue lives predicted by the NN-NARX model and those of experimental data may be reduced by using different selection of training fatigue data. It is hoped that using the different training data, as previously pointed out, NN would give better prediction results of fatigue lives, indicated by improvement in the corresponding MSE values. Related to this, the improvement of the MSE prediction values may also be produced with respect to the variation of the hidden nodes number in a sensitivity analysis, which is still not further considered in the present study and left as further study. Nevertheless, in the present study the author would like to also point out that to further and better describe the produced discrepancies in fatigue lives, the informative bounds of NN prediction would be also important to develop. With such information, the noticeable discrepancies in fatigue lives can be better described and the obtained NN fatigue life prediction will be strongly supported by comprehensive information of fatigue lives, which will further support any subsequent product design decisions. For example: the noticeable discrepancies as shown in Fig. 5. Also, the produced NN-NARX model's fatigue lives were all non-conservative with respect to those of experimental data. The work is being currently accomplished by the author for another presentation.

Finally, it is important to note here that the NN-NARX model is first applied for the problem considered in the present study. The applications have considered and taken into account multivariable and multiaxial aspects in fatigue life assessment of composite materials, which have been shown here its applicability and feasibility. NARX model has been known previously in many fields of applications, among others, [19, 20]. Now, its application has been extended to multivariable and multiaxial fatigue analysis.

VI. Conclusions

Multivariable and multiaxial fatigue life assessment of composite materials using neural networks has been investigated and presented in the paper.

NN-NARX model has been employed in the study. It has been shown that the NN model simulation results were adequately agree with the experimental data for several *R* and θ values examined, with the produced MSE values of 0.123 and 0.27 for E-glass/polyester and E-glass fabrics/epoxy, respectively, thus showing the applicability and the feasibility of the NN-NARX model for the problem considered.

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Further sensitivity analysis with respect to the variation of the hidden nodes number as well as further applications to other materials widely are recommended as further research and study.

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