GMDH-Kalman Filter Prediction of High-Cycle Fatigue Life of Drilled Industrial Composites: A Hybrid Machine Learning with Limited Data

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Abstract. In industrial composites, drilling is one of the most common operations and complex processes during the final assembly, which can generate undesirable damage to the manufactured part. Data collection from a given composite's fatigue life is often costly and time-consuming. To address this challenge, the current case study aims to adapt a hybrid machine learning to predict the fatigue life of the drilled Glass Fiber Reinforced Polymer composite laminates (with both unidirectional and woven lay-ups) under a limited and noisy data assumption. Composite specimens were drilled at various cutting speeds and feed rates. The size of the delamination around the hole was scanned by a microscopic camera. Cyclic three-point bending tests were conducted, and results indicated that the drilling-induced delamination size and the composite lay-up affect the specimens' fatigue lives. The latter were predicted in two steps. In the first step, an offline deterministic model was established using the group method of data handling along with a singular value decomposition. Pareto multi-objective optimization was applied to prevent overfitting. In the second step, the Kalman filter was employed to update the polynomial of the deterministic model based on minimizing mean and variance of error between the actual and modeled data. Results showed an excellent learning reliability, with a correlation coefficient of 97.6% and 96.5% in predicting the fatigue life of unidirectional and woven composite laminates, respectively. A sensitivity analysis was performed and indicated that the fatigue life of the samples has been more affected by the drilling feed rate, compared to the cutting speed.

Keywords: Artificial Intelligence, Machine Learning, Limited Data Modeling, Composite Materials, Complex Production Process, High-Cycle Fatigue Life.

Abbreviations

GMDH	Group Method of Data Handling
SVD	Singular Value Decomposition (SVD)
GA	Genetic Algorithm
ANN	Artificial Neural Network
UKF	Unscented Kalman Filter
GFRP	Glass Fiber Reinforced Polymer
SVR	Support Vector Regression
MSC	Monte Carlo Simulation
DOE	Design of Experiment
U_n	Unidirectional
W_n	Woven
GS	Generalized Structure

1. Introduction

Composite materials have been key in design of lightweight structures over decades, and their industrial applications are still rapidly expanding (Crawford, Sourki et al. 2021) [1]. Glass Fiber Reinforced Polymer (GFRP) composites, due to their key advantages of high specific stiffness, high specific strength, along with low cost and corrosion resistance, are widely selected in applications ranging from automobile to aerospace structures (Akbari Shah Khosravi, Gholizade et al. 2016) [2]. Drilling using a twist drill is one of the most common operations used for joining composite components (H. Hocheng and C.C. Tsao 2003) [3]. This operation is often conducted in the last stage of production. Therefore, part rejection due to the low quality of the drilled hole can be much costly. In aerospace manufacturing sector, it was reported that approximately 60% of the composite components' rejections occur at the drilling step, which accounts for a large portion of production energy waste (H. Hocheng 2012) [4]. Several damage modes, such as delamination, matrix cracking, fiber breakage and hole shrinkage, may occur during drilling composites (Hocheng and Tsao 2005) [5]. The drilling-induced delamination is the most major defect mode that adversely affects the fatigue life of the final part (Akbari Shahkhosravi, Yousefi et al. 2019) [6] and (Gholizade, Akbari Shah Khosravi et al. 2017) [7].

The fatigue behavior of GFRP composites has been widely studied in the last few years (Loos, Yang et al. 2013) and (Jeannin, Gabrion et al. 2019). Open-hole composite laminates in a subsequent fatigue loading showed multiaxial stress around the hole (Harris 2003) . Several investigations approved that the delamination cracks developed during the drilling operation can grow in low-stress fatigue loads (Tsao and Hocheng 2007) and (Nixon-Pearson and Hallett 2015). However, there has been no detailed investigation on drilling optimization to increase the fatigue life of the GFRP composite materials.

Machine learning algorithms have been proven to be a promising tool for prediction and optimization purposes in various applications (Khayyam, Naebe et al. 2015) [18] and (Wanigasekara, Oromiehie et al. 2021) [19]. When using a limited training data-set, there is a concern about the reliability of the ensuing prediction model. However, limited training data-set is often inevitable in industrial applications due to the cost and time of trials (Nijssen 2006) [17]. According to the central limit theorem (H. Khayyam, G. Golkarnarenji et al. 2018) [20], a sample size of less than 25-30 is considered a small or limited data-set. Machine learning provides different techniques for prediction and optimization purposes, which can be selected depending on the given problem's scope, the nature of the data-set and desired outcomes (H. Khayyam, G. Golkarnarenji et al. 2018) [20].

For limited training data-sets, prediction modeling using e.g. Support Vector Regression (SVR) combined with a Genetic Algorithm (GA) indicated a sufficiently accurate approach (Golkarnarenji, Naebe et al. 2018) [21]. Khayyam et al. provided a novel hybrid machine learning algorithm for such modeling under limited data [22]. The model was robust against uncertainties by utilizing an Unscented Kalman Filter (UKF) approach, which was easier to approximate a probability distribution. The model showed accurate predictions for a collected data-set from a carbon fiber production line, and the capability of the model for applying to various industrial applications (Golkarnarenji, Naebe et al. 2019) [23]. The latter study specifically used a Taguchi design of experiments approach combined with two different machine learning techniques: Artificial Neural Network (ANN) and SVR. It was reported that the average error of both methods was less than 4.1% for predicting the Young's modulus and the tensile strength of the carbon fibers. The SVR model was more accurate in terms of Young's modulus, and the ANN model accuracy slightly surpassed the SVR model in terms of the fibers tensile strength prediction (Golkarnarenji, Naebe et al. 2019) [23].

1.1.Objective and organization of the work

As reviewed above, drilling is the most common way to assemble GFRP composite components. However, the drilling-induced delamination/damage brings concerns regarding the fatigue life of assembled composite components. Therefore, the current case study aims to adapt machine learning algorithms to predict and optimize the fatigue life of drilled GFRP composites.

The work was divided into two parts; experimental and modeling. The first part was associated with the design of experiments. GFRP composite specimens were produced with two different lay-ups (unidirectional and woven), and then holes were introduced to the samples though high-speed drilling. Samples were drilled under different feed rates and cutting speeds. Next, an optical analysis was conducted to assess the induced delaminations around the drilled holes, and an adjusted delamination factor was computed for each sample. Finally, the drilled samples underwent static three-point bending tests, followed by cyclic fatigue test. In the second part of the study, the measured fatigue life of the components was modelled using a hybrid machine learning (combination of Group Method of Data Handling (GMDH) -type neural network and a UKF). The fatigue life predictions were based on the drilling parameters and the size of delamination around the hole. Finally, a sensitivity analysis was performed using the trained model, to assess which process parameter would affect the composite fatigue life more dominantly.

Part I

2. Design of experiment

A modified Taguchi experimental design (Khayyam, Fakhrhoseini et al. 2017) was employed to ensure the optimal design of experiments. Namely, the drilling process parameters were under three levels: feed rates (f=50, 100, 150 mm/min) and cutting speeds (u=3,000, 6,000, 10,000 rpm). Each test was conducted three times, to increase the adequacy and validity of the subsequent prediction models.

2.1 Materials

The test materials were unidirectional (GF 12/200 DLN) and woven (VV 770) prepreg glass/epoxy with IMP503 resin. Fiber volume fraction in unidirectional and woven specimens was 20.16% and 28.23%, respectively. The materials were vacuumed and cured by an autoclave under 125°C and for one hour. The composite palates' quality was checked by the ultrasonic C-scan method. Finally, by using a water jet machine, plates were cut with dimensions of 170×20 mm^2, and the standard deviation of cut dimensions was less than %10. Specifications of the samples are presented in **Error! Reference source not found.**. More detailed material characteristics of the specimens were reported in the study (Akbari Shahkhosravi, Yousefi et al. 2019) [24].

Table 1. Specifications of the composite samples tested.

Composite Specimen	Moulding Process/ Lay-up	Thickness (mm)	Figure
Unidirectional (U_n)	$[0]_{32}$	5	

Woven (W_n)	$[0/90]_8$	5	

2.2. High–speed drilling process

A FIDIA vertical machining center was used to drill the composite specimens. The maximum spindle speed and feed rate of the drilling machine were 24,000 rpm and 200 mm/min, respectively. The drilling process did not involve any cooling liquid; and to avoid extensive delamination, the specimens were drilled on an appropriate back-up plate. The procedure is illustrated in **Error! Reference source not found.**. The cutting tools were standard HSS twist drills with a 4 mm diameter and helix angle of 30 degree. The cutting tool was changed every five drillings to avoid wear effect. The specimens were drilled by various feed rates and cutting speeds, as outlined by a Design of Experiments (DOE) approach (see Table 3 and 4). The location of the hole was at the center of the specimens.

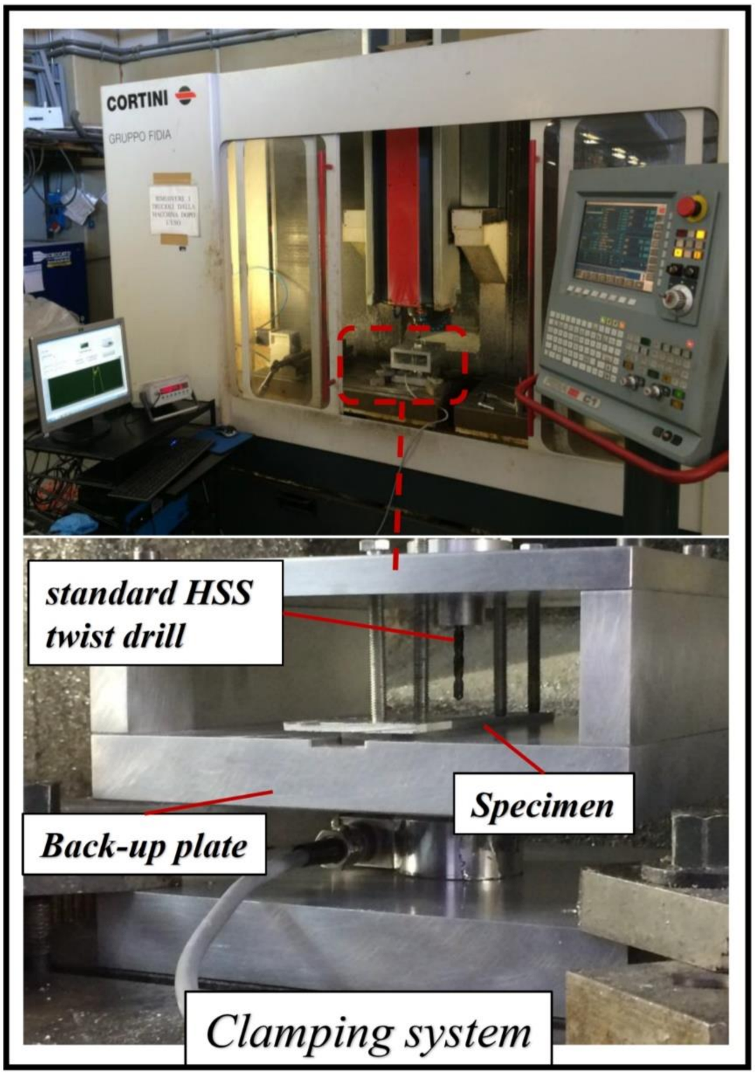

Fig. 1. The drilling procedure using a back-up plate.

2.3. Optical analysis of the drilling-induced delamination

Upon drilling, the delamination around each specimen hole was scanned by a microscopic camera, using an optical zoom up to 320X and a resolution of 96-300 dpi (**Error! Reference source not found.**). For evaluating the drilling-induced delamination size, a delamination factor, as proposed by (Davim, Rubio et al. 2007) [25], was computed. The latter study specifically proposed an adjusted delamination factor, F_{da}, that incorporates both crack size and the damaged area around the hole. The proposed adjusted delamination factor:

$$F_{da} = \alpha \frac{D_{max}}{D_0} + \beta \frac{A_{max}}{A_0} \qquad (1)$$

D_0 is the nominal diameter of the drill bit. D_{max} is the maximum diameter of the damaged area, A_d is the damaged area and A_0 and A_{max} are the areas associated with the nominal hole and maximum diameter, respectively. α and β are the model coefficients and can be computed as:

$$\beta = \frac{A_d}{A_{max} - A_{max}} \text{ and } \alpha = 1 - \beta \qquad (2)$$

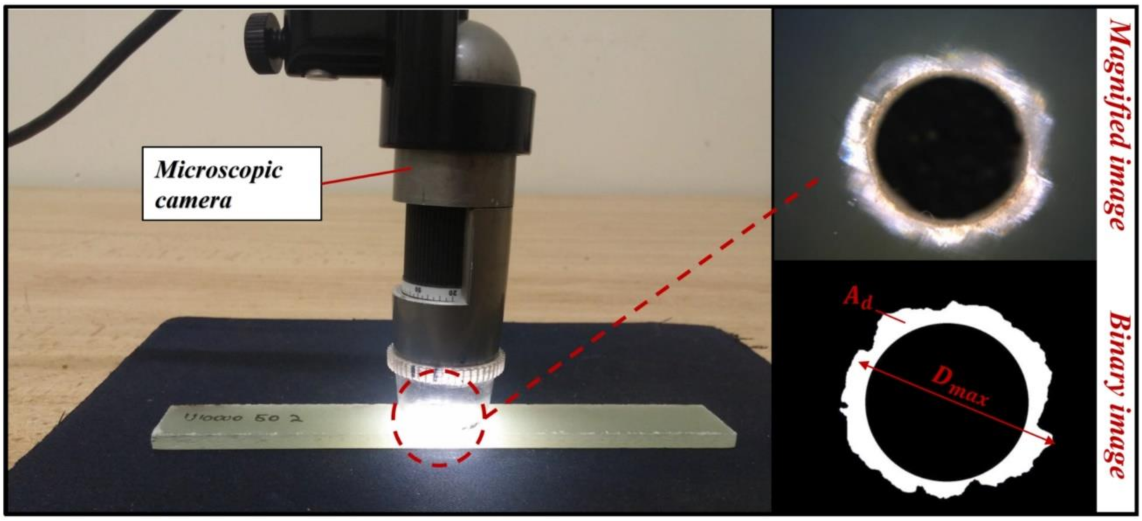

Fig. 2. The delamination scanning procedure. (D_{max}: maximum diameter of the damaged area; A_d: dam-aged area).

2.4. Quasi-static loading

Prior to the cyclic fatigue testing of drilled samples, three-point bending test with quasi-static loading conditions was conducted to find a suitable force range (magnitude) for the subsequent cyclic loading test. A servo-hydraulic Dartec 9600 universal testing machine with a load cell capacity of 50 kN was used for this aim. The loading crosshead speed was 1 mm/min, in a displacement control mode. A data acquisition system recorded the applied load and the associated displacement. Tests were conducted at 24℃ (room temperature).

2.5. Cyclic loading

Three-point bending cyclic experiments were conducted using Dartec universal testing machine and according to the ASTM D7615 (D7615M-11 2019) [26]. Tests were conducted in the load-control mode, with a loading frequency of 5 Hz. The cyclic loading parameters were proposed considering the static strength of the UD and woven specimens (**Error! Reference source not found.**). The test setup is presented in **Error! Reference source not found.**.

Table 2. Identified cyclic loading parameters for the composite samples.

Specimen	Frequency (Hz)	P_{max} (N)	P_{min} (N)
Unidirectional	5	750	400
Woven	5	1,531	484

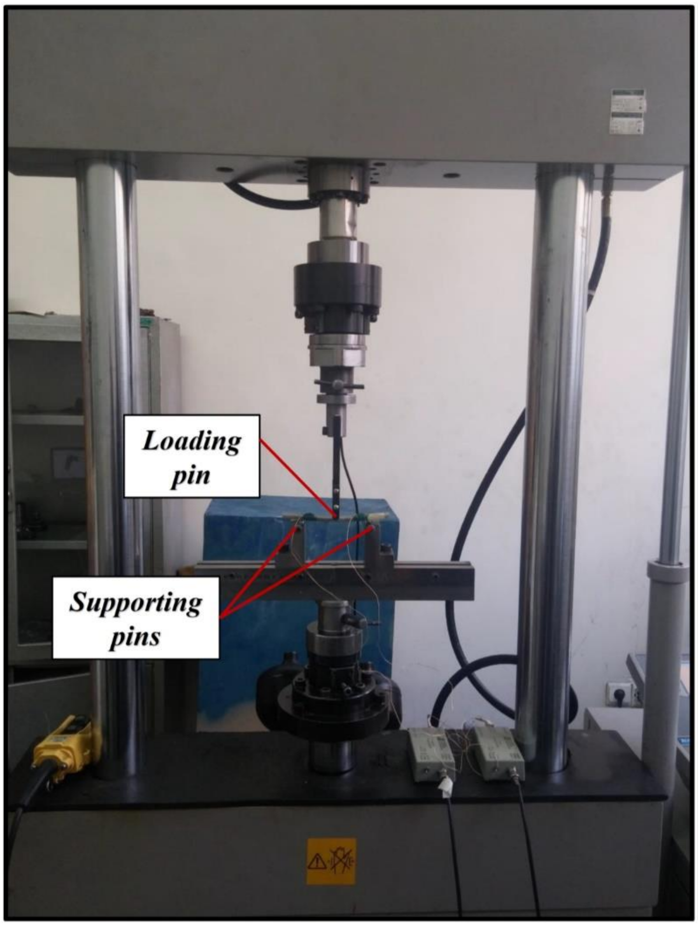

Fig. 3. Servo-hydraulic Dartec 9600 universal testing machine - Quasi-static and cyclic loading tests setup.

3. Experimental results and discussion

The results of the quasi-static tests are presented in **Error! Reference source not found.**, for representative unidirectional and woven specimens. The maximum strength for the unidirectional and woven specimens was 1.083 kN and 1.9 kN, respectively. **Error! Reference source not found.** illustrates the cyclic loading results for representative unidirectional and woven specimens. The fatigue cycles before failure are reported in **Error! Reference source not found.** and **Error! Reference source not found.** for all unidirectional and woven specimens, respectively. The result reveal that increasing the cutting speed and decreasing the feed rate could increase the fatigue life of the tested composites.

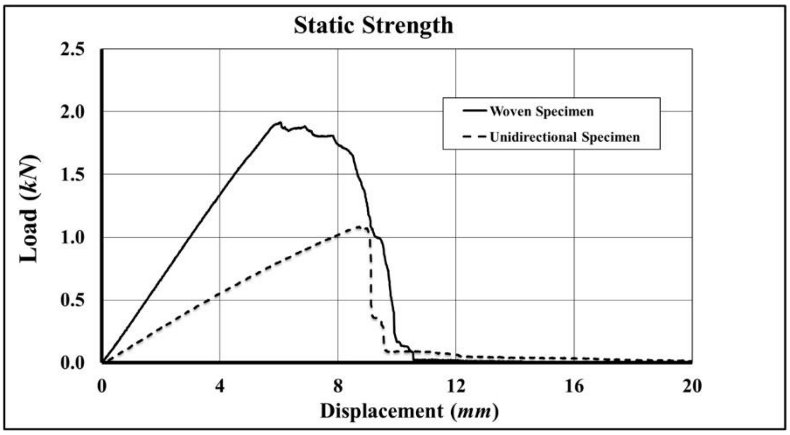

Fig. 4. Load-displacement response of the quasi-static bending of unidirectional and woven (representative) specimens.

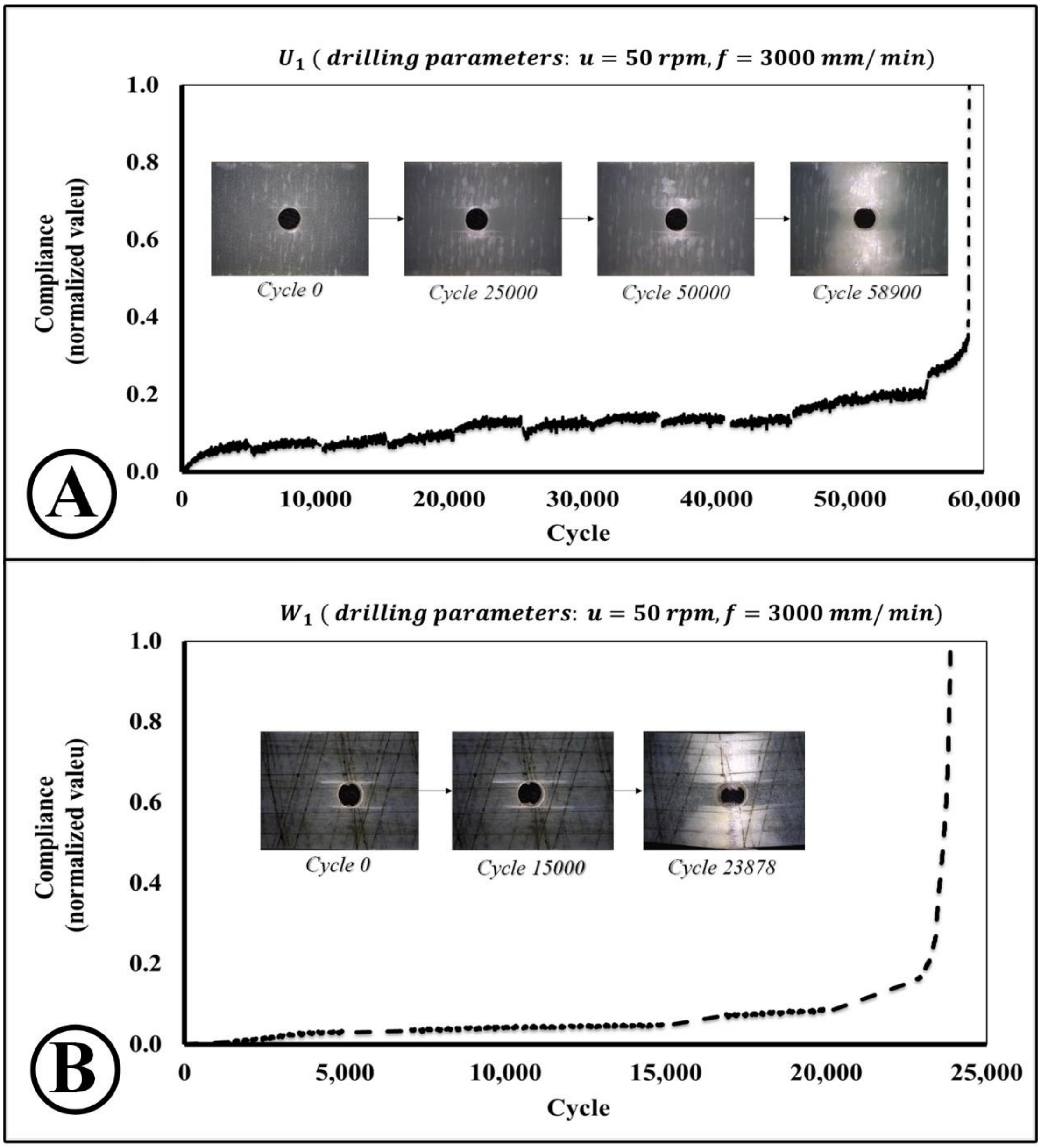

Fig. 5. Sample cyclic loading results for A: U_1 (unidirectional, u=50 rpm, f= 3,000mm/min) and for B: W1 (woven, u=50 rpm, f= 3,000mm/min).

Table 3. Adjusted delamination factor and fatigue cycles for unidirectional specimens.

Specimen	f (mm/ min)	u (rpm)	F_{da}	Cycles before failure
U_1	50	3,000	1.467	58,900
U_2	50	3,000	1.462	59,010
U_3	100	3,000	1.51	37,345
U_4	100	3,000	1.554	37,326
U_5	100	3,000	1.493	37,551
U_6	150	3,000	1.515	32,801
U_7	150	3,000	1.526	32,705
U_8	150	3,000	1.529	32,541
U_9	50	6,000	1.442	62,499
U_{10}	50	6,000	1.433	62,634
U_{11}	100	6,000	1.481	42,970
U_{12}	100	6,000	1.499	41,845
U_{13}	100	6,000	1.475	42,844
U_{14}	150	6,000	1.511	41,291
U_{15}	150	6,000	1.512	41,284
U_{16}	150	6,000	1.502	41,977
U_{17}	50	10,000	1.408	85,568
U_{18}	50	10,000	1.421	84,416
U_{19}	100	10,000	1.451	50,002
U_{20}	100	10,000	1.458	48,917
U_{21}	100	10,000	1.438	51,341
U_{22}	150	10,000	1.496	46,750
U_{23}	150	10,000	1.538	45,519
U_{24}	150	10,000	1.481	76,891

U=Unidirectional, *u*=cutting speed, *f*=feed rate, F_{da}=adjusted delamination factor

Table 4. Adjusted delamination factor and fatigue cycles for woven specimens.

Specimen	f (mm/ min)	u (rpm)	F_{da}	Cycles before failure
W_1	50	3,000	1.378	23,878
W_2	50	3,000	1.369	23,986
W_3	100	3,000	1.469	17,176
W_4	100	3,000	1.486	16,856
W_5	100	3,000	1.444	17,852
W_6	150	3,000	1.549	17,026
W_7	150	3,000	1.578	16,982
W_8	150	3,000	1.537	17,400
W_9	50	6,000	1.296	1.00E+07
W_{10}	50	6,000	1.225	1.00E+07
W_{11}	100	6,000	1.351	48,621
W_{12}	100	6,000	1.372	48,476
W_{13}	100	6,000	1.345	48,958
W_{14}	150	6,000	1.402	18,745
W_{15}	150	6,000	1.388	19,847
W_{16}	150	6,000	1.427	18,800
W_{17}	50	10,000	1.252	1.00E+07
W_{18}	50	10,000	1.235	1.00E+07
W_{19}	100	10,000	1.297	1.00E+07
W_{20}	100	10,000	1.304	1.00E+07
W_{21}	100	10,000	1.296	1.00E+07
W_{22}	150	10,000	1.368	46,696
W_{23}	150	10,000	1.404	46,768
W_{24}	150	10,000	1.358	49,753

W=Woven, *u*=cutting speed, *f*=feed rate, F_{da}=adjusted delamination factor

Part II

4. Predictive modeling for the fatigue life data

As shown in Fig.6, the fatigue life prediction (number of cycles before failure) can be realized either by using delamination factor, or directly the drilling (control) parameters themselves; here considering the simplicity for industrial applications, the latter approach was opted. Accordingly, to predict the fatigue life of the tested composite specimens in Part I (Tables 3 and 4), a hybrid (two-step) machine learning algorithm (**Error! Reference source not found.**) was proposed as follows.

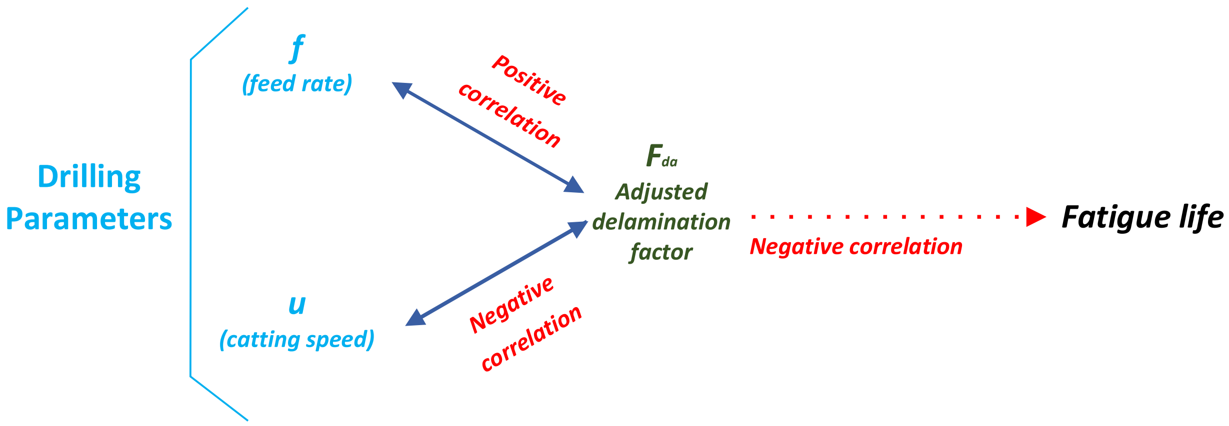

Fig. 6. The interrelationship's between fatigue life of sample with drilling parameters and the delamination factor.

4.1 Step 1-Offline modeling based on limited data

In this step, a polynomial model (GMDH-type NN) was trained to explain the relationship between the drilling parameters (inputs) and fatigue life (output). The GMDH- NN algorithm can be considered as a set of neurons of which several pairs in each layer are connected through a quadratic polynomial and produce new neurons in the next layer (Khayyam, Jamali et al. 2020). A GMDH model with multiple inputs and one output is a subset of components of the base function:

$$Y(x_i, \ldots, x_n) = a_0 + \sum_{i=1}^{m}(a_i f_i) \tag{3}$$

where f_i are elementary functions dependent on different sets of inputs, a_i are coefficients, and m is the number of the base function components. However, GMDH is usually based on polynomial reference function such as Kolmogorov-Gabor polynomial shown in Eq. (4). Different reference functions can be also adapted, e.g. harmonic and logistic (VukovicD.B, Romanyuk et al. 2022).

$$Y(x_i, \ldots, x_n) = a_0 + \sum_{i=1}^{m}(a_i x_i) + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ij} x_i\, x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} a_{ijk} x_i\, x_j\, x_{k+\cdots} \tag{4}$$

For model learning, 60% of the dataset was used for training purposes and the rest for validation. The model topology and the polynomial coefficients of each neuron within the Generalized Structure (GS) of GMDH were defined using the multi-objective GA and Singular Value Decomposition SVD algorithms, in order to simultaneously minimize the training and prediction errors. Pareto optimum nondominated models were achieved through applying nondominated sorting GA (NSGA)-II. In GS-GMDH, all neurons in a previous layer are often used to build a new neuron (Jamali, Ghamati et al. 2013) [27]; (Jamali, Nariman-Zadeh et al. 2009) [28]. The evolutionary process initiation began with a random generation of the first population of an alphabetical chromosome following crossover and mutation, and tournament selection (Khayyam, Jamali et al. 2020) [29]. Tracking the training and prediction errors in the model could lead to an improvement of the entire population of symbolic strings.

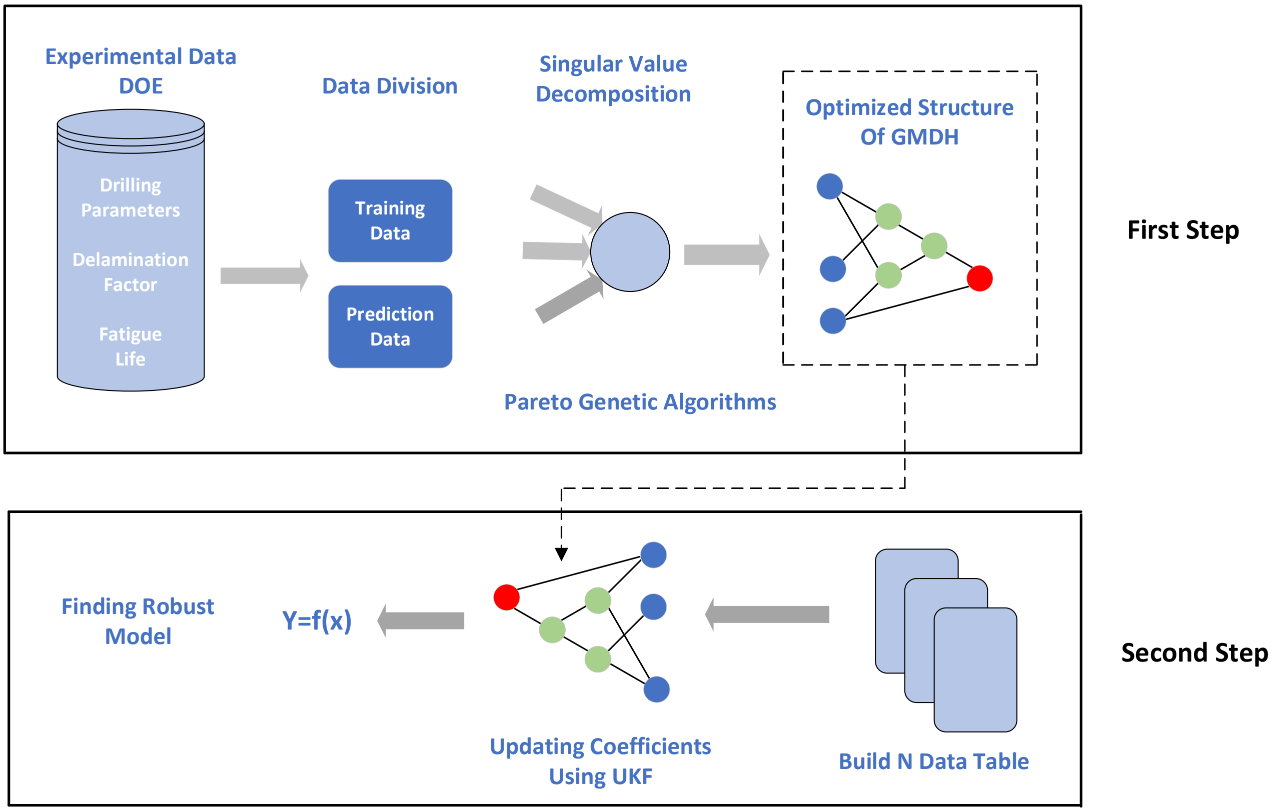

Fig. 7. Proposed two-step algorithm to create a robust fatigue life prediction model in the present study; the method is generic and may be applied to other processes.

4.2 Step 2-Online updating for model robustness

The second step of the hybrid model was an online update fed from the 1st step of the model (**Error! Reference source not found.**). The online procedure was specifically aimed to increase the robustness of the predictions. For this aim, the UKF was used to eliminate the uncertainties in the input-output data (Khayyam, Jamali et al. 2020) [22]; (Masoumnezhad, Jamali et al. 2015) [30]. Furthermore, a variation from nominal values of main data was considered, as a potential uncertainty source. For this purpose, N data table sets were built around the nominal values using the Monte Carlo Simulation (MCS) (Chiacchio, Aizpurua et al. 2020).

5. Modeling results and discussion

The above discussed GMDH-type NN, followed by the UKF application, was trained and employed to model the data-set of **Error! Reference source not found.**. An optimal structure of a GMDH-type NN with three hidden layers is shown in **Error! Reference source not found.**-A. **Error! Reference source not found.**-B shows a correlation coefficient of 97.6% between the actual values and the predicted ones. Similar to the previous section, the optimal structure of NN with three hidden layers, was employed for the modeling of the data-set of **Error! Reference source not found.** (**Error! Reference source not found.**-C). **Error! Reference source not found.**-D shows a correlation coefficient of 99.1% between the actual values and the predicted ones, representing a reasonably accurate model. Finally, in order to achieve a simpler model, we attempted to reduce the number of hidden layers of the NN to 2, with results (**Error! Reference source not found.**-E and F) showing still a sufficient predictability of the model.

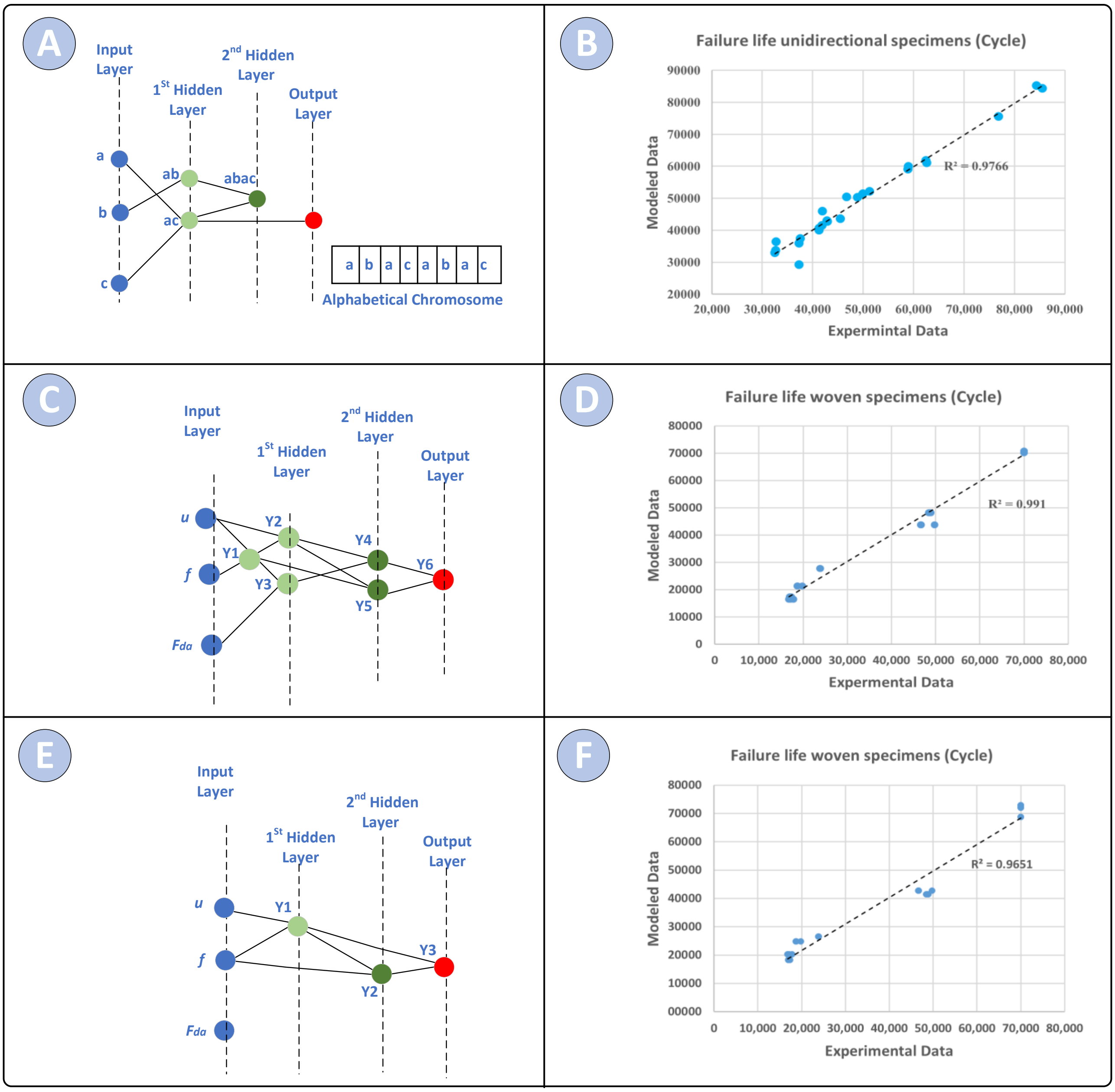

Fig. 8. A: Using GA (the sequence of genes creates an alphabetical chromosome) to optimize the structure of GMDH-type NN for modeling the first data-set (unidirectional composite specimens). **B:** Comparison of experimental and modeled data based on the neural network shown in (A). **C** and **E:** Optimized structure of GMDH-type NN with 3-(Hidden Layer) HL and 2-(Hidden Layer) HL, respectively, for modeling of the second data-set (woven composite specimens). **D** and **F:** Comparison of experimental and modeled data based on the neural network shown in C and E, respectively.

6. Sensitivity Analysis

A sensitivity analysis was employed to investigate the dependence of the output (number of cycles to fail) on the drilling variables variations in woven specimens. For this purpose, using Eq.4 and Eq.5, the derivative of the output was calculated relative to each independent variable, while the other variable was kept constant.

$$S_1 = \left.\frac{\partial \text{cycles}}{\partial \text{u}}\right|_{\text{f=constant}} \tag{5}$$

$$S_2 = \left.\frac{\partial \text{cycles}}{\partial \text{f}}\right|_{\text{u=constant}} \tag{6}$$

Error! Reference source not found.-A shows the output variation relative to *f* , while *u* was equal to 3000, 7000, or 10000. As can be seen, the graph trend is divided into three sections, increasing for small values of *f*, decreasing for medium values of *f*, and increasing again for large values of *f*. The output derivative with respect to *f* is negative in the wide range and positive in the narrow bound. For example, for the value *f* = 120, the output derivative is always negative, which means that the cycles required to fail at this level of *f* will be decreasing (for all values u).

Error! Reference source not found.-B shows the output variation relative to the *u*, while *f* was equal to 50, 100, or 150. The output derivative with respect to *u* is negative except for the end section of *f*=150. Overall, based on the range of variations in **Error! Reference source not found.**, it can be concluded that the fatigue life of the samples has been sensitive much higher to the feed rate than to the cutting speed; and in both cases under a highly nonlinear regime.

7. Concluding remarks

Drilling is one of the most complex production processes in the assembly of composite parts, which if not optimized, can generate undesirable damages to the final structure. This study was aimed to use a robust, hybrid machine learning framework (namely GMDH)-type NN along with a UKF) to predict the fatigue life of open-hole unidirectional and woven GFRP laminates based on the associated drilling parameters; as well as quantifying the induced delamination around the drilled hole. The experimental results showed that the induced delamination is highly dependent on the drilling parameters themselves. The delamination area made a significant difference to the fatigue life of the specimens. The learning model, despite the embedded noise using the Monte Carlo Simulation, provided an accurate method (as high as 99.1%) in predicting the fatigue life of the samples, despite limited experimental data. In general, there are two main tasks in designing the GMDH-type NNs, namely the network structure/topology optimization and the weighting identification. Among different approaches, here a multi-objective GA was used for the former task (while preventing overfitting), and the SVD was used for training the network parameters through a factorization of learning matrix. Using the UKF, the mean of the squared estimated error was minimized and the convergence rate was increased, despite the simulated noise in data. Potential extension of this area of research for industrial applications may include the consideration of the cutting tool wear (Feito et al., 2016), and possibly under a group multicriteria decision making (MCDM) environment (Osmond, et al, 2021).

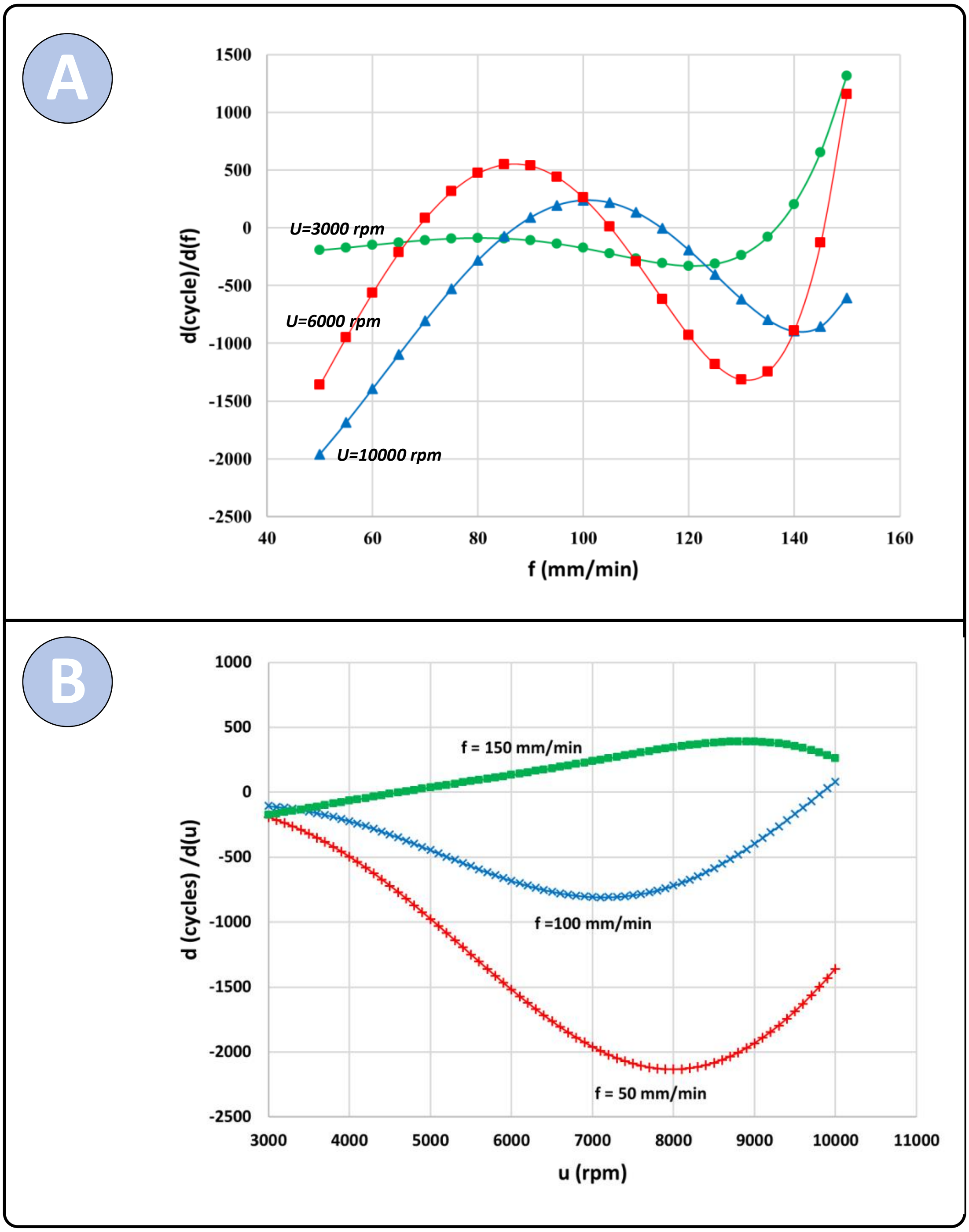

Fig. 9. Sensitivity of the output (number of cycles to fail) relative to **A:** the feed rate (f) input and **B:** the cutting speed, for woven composite samples.

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