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Knowledge based data boosting exposition on CNT-engineered carbon composites for machine learning

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ABSTRACT

Machine Learning (ML) is useful in predictive analytic or prognostic modeling for materials and engineering. It is, however, challenging to gather sufficient and representative data. Experiments are possible only in small numbers due to specialty materials, manufacturing, infrastructure, and testing involved. Simulation and numerical models need skills and appropriate validation. If the dataset at hand is too small in size to train ML, professionals tend to create synthetic data, which may not necessarily meet the quality required of the new data.

A Knowledge-based Data Boosting (KDB) process, named COMPOSITES, that rationally addresses data sparsity without losing data quality is systematically discussed in this paper. A study on inter-ply fracture toughness of carbon nanotube (CNT) engineered carbon fibre reinforced polymer (CFRP) composite laminates is used to demonstrate the KDB process. This involved strengthening of inter-ply interfaces using CNT advocated for improving delamination resistance of the CFRP composites. It is demonstrated that the KDB process helped augment the dataset reliably and improved the best fit regression lines. The process also made it possible to define boundaries and limitations of the augmented dataset. Such sanitised dataset is certainly valuable for prognostic modeling.

KEYWORDS: Carbon Composites, Knowledge-based Data Boosting, Prognostic Modeling, Machine Learning, Fracture Toughness

(1) INTRODUCTION

The field of Machine learning (ML) is fairly well developed where a machine is allowed to learn from examples and history without being explicitly programmed. ML is influencing many application areas in engineering, including composite materials [1], materials design [2], manufacturing [3-4], optimization [5] and prognosis [6-9].

ML depends heavily on algorithms and data. Many algorithms and programming frameworks are now available [e.g. 10]. However, it is impossible for a machine to learn without data. Such dataset/s shall be accurate and sufficient for any sound ML exercise.

ML requires to be built and progressed through 3 stages, namely; training, validation and testing. All these 3 stages require data. Their proportion, in general [11], is shown in Figure 1. It is clear that majority of the data is needed for training ML models.

Figure 1: Data requirement for ML [11]

In many cases, synthetic data [12] or data augmentation process [13] are adopted. Use of synthetic data, fully or partially, is not advisable for engineering prognosis applications, as the risk involved is high. Data augmentation certainly works well with imaging. Popular augmentation techniques, such as Flip, Rotation, Scale, Crop or Translation can easily increase the data and enhance the learning capability. However, boosting numerical data is not possible using these techniques. Statistical methods can certainly help with generating numbers, but there is no guarantee that the generated data is accurate and representative of the property or the parameter in question. These cannot replace engineering judgment and acumen required in making reliable predictions about a material parameter or composition.

Experiments may be conducted to produce more data, provided they are affordable. Simulation and numerical models also need skills and proper validation. If either one or both of these cannot meet the requirements for the quality and the size of the dataset to train ML, a better approach is required to address the quality aspect of the new data while generating it to boost the existing dataset.

In this paper, a Knowledge-based Data Boosting (KDB) process proposed in author's earlier short publication [14] is presented in detail and discussed. The procedure is meant to address data sparsity systematically and reliably without compromising the data quality. The proposed KDB process, acrostically termed 'COMPOSITES' consists of 10 steps that are essential starting from identifying data, understanding physics, sanitising the available data, to final scrutiny of the boosted data set. This provides a novel engineering way of creating near-real data for machine learning. This process can be adopted to any case that has countable variables and quantities, but requires its scant data to be augmented to a size useful for ML.

A study on inter-ply fracture toughness (ILFT) of carbon nanotubes (CNT) engineered CFRP laminates is used to explain and substantiate the KDB process. This involved nano-scale strengthening of inter-ply interfaces in composites advocated for improving its delamination resistance [15]. This is still an area under research, with limited case studies and available datasets. For composites, experiments and testing are only possible in small numbers due to the specialty materials, manufacturing, infrastructure, and test methods involved. It is demonstrated that the KDB process helped augment the dataset size and improved the R-Squared for the regression lines.

The KDB model also facilitated understanding of the data values, operational boundaries, and limitations of the augmented dataset.

The presented case study demonstrates the power of the COMPOSITES process for knowledge based data augmentation in engineering.

(2) THE KNOWLEDGE-BASED DATA BOOSTING (KDB) PROCESS

Generation of any engineering data requires understanding of the parameters involved and the basic phenomena behind those data points. Adding new data points to an available dataset requires the same attention and rigor as before in order to uphold the accuracy and the reliability. Below are the 10 generic steps that sum-up the proposed KDB process. These steps also form an acoustic 'COMPOSITES'.

(1)	<i>Collect</i>	Gather authentic engineering, semi-processed/ raw, data.
(2)	<i>Organize</i>	Sort/ select data points based on certain parameter or criterion.
(3)	<i>Mathematics</i>	Tabulate and plot data points to check scatter, trend and deviation.
(4)	<i>Physics</i>	Examine underlying reasons for the data point values.
(5)	<i>Oddities</i>	Identify and remove outliers and extremity points.
(6)	<i>Space</i>	Mark the space or domain within which the data may be boosted.
(7)	<i>Infer</i>	Form guidelines to be observed while boosting the data.
(8)	<i>Translate</i>	Form mathematical propositions based on inferred guidelines.
(9)	<i>Employ</i>	Apply those propositions to augment the data and visualize it.
(10)	<i>Scrutinise</i>	Examine the new dataset considering all details and build suggestions.

The particulars of the KDB process and the 10 steps therein are available in ref. [14]. The implementation of the process is demonstrated in subsequent sections below.

3. INTER-PLY FRACTURE TOUGHNESS STUDY

A study is conducted for an inter-ply fracture toughness of CFRP composites, a schematic of which is shown in Figure 2. Such composites typically consist of many layers or plies stacked one above the other and cured using heat, vacuum and pressure to bond the plies together and consolidate them into a laminate. One of the research works on woven CFRP composites from the author's the then group is referred to in this study [17-19] to gather necessary information and the data.

Figure 2: Schematic of a composites

Inter-ply fracture, commonly termed as delamination, is one of the major failure modes for CFRP composites. Delamination is proving to be a point of weakness and a major disadvantage for composite laminates. The inter-ply region between the individual plies is a matrix-dominated region and does not have any explicit reinforcement that can resist crack initiation, formation, and propagation. One of the methods advocated to strengthen this region is to add some sort of compatible reinforcement of a suitable size. The addition of nano-fillers, such as carbon nanotubes (CNT), is seen to improve the inter-ply properties of CFRP laminates.

Quantitatively, interlaminar fracture toughness (ILFT), which is the strain energy released per unit area of the crack propagation along the CNT reinforced ply interface is used to determine the improvement in the delamination resistance.

4. RESULTS AND DISCUSSION

In this study, only the mode I fracture and the effects of the content and the type of CNT on the fracture toughness are considered. The KDB process is then followed systematically to augment the data set as discussed below.

4.1 Collect: The Double Cantilever Beam (DCB) test data in the form of Mode I inter-ply fracture toughness (i.e. G_{IC} kJ/m²) is collected selectively from ref [18] representing delamination resistance of a bi-directional CFRP composites without nano-fillers and with a variety of CNT added in to strengthen the inter-ply interfaces. The fabrication and testing of the DCB coupons, for which the data was gathered, were conducted in a controlled environment. A total of 20 different cases were identified.

4.2 Organise: Out of these 20 cases, only 16 relevant cases were taken for further analysis as they were for the samples cured in an autoclave; the rest were cured differently. This was to ensure that the manufacturing process aligned with the common industry practices and the boosted dataset remained useful. Each case was based on unique nano-reinforcement in the form of types of CNT, their %, as well as the amount of process vacuum applied.

The final data points were a summary of the test campaign for these 16 cases. The points were available in the form of the minima, mean, and the maxima, covering the test scatter. Thus, these 16 cases resulted in a reliable 48 data points.

These 48 data points were tabulated, and then plotted in an X-Y domain, which provided overall picture of the variations in G_{IC} kJ/m² values as a function of weight of CNT per unit area of the inter-ply interface, as seen in Figure 3.

Figure 3: Chosen set of data points for Mode I inter-ply fracture toughness

This amount of data (only 48 points) is certainly sparse and insufficient for any prognosis. There is need to boost this data set.

4.3 Mathematics: Subsequently different trend line functions, such as, linear, moving average, polynomial, etc., were tried. The 2nd order polynomial functions were found to fit the data and represent the expected non-linear trend in a reasonable manner. The plots are shown in Figure 4. Separate trend lines were intentionally plotted for the minima, mean and the maxima to understand the variance and the possible data boundaries.

Figure 4: Trends and CoD for Mode I inter-ply fracture toughness of CFRP

It may be seen that the trends were certainly not the best-fits and the R-squared (i.e. CoD) values were poor in all these cases.

4.4 Physics: Certainly, the scatter and the trends were such that any predictions made would be tentative. It was therefore essential to understand the materials, manufacturing, phenomenon, crack propagation and the crack arrest to evaluate the underlying reasons for the values at the data point as they were.

The samples were fabricated using bi-directional, 12k, plain weave, carbon fabric with CNT at a ply interface. This carbon fibre prepreg consisted of Epoxy L-930HT matrix, which was found to bond well with MW and other CNTs used [20] in this study. It was also known from in another study [21] that carbon-based materials bond well with epoxy resins showing enhancement in properties.

CNT have tendency to agglomerate. However, the study from where the data points are obtained [18], had addressed this comprehensively and innovatively. As highlighted in [20], the CNT dispersion was achieved by using “dry CNTs on transfer media” process. First, the CNT were mixed separately in Ethanol in 1:500 proportion and sonicated for 1-3 hours depending on the type of CNT used. The variety of CNT ranged from multi-wall (MW), single wall (SW), non-functionalized, and functionalized with groups, such as carboxyl (-COOH) or hydroxyl (-OH), etc. The purpose of the sonication was to eliminate agglomeration of CNT such that they get evenly dispersed at the ply interfaces. In order to achieve that, the CNT-Ethanol mixture was first spread on a Teflon sheet after sonication, and after the Ethanol evaporated out, a layer of carbon prepreg was laid on top of that. Since the prepreg had sufficient tackiness, the CNT quickly adhered to it after flipping upside down. Thus prepared

prepreg layer, was then used in to a lay-up to form a laminate. This ensured uniform transfer and retention of CNT at the inter-ply interface.

Despite all this care, the spread of CNT over the prepreg surface was still random. This possibly had resulted in some scatter in the test results. The scatter, however, is already accounted in for while choosing those 48 data points. It was noticed that the sonication period had little influence on the fracture toughness values.

All the DCB samples were cured in an autoclave as per the cure cycle recommended by the prepreg manufacturer [18] under pressure (85 psi) and temperature (120 deg C for 2 hours). Vacuum was applied for debulking and removing volatiles. The amount of vacuum varied between 15-25 mmHg. These variations may be considered small in this particular study because the 12k prepreg has large enough pores between the knits to allow the volatiles to escape easily, even at low vacuum. The role of vacuum in compaction also was expected to be minimal in this study, because the pressure applied on to the lay-up in the autoclave was much higher. These observations, however, are not confirmable further, and may have led to some scatter in mode I fracture toughness data. All such scatter is already accounted in for in the data values.

Note that a very small amount of CNT was used to strengthen the interface. The amount of CNT used varied from 0.24 g/sqm to 1.48 g/sqm of the prepreg area, while the baseline samples had no CNT. All tests were conducted according to the test standard, ASTM D 5528 [22].

It was noticed from Figure 3 that, while addition of CNT does help, there are no visible benefits of adding CNT beyond 0.99 g/sqm of the prepreg area. It is certain that for the CNT-engineered composites, the inter-ply matrix interface as well as the fibre-matrix characteristics at the interface get altered [18]. With the right proportion of CNT, significant fibre bridging between numerous fibres from the adjacent plies occurs. These fibre bridges are developed due to the interlocking of CNT that are embedded into the surrounding matrix. The fibre bridging sustains load much longer than the usual matrix–matrix adhesion bonding providing about 30-35% higher fracture resistance. Composites with higher content of CNT end up having a resin-CNT-rich thick interface. Due to the higher density of CNT, most of CNT stay in between the joining plies rather than penetrating into the fibres promoting fibre bridging. If the CNT content is still higher, the CNT agglomerate within the interface and provide little resistance to crack propagation. On the contrary, it weakens the interface worsening the situation. It is therefore necessary to use optimum CNT content. SWCNT show better dispersion and bonding in between the adjacent fibres than MWCNT. However, SWCNT are unable to cause effective fortification of interlaminar matrix region due to partial agglomeration.

Dispersion of CNT uniformly in a resin system is challenging due to the presence of the Van der Waals forces. The scrutiny of the data presented in ref. [18] points to approximately 2h of sonication per 1 g/ sqm loading of CNT for good dispersion. Functionalization of CNT can help achieve stabilization and good dispersion of CNT within the base matrix [19]. The carboxyl or hydroxyl groups present on the CNT surface provide conducive environment for chemical reactions to take place. This dataset does include points for functionalized CNT cases. In conclusion, the data gathered is representative enough. It is observed that, as compared to

the nonfunctional MWCNT, functional MWCNT show better dispersion in-between the adjacent fibres.

This provided further insight into the data set at hand.

4.5 Oddities: Out of the 16 cases, there are 6 cases, which have functionalized and non-functionalized data points at the same CNT content. This may cause fuzziness in providing optimum solutions in future. It is, therefore, decided to take out the repeat points with lower improvements in GIC values to make the dataset impactful and targeted. The results of these exclusive 10 cases (30 data points) selected for further analysis are shown in Figure 5.

Figure 5: Trends and coefficient of determination for sanitised Mode I inter-ply fracture toughness data

The R-squared values, although have improved with 3rd order polynomial fit, the scatter and number of data points are still unacceptable for ML.

4.6 Space: It was noticed that beyond certain CNT content, the G_{IC} results deteriorated. In order to mark that boundary, it was decided to examine the % improvement in G_{IC} rather than the absolute values and discard all those negative data points. From the original dataset it was observed that the maximum improvement in G_{IC} is 52% and the second highest values is 46%. It is therefore prudent (and still conservative) to set a limit of 50%, which essentially means that CNT can only improve the delamination resistance up to 50%. The point at 52% is therefore brought down to 50%. The data plot within this marked space is shown in Figure 6.

Figure 6: Data plot within the defined space

Sub-division of the space based on the type of CNT is possible, but is not practical in this particular case study, because the whole dataset is already lean and sparse.

4.7 Infer: Understanding of the physics behind the chosen data points helped in inferring guidelines for data boosting. It appeared more logical to boost the data in a sequential manner.

First, vary the G_{IC} values without changing the CNT content while boosting the data. This may be termed as ‘vertical KDB’ for convenience. Create new points (NP) using the minima, mean and the maxima values. Further data boosting is to be carried out by varying the CNT content between two measured points. It is fair to assume that between any two close-enough points, the variations in G_{IC} are linear. This may be termed as ‘horizontal KDB’. The same applies to the diagonally opposite points, which are also the proximity points, one from the minima and the other from the maxima range; this operation is named as ‘diagonal KDB’. All these operations shall logically cover the likely scatter in the data within the bound space.

The above-mentioned operations may be followed by fitting the trend lines to check CoD. If necessary, create newer point by varying the CNT content in small % in the proximity of the current points. This is also logical given the fact that the CNT content to be used for engineering the composites is small and some variation is expected in reality. This may be done by either a moving average [22] or using the obtained trend lines. Care shall be taken that no new point falls outside the marked space.

Besides, it is identified from Figure 6 that there are two zones requiring attention.

One is the relatively large gap between the first and the second points. It is noticed that even the 0.24 g/sqm of CNT resulted in 30-40% increase in the fracture toughness. Such sharp rise GIC shows that a small quantity of CNT does provide a notable inter-ply reinforcement. The effect is certainly positive and the trend is linear enough for interpolating the data. As such, the concern for the large gap between these 2 points is trivial.

The second region to be watched, is beyond 0.99 g/sqm of CNT. The data point beyond this, which is at 1.47 g/sqm, shows little improvement in the fracture toughness. The gap between this and the preceding point is also significant. This will need to be attended to.

4.8 Translate: The above guidelines are then translated into the mathematical propositions as depicted in Figure 7 along with geometrical presentation.

Vertical Operation

$$NP(h) = LL(h) = ML(h)$$

$$NP(v) = \frac{LL(v) + ML(v)}{2}$$

Horizontal Operation

$$NP(h) = \frac{LL(h) + LR(h)}{2}$$

$$NP(v) = \frac{LL(v) + LR(v)}{2}$$

Diagonal Operation

$$NP(h) = \frac{LL(h) + UR(h)}{2}$$

$$NP(v) = \frac{LL(v) + UR(v)}{2}$$

Figure 7: Possible operations to create NP

The vertical, horizontal and diagonal KDB propositions may be applied sequentially to create new points. The effect of these operations on the respective R-squared values is not vital at this stage. All these new points may be then added to the original dataset to redraw the well-fit trend lines. The CoD may be examined as well as the regions of concern may be revisited.

4.9 Employ: As planned, the above propositions are implemented. The results are shown in Figures 8 to 11.

Figure 8: Dataset after vertical KDB operation

Figure 9: Dataset after horizontal KDB operation

Figure 10: Dataset after diagonal KDB operation

Figure 11: Dataset after all NP and original data merged

4.10 Scrutinise: As seen from Figure 11 that CNT content beyond 1 g/sqm does not help in improving Gic values. As inferred earlier, this zone may be of little use. This, in fact, will provide a misleading prognosis, if those data points are still included in the final dataset. Figure 12 shows the plots after the points beyond 0.99 g/sqm are removed. These also show an improvement in the CoD.

Figure 12: Data plots after points beyond 0.99 g/sqm CNT are removed

Figure 13 shows third-order polynomial trend-lines offering a much better fit than the earlier second-order trend lines.

Figure 13: Data plots with third order polynomial trend lines

The boosted dataset now has 83 points as compared to the original 30 points. None of these points shows negative improvement, except 3 points that amount to zero improvement. Although these may be the outcome in a real situation, the probability of occurrence of this is low given the wide scatter in that zone. Hence, it is better to remove those 3 points at this stage to avoid fuzziness in prognostic modelling.

Thus, the final newer dataset contains 80 points augmented from 30 data points; this essentially means that the final dataset augmentation factor is 2.67. This factor can be further ramped up by adding either a controlled noise to the trend lines to create additional newer points logically. This is, however, is not pursued as the current exercise deemed sufficient to prove the proposed COMPOSITES KDB process.

Figure 14: Final sanitised knowledge-based boosted dataset (minima, mean and maxima)

The final dataset with three trend lines and their equations are shown in Figure 14, while Figure 15 shows a single trend line and its equation if all data points are merged together. Both these prove that with the proposed COMPOSITES approach, the R-squared has improved significantly.

Figure 15: Final sanitised knowledge-based boosted dataset (Single)

When investigated further, the new dataset does suggest that there may be more than one optimum solutions, such as, either

- a. Preferentially use functionalized MWCNT for cases below 0.65 g/sqm of prepreg, or
- b. use any type of CNT when the target load is equal or above 0.65 g/sqm of prepreg.

It may be noted that this dataset is not useful beyond 1 g/sqm content of CNT irrespective of their type.

One may utilise these guidelines while setting up prognostic models based on the boosted dataset.

5. CONCLUSIONS

A knowledge-based data boosting (KDB) method devised for data augmentation in engineering applications reliably is discussed. The 10-step, COMPOSITES, process proposed for the KDB is demonstrated successfully using a study on inter-ply fracture toughness of CNT-engineered CFRP composites. A data augmentation factor of 2.67 was achieved after sanitising and augmenting the original dataset without compromising accuracy of the data points. The KDB process not only helped in adding newer points but also provided sufficient insight into its use for prognosis. It

added value by highlighting the boundaries as well as the possibility of having more than one solutions.

6. REFERENCES:

1. Chen CT, Gu G, Machine learning for composite materials, MRS Communications, Jun 2019, Vol 9 (2), pp 556-566. <https://doi.org/10.1557/mrc.2019.32>
2. Sherman S, Simmons J, Przybyla C, Mesoscale characterization of continuous fiber reinforced composites through machine learning: Fiber chirality, Acta Materialia, Dec 2019, Vol 181, pp 447-459. <https://doi.org/10.1016/j.actamat.2019.10.001>
3. Sharp M, Ak R, Hedberg T, A survey of the advancing use and development of machine learning in smart manufacturing, Journal of Manufacturing Systems, July 2018, Vol 48 (C), pp 170-179. <https://doi.org/10.1016/j.jmsy.2018.02.004>
4. Escobar CA, Morales-Menendez R, Machine learning techniques for quality control in high conformance manufacturing environment, Advances in Mechanical Engineering, Feb 2018, Vol 10 (2). <https://doi.org/10.1177/1687814018755519>
5. Fernandes H, Zhang H, Figueiredo A, Malheiros FIL, Sfarra S, Ibarra-Castanedo C, et. al, Machine learning and infrared thermography for fiber orientation assessment on randomly-oriented strands parts, Sensors, 2018, Vol 18(1), p 288. <https://doi.org/10.3390/s18010288>
6. Pathan MV, Ponnusami SA, Pathan J, Pitisongsawat R, Erice B, Petrinic N, et. al, Predictions of the mechanical properties of unidirectional fibre composites by supervised machine learning, Scientific Reports, Vol. 9, No. 13964, Sep 2019. <https://doi.org/10.1038/s41598-019-50144-w>
7. Bunker RP, Fadi T, A machine learning framework for sport result prediction, Applied Computing and Informatics, Vol 15 (1), pp 27–33, Jan 2019. <https://doi.org/10.1016/j.aci.2017.09.005>
8. Abueidda DW, Almasri M, Ammourah R, Ravaioli U, Jasiuk IM, Sobh NA, Prediction and optimization of mechanical properties of composites using convolutional neural networks, Composite Structures, Vol 227, Article 111264, Nov 2019. <https://doi.org/10.1016/j.compstruct.2019.111264>
9. Chen, L, Tran H, Batra R, Kim C, Ramprasad R, Machine learning models for the lattice thermal conductivity prediction of inorganic materials, Computational Materials Science, Vol 170, Article 109155, Dec 2019. <https://doi.org/10.1016/j.commatsci.2019.109155>
10. Machine Learning Algorithms in 7 Days, Video by Sengupta S, 1st edition, Safari, an O'Reilly Media Company, Mar 2019. [DOC: 13 JUL 2020] https://subscription.packtpub.com/video/big_data_and_business_intelligence/9781789800289
11. Bisong EO, Building machine learning and deep learning models on google cloud platform: A comprehensive guide for beginners, Chapter 14, Principles of Learning, Apress, Berkeley, CA, p 176, 2019. https://doi.org/10.1007/978-1-4842-4470-8_14
12. Surendra H, Mohan HS, A review of synthetic data generation methods for privacy preserving data publishing, International Journal of Scientific & Technology Research Vol 6 (3), pp 95-101, Mar 2017. <https://www.ijstr.org/final-print/mar2017/A-Review-Of-Synthetic-Data-Generation-Methods-For-Privacy-Preserving-Data-Publishing.pdf>
13. Mikołajczyk A, Grochowski M, Data augmentation for improving deep learning in image classification problem, 2018 International Interdisciplinary PhD Workshop, Swinoujście, pp 117-122, 2018. <https://ieeexplore.ieee.org/document/8388338>

14. Joshi SC, COMPOSITES: A pragmatic knowledge-based engineering data boosting process, Open Access Journal of Engineering Sciences, Mar 2020. <https://springfieldpublishers.com/journal-of-engineering-sciences/pdf/OAES.MS.ID.000101.pdf>
15. Boon YD, Joshi SC, A review of methods for improving interlaminar interfaces and fracture toughness of laminated composites, Materials Today Communications, Vol 22, Article 100830, Mar 2020. <https://doi.org/10.1016/j.mtcomm.2019.100830>
16. Numerical Methods, by Babu Ram, Pearson India, Mar 2010, ISBN: 9788131732212. <https://www.worldcat.org/title/numerical-methods/oclc/1024277468>
17. Dikshit V, Bhudolia S, Joshi SC, Multiscale Polymer Composites: A review of the interlaminar fracture toughness improvement. Fibers, Vol 5 (4), p38, 2017. <https://doi.org/10.3390/fib5040038>
18. Dikshit V, Manufacturing and performance studies of laminated composites with Nano-reinforced inter-ply interfaces, PhD Thesis, Nanyang Technological University, Singapore, 2014. <https://hdl.handle.net/10356/63276>
19. Joshi SC, Dikshit V, Enhancing interlaminar fracture characteristics of woven CFRP prepreg composites through CNT dispersion, Journal of Composite Materials, 2011. <https://doi.org/10.1177/0021998311410472>
20. Dikshit V, Joshi SC, Manufacturing of multiscale interlaminar interface composites and quantitative analysis of interlaminar fracture toughness, Chapter 12, Fiber-Reinforced Nanocomposites: Fundamentals and Applications, pp 261-278, 2020. <https://doi.org/10.1016/B978-0-12-819904-6.00012-8>
21. Bustero I, Gaztelumendi I, Obieta I, Mendizabal MA, Zurutuza A, Ortega A, Alonso B, Free-standing graphene films embedded in epoxy resin with enhanced thermal properties, Advanced Composites and Hybrid Materials, Vol 3, pp 31-40, 2020. <https://doi.org/10.1007/s42114-020-00136-6>
22. ASTM D5528-13, Standard Test Method for Mode I Interlaminar Fracture Toughness of Unidirectional Fiber-Reinforced Polymer Matrix Composites; ASTM International: West Conshohocken, PA, USA, 2013. <https://www.astm.org/Standards/D5528>