SPE COMPOSITES

FALL 2025

Composites Connection™

Official Newsletter of the SPE Composites Division
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SPE COMPOSITES
FALL 2025
Composites Connection™
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Chairman's Message:

Dale Brosius

Dear Composites Division members,

This summer, I assumed my elected role as Chair of the SPE Composites Division. I am looking forward to serving you, our members, over the forthcoming two years. First, I want to recognize the strong leadership of the outgoing Chair, Dr. Alex Kravchenko, and his predecessor John Busel, for their great contributions in the past four years, steering the division through Covid and the aftermath, and significant changes throughout the composites landscape.

As many of you know, this in not my first journey as division chair. I also served in this role from 2011 to 2013, following several other board positions. After being Chair, I filled the role of Councilor for the division from 2017 to 2024, which gave me great insight and exposure to the Society as a whole, as SPE has evolved to serve members in a highly connected and digital age. Since I joined SPE in 1992, I have gained greatly from my participation. I am now looking at how I can give back to provide greater value to both the division and our individual members.

Between 2013 and 2025, a lot of things have occurred within our industry. In automotive, we have moved from hybrids to a focus on battery electric vehicles, but the challenges for composites continue to be cost and cycle time. The carbon fiber intensive BMW i3 entered production in September of 2013 and ceased production in 2022. The Airbus A350, with over 50% advanced composites content, entered commercial service in 2015. Wind turbine blades have increased from 50-60 meters long to over 110 meters today, and the wind industry is today the largest market for composite materials. Graphene is the new "nanomaterial" and it's promise is still to be fully realized. And a whole industry has been created around recycling of composites but still needing to be scaled.

I have been fortunate to have attended all the previous 24 editions of the SPE Automotive Composites Conference and Exhibition, and the 25th edition is coming up September 3-5 in Novi, Michigan. I have served as the chair of this conference four times – 2006, 2007, 2008 and 2015, and been a presenter, moderator and panelists on numerous occasions. This year's event promises to once again deliver great content, novel insights, robust discussions and ample time for networking with fellow composites enthusiasts.

I've long believed (and promoted) that the greatest value of SPE is in the networking opportunities, and the relationships that are developed as a result. I thank each of you for your continued membership and support of the Society and the Division. I hope to see you at ACCE in September!

Best regards,
Dale Brosius
Chair, SPE Composites Division

SPE Junior Researchers

By: Eve Vitale, SPE Foundation Executive

Positive Plastics Education™ is Empowering Futures at the SPE Foundation!

Thanks to the generous support of our partners, the SPE Foundation is providing new scholarships to a record number of applicants this year, engaging hundreds of Girl Scouts through the Girl Scout Patch Program, and exposing more than 17,000 students to Positive Plastics Education™ through PlastiVan®. See how we're changing the perception of plastics and introducing students to the amazing world of polymers.

Investing in Tomorrow: Plastics Hall of Fame Scholarships

To honor dedicated students pursuing careers in the plastics industry and address the increasing demand for support, **the Plastics Hall of Fame is pleased to offer four $5,000 scholarships through the SPE Foundation.** Following a record-breaking year in 2024, during which the SPE Foundation awarded over $262,000 in scholarships, these new awards will allow us to assist even more students amid an unprecedented number of applications. Additionally, we are excited to present our inaugural **Michael P. Sepe Scholarship** and two scholarships through ALPS Inspection this year. These collaborations enable us to make a significant impact on future plastics professionals facing rising educational costs.

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This Issue:

From Indiana to Florida: Girl Scout Patch Program Hits the Road with Polymer Science!

On April 5th, the SPE Foundation hosted an event in Valparaiso, Indiana, with the Girl Scouts of Greater Chicago & Northwest Indiana. Girls in grades 4-12 explored polymers, thermoplastics, recycling, and careers in the plastics industry, earning our "Color Your World with Polymer Science" patch. This marked our fourth event with this Girl Scout Council, enabling us to introduce hundreds of girls to the fascinating world of polymer science.

With sponsorship from DuPont™ Tedlar®, on April 12th, the SPE Foundation participated in the Girl Scouts of West Central Florida's STEMapalooza at Florida Polytechnic University, engaging over 1,800 Girl Scouts in similar activities. The SPE Foundation is committed to collaborating with Girl Scout Councils to inspire girls to seek ways they can become changemakers in our industry.

SPE Foundation Donors Honored at ANTEC®

Our new members of the SPE Foundation Ambassador Giving Society and those who moved up a level were honored at this year's ANTEC® Awards Luncheon. Established in 2024, the Ambassador Giving Society recognizes donors who have given $10,000 and above to support the work and mission of the SPE Foundation. You can view the list of the Ambassador Giving Society's 66 individuals and organizations on the SPE Foundation's website.

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PlastiVan® in Action!

Positive Plastics Education™ thrived in classrooms across the U.S. and Canada during the 2024-2025 academic year! **Over 17,000 middle and high school students participated in a PlastiVan® visit thus far,** where they discovered opportunities in science and engineering within the plastics industry and learned how they can contribute to sustainable solutions that make a real difference in the world.

We sincerely thank our generous PlastiVan® sponsors for the 2024-2025 academic year; their support allows us to sustain this meaningful work:

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SPE Detroit Section
SPE Milwaukee Education Foundation
SPE Northwestern Pennsylvania Section
SPE Palisades-MidAtlantic Section
SPE Vinyl Plastics Division
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Honoring Excellence: A Tribute to Patsy & Glenn Beall

This March, the SPE Foundation launched the **Patsy & Glenn Beall Honored Service Member Scholarship Endowment campaign.** Named in tribute to the legendary Patsy and Glenn Beall, this scholarship will honor a dedicated student who exemplifies exceptional leadership and commitment within their SPE Student Chapter. It will provide both financial support and inspiration for future leaders in our industry. Scholarship endowments allow us to recognize deserving students while honoring our esteemed colleagues and friends. You can help make this meaningful award a reality by visiting give.4spe.org/patsyandglennbeallscholarship.

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This Issue:

SPE Junior Researchers continued...

SPE Foundation 2024 Impact Report

The SPE Foundation remains dedicated to inspiring future plastics professionals and highlighting the numerous ways plastics impact our world. From Plasti-Van® and Girl Scout Council Patch Programs to scholarships and 3D Printer Grants, discover more about our mission and the contributions of our partners in our 2024 Impact Report!

We couldn't achieve this without the generous support of our SPE Chapter partners. If you're interested in making a difference and sharing what our work and industry can offer students, let's start the conversation! Contact Eve Vitale, Chief Executive, at evitale@4spe.org.


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ANTEC® 2026
March 9-12 · Pittsburgh, PA
ANTEC® 2026 is where you will find the latest breakthroughs in plastics technology, advanced polymer research, and next-generation processing solutions. This is more than a conference—it's a launchpad for solving real-world challenges in science, engineering, and industry.
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Keynote Speakers For ACCE Announced

Chad Duty,
Chief Executive Officer
at IACMI The Composites Institute,
Knoxville, Tennessee
Will Present:
Decade Of Innovation: Iacmi's Impact
at SPE® ACCE 2025 Event, Sept. 3-5, 2025

Chad Duty is the Chief Executive Officer of the Institute for Advanced Composites Manufacturing Innovation (IACMI, or IACMI-The Composites Institute), a role he assumed April 1, 2023. IACMI is a U.S. Department of Energy (DOE)-sponsored public/private partnership targeting high-volume applications of composites in energy-related industries.

A professor in the Mechanical, Aerospace & Biomedical Engineering Department at the University of Tennessee (UT), Chad also holds a joint faculty appointment with the Oak Ridge National Laboratory (ORNL).

He has more than 20 years of research experience in advanced manufacturing – spanning technologies in thin film processing, printed electronics, solar energy, and additive manufacturing of polymer composites. Before joining UT in 2015, Chad served as a research scientist and group leader at ORNL beginning in 2004 and helped to establish the DOE's Manufacturing Demonstration Facility at ORNL. Duty began his career as a senior aeronautical engineer at Lockheed Martin.

He has a doctorate in mechanical engineering from Georgia Tech and bachelor's degree in mechanical engineering from Virginia Tech.

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This Issue:

Casey Putsch, Founder and President of the Genius Garage Educational Programs,

Car Builder, Racing Driver, Watchmaker and Automotive YouTube Personality will present:

Composites Enable Innovative, Efficient, and Recyclable Vehicles and Can Help To Change The Nature of Mass Production

at SPE® ACCE 2025 Event, Sept. 3-5, 2025

The Omega Car creator, founder and president of the Genius Garage Educational Programs, car builder, racing driver, watchmaker, and automotive YouTube personality.

Casey Putsch is an unconventional rebel in the world of engineering and design. Most recently he has been known for creating the highly efficient diesel-powered Omega Car prototype which easily achieves over 100mpg, while matching the 0-60 times of a Tesla 3 and beating the original Dodge Viper. The car showcased the ability for ICE powered vehicles to have a lower carbon footprint than EVs from manufacturing through each mile of their life. Casey has also been known for creating a replica of the 1989 Batmobile powered by a Vietnam era drone anti-submarine helicopter engine as well as the only full-scale flying model of the Quetzalcoatlus Pterosaur with a 38-foot wingspan.

Notably, Casey is the founder and president of the 501(c)3 Genius Garage educational charity that bridges the gap from academia to industry by mentoring the best engineering students in the country with hands-on projects including professional level racing cars and building airplanes. Genius Garage has been responsible for helping its students land jobs from Tesla to Lockheed Martin and everywhere in between.

Casey has been honored with a lifetime achievement award in education from both President Trump and President Biden as well as with a flight with the United States Air Force Thunderbirds. Casey is also a car collector that enjoys watchmaking, vintage car racing, motorcycles, and yacht racing.

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ACCE Keynote Speakers continued...

Amanda Nummy, Senior Polymer Engineer

at Hyundai Automotive Technical Center, Inc. (HATCI) will present:

Balancing Multiple Objectives In Composites Design

at SPE® ACCE 2025 Event, Sept. 3-5, 2025

Amanda Nummy is a senior polymer engineer with a decade of experience in the automotive industry, trailblazing holistic design approaches to material selection and use, and bringing creativity from nature-inspired innovation. She earned a bachelor's degree in Polymer, Textile, and Fiber Engineering from Georgia Tech, a master's degree in Materials Science and Engineering from Wayne State University, and a master's degree in Biomimicry from Arizona State University. She also recently earned her Professional Certification in biomimicry, one of only 110 individuals globally that have achieved this level of expertise in the emerging field, leading and facilitating a new design thinking methodology for sustainability and regenerative practices across multidisciplinary teams.

In her current role, she is responsible for plant support and application development of all plastic components for North and South America and leads several global collaborations for fuel cell and battery electric vehicle development. Notable research and product development experience throughout her career includes hydrogen and biomedical fuel cells, specialty textiles, nanomaterials, carbon capture, built environment design, advanced processing and recycling technologies, reclaimed ocean plastics, recycled single-use PPE waste for automotive use, automotive shredder residue circularity, thermal runaway test method development, and lightweight composites.

She is the author of several papers published within the industry, and has given technical presentations, keynote speeches, and guest lectures to diverse audiences around the world, advocating for the thoughtful and responsible use of polymeric materials and alternative energy as part of the complex system of solutions that will be needed to ensure a sustainable future.

This Issue:

ACCE Award Winning Paper

Assessment of Damage Evolution in Thermoplastic Composite Using Acoustic Emission and Deep Learning Models

Tanzila B. Minhaj, Richard Dela Amevorku, Bhoj B. Chaudhary, Manoj Rijal, Mannur J Sundaresan North Carolina A&T State University

Abstract

As carbon/thermoplastic materials are being widely used in the aerospace industry due to improved impact resistance, ease in manufacturing, and recyclability, monitoring and detecting damages in these material systems has never been crucial. Even though the acoustic emissions technique can serve as an effective means of detecting damages in these systems, source quantification is still a challenge when using AE. This paper explored approaches to classify the three types of damage mechanisms in Carbon/thermoplastic composites, namely matrix crack, fiber break, and delamination with deep learning algorithms. Acoustic emission signals gained during a quasi-static tensile test of Carbon/thermoplastic (PAEK), tensile coupons were analyzed to predict and classify failure modes. Long-short Term Memory (LSTM) model, Convolutional Neural Network (CNN) model and CNN-LSTM model were developed to compare the performance of the deep learning algorithms in classifying these types of signals. CNN model consistently outperformed the LSTM model and was able to capture the spatial and temporal dependencies well enough. Also, the study investigated the most contributing hyperparameters in achieving the highest accuracy and correct prediction. After a detailed examination, three architectures of the CNN-LSTM model were proposed for an accuracy of above 90 percent. The accuracy and prediction capability of the models implies the possibility of real-time execution in detecting and classifying failure mechanisms in thermoplastic (PAEK) composites.

Introduction

Thermoplastic composites are increasingly being used in the aerospace industry due to their ease of manufacturing, repairability and excellent mechanical and thermal properties. There is insufficient literature with a detailed study on the characteristics of AE signals from the damages in the PAEK thermoplastic composite material, though studies on the mechanical behavior of thermoplastic materials are readily available. The first acoustic emission (AE) analysis of the composites was performed by Randolf [1] [2]. Laksimi et al. [3] studied the difference between Matrix-crack, Fiber-break, etc. using AE parameters like hit number, amplitude, duration, etc. They found that matrix-crack has a medium amplitude range with duration larger than fiber-break. Choi et al. [4] observed that the fiber break frequency is higher than that of the matrix crack. Wang et al. [5] presented the fracture morphology of a PAEK thermoplastic composite material, providing images that showed the rough surface with dents of thermoplastic (PAEK) matrix material and comparatively higher ductile

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fracture. They showed that the PAEK thermoplastic composite matrix material has better mode I and II fracture toughness because of high plastic deformation. Based on this knowledge of the material, the AE signals can be analyzed. Yang et al. [6], in their paper, clustered the AE signals for different damages in thermoplastic composites. They tried to label their clusters based on the frequency. They considered matrix-crack events to have a frequency of around 150 KHz., and for fiber-break to be around 250 kHz. In both cases, the waveforms for the frequency domain (FFT) had two peak frequencies. Marec et al. [7] presented waveforms for the time domain and frequency domain (FFT) for matrix crack and fiber break. Godin et al. [8] found four clusters of the AE signal waveforms in composite materials that showed obvious amplitude differences. They found delamination to have the highest amplitude. Their waveforms also indicated that the duration of the matrix crack event is moderate, while delamination has the longest duration and fiber-break has the shortest. Jacques [9] found the reliability of AE signals from bonded sensors. However, no literature is available to confirm the exact signal properties of failure modes in thermoplastic materials.

Bang et al. [10] identified cracks in thermographic images using the deep learning algorithm RCNN. Bao et al. [11] simulated the damage in thermoplastic composite pipes under noisy conditions characterized by their depth and radii. They classified signals from different locations using random forest and long-short-term memory (LSTM) algorithms to detect the location and quantity damage severity through a regression analysis model. Their model, trained on simulated data and validated with experimental data, used strain-time waveforms, and showed better accuracy with the LSTM model. Howev-

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er, performance decreased with increased noise. Wei et al. [12] used a CNN algorithm for segmenting impact damage using infrared thermographic images from thermoplastic composites as their dataset. Ai [13] et al. developed a random forest algorithm and SAE deep learning algorithm to localize damage in thermoplastic impact damaged specimens. They found higher accuracy when using frequency domain waveforms as input data than using time domain waveforms.

In this research, the dataset was formed with the waveforms received in the experiment, thus offering the potential to use the model in real-time application. AE signals from the PZT sensor bonded on thermoplastic composite tensile test specimens were classified and labeled as Matrixcrack, Fiber-Break, and Delamination based on the modal acoustic analysis [14]. It is expected that the matrix crack should have the leading S0 part followed by the A0 mode. However, in thermoplastic materials, the rarity of these types of signals indicates the matrix crack signal properties may differ from other composite materials. Hence, further study is required to identify exact matrix-crack events. In this study, the data set contains three different waveforms. Delamination waveform shows very low frequency and dominant Ao mode, while fiber break waveform shows higher acoustic modes with short duration and high frequency. This paper focuses on classifying the different experimental waveform datasets. LSTM, CNN, and CNNLSTM models were developed to identify the most effective algorithms for classifying failure modes. Since these waveforms were derived from experimental data, they contained significant noise. The study explored the idea that max-pooling operations could help eliminate noise. While the LSTM algorithm is typically suited for time series data, a one-dimensional convolutional neural network was found to be the most effective in classifying time-domain 1D waveform time series.

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Figure 1: The experimental setup

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ACCE Award Winning Paper continued...

Methodology

Experimental procedure

During the quasi-static tension test, the acoustic emission (AE) signals were collected as the specimen was loaded until failure. The specimen was prepared following ASTM Standard D3039. The 1" x 12" coupon made of carbon fiber-reinforced thermoplastic (PAEK) polymer with a lay-up sequence of [45/0/-45/90]2s was loaded monotonically until failure. The fiberglass tab was bonded at both ends of the specimen to ensure effective load transfer from the grip to the specimen. MICRO-II AE system and AE Win software were used to acquire data. Four bonded PZT sensors with a frequency response of up to 3 MHz were used to collect the AE data. A trigger threshold of 45 dB and an analog band-pass filter with 100 kHz high-pass filter and 3 MHz low-pass filter were used to eliminate most of the mechanical noise from the system. A sampling rate of 20 MHz was used to discretize the voltage output from the PZT. The experimental setup is shown in Figure 1.

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Preprocessing of the signal data

For labeling unique events as different damage, distinct features are found in the literature. It is already known that signals from fiber break usually have a very high frequency because of the duration of these source events. It has been found that fiber break-type damage can have a frequency ranging from around 700/800 kHz and above with low amplitude. A signal from a matrix crack is expected to have a small to prominent S0 mode followed by A0 mode because of transverse matrix crack being mostly the mode I type fracture. The frequency ranges from 250 KHz to 700 KHz was considered in this study as a matrix-crack event. Signals from delamination have very low frequency, up to around 200 KHz, with very high amplitude (up to 10V). The acquired AE signals were thus visually inspected using amplitude, frequency content, and mode shapes present, to create a labeled dataset of failure mode. The sample signals and their FFT of the failure modes collected from the experiments are depicted in Figure 2, emphasizing features such as amplitude, duration, frequency content, and mode shapes. Figure 2(a) shows the signal expected from a matrix crack, with a frequency ranging from 200 to 600 kHz, low amplitude, and moderate duration (~ 40 μs). Figure 2(b) shows delamination signals with high amplitude (>1 V) and low frequencies up to around 200 kHz. Figure 2(c) shows fiber-break AE signals with very short duration (~20 μs) and frequencies reaching up to 2 MHz. About 43394 waveforms were retained from the experiment. Not all of them could be categorized, requiring further analysis as there is also the possibility that the signal can be coming from mixed failure modes instead of a single dominant damage mechanism.

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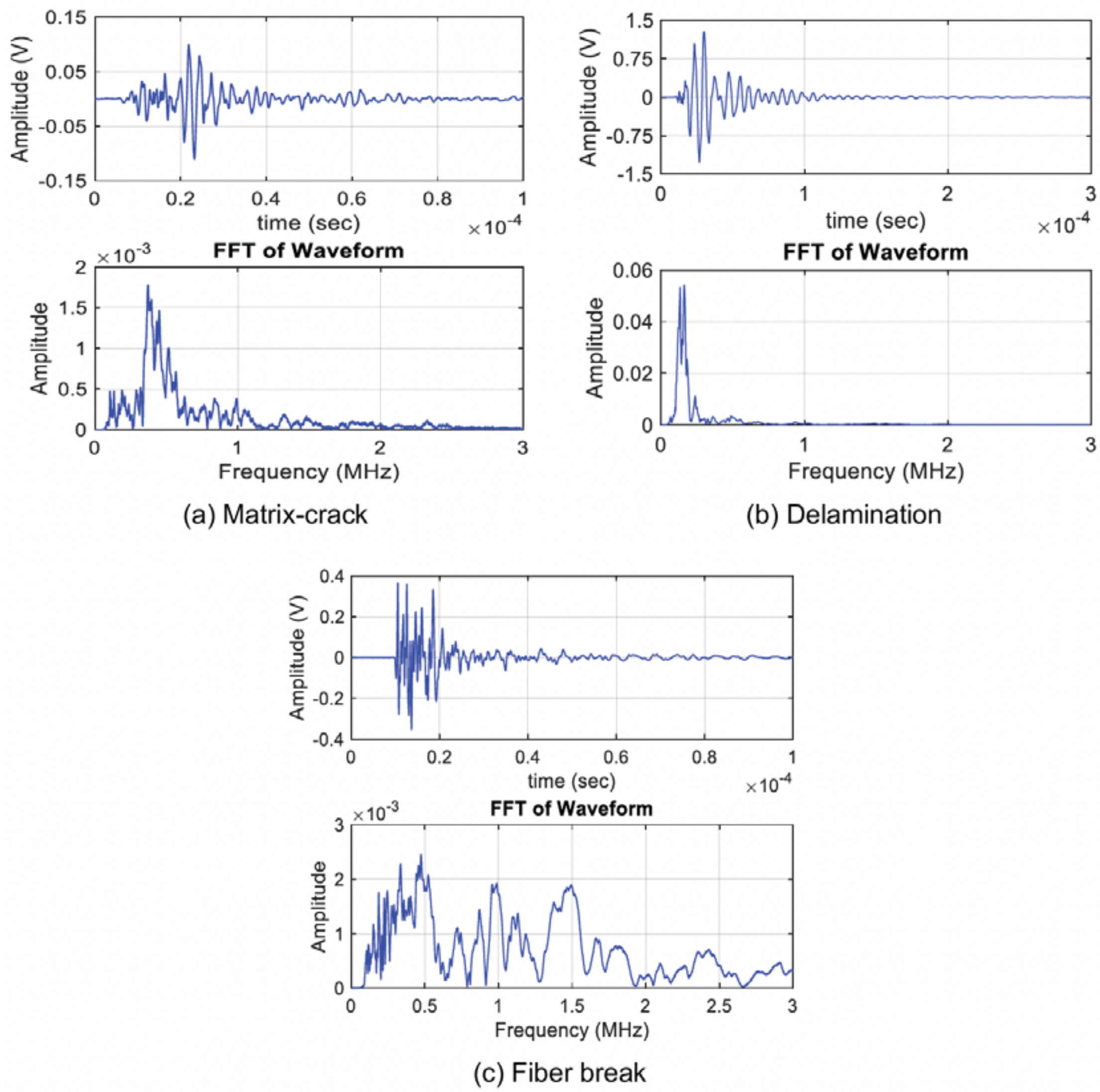

Figure 2. Sample AE signal and their FFTs. (a) Matrix crack (b) Delamination (c) Fiber-break

To prepare the dataset for the classification models, all the AE signals obtained during the quasistatic tensile test were first attempted to be clustered into groups using the cross-correlation method for exploratory data analysis [15]. The waveforms that were clustered with a very high correlation coefficient, i.e. 0.95, were meticulously chosen as fiber-break upon visual inspection and considering features discussed before. Matrix-crack and delamination waveforms were collected in the same manner. However, for delamination, a cross-correlation co-efficient of 0.80 was assigned to account for the longer duration of this failure mode. For matrix-crack, a medium correlation coefficient of 0.85 was used. The clusters contain the waveforms which can be exported into the datasheet in Excel. The Excel tables for the dataset have been given below.

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-0.03112793	-0.02410889
-0.05157471	-0.02197266
-0.07171631	-0.0201416
-0.09094238	-0.01831055
-0.10955811	-0.01647949
-0.12695313	-0.01495361
-0.14312744	-0.01281738
-0.15838623	-0.01098633
-0.17242432	-0.00915527
-0.18463135	-0.00793457

Matrix-crack

-0.00061035	0.00061035
-0.00030518	0
-0.00030518	-0.00061035
-0.00030518	-0.00091553
-0.00061035	-0.00061035
-0.0012207	0
-0.0012207	0.00061035
-0.00091553	0.00061035

Fiber-Break

-0.00152588	-0.00183105
-0.00152588	-0.00305176
-0.00152588	-0.00427246
-0.0012207	-0.00518799
-0.00061035	-0.00610352
-0.00030518	-0.00671387
-0.00061035	-0.00762939

Delamination

The data table for three types of AE signals

Here, each column represents a single time domain waveform amplitude in volts. Therefore, each of the columns is one AE signal. When the specific failure modes generates the elastic acoustic emission signal, it propagates as a stress wave, causing tension and compression in its propagation path. These tension and compression are recorded as negative and positive amplitudes of the time domain waveforms.

For supervised learning, labeled data is essential to train models and make predictions. The primary purpose of this study is to predict the type of damage from the unknown signal by training the model feeding a known labeled signal dataset. Signal data were labeled as ‘0’ for Matrix-Crack, ‘1’ for Fiber-Break, and ‘2’ DL for Delamination. Therefore, the combined dataset should have all the signal waveforms, and a designated label value for each signal. By using windows of 100 μs, the essential damage features were captured for each type. This approach was chosen because whole waveforms can have multiple events. The goal was to train a deep learning model to recognize damages based on the pure waveform of each respective damage type.

Initially, the zero-padding method was tried after taking the signals for three types of damages with their original predicted length, i.e., 30 μs for fiber break, 65 μs for presumable matrix crack, and 100 μs for delamination. As the 1D CNN algorithm only performs on equal sequence length, zeros were added at the end of the shorter waveforms to make all of them equal-sized. However, it was discovered that the algorithm mistakenly treats zero padding as a feature during training, resulting in unintended high accuracy. Consequently, that model cannot predict any signals without the same size or zero padding. Hence, the same duration was accounted for waveforms for all three types of damage to maintain equal sequence length. Therefore, the final sequence length of the data table was 2271. This method adds electronic noise data in fiber break and matrix crack in portions of signals after the event has ended. However, the algorithms discussed in the next section could remove the unwanted noises and capture the most important characteristic features.

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The architecture of the deep learning models

In this paper, a hybrid model of 1D convolution neural network (CNN) and long-short term memory (LSTM)- was explored for predicting AE signal data with 100% accuracy through extensive hyperparameter tuning. The study aimed to investigate the key mechanisms of the algorithm that most significantly affected the classification of these types of signals. It was desired to find out the optimum model that effectively removed the noise and could extract the significant feature from the signals in the classification task. Figure 3 shows the models that were studied, compared, and optimized for this research.

Figure 3(a) presents the first CNN-LSTM model-1, which included two CNN layers with 8 and 16 filters having kernel size three and stride size one, respectively. Two max-pooling layers [16] with pool size 4 and strides 4 after each CNN layer. It is to be noted that the stride refers to the steps taken by each operation. There is one LSTM layer with 4 LSTM unit cells and two dense or fully connected layers with 10 and 16-unit cells. There is finally the dense output layer for the required number of classes which is 3. The number of epochs was 100 and batch size was 16. Rectified linear unit or Relu activation function handles the negative signal values in a following way,

ReLU (x)=ReLU (0, x),

Which means ReLU changes all negative values into zero and keeps the positive values the same. ReLU is extensively effective for handling these types of signal data. Therefore, ReLU was used for regularization of the dataset in all the models.

The next approach CNN-LSTM model-2 in Figure 3(b) comprised two CNN layers with 32 and 64 filters, respectively, while each filter having a kernel size of three with a stride of one. The kernels are randomly initialized weights with which the amplitude (V) data are multiplied. With a stride of one, the sums of the dot product of three consecutive amplitude values and the kernel weights are calculated to provide the output of each CNN layer. A max pooling layer with a pooling size of 10 was applied to the output of each CNN layer. With a default stride of 10, the max-pooling layer creates a new output by selecting the maximum value out of a set of 10 consecutive feature values from the output of each CNN layer.

After applying the max pooling to the second CNN layer, the output was flattened and reshaped into a compatible shape for the LSTM layers. Two LSTM layers were used with 32- and 16-unit cells, respectively. The output of the second LSTM layer is fed into a fully connected layer with 16 units, and then to the output layer with 3 units. 100 epochs were needed to get optimized accuracy and loss. Batch size was 16.

As the max-pooling operation in this approach was taking one maximum value out of ten features, the third approach CNN-LSTM model-3 was developed by layering up seven 1D convolution layers with one max-pooling layer of value 2 after each CNN layer to make the algorithm pick one maximum value out of two features at one layer. Thus, the possibility of losing any important feature was minimized. After seven 1D CNN layers, the model has three LSTM layers with 20, 15, 10-unit cells. At the output level, the model has a dense layer with a value of 3 for three classes. Figure 3(c) shows the details of the model architecture. The optimum epoch number was found to be 90 and the batch size was 64.

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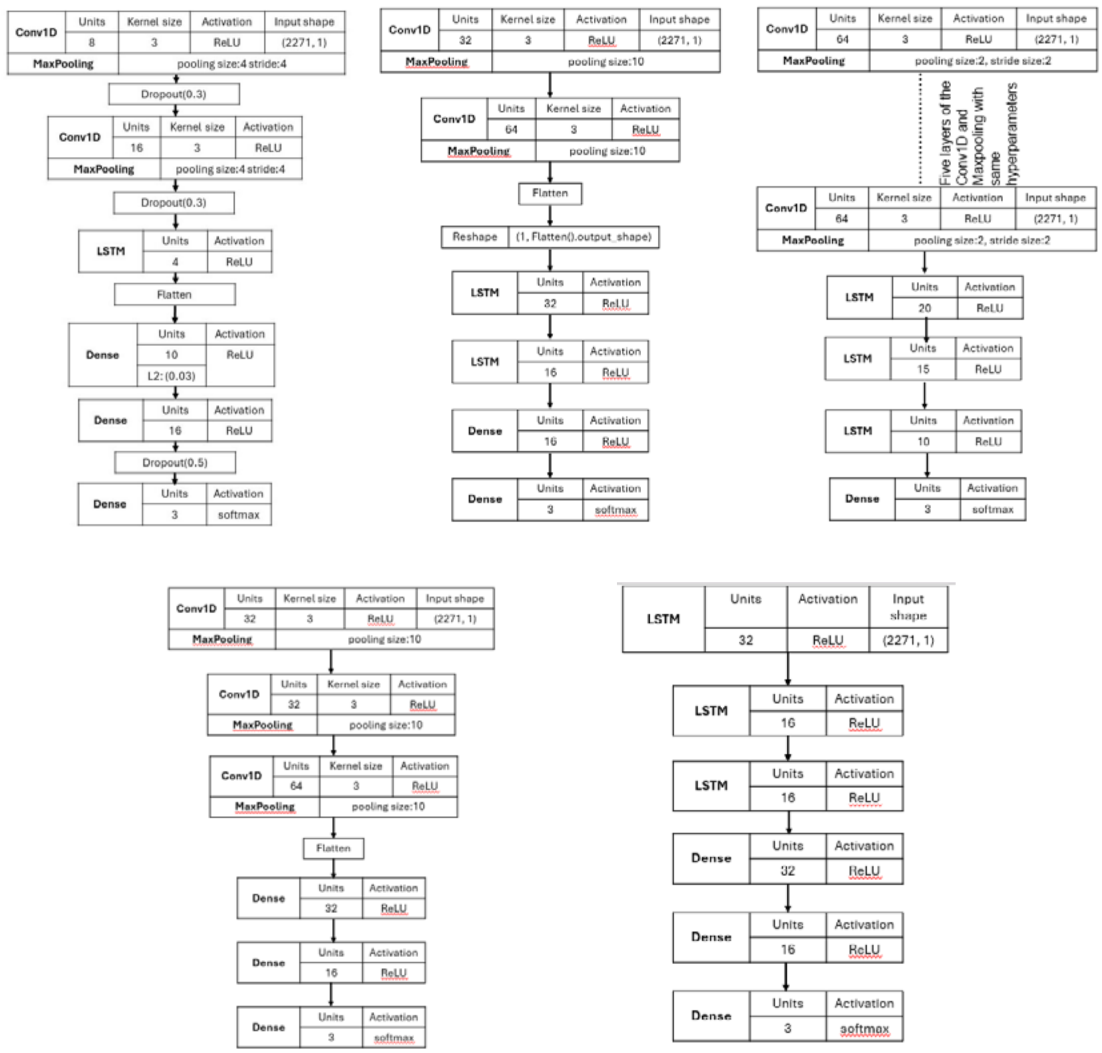

Figure 3. Architecture of the models (a) CNN-LSTM model-1 (b) CNN-LSTM model-2 (c) CNNLSTM model-3 (d) CNN model (e) LSTM model

Figure 3(d) and Figure 3(e) show one CNN model and one LSTM model, respectively. The results of hybrid models with the pure CNN and LSTM models were compared to see if the hybrid models offered any advantages in the classification task. The CNN model contained three 1D convolution layers with 32, 32 and 64 filters, respectively. After each convolution layer, one max pooling layer with a pool size of 10 was used. Then two dense layers with 32 and 16 neurons were included before the final output layers.

Figure 3(e) presents the LSTM model that comprised three layers with unit cells 32, 16, and 16 correspondingly and two fully connected layers with 32 and 16 neurons. The loss function of sparse categorical cross entropy', and 'Adam' optimizer with a default learning rate of 0.001 were used for all the models. Although for CNN-LSTM model-3, the learning rate 0.01 produced the equivalent result too. Learning rate 0.01 can expedite the computation

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time for this model. The initial values were randomly introduced. For labeling the data, either 'one hot encoding, or 'one label encoding' can be used. A total of 222 waveforms with a sequence length of 2271 were used as the dataset. The dataset was split into 80% training data and 20% test data. During the training procedure, 20% of the individual batch size was used to validate the model. Once each model was trained, the algorithm provided the accuracy and loss curve to show the overfitting and underfitting issues, which are provided in the result section. To get further information about the model, a whole new signal dataset with a different number of sample data points was fed to the different trained model to predict. The predictions were examined to check if they were classified accurately. The confusion matrix comparing the number of the actual class of the signal and the predicted class of the signals is included in Table 1 for individual models as well.

In the result and discussion part, the confusion matrix as well as the results for precision, recall, F1 score, and supports are discussed to show the best-found model. It is to be noted that the new dataset was prepared from the same experiment to keep all other conditions the same.

Result and Discussion

The plots of the loss and accuracy curve for the architectures are shown in Table I. The test loss, accuracy, epoch number and batch number have been enlisted as well. Table II shows the precision, recall, F1 score and support data for each trained model. The values of the indicators for different models are discussed below.

The CNN-LSTM model-1 produced 93.33% accuracy. The test loss is expected to be close to or little higher than the training loss and in an accuracy plot, the test loss is expected to be close or a little lower than the training plot. Throughout the experiment, the CNN-LSTM model-1 consistently exhibited a lower train loss curve and a higher test accuracy. This indicates the complexity of the model. A complicated model often cannot obtain the generalized pattern of the dataset.

From the confusion matrix for this model, it is evident that this model is not the best at predicting matrix-crack and often mixes it up with delamination. The model predicted 95% fiber break correctly and 5% as matrix crack. It predicted 92% delamination correctly but made a mistake about almost 8% and predicted as matrix crack. It predicted almost 17% data of all the matrixcrack signal data as delamination. As stated previously, one reason for this could be the model being complicated. Another reason can be that the matrix crack generated AE signals need to be further studied because those signals can be a combination of different damages with higher modes. Table II shows that the support data for this model was 45 in total. The number of different damage signals was almost uniform. The new data could be wrongly identified too. Besides that, Table II includes the precision, recall and F1 score of the model. They are significant indicators of a model. MC, FB and DL denote matrix-crack, fiber-break and delamination respectively in Table II. Recall value ensures identifying positive case, whereas precision values confirm the accuracy of the positive prediction. F1 scores balance these two indicators. These three indicators are 1 for fiber break for the CNN-LSTM model-1. Therefore, this model is best at predicting fiber-break.

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The CNN-LSTM model- 2 produced 98.7% accuracy. The loss and accuracy plots show sufficient convergence and closeness of the test and train/validation loss and accuracy, which implies the model correctness. Surprisingly, this model predicted all the matrix-crack and delamination with 100% correctness but predicted 7% fiber-break as delamination, which is very unlikely due to the difference in these two types of signals in amplitude, frequency, duration. The most probable reason behind this can be incorrect labeling of new data. As was shown in Table II, the support data for this model was 39 in total. More research is needed to prove the fact. Another probable reason can be the higher max pooling value, which forces the algorithm to choose maximum feature data out of 10 subsequent values. This may throw some important features of the signals. The precision, recall and F1 score from Table II were the highest, i.e. 1, for matrix crack.

The CNN-LSTM model-3 closely resembles the CNN-LSTM model-2. The accuracy is 97.77%. The loss is slightly higher in model-3 (0.2282) than model-2 (0.0372). The max-pooling operation in the later model was noticeably slow, distinguishing it from the earlier version. After being multiplied by a set of randomly initiated weightages of the CNN filters, the algorithm would pick the maximum feature value out of two at each CNN layer. The loss and accuracy plots show that although the test and training loss and accuracy are close, the convergence was not enough. Further study is needed on the epoch number. This model was tested on 198 new signal data as per the support value from Table II. The model predicted only 5% incorrectly, which could be because of incorrect labeling of the new data. The precision is 100%, recall and F1 scores are 96% and 98% respectively, which refers to the reliability of the model. Further study to observe the type of damage those were predicted incorrectly in that 5% needs to be explored.

The fourth model, Model-4, is composed of only 1D CNN layers and fully connected dense layers. The accuracy is 99% and the performance of this model is similar to the CNN-LSTM model-2. Nevertheless, the loss and accuracy plot show little overfitting and complexity of the model. The confusion matrix, hence, the precision, recall and F1 score are exactly the same as the CNNLSTM model-1. The Max pooling operation at after each two layers of CNN with value 10 units could be the governing factor for both models. This comparison proves that, in classifying different damage signals, CNN architecture is the most effective, whereas LSTM has little effect on the job. The fact is proven undoubtedly with the fifth case.

The fifth model, Model-5 from the Table-1, is built using only LSTM layers and fully connected dense layers. The accuracy and loss plot shows the model's inability to capture the features of the different signals effectively.

From the comparison, it can be conclusively stated that the 1D convolution neural network algorithm is quite strong in classifying the one-dimensional time-domain experimental dataset. On the other hand, the LSTM algorithm is not good at handling practical waveform datasets with noise, which is also supported by the literature described in the introduction. The max-pooling layer could be effective in slowly removing the noise after the filtering operation of a convolutional neural network. In the second, third and fourth approach, the max pooling layers were utilized to get better accuracy and loss curve.

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From the detailed discussion above, CNN-LSTM model-2 and 3 can be our candidate models. The precision, recall and F1 score ensure these models can predict the positive cases accurately, which is very crucial in damage detection.

Although the results from two CNN-LSTM algorithms (model 2 and model 3) are close, sometimes it's beneficial to let the model pick important features slowly like model 3. But if the dataset is huge, the latter can take longer time to train. In that case, depending on the sequence length, the Max-pooling layer can be increased or decreased. For higher sequence length, a combination of max-pool values 5 and

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Table I. Comparison between different models

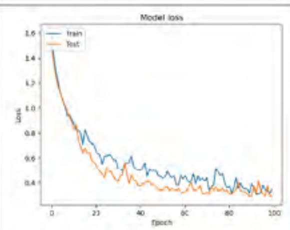
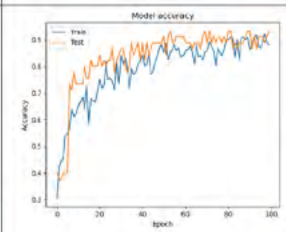
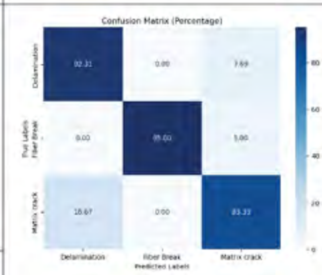
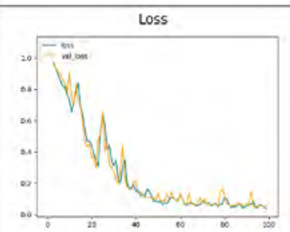
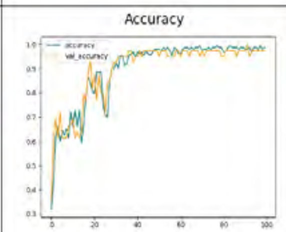
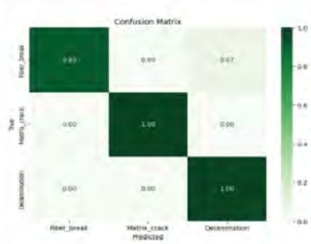
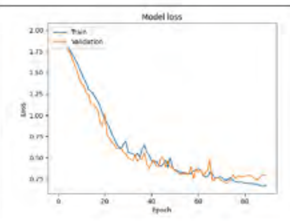
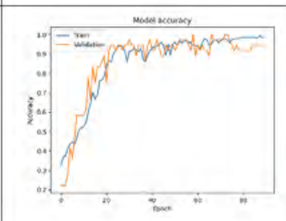
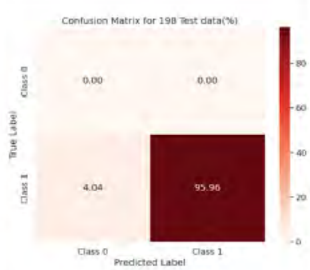
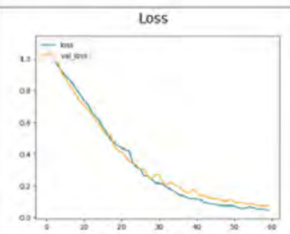
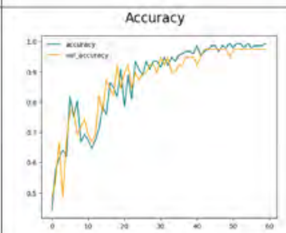
Model	Loss	Accuracy	Confusion matrix
Model-1 (CNN-LSTM) Epoch-100 Batch size-16	 0.2	 0.9333	
Model-2(CNN-LSTM) Epoch-100 Batch size-16	 0.0372	 0.9869	
Model-3(CNN-LSTM) Epoch-90 Batch size-64	 0.2283	 0.9777	
Model-4(CNN) Epoch-60 Batch size-32			

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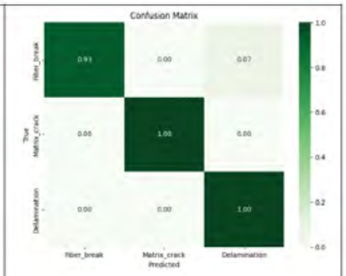
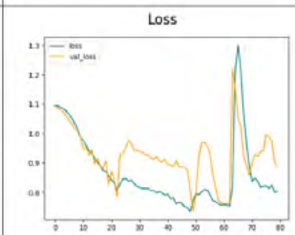
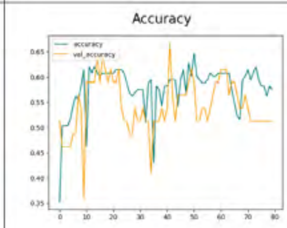
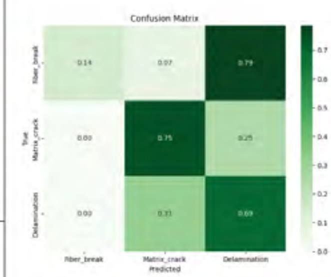
Table I. Comparison between different models... continued

	0.0424	0.99	
Model 5(LSTM) Epoch-80 Batch size-64	 0.8044	 0.5752	

2 can be used. It is important to choose a batch size that contains a sufficient variation of the dataset to get an accurate model. From the result for CNN model and LSTM model, it can be concluded that, to classify one dimensional waveform dataset with noises, one dimensional convolutional neural network with carefully chosen Max pooling unit values can be the effective algorithm.

Therefore, depending on data size and sequence length, a combination of model 2 and 3 can be used to get better accuracy. As the max pooling operation reduces the features to only the most important ones, at the end of the CNN layers, two to three LSTM layers with few unit cells can be added to memorize.

In addition, few approaches can confirm this conclusion and validate the robustness of the models. Testing the CNN-LSTM model-2 requires a dataset of comparable size to CNN-LSTM model-3. Careful preparation and identification of the new signal dataset are necessary to develop the confusion matrix. The epoch number of CNN-LSTM model-3 should be worked on more to get a better loss and accuracy plot. The 5% incorrectly predicted damage data needs to be correctly identified and checked to find out the reason to bolster the model architectures more.

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Table II. Comparison among the candidate models

Model	Precision		Recall		F1-score		Support
CNN-LSTM model 1	DL	0.86	DL	0.92	DL	0.89	13
	FB	1.0	FB	1.0	FB	1.0	20
	MC	0.91	MC	0.83	MC	0.87	12
CNN-LSTM model 2	FB	1.0	FB	0.93	FB	0.96	14
	MC	1.0	MC	1.0	MC	1.00	12
	DL	0.93	DL	1.0	DL	0.96	13
CNN-LSTM model 3	1.0		0.96		0.98		198
CNN model 4	FB	1	FB	0.93	FB	0.96	14
	MC	1	MC	1	MC	1.0	12
	DL	0.93	DL	1	DL	0.96	13

Summary and Next Steps

The models were successful in classifying the three failure modes with reliable accuracies. The 1D CNN model was outstanding in classifying the experimental one-dimensional time domain waveforms. The study presented two candidate hybrid models with CNN and LSTM architectures that achieved up to 98 percent accuracy, along with a decent accuracy and loss curve. The two models predicted with higher precision and recall value up to 100%. Moreover, the study revealed that the classification of experimental time series waveform data by the LSTM algorithm is less efficient. Comparison between different models implied that max-pooling can effectively reduce noise. There are a lot of other scopes to strengthen the models and fill up the holes in the procedure to make them classify signals with 100% accuracy including but not limited to, checking the label of the prediction data carefully and identifying them properly, testing them with the same augmented dataset, working with the epoch numbers and above all making a better training dataset with higher sample data point of correctly identified waveforms.

As people are still trying to characterize the damage in thermoplastic materials, efforts must be made to identify them correctly using acoustic emission at first. Extensive signal analyzing is needed to characterize the type of damage and explore the concept of localizing the damage from the signal analysis. Characterizing them properly could help to build an authentic dataset for the classification and even localization of the damage. To get the best accuracy, the number of sample points in the dataset should be increased. Further effort should be extended to build a huge dataset both for training and prediction. Deep learning algorithms are strong enough to capture any kind of feature individuality. Depending on the strength of the dataset, it is even possible to build a fully automated damage detecting device with the help of deep learning models.

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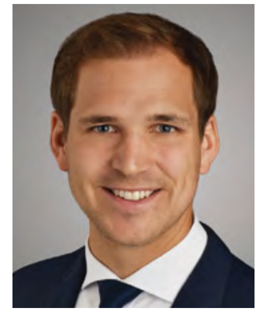

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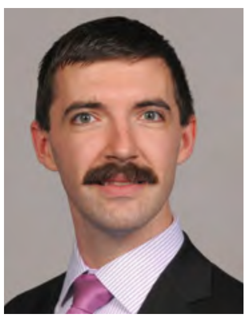

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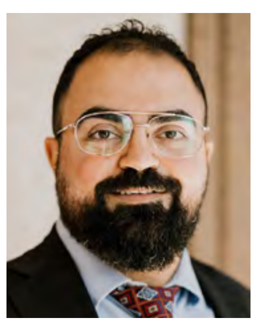

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