Predicting Whole Helmet Blunt Impact Performance from Isolated Pad Testing Using Machine Learning

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Abstract. Helmet blunt impact performance evaluation has traditionally relied on whole helmet impact testing. Assessing the performance of helmet pads using this process can be costly, given the destructive nature of the tests and need to consume helmet shells. Additionally, the presence of the helmet shell introduces added complexity and variations, masking differences in pad performance. To overcome these limitations, this study employed machine learning (ML) to establish the intrinsic link between helmet pad properties, from isolated pad impact testing, and their performance in the helmet. This novel approach to rapidly estimate helmet performance eliminates the need for extensive helmet testing or computational analysis. The proposed methodology, combining isolated pad testing and ML prediction, significantly reduces the time and effort required for pad evaluation. This approach enables the efficient screening of helmet pads, promoting accelerated innovation in pad development and facilitating faster, more efficient testing and evaluation processes for helmets. High-rate material property and structural impact response tests were conducted on commercial off-the-shelf helmet pads. Finite element models of whole helmet and individual pad tests were constructed and validated using experimental data. Parametric simulations generated synthetic training data for the ML model, which predicted headform acceleration from isolated pad testing metrics. The approach was applied to 4 combat helmets (ACH and ECH, size large and medium) at 3 temperatures (hot, ambient and cold) and 3 impact velocities (10, 14 and 17 ft/s). Results showed that a gradient boost tree ML model accurately predicted headform acceleration using maximum acceleration, compressed thickness, and impact velocity from isolated pad testing. Validation studies confirmed that predicted accelerations were less than <15g of measured values across all conditions and helmets. However, the study's findings are limited to the specific helmets and pads investigated, and different models may be required for other helmet types and pad designs.

1. INTRODUCTION

Combat helmets rely on both a rigid outer shell and a suspension system to absorb impact forces and protect the head from direct trauma [1, 2, 3]. The current method for evaluating US Advanced Combat Helmets (ACH) and Enhanced Combat Helmets (ECH) performance involves whole-helmet impact testing using a drop tower setup [1, 4, 5], which assesses the effectiveness of helmet pads by measuring headform acceleration under controlled impact conditions. Specifically, this testing ensures that head accelerations remain below 150 g after two consecutive impacts at seven designated locations (crown, front, rear, left/right side, left/right nape) and under three temperature conditions (hot, ambient, cold) at an impact velocity of 10 ft/s [1, 4, 5].

Although effective, whole-helmet testing is both costly and time-consuming. The need to sacrifice helmet shells and complete pad systems limits the rapid development of innovative pad designs. Additionally, testing the helmet and pads together introduces variability and uncertainties, such as pad positioning, chin strap tightness, and helmet shell properties, which can obscure the intrinsic effects of pad material modifications. The increasing demand for enhanced protection requiring performance at higher impact velocities (14.1 ft/s and 17.3 ft/s) while maintaining the same acceleration threshold [2, 3] further underscores the need for a more efficient and cost-effective approach to evaluating new pad designs.

Since headform acceleration for a specific helmet in whole-helmet testing for pad-based liner systems is primarily dictated by pad properties as other conditions remained constant, it is possible to predict helmet performance based on pad behavior. A machine learning (ML) model can establish the relationship between input and outcome in complex impact events [6, 7], offering an efficient predictive framework for evaluating pad designs. However, obtaining both pad impact data and whole-helmet acceleration data through experimental methods alone is prohibitively expensive and time-consuming, making the experimental approach impractical.

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Finite element models (FEMs) provide powerful virtual representations of physical testing setups [2, 8, 9], enabling systematic variation of pad properties to generate synthetic data for ML model training. However, FEMs are computationally demanding and require specialized expertise, limiting their accessibility for rapid evaluations. To address these challenges, a fast-running ML model can be trained on synthetic FEM-generated data to correlate pad response to whole-helmet acceleration, offering near-instant predictive capabilities.

Consequently, the Johns Hopkins University Applied Physics Laboratory (APL), in collaboration with U.S. Army Aberdeen Test Center (ATC) conducted the current study to develop a cost-effective ML-driven screening method. This approach aims to identify underperforming pads before committing to full system-level helmet drop tower testing, thereby accelerating development cycles and reducing costs.

2. METHODS

To develop a fast-turnaround helmet pad assessment approach, the Team Wendy Zorbium Action Pad™ 7-Pad NSN Liner System was selected as the baseline. The material properties of these pads were characterized for finite element modeling (FEM). Additionally, a standalone pad testing system was developed at the U.S. Army Aberdeen Test Center (ATC) to evaluate individual pad impact responses under conditions similar to whole-helmet tests. Whole-helmet impact data was obtained from prior testing.

Finite element models of both pad and helmet testing were developed at APL for large and medium-sized ACH and ECH. The pad properties in these FEMs were systematically varied to generate synthetic paired data correlating pad impact response and helmet accelerations. Machine learning (ML) models were then trained using this paired dataset and validated against experimental pad and helmet testing data. Results from large ACH were used to demonstrate the development process.

2.1 Material property testing of Team Wendy pads

The rate-dependent material properties of the Team Wendy pads were characterized by compressing crown, trapezoid, and oblong pads between two rigid platens using Instron machines (Figure 1, left) at four different compression velocities (0.002, 0.02, 0.2, and 2 m/s) under hot (54±3.0°C), ambient (20±5.6°C), and cold (-10±3.0°C) temperature conditions. Force-compression data was converted into engineering stress-strain curves (Figure 1, right) by dividing the pad nominal cross-sectional area and initial thickness, assuming homogeneity and disregarding the multilayer construction of the pads.

To validate the material response, FEMs of the pad compression tests were developed. Pads were meshed with hexahedral elements and modeled using the Fu-Chang foam material model [10], incorporating rate-dependent stress-strain curves obtained from experiments for each temperature condition. The compression plates were modeled as rigid bodies, with the bottom plate fixed and the top plate constrained to allow only vertical motion, simulating the experimental compression test conditions. A friction coefficient of 0.5 was applied at the plate-pad interface in the pad compression FEM to represent interaction between the steel plate and pad fabric. Sensitivity studies with lower and higher coefficients showed negligible effect on the simulated force-deflection responses.. These validated pad models were consistently applied across all FEMs used in the study.

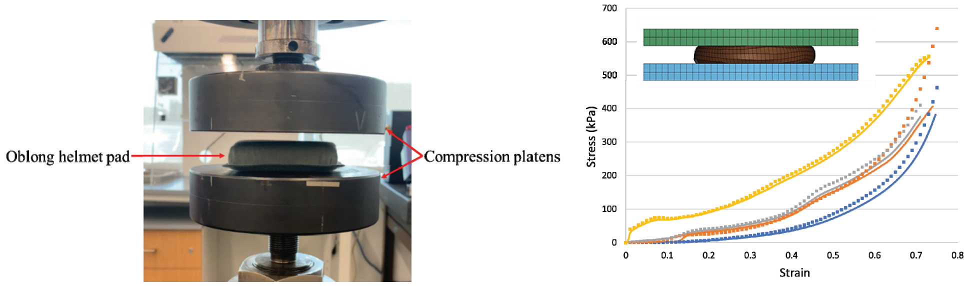


Figure 1. Pad material property testing setup (left) and comparison of experimental engineering stress-strain curve (right, symbols) with verified FEM response (right, solid lines)

2.2 Stand-alone pad impact testing setup, FEM development, and validation

The impact response of individual Team Wendy pads was evaluated using a custom-designed standalone pad drop tower test fixture at ATC as shown in Figure 2. This setup replicates pad impact conditions in whole-helmet testing, utilizing a monorail-guided concave drop mass and a rigid convex bottom anvil. Pads were attached to the inside of the drop mass, and two consecutive impacts were conducted within a one-minute interval. Tests were performed at 10 ft/s under hot, ambient, and cold conditions, with three pads tested per condition. Impact accelerations were recorded using PCB353B18 accelerometers (PCB Piezotronic, Depew NY, USA), while a Keyence G157 (Keyence Corportation of America, Itasca, IL, USA) laser measured the distance between the drop mass and anvil. Acceleration time history and displacement data were used for FEM and ML model validation.

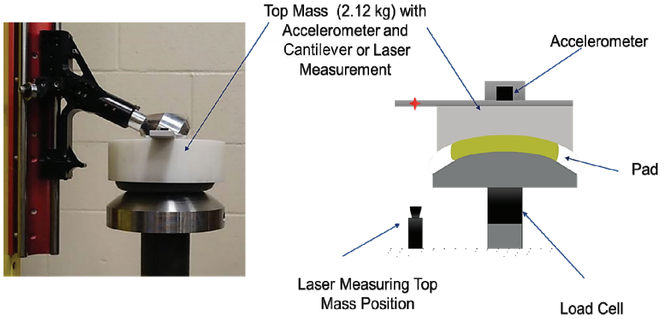


Figure 2. Standalone pad drop tower test fixture (left) and schematics of the test setup (right)

The FEM of the pad test setup was constructed using CAD geometries of the physical fixture (Figure 3 left). The test assembly was auto-meshed with tetrahedral elements and treated as a rigid body. Care was taken to ensure the total mass of drop mass and each component to match exactly to experimental setup. The same pad models from the pad compression tests were incorporated, with pads settled and positioned to conform with bottom face of the concave drop mass. The FEM was constrained to allow only vertical motion of the drop mass while keeping the anvil fixed, ensuring consistency with the experimental setup.

Impact simulations were conducted using LS-DYNA (R9.1.0 11398, Ansys, Inc. Canonsburg, PA, USA) by assigning an initial velocity of 10 ft/s to the drop mass and pad, along with a constant 1 g acceleration to simulate gravity. The nodal acceleration history at the center of the drop mass corresponding to the physical pad test was extracted and filtered at CFC1000 for comparison with experimental results (Figure 3 right).

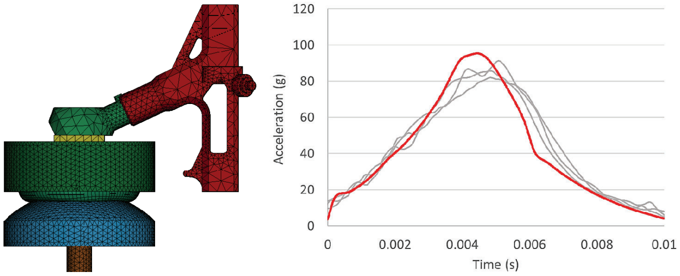
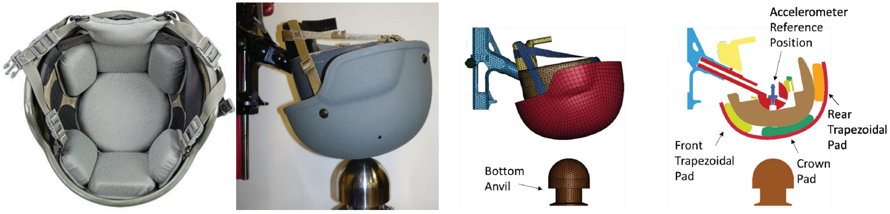


Figure 3. Standalone pad drop tower test FEM (left) and comparison of acceleration time history from experimental testing (right, gray) with FEM (right, red)

2.3 Whole helmet testing, FEM development, and validation

Whole-helmet test data were obtained from prior helmet impact tests conducted at ATC and the Combat Capabilities Development Command Soldier Center (Soldier Center). The combat helmet test protocol, originally described by McEntire and Whitley, was adapted from the Federal Motor Vehicle Safety Standard (FMVSS) 218 for motorcycle helmets [1, 4, 5]. A Team Wendy 7 pads system was installed in the layout dictated by the test protocol as shown in Figure 4a. Testing involved securing the helmet to a Department of Transportation (DOT) headform mounted on a uniaxial monorail drop tower (Figure 4b) and releasing the assembly from a height that resulted in an impact velocity of 10.0 ft/s. A laser gate positioned near the bottom of the monorail measured the drop mass velocity immediately before impact. Prior to each test, the headform was rotated to one of seven orientations to evaluate impacts at different helmet locations: crown, front, rear, left side, left nape, right side, and right nape. Figure 4b illustrates a crown impact test, where the apex of the helmet makes contact with the hemispherical steel anvil at the base of the drop tower. A uniaxial accelerometer was used to measure headform acceleration during impact.

The finite element model (FEM) for whole-helmet testing was developed using a methodology similar to the pad test FEM. The drop tower, DOT headform, chin strap support, and impact anvil were meshed with tetrahedral elements derived from CAD geometries and modeled as rigid bodies (Figure 4c). The helmet shell (for both large and medium ACH and ECH helmets) was meshed using fully hexahedral elements. The same pad models from the pad testing FEM were incorporated, with pads positioned according to test protocol [4]. To ensure proper pad positioning, settling simulations were conducted to allow the pads to conform to the helmet shell inner surface and headform outer surface, as shown in Figure 4d. Settling simulations were performed by first aligning the undeformed pads to their CT-derived locations. A distributed load was then applied to the inner pad surfaces to press them against the helmet shell, replicating experimental conditions. The resulting nodal positions were saved for subsequent simulations. The helmet-headform assembly was then rotated around the ball joint to model impacts at other locations, following the experimental procedure (Figure 5). Due to the symmetry of the helmet FEMs, left-side and left-nape impacts were not explicitly simulated, as they would yield identical results to their right-side counterparts.



(a) (b) (c) (d)

Figure 4. Team Wendy 7 pads layout (a) Monorail whole helmet test setup (b) whole helmet FEM overview (c) and mid-plane cross-section showing settled pads (d)

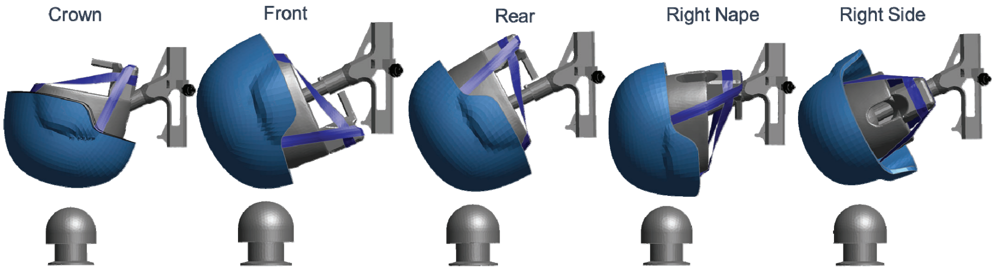


Figure 5. FEM of whole helmet testing setup for 5 impact locations

Impact simulations were conducted using LS-DYNA by assigning initial velocities of 10, 14, and 17 ft/s to the headform and helmet assembly. Acceleration histories (Figure 6 top) and peak accelerations (Figure 6 bottom) from the FEMs were extracted and compared to experimental results to validate the helmet FEMs.

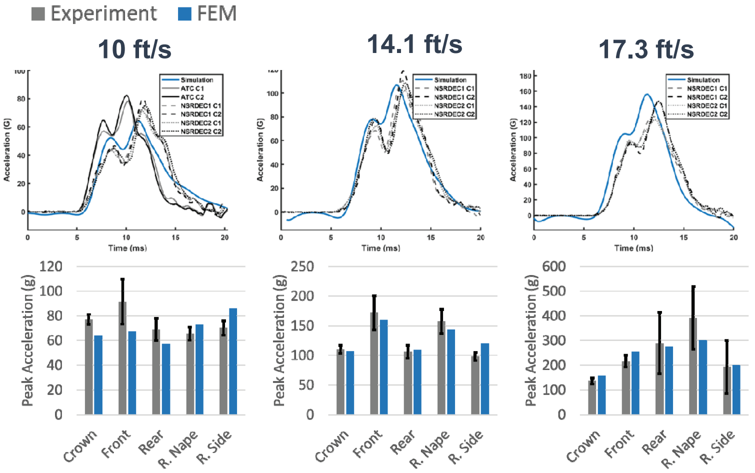


Figure 6. FEM of whole helmet testing setup for 5 impact locations

2.4 Parametric FEM simulation to generate synthetic data for ML training

In principle, a transfer function exists between pad impact responses and the corresponding headform acceleration observed in helmet testing. Machine learning (ML) can be used to establish this transfer function, provided that sufficient data is available from helmet pads with varying material properties. However, obtaining such a dataset experimentally would be prohibitively expensive and time-consuming, making it impractical. To address this challenge, synthetic data can be generated at a reasonable cost using finite element models (FEMs) for both pad impact testing and helmet testing, with systematic variation of pad material properties. Pad density and the ordinate and abscissa of the stress-strain curves were scaled to create helmet pads with varying stiffness. A design of experiments (DOE) approach using Latin Hypercube Sampling (LHS) was implemented to explore the parameter space [11]. The design variables included, pad density, varied from 50 to 500 kg/m³ [12]; Stress-strain curve scaling factors: Ordinate and abscissa scaling factor ranged from 0.1 to 5, with 1 representing no scaling. A total of 50 unique pad property combinations were generated, and simulations were conducted using LS-DYNA at three impact velocities (10, 14, and 17 ft/s) for all three pad shapes and across five helmet impact locations.

2.5 ML model development and validation

Fast-running machine learning (ML) models were developed and optimized using the synthetic dataset generated from the paired pad and helmet impact FEMs, where pad material properties were systematically varied. Several variables with potential predictive power for helmet acceleration were evaluated, including: Maximum pad compression (percentage and absolute thickness); Maximum compressed thickness; Maximum internal energy; Maximum acceleration; Impact velocity; Time to peak acceleration. These variables were used as input features for ML models developed in Python 3 using the scikit-learn library [13], with the goal of predicting helmet acceleration from pad impact characteristics.

To evaluate model performance, a leave-one-out (LOO) cross-validation approach (Figure 7) was employed. In this method, the ML model was trained on the entire paired dataset, excluding one data point. The trained model was then used to predict the helmet acceleration for the omitted data point. The difference between the predicted and FEM values was recorded as the prediction error. This process was repeated for all data points in the dataset to compute the total prediction error. The inclusion or exclusion of a predictor variable was determined based on whether it significantly reduced the total prediction error in the LOO process. Similarly, selection of a better ML model was also based on minimizing the total prediction error. The final selected and training ML model based on the whole dataset along with the predictor variables were validated using experimental test data from pad impact and whole-helmet testing experiments.

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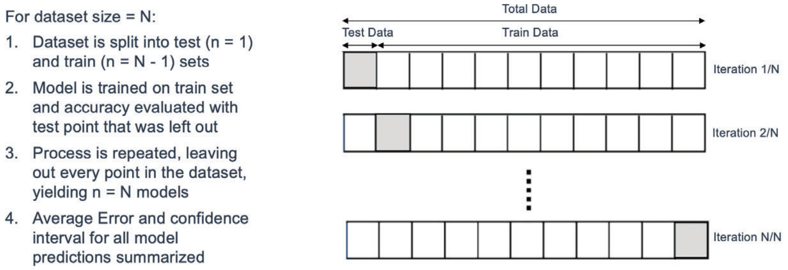

For dataset size = N:

1. Dataset is split into test (n = 1) and train (n = N - 1) sets
2. Model is trained on train set and accuracy evaluated with test point that was left out
3. Process is repeated, leaving out every point in the dataset, yielding n = N models
4. Average Error and confidence interval for all model predictions summarized

Figure 7. Illustration of leaving one out (LOO) cross-validation approach

3. RESULTS

Accelerations vs. pad compression from crown pad simulation and absorbed energy vs. helmet acceleration for ACH large is shown in Figure 8 below. The LHS design of experiments (DOE) generated a total of 50 cases, exploring a three-parameter design space with ordinate and abscissa scaling factors ranging from 0.1 to 5 and pad density varying from 50 to 500 kg/m³. Paired simulations of pad and helmet impact tests were conducted for three pad shapes and five impact locations at impact velocities of 10, 14, and 17 ft/s. This resulted in a total of 450 pad impact simulations; 750 helmet impact simulations per helmet type for each of the 4 helmets.

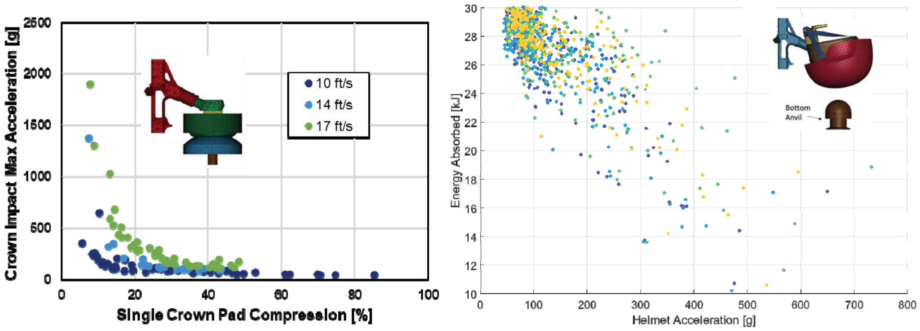

Figure 8. Illustration of DoE FEM generated synthetic data from standalone pad testing crown pad model and ACH large whole helmet impact

A total of 11 machine learning (ML) models from Python 3 scikit-learn were evaluated using the leave-one-out (LOO) cross-validation approach. The analysis identified maximum acceleration (A_{max}), maximum compressed thickness (C_{max}), and impact velocity (V) as the most effective input predictors for ML models. For the ACH large helmet, the Gradient Boosted Tree ML model demonstrated the best predictive performance for most impact locations, except for the front impact location, where the K-Nearest Neighbors (KNN) model was found to be the most accurate. Table 1 summarizes the selected ML models for each impact location, along with their root mean square error (RMSE), relative percentage error, and 95% prediction confidence interval.

Table 1. Final selected ML model and model performance for ACH large helmet

Impact Loc.	Model Type	Predictor Vars.	RMSE (g)	Error (%)	CI 95% (g)
Crown	GBT	A_{max}, C_{max}, V	4.38	5%	2.47
Side	GBT	A_{max}, C_{max}, V	7.66	8%	4.72
Rear	GBT	A_{max}, C_{max}, V	8.92	11%	7.51
Front	KNN	A_{max}, C_{max}, V	6.17	6%	5.24
Nape	GBT	A_{max}, C_{max}, V	7.41	8%	6.87

Figure 9 compares ML predictions with finite element model (FEM) acceleration outputs and experimental helmet testing results. The ML-predicted helmet accelerations for each impact location

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under hot, ambient, and cold conditions, using experimental pad test data, closely matched the experimental helmet testing data.

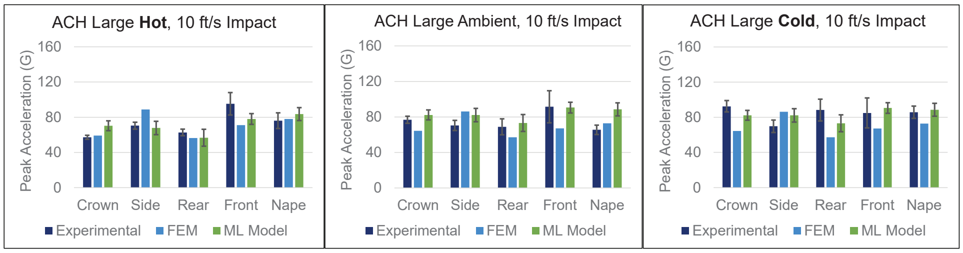

Figure 9. Comparison of experimental, FEM and ML model predicted peak accelerations in whole helmet testing at crown, side, rear, front and nape impacts

4. DISSCUSSION

This study developed a finite element modeling (FEM) and machine learning (ML)-based approach to enable cost-effective evaluation of helmet pad performance in large and medium-sized ACH and ECH helmets without the need for extensive, expensive whole-helmet testing.

The Team Wendy pad system was selected as the baseline due to its widespread use in ACH and ECH helmets in a 7-pad configuration, consisting of crown, trapezoidal, and oblong pads. These pads are polyurethane-based multilayer structures, composed of a comfort layer, an energy absorption layer, a moisture barrier, and an outer fabric cover. To simplify the FEM, the pads were treated as homogeneous materials, as their overall compression behavior predominantly dictates helmet response and the layered deformation mechanics of the pads were not a focus of this study. The strong agreement between experimental stress-strain curves and FEM predictions across all compression velocities confirmed that this approach effectively captured the pads' overall impact compression response.

A custom-designed standalone pad impact test setup was developed to replicate impact compression conditions similar to whole-helmet testing. The test setup used the same accelerometers and data processing methods as the helmet tests to ensure consistency. The drop mass (2.12 kg) was carefully selected to achieve at least 75% compression of the pad, ensuring activation of the energy absorption layer. Similar to helmet testing, each pad underwent two consecutive impacts within one minute to assess pad recovery. Higher acceleration and pad compression were typically observed in the second impact like the whole helmet tests.

The FEM of the pad test setup was developed using CAD-based geometries, ensuring an exact replication of the test fixture. Similarly, whole-helmet FEMs were constructed following the same methodology. These virtual models were used to generate paired pad impact and helmet acceleration data, eliminating the need for costly experimental testing. Since the test fixture and headform are significantly stiffer than the helmet pads, they were treated as rigid materials in the FEMs. The helmets were modeled as elastic materials, based on the observation that ACH and ECH helmets generally withstand 10 ft/s impacts without significant deformation. However, permanent deformation can be observed at higher impact velocities (14 and 17 ft/s). Since this study primarily focused on pad-induced acceleration changes, it was justified to model the helmet shell as elastic without considering its post-yield behavior.

As shown in Figure 3 and Figure 6, the FEM predictions for both pad and helmet testing closely matched experimental results in both waveform shape and amplitude, confirming the validity of these models as accurate virtual test replicates. The helmet acceleration predictions from FEMs fell within or closely matched experimental averages and variations for impact velocities up to 17 ft/s.

The validated FEMs were used to generate paired pad response and helmet acceleration data, mitigating the prohibitive costs of experimental data collection. The Team Wendy pad stress-strain curves and pad density were systematically scaled to generate softer and stiffer pads. The scaling factors ranged from 0.1 to 5, and density varied between 50 and 500 kg/m^3, covering a wide range of material properties. The LHS approach ensured thorough exploration of the design space while limiting the number of required simulations. The resulting helmet acceleration values ranged from ~50 to 750 g, providing an adequate dataset that included both accelerations below the 150 g acceptance threshold and those exceeding the limit, ensuring a balanced dataset for ML training.

A comprehensive evaluation of predictive input variables and ML models was conducted using the leave-one-out (LOO) cross-validation approach. ML models for each impact location were trained using data from all three pad types (crown, trapezoid, and oblong) as input features, with whole-helmet impact accelerations at the corresponding location as the output response. Although each impact site may have a dominant pad, neighboring pads also contribute to the response, and the ML model learns to weight each pad's contribution accordingly through training. The Gradient Boosted Tree (GBT) model was identified as the most accurate for most impact locations, achieving an average RMSE of less than 10 g and a relative prediction error of 5–11%. For frontal impacts, the K-Nearest Neighbors (KNN) model performed best, with an RMSE of 6 g and a 95% confidence interval of 5 g. To contextualize these results, a prediction error of 10 g represents only ~7% of the 150 g acceptance threshold, demonstrating that the ML model's predictive accuracy is well within acceptable limits.

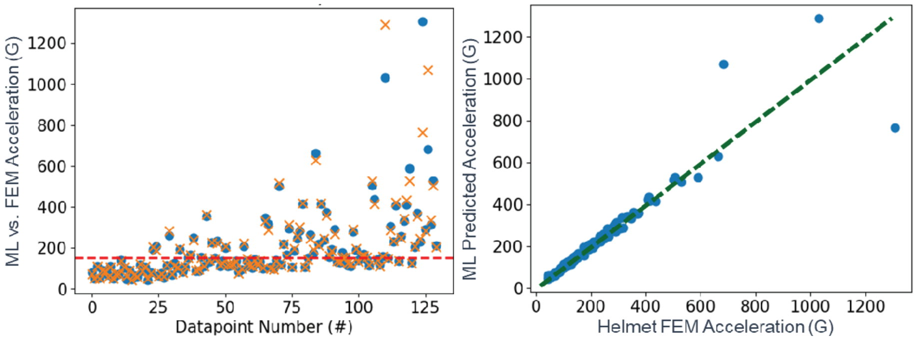

Figure 10. Overlay (left) and cross-plot (right) comparison of FEM and ML model predicted peak helmet accelerations for ACH

A comparison of ML-predicted helmet accelerations with FEM predictions is shown in Figure 10. In an ideal scenario, ML and FEM predictions should align perfectly, with data points overlapping in an overplot or lying on the x = y dashed line in a cross-plot. As observed in Figure 10, the ML models closely replicate FEM predictions, particularly for accelerations below 400 g. However, discrepancies emerge at higher acceleration levels (>600 g), where ML predictions tend to significantly deviate from FEM acceleration. This deviation likely results from nonlinear effects in the FEMs, particularly when the helmet pad bottoms out and acceleration spikes sharply. However, in these cases, both ML and FEM predict accelerations exceeding the 150 g acceptance threshold, meaning both methods would correctly identify the pad as failing, despite differences in absolute values. Accelerations exceeding 400 g were retained to ensure the ML model remained stable at extreme conditions and did not produce false pass predictions. Accuracy at these high acceleration levels was not prioritized, as they far exceed the 150 g pass/fail threshold.

The ML models were further validated using experimental data from standalone pad impact tests conducted at ATC. The maximum acceleration (A_{max}), maximum compressed thickness (C_{max}), and impact velocity (V) were extracted from pad impact test results and used as inputs to the ML models to predict helmet acceleration. As shown in Figure 9, despite differences in batch production and significant time gaps between the pad and helmet test data, the ML-predicted helmet accelerations closely matched experimental helmet test results or fell well within experimental variations. These results further confirm that the ML approach accurately predicts helmet acceleration based on pad response, highlighting the intrinsic link between the two testing methods.

To further simplify the process of predicting helmet acceleration from pad response, a graphical user interface (GUI)-based software tool was developed. As shown in Figure 11, the software allows users to specify test conditions and import pad impact test data via the "Simulation Inputs" section (top left); visually verify imported data via plotted graphs (bottom left); automatically compute key metrics (A_{max}, C_{max}) in the background; select a helmet type and size, then run simulations to instantly obtain predicted accelerations (displayed on the right); and export results for further analysis as needed.

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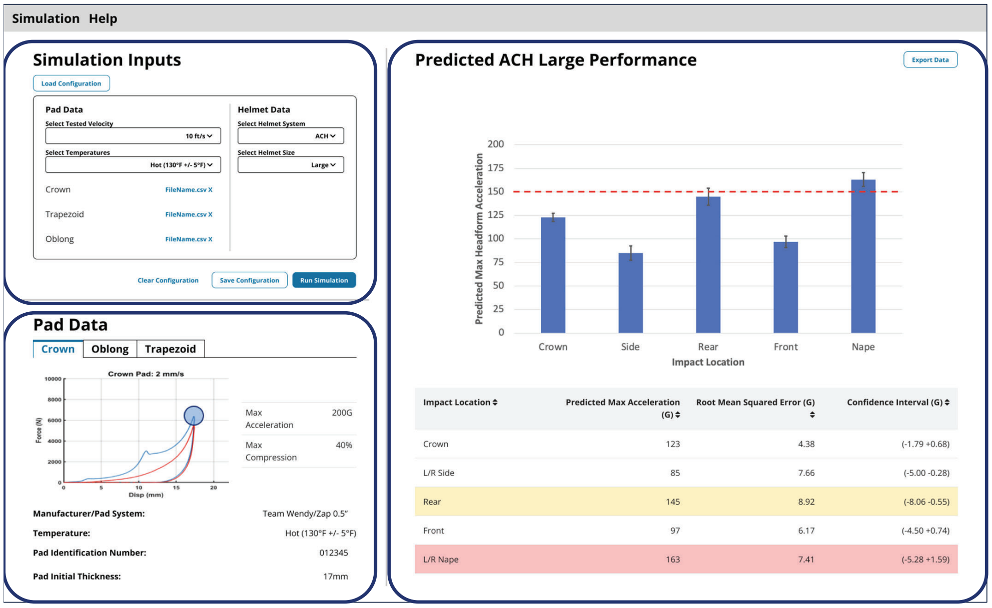

Simulation Inputs

Pad Data

Select Tested Velocity: 10 ft/s

Select Temperatures: Hot (130°F +/- 5°F)

Crown FileName.csv X

Trapezoid FileName.csv X

Oblong FileName.csv X

Helmet Data

Select Helmet System: ACH

Select Helmet Size: Large

Pad Data

Max Acceleration 200G

Max Compression 40%

Manufacturer/Pad System: Team Wendy/Zap 0.5″

Temperature: Hot (130°F +/- 5°F)

Pad Identification Number: 012345

Pad Initial Thickness: 17mm

Predicted ACH Large Performance

Impact Location ⬍	Predicted Max Acceleration (G) ⬍	Root Mean Squared Error (G) ⬍	Confidence Interval (G) ⬍
Crown	123	4.38	(-1.79 +0.68)
L/R Side	85	7.66	(-5.00 -0.28)
Rear	145	8.92	(-8.06 -0.55)
Front	97	6.17	(-4.50 +0.74)
L/R Nape	163	7.41	(-5.28 +1.59)

Figure 11. Pad to Helmet Performance Prediction Software

Limitation of the current study include the exclusive use of Team Wendy pads as the baseline pad system. Although scaling factors and density variations were explored to simulate a range of stiffness levels, all synthetically generated pads retained stress-strain characteristics similar to open-cell foam helmet pads (Figure 1). Other novel materials may exhibit significantly different stress-strain behaviors, potentially reducing ML model accuracy when apply to new material classes. Additionally, this study used Team Wendy ZAP pads in a 7-pad layout, following ACH/ECH testing standards. Since the ML models were trained on this specific configuration, changes in pad shape, size, or placement may alter the relative contributions of each pad to helmet acceleration, affecting ML prediction accuracy. Finally, the helmet itself significantly influences blunt impact protection. Different ML models were required for various helmet sizes and types, suggesting that future studies should expand ML model training to include non-standard pad materials and configurations, further enhancing the model's predictive capability and the software's applicability.

5. CONCLUSION AND FUTURE WORK

This study developed a cost-effective standalone pad testing system and a machine learning-based software tool to predict peak accelerations in helmet impact tests for medium and large-sized ACH and ECH helmets. Finite element models (FEMs) of both pad and helmet testing systems were generated and validated throughout the study. Machine learning (ML) models were trained using synthetic paired data, obtained by systematically varying pad stiffness within these validated FEMs.

Among the evaluated features, peak acceleration (A_{max}), maximum compressed pad thickness (C_{max}), and impact velocity (V) were identified as the most indicative predictors of helmet acceleration. The ML model predictions closely matched experimental helmet test results for ACH and ECH helmets, achieving a root mean square error (RMSE) of less than 10 g across all temperature conditions and impact locations at 10 ft/s. These results confirm the validity of using ML models to predict helmet acceleration responses based on standalone pad impact testing, eliminating the need for costly whole-helmet testing in early-stage evaluations. Limitations of this study is the exclusive use of Team Wendy pads as the baseline pad system. As discussed, since these pads are polyurethane-based open cell foam with specific size shape and pad layout dictated by the testing protocol [4], the ML prediction error will likely increase when applied to pads with significantly different mechanical behaviors, or different shape, size and layout. Additionally, the helmet shell plays a critical role in whole-helmet impact response. Specific ML models were developed for each size of ACH and ECH helmets, meaning that new models must be trained for other helmet types following the same correlation process between pad impact response and whole-helmet acceleration. These limitations can be addresses in future studies to further enhance the capability of the ML models.

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Overall, the instantaneous results provided by the ML models, based on low-cost standalone pad testing, offer a valuable tool for reducing the cost and material requirements of whole-helmet testing. This approach has the potential to significantly shorten the development cycle of next-generation helmet pad systems, accelerating innovation in impact protection technology and ultimately improving soldier safety and survivability.

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