A Probabilistic Uncertainty Quantification Approach to Finite Element Modeling in Human Rib Biomechanics

Vivek B. Kote, Lance L. Frazer, Avani Shukla, Ashley Bailly, Sydney Hicks, Derek Jones, Drew DiSerafino, Matthew Davis, Timothy Bentley, Barry Shender, James Sheehy, Daniel P. Nicolella

I. INTRODUCTION

The thorax is frequently injured in dynamic events, with rib fractures being the most common injury associated with a higher risk of fatality [1-4]. Therefore, understanding the mechanisms of these injuries and predicting the risk of rib fracture in dynamic events would be valuable in assessing overall injury severity. Traditionally, anthropometric test devices (ATDs) have been used to study the risk of injury in traumatic events. ATDs primarily compare gross measures like load or deformation in a specific body area against macro-level injury criteria. However, this approach overlooks the tissue-level mechanics associated with the injury mechanism, which could offer further insight into the causation of an injury. These limitations can be addressed by using in-silico techniques like finite element (FE) models, which offer detailed tissue-level responses during a dynamic event. Typically, biomechanical FE models represent population-level representative anthropometry (e.g. the 50th percentile male or similar average anthropometry) and use material properties corresponding to averages from experimental data. As such, model results may not be applicable to diverse populations [5-7] and do not account for the uncertainty and variability contained within and between population groups. This study aims to address this gap by implementing a probabilistic modeling approach to assess rib anterior posterior (A-P) dynamic loading. This probabilistic approach accounts for the anthropometric anatomic variability using a statistical shape model (SSM), and the inherent variability observed experimentally in rib bone tissue material properties. The predictive performance of this modeling approach is then quantified by comparing the experimental and computational corridors using the normalised area metric between the two cumulative distribution functions (CDFs) at discrete points [8]. Finally, a global sensitivity analysis is performed to quantify how the uncertainty and variability in each of the independent variables in the study contributes to the overall uncertainty and variability in the model response [9].

II. METHODS

Computational Modeling

A baseline FE model of the 6th rib was created in LS-DYNA to represent the experimental anterior-posterior (A-P) rib bending setup from Agnew, *et al*. and Kang, *et al*. [10-11]. Since uncertainty in the trabecular property has little effect on the force-displacement response in A-P loading, only uncertainty in the cortical bone properties was modeled [12]. The material properties were implemented as independent random variables and included the cortical bone elastic modulus, density, yield stress, strain rate parameters, shell thickness, and failure strain. Using a previously established framework, a statistical shape model (SSM) of the rib was generated using quantitative computed tomography (QCT) scans from 17 male cadavers [13]. The SSM was built using the minimum number of principal components (PCs) needed to explain 95% of the observed shape variability. In total, 10 independent random variables were used. The probabilistic analysis and subsequent determination of probabilistic sensitivity factors were conducted using a previously developed AI-based surrogate model [8]. To predict the probabilistic rib force-displacement response, the response surface was sampled 10,000 times using Latin Hypercube Sampling (LHS). This analysis accounts for variability in rib anatomy and uncertainty in rib bone tissue mechanical properties, enabling population-level analysis rather than focusing on a single average individual. Using this analysis, we also computed the main (isolated variable effect) and total (combined main and interaction effects) global probabilistic sensitivities for each variable. Error between the experimental rib response data and probabilistic rib model response was quantified using the normalised area between the two CDFs at discrete points in the force-displacement curve [14].

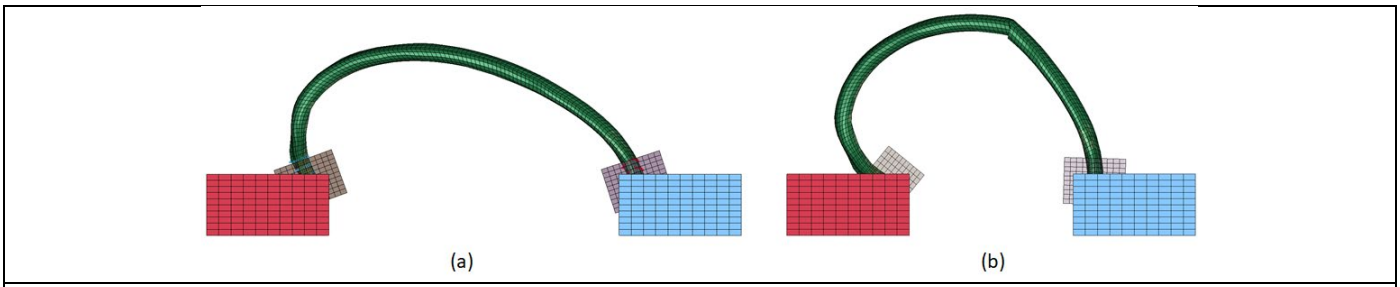

Fig. 1. Initial and final configurations of the rib A-P finite element model: (a) and (b) show the initial and the final configurations. The vertebral mounting fixture is shown in red, and the sternal fixture is shown in blue.

V. B. Kote (e-mail: vivek.kote@swri.org; tel: +12105222528), L. L. Frazer and D. P. Nicolella work at Southwest Research Institute in San Antonio, Texas, USA. A. Shukla is a student at Carnegie Mellon University, Pittsburgh, Pennsylvania, USA. A. Bailly is a student at Texas A & M, College Stations, Texas, USA. S. Hicks is a student at the University of Houston, Texas, USA. D. Jones, D. DiSerafino and M. Davis work at Elemance LLC, Winston-Salem, North Carolina, USA. T. Bentley works at the Office of Naval Research, Arlington, Virginia, USA. B. Shender works at Naval Air Warfare Center Aircraft Division, Patuxent River, Maryland. J. Sheehy works at the Naval Air Systems Command, Patuxent River, Maryland, USA.

III. INITIAL FINDINGS

A total of four rib shape PCs captured 95% of rib shape variability (Fig. 2). The probabilistic rib model response corridors showed excellent agreement with the experimental corridors (Fig. 3). From the probabilistic sensitivity analysis, the rib pre-fracture force-displacement response was most affected by elastic modulus, followed by shape and cortical shell thickness. Variability in rib anatomy explains almost 20% of the rib force-displacement variance. Similar results for main and total sensitivities showed that the interaction between the variables was not significant (Fig. 3).

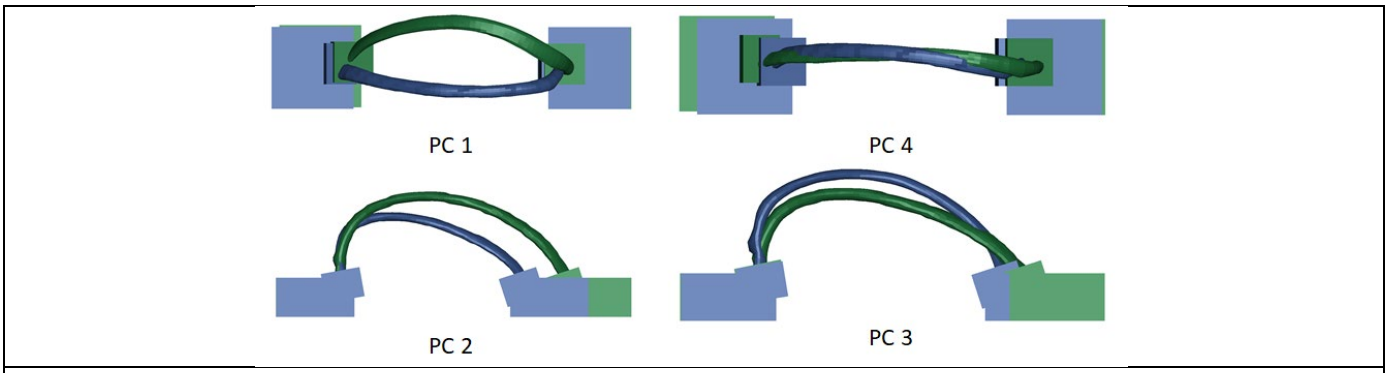

Fig. 2. Four principal components captured 95% of the variability in rib morphometry. Lower bound (blue) and upper bound (green) of each rib shape variable (PCs) are shown.

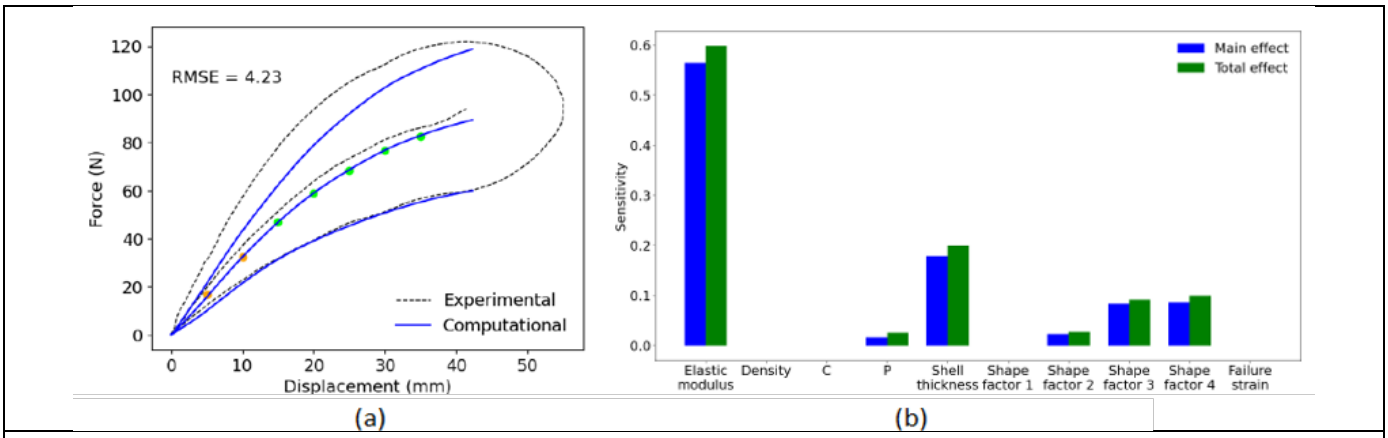

Fig. 3. Pre-fracture force-displacement response (a) and sensitivity analysis (b). Predictions for the mean force response had an overall RMSE of 4.23 N compared to the experimental mean. Normalised area metrics are shown in green (less than 15%) and orange (15–30%). Sensitivity analysis reveals elastic modulus, shell thickness and shape as the variables that explain most of the experimental variance.

IV. DISCUSSION

This study highlights the importance of using a probabilistic modeling approach to account for the inherent uncertainty and variability present in biomechanical systems. Results from deterministic average models regarding injury risk or safety may lead to overconservative or inefficient systems. In contrast, probabilistic modeling enables the estimation of injury risk across populations and sub-populations. Another highlight of this study is the use of a surrogate model for rapid examination of a response over a diverse population. This more efficiently enables a global sensitivity analysis to quantify the importance of the uncertainty and variability contained within independent variables on the model predictions and allows researchers to identify which model parameters may require additional experimental data (to reduce the uncertainty) or which components of a system are most critical to injury (relevant when, for example, designing new seats for safety).

V. ACKNOWLEDGEMENTS

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VI. REFERENCES

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