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Probabilistic Response Of A Validated And Verified Parametric Cervical Spine Finite Element Model

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ABSTRACT

Biological systems are often modeled using computational methods such as finite element modeling because of the complex nature of the system being analyzed. However, most computational analyses fail to account for the variability and uncertainty of the model inputs and boundary conditions, which leads to an inability to predict a probability of injury in the given biological system. The goal of this study is to calculate the probabilistic response of a cervical spine finite element model by incorporating variability into the model inputs such as soft tissue properties and geometry. The geometry of the finite element model was created by using a set of geometry parameters that can be measured from Computed Tomography (CT) scans. The parameters were measured from CT scans of both male and female volunteers. Material properties for the soft tissues of the cervical spine were determined from literature and experimental data. Once the data was collected, random distributions were fit to both the geometry and material data. The software package NESSUS was used to calculate the probabilistic response of the cervical spine model. This methodology can be used to predict the probability of injury not only in the cervical spine but many other biological systems.

INTRODUCTION

Computational analysis methods such as the finite element method (FEM) are widely accepted in computational biomechanics as an important tool used in the prediction and analysis of biological structures subjected to injurious loading conditions. These methods are ideally suited to simulate the behavior of complex biological structures that often include complicated geometry, non-linear material behavior, and time dependent phenomenon. Predicting the probability of injury is a major goal of computational biomechanics. However, the actual probability of injury is not computed per se; only quantities such as the stresses and strains in the hard or soft tissues are computed and compared to a measure of the bone or tissue strength in order to estimate the risk of injury. A major limitation of the application of computational methods in injury research is their inability to account for variability and uncertainty in important system

parameters such as loading, material properties, and anatomy and the effect of this variability on the computed model response. Thus, the usefulness of conventional FEA is severely limited in predicting actual probabilities of injury.

Biological systems have a large amount of variations in both material properties and geometries and incorporation of measures of this variability and uncertainty is required in a numerical analysis in order to compute a probability of injury (Thacker et al., 2006). Our goal is to capture the probabilistic response of the cervical spine by incorporating distributions and standard deviations for both the tissue material properties and the geometry as shown in the schematic in Figure 1.

The geometry of the cervical spine finite element model was built using a discrete set of geometric parameters that can be measured from Computed Tomography (CT) scans. These parameters were measured from CT scans of 100 volunteers, 50 males and 50 females. The material properties of the soft tissues of the cervical spine were determined from both the literature and experimental data. Random variable distributions were fit to the geometric and material data. The probabilistic response of the cervical spine model was determined using the probabilistic software package NESSUS® to run the simulations and calculate the responses given the statistical properties for the model variables. The resulting probabilistic spine model gives us the ability to determine the probability of a particular response that would result in injury. By having the ability to predict the probability of injury, the model has many applications in the field of biomechanics.

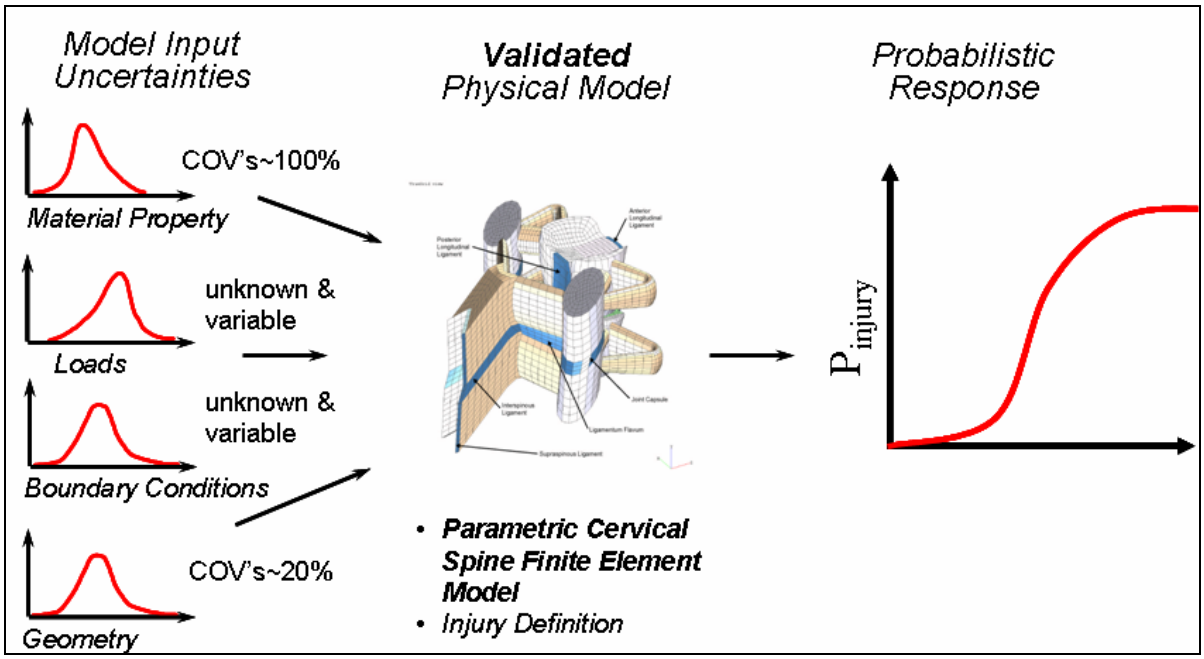

Figure 1: Schematic showing the process of propagating model input variability into a finite element model to determine a probabilistic response.

METHODS

A verified and validated parametric finite element (FE) model of the C5/C6 motion segment was used to determine the probabilistic response. The FE model was created by using the Truegrid® preprocessing software to build a mesh based on a set of geometry parameters that define the surface geometry of each vertebra. A total of 35 geometry parameters define each vertebral level.

The mesh consists of a combination of brick, shell and spring elements. Boundary conditions were applied such that they recreated the constraints of the experiments being modeled. For this analysis, the FEM of the C5/C6 motion segment was subjected to a 2 N-m moment in both flexion and extension. During the quasi-static loading, the degree of rotation of the C5 vertebra with respect to the C6 vertebra was recorded.

During the validation and verification process, deterministic values were used for both the geometry and material properties of the FE model of the C5/C6 motion segment. For the probabilistic analysis those deterministic values were used as mean values and a lognormal distribution was assumed for each variable. As shown in Table 1, all variables except for the cross section areas of the anterior longitudinal ligament (A.L.L.) and the posterior longitudinal ligaments (P.L.L.) were assumed to have a coefficient of variation (C.O.V.) of 10%.

Table 1. Random variable inputs to the probabilistic FE model.

	Mean	StDev	C.O.V.
Bulk Modulus A.L.L. (psi)	3000000	300000	10.0%
Bulk Modulus P.L.L. (psi)	4200000	420000	10.0%
I.S.L. Stiffness (N/mm)	0.125	0.0125	10.0%
L.F. Stiffness (N/mm)	0.25	0.025	10.0%
J.C. Stiffness (N/mm)	0.089	0.0089	10.0%
Bulk Modulus Annulus (psi)	2783000	278300	10.0%
Cross Section A.L.L. (mm^2)	12.4853	0.8551	6.8%
Cross Section P.L.L. (mm^2)	15.0556	0.995	6.6%

With both material properties and geometry random variables defined, the NESSUS® probabilistic engineering analysis software was used to perform the probabilistic analysis. The problem is set up in NESSUS® so that both the geometry and the material properties are considered random (Figure 2). NESSUS® will first perturb the geometry by running the TrueGrid® software to build the mesh and then that mesh is used in the LS-Dyna model where the material properties are perturbed. For this analysis, a Mean Value (MV) response using forward difference was used to look at the probabilistic response of the C5/C6 motion segment. With the two geometry variables and the six material property variables, NESSUS® initiated a total of 9 finite element runs.

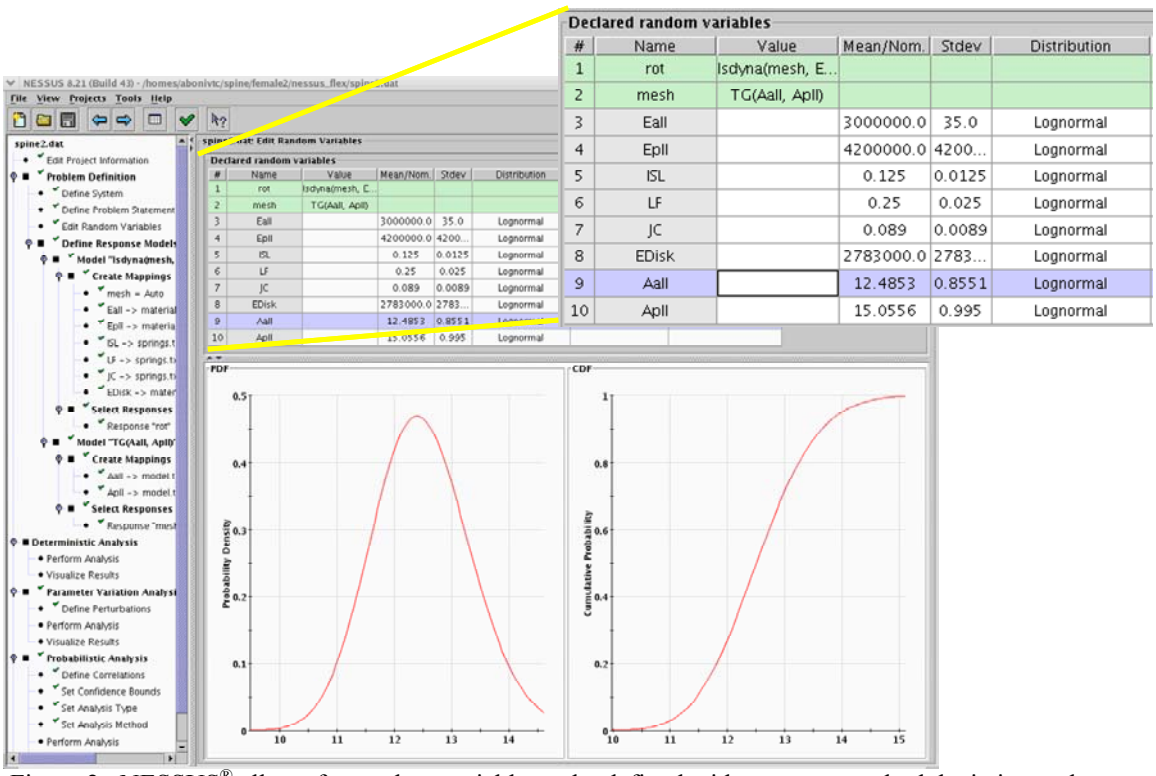

Figure 2: NESSUS® allows for random variables to be defined with a mean, standard deviation and distribution type.

RESULTS

The results of the forward difference mean value analysis were compared to experimental results obtained by Wheeldon et al. (2006). Figure 3 shows the experimental results with one standard deviation corridors along with the probabilistic response of the FEM. The results show that even when assuming a relatively small C.O.V. of 10%, there can be large variations in the response, particularly in flexion.

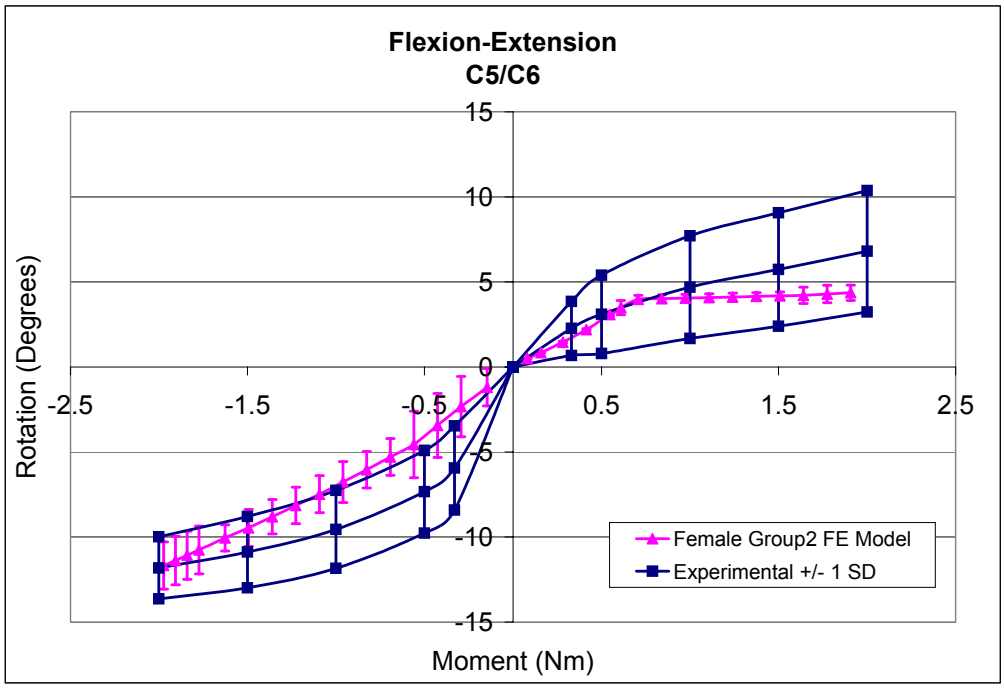

Figure 3: Probabilistic response of a C5/C6 motion segment in flexion and extension shown with C5/C6 experimental data +/- 1 SD.

The NESSUS® software also has the capability to return importance values for the random variables at each point in the loading curve. Figure 4 shows how the importance values of the variables change throughout the range of motion. When the applied moment is low, the disk modulus has low importance but at higher moments the importance is increased. This added information can help focus the researcher's efforts towards variables that most influence the response.

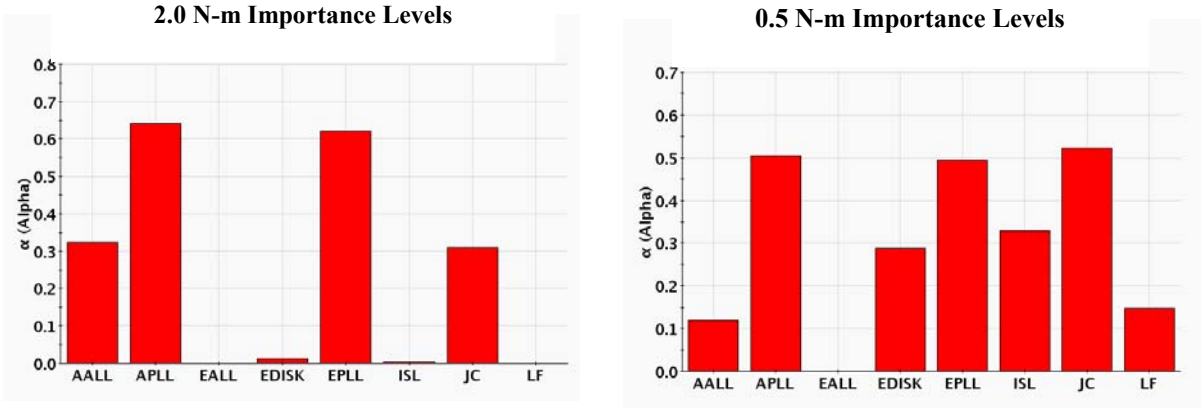

Figure 4: Importance levels for flexion at 0.5 N-m (right) and at 2.0 N-m (left).

CONCLUSIONS

A probabilistic finite element model of the C5/C6 motion segment has been created and run in order to determine a probabilistic response for flexion and extension. The results of the probabilistic analysis were compared to experimental data and show that variability in both geometry and material properties needs to be accounted for when using a numerical model to make predictions of biological responses.

ACKNOWLEDGEMENTS

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DISCUSSION

PAPER: **Probabilistic Response of a Validated and Verified Parametric Cervical Spine Finite Element Model**

PRESENTER: ***Warren L. Francis, Southwest Research Institute, Medical College of Wisconsin, GADAB Engineering***

QUESTION: *Richard Kent, University of Virginia*
This was a nice presentation and I agree that this is the right way to approach this sort of issue. So, the implicit motivation behind this probabilistic type of modeling is to match a population distribution or something like that, right? So the genius here goes into the details. It's difficult on a couple of levels. So I have two questions: one goes to sort of the issue of nonlinearity, which biological things are, in particular, materials. So in other words, the distribution of the coefficients in, say, a QLB model do not give you the distribution of the output of that model. You know what I mean? You can't just take a mean and standard deviation of a nonlinear set of coefficients. That will affect the curve in very strange ways. It wouldn't necessarily give you the distribution of curves that you would get. So, there's a nonlinearity that's associated with a lot of biological tissues. So, a) how do you deal with that? b) There are additional constraints, I think, that maybe you didn't discuss but maybe you have it in there. So for example, you wouldn't have someone with a very small ALL and a big, huge PLL.

ANSWER: Right.

Q: But if you just have probability distributions, you have an equal probability picking teeny and huge as you do of picking teeny and teeny.

A: Right.

Q: Whereas teeny and teeny probably happens in the world and teeny and huge doesn't.

A: Right.

Q: And so, there are constraints between those things. And so, how do you incorporate those realistic constraints so that you get something on a system level that's actually physically realizable?

A: Well, let me answer the second question first and that's—First of all, in the software, you can set up correlations. You can define correlations between variables so that, exactly that doesn't happen. Second of all for that same question, we're doing statistical analysis, especially on the geometric parameters. We're doing correlation analysis because again, there's no reason to say he's got a huge vertebral body, but a, you know, really small, you know, lamina or something. So, those are all constraints that'd be fed into it to help narrow down those sorts of errors.
Now the first question was about the determining the distribution of material properties for, like, viscoelastic material or something like that. Right? Well, I think right now the best we can do is take experimental data on that, like Amber said, on that Level 1 where we just have an isolated ligament and that's all you have and just take as much experimental data as you can using optimization routines with the material—

Q: So maybe that's my point is: So that you get a whole bunch of experimental data and you fit a model to it.

A: Right.

Q: That has some set of coefficients. The distribution of those coefficients doesn't give you the distribution of the model because it's nonlinear. And so, you know, the two coefficients both affect the outcome.

A: Yeah. That's a good point.

Q: And so, just getting the probabilities of the two coefficients give you a curve that may not match anything. It just has to do with—So, that's sort of a detail that—You know, some people use, like, stochastic linearization techniques to constrain some of the variables and then only allow one to vary--

A: Right.

Q: Stochastically or something like that.

A: Yeah, yeah. I understand.

Q: *Guy Nusholtz, Daimler Chrysler*
Just a sort of a quick, simple question: How long does it take to run these models? When I've done stochastic processes, it's almost invariably requires a parallel processor because you're running, you know, 400 or 500—

A: Right.

Q: Processes at once to get the thing out there.

A: Well, it depends on the methods you use.

Q: Several hundred hours.

A: If you're using standard Monte Carlo, which, of course, is the default, which is the best of course, yeah. That's the case. You need thousands of runs. But if you use a more advanced method, which some of the people we work with specialize in, thank God, it takes a lot fewer runs. That's why there are those advanced mean plus iterations. There's tons of methods that are built into this software because the problem's really difficult and the response surface is really complicated, and it takes those advanced methods to focus in on a solution. And for this particular model, it only takes a couple of hours to run. So you know, it depends on—For a mean value analysis, you're just doing the number of variables plus one so that's real simple. But when you move to the more advanced techniques, even with the really good techniques, you can go into a few days of run time for a simple model.

Q: Sort of following up on what Richard said: How do you deal with the correlations between different variables?

A: Yeah. In a sense, there's—you can define correlations in between variables.

Q: Yes. Defining the thing, but how do you formulate it? How do you get the data to define those correlations?

A: Well like I said, we've taken all this experimental data and handed it to our statistician to define all the correlations for us. We haven't, as yet, taken, like the gentleman said earlier, the areas and defined the correlations explicitly yet; but of course, we'll get that.

Q: But if you're going to do it like on your Level 1 where you're just pulling the ligaments, you've got separated—You've got independent—You don't have the relationship when you do this and something else happens. So—I mean, there's a piece of information, which there's a question of how do you get that, not necessarily how do you incorporate it into the model. Okay. I mean, you can get all sorts of things to a statistician and you don't know what you're gonna get.

A: Right.

Q: Okay. Thank you.

Q: *Erik Takhounts, NHTSA*
I think I want to congratulate you. I think it's very interesting research and you're definitely on the right track, and I believe myself that probabilistic methods and model development are the future of model development. I'm not sure about the particular implementation of your probabilistic data. For example, your objective function one time you showed, that's the way I understood, is moment versus angle characteristic. That's what you wanted your certain Level 1 validation sort of technique to fit. Once again going back to my experience: Once I do that, suppose I come up with parameters that best fits this moment/angle curve and then I do a tension test on the same systems that are really optimized for that, and it totally blows me off.

A: Well, what was presented there and what was presented in Amber's: Once we get to the motion segment level, the only time we're fitting data is on the ligaments individually and the disk with the vertebral

bodies attached all posterior elements removed. Once we fit our material characteristics to that, and once we move up to the motion segment level, we take our hands off it and it kind of is what it is.

Q: Have you actually tried to do that: take your hands off?

A: Yeah, that's the results that she presented. That's why some of them aren't that great because if there are problems—Like for instance, she presented that in the rotation, we're really missing the boat on it. We're missing some stiffness, some real stiffening in the more extreme angles. So now we've requested—We have very little disk data right now and all of it's just tension depression. We don't have any torsional disk data, you know, so now we need more data to have a better disk model, just the disk. Refine the disk model, put it back in and try it again.

Q: I just think that my point is that the problem that you're describing is a lot more complex than I think I saw in this presentation, but that's a very good presentation. Thank you.

A: Thank you.