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A Stochastic Model of Trunk Muscle Coactivation During Trunk Bending

Gary A. Mirka, PhD, and William S. Marras, PhD

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Biomechanical models of the spine have traditionally assumed that workplace lifting conditions (weight, posture, motion, etc.) precisely dictate the magnitude of individual muscle forces necessary to maintain a biomechanical balance within the trunk. However, because there are a large number of muscle groups within the trunk there is also an infinite number of possible combinations of muscle forces that can satisfy this biomechanical balance requirement for a given condition. Currently there are no methods available to predict this possible variability in muscle activity. Such variability in a multiple muscle system can result in variations in spinal loading. To quantitatively capture this trunk muscle variability during bending motions, such as those involved in lifting, a stochastic (probabilistic) model of trunk muscle activation was developed. The model was based on a simulation of experimentally derived data and predicted the possible combinations of time-dependent trunk muscle coactivations that could be expected given a set of trunk bending conditions. These simulated muscle activities were then used as input to an electromyographically assisted biomechanical model so that the magnitude and variability of the spine reaction forces could be estimated. This procedure allows one to assess the range of spinal loads that would be expected with a particular task. Significant variability in muscle activities was observed for each specific lifting condition and explained biomechanically. The results indicated that the variability in trunk muscle force had a small effect on spinal compression variability (±7% of the mean compression), but greatly influenced both lateral (±90% of mean) and anteroposterior shear forces (±40% of mean). A validation study confirmed that the model predictions were reasonable estimates of muscle activity variability under previously untested conditions. This work could help explain how some repetitive lifting motions could increase the risk of acquiring a low back disorder and the simulation model could help drive electromyographically assisted models without the need for recording actual electromyographic activity. [Key words: trunk motion, lifting, ergonomics, modeling, electromyography]

From Biodynamics Laboratory, Department of Industrial and Systems Engineering, The Ohio State University, Columbus, Ohio. Dr. Mirka is currently affiliated with the Department of Industrial Engineering, North Carolina State University, Raleigh North Carolina.
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The incidence of occupation-related low back disorders has grown to epidemic proportions in the indus trialized world in terms of both incidence as well as cost.[2,3,8,20,27,75,76,79] Many have indicated that the risk of low back disorder is associated with occupational factors; specifically, manual materials handling or lifting. The National Institute for Occupational Safety and Health[58] investigated the relationship between low back disorders and occupational lifting factors and found 60% of low back disorder claims were associated with overexertion. Furthermore, an abundance of research has suggested a link between risk of injury during heavy work and the biomechanical stresses placed on the spine.[13,14,25,58]

Biomechanical models of the lumbar region have been developed in an effort to improve our understanding of how occupation-related low back disorders occur. Most models assume that external moments imposed about the spine are countered by the activity of the trunk musculature. Because of their mechanical disadvantage relative to external loads, the muscle forces are many times greater than the external loads and therefore become the primary loaders of the spine. The resultant vector created by the summation of these muscle forces must be resisted by the spine, resulting in compression, shear, and torsional forces. Hence, it is imperative to the understanding of spinal loading (both acute and cumulative) to accurately predict muscle behavior during the performance of occupational tasks.

During the last 20 years, the development of these models has gone through a gradual metamorphosis. Early formulations consisted of single equivalent muscle models of the trunk. Chaffin et al[13,14] predicted the muscle forces necessary to counteract a load held in the hands during a sagittally symmetric isometric exertion. Their approach was to develop a simple two-dimensional free body diagram using a single extensor muscle equivalent supplying the restorative moment necessary to counter the external load. They calculated spinal compression using simple mechanical principles. Similar approaches have also been used to predict spinal compression associated with a task.[58] These compression values are then compared to spinal loading tolerance limits to assess risk of low back disorder.[17,74] However, no validation studies have shown that these guidelines[58] have had a significant impact on the incidence of low back injury.

More recent research has evidenced that single equivalent extensor muscle models may be limited in their ability to assess risk of low back disorder because they are unable to accurately model shear and torsional forces that occur in the spine during complex lifting tasks. Epidemiologic evidence has shown that twisting and asymmetrical trunk motions involving shear and torsional spinal loading are related to increased risk of injury.[2,29,30,50,73] In vitro studies of spinal specimens have shown that spinal motion segments have lower capacity to withstand compression while simultaneously withstanding torsional or shearing loads.[23,61] Additionally, the stress–strain relationships of the lumbar tissues are significantly altered when shearing loads are used in combination with compressive loads[23] and when cyclic torsional loads are applied.[18,38] These findings suggest a need for multiple muscle system models that can more accurately evaluate more complex spinal loading that may occur during lifting.

Multiple muscle system models[5,26,28,31–33,43,48,52–54,59,62,64–66] have evolved in response to this need and include three-dimensional trunk mechanics employing multiple agonist and antagonist trunk muscles used to define three-dimensional spinal reaction forces. Generally, these models use more accurate anatomic data regarding the location, cross-sectional area, and line of action of the individual muscles. Thus, by increasing the accuracy of the modelled anatomy, the potential for understanding the more complex three-dimensional forces exerted on the spine was recognized.

However, these more complete analyses produce a situation in which the number of unknown muscle forces exceed the number of static equilibrium equations and results in a system of equations that are statically indeterminate. Several methods to overcome these problems have been tested. First, one solution was to simply assume some of the muscle forces were zero, thus making the system determinate.[64] The results of this approach did not generally conform to experimental observations.[26,39,40] Furthermore, these assumptions were found to be even less realistic when significant forces were introduced or a dynamic component was added.[45,46,67,81]

The second approach was to solve the problem of static indeterminacy through either linear or nonlinear optimization. Linear programming has been used most often.[1,4,5,15,64,66,69,70] Linear programming models minimize a stress in the body subject to the constraints that static equilibrium conditions must be maintained. Generally, solutions to linear programming formulations of biomechanical problems tend to oversimplify the system. That is, there are far fewer muscles active in the optimal solution that are active during actual lifting conditions. This points to a fundamental limitation of such models, which is that the number of nonzero values at the optimal solution can be at most equal to the number of constraint equations (excluding non-negativity constraints). Therefore, with only six constraint equations, the number of active muscles can be, at most, six.[42]

This limitation results in the inability of the linear programming models to predict antagonistic and synergistic muscle activity. During realistic lifting conditions, the biomechanical system is in a constant state of flux. Muscle groups activate and deactivate constantly to maintain constant control over the trunk mass throughout the path of motion. Validation of most optimization studies required subjects to achieve muscle steady state during an isometric exertion. During isometric steady state there is limited coactivation of the trunk muscles; thus, the predicted optimal solutions may correlate well with EMG data. However, the literature has shown that forces and low back disorder risk increase significantly under realistic dynamic motion lifting situations.[10,19,21,35,36,39,41,50-52] Under these dynamic load conditions there is a large amount of muscle coactivation and the predicted optimal solutions do not correlate well with recorded EMG data.[45,46]

The fundamental problem associated with omitting antagonism and synergism from biomechanical models of the trunk is that the spinal reaction forces are misrepresented. "Optimal" linear programming solutions of spinal reaction forces misrepresent shear and torsional spinal forces because all muscle forces in the multiple muscle system are not represented. Thus, linear optimization is unable to generate accurate predictions of actual spinal loads under typical complex loading conditions. In addition to these problems, linear optimization models accommodate neither the differences between individuals nor the differences in strategies taken within an individual. Schmidt[68] has shown that there is variability in the performance of the simplest of tasks. It has further been shown that physical factors such as fatigue may influence the degree of variability present.[60] Thus, another limitation of optimization is its inability to predict variability in the biomechanical system, specifically, muscle force variability.

The prediction of spinal load variability associated with work is extremely important in predicting occupation-related low back disorder risk. Both Herrin et al[25] as well as Marras and associates[50] have shown through biomechanical analyses of the workplace that risk of low back disorders was more a function of the peak, though often infrequent, loads imposed on the spine by the work. Thus, it is essential to document not only the average spinal loading associated with a task, but also the extreme spinal loading associated with the work.

A third means of overcoming the problem of static indeterminacy as well as a means to overcome the problem of individual variation has been to employ biologically-assisted models. These models use bioinstrumentation to directly estimate muscular force and thereby circumvent the problems associated with estimating "ideal" muscle forces. This approach is capable of addressing the variability issue because the individual's history of muscle activity is used to "drive" the models, thus accounting for the between-subject and within-subject variability.

The most widely used bioinstrumentation method for indirectly measuring muscular forces is electromyography (EMG).[9,37] Some of the more successful biologically-assisted models have used this EMG-force relationship in what are often called "EMG-assisted" biomechanical models. Two of the EMG-assisted models of the lumbar region include those of the McGill group[52–54] and those of the Marras group.[22,48,49,62] These models use EMG inputs from the various muscles of the trunk in the calculation of the spinal reaction forces. The fundamental principle of these EMG-assisted biomechanical models is that muscle tissue has a maximum capacity or "gain" factor that limits its ability to exert force as a function of its cross-sectional area. Early models[52,53] used this gain factor as an error term that was permitted to change between exertions. Later models[22,48] have preset this gain value so that the results were more physiologically correct. The normalized EMG is then used to mediate the amount of force exerted by the muscle. In addition, these models contain factors that modify the EMG signal based on the velocity of contraction and the location along the muscle's length–tension curve so that an accurate representation of the actual muscle force can be calculated. Then, using basic mechanical principles, estimates of the spinal reaction forces (compression and shear) can be found. Marras and Sommerich[49] have validated an EMG-assisted model by showing that the model was capable of accurately predicting the measured external trunk torque exerted by subjects during both isometric and isokinetic conditions. More recent studies have also been able to validate the model under isoinertial (constant acceleration) conditions.[22]

One of the benefits of using these EMG-assisted models compared to optimization is that the variability between subjects and between trials within a subject can be quantified because the results reflect data actually collected during an exertion. This permits investigation of the probabilistic (stochastic) behavior of the biomechanical system and the subsequent variations in trunk loading. Insights into the variability of the trunk loading can be gained by collecting EMG data over many repetitions of a task and using this data to predict variations in spinal loading via the model.

One of the major limitations of such models is that the recording of EMG signals under occupational conditions or even laboratory simulations of an occupational task is extremely time consuming and can be impractical for routine use. Thus, the usefulness of such models is severely limited for application to industry.

Several studies have attempted to predict trunk muscle activity during simulated lifting conditions. Such information could be used to as input to an EMG-assisted model. However, these attempts have not been able to successfully account for variability in muscle activity over tasks or trials. Marras and Mirka[46] used multiple regression techniques to try and predict the activity levels of the ten trunk muscles. These results showed that prediction of the extensor muscles was relatively good ($0.75 < R^2 < 0.92$) whereas prediction of the antagonist flexors was less accurate ($0.45 < R^2 < 0.62$). Another approach[59] was to develop neural networks that empirically model the relationship between the external moments that occur during lifting and the internal muscle forces required to perform the lift. The author reports R^2 values between 0.4 and 1 with majority of the values being greater than 0.9 but thus far this work has been limited to isometric exertions. However, using these methods, the resulting predictions of each model would be identical given the same input lifting parameters, indicating a deterministic model. Thus, these approaches are unable to predict the variable nature of the trunk muscle control system.

Therefore, a significant void exists in our knowledge of the trunk biomechanical system. There remains a need to predict continuous trunk muscle activities as well as the variation in muscle activities expected during occupational motions so that variations in spinal loading can be predicted for specific tasks.

Purpose of the Study

The goals of this research are threefold. First, record and model the critical features of muscle force variability present during trunk bending. Second, use this information to create an EMG generator (stochastic model) that generates EMG values suitable for input into an EMG-assisted biomechanical model. The output from this model will be a time history of EMG activity for each of the trunk muscles given specific trunk bending specifications (moment load, velocity, range of motion, etc.). Since the model will be probabilistic it will be capable of estimating trunk muscle activity variability with multiple runs of the model. The final objective of this study is to validate the EMG generator model.

■ Experimental Data Collection

To understand trunk muscle activity variability, it was necessary to collect information about muscle activities over many repetitions of specific motions. The subjects in this experiment were asked to perform highly controlled bending motions repeatedly. During the repeated performance of the experimental trunk bending motions the activities of the trunk muscles were continuously recorded using EMG.

Five male college students served as subjects in this portion of the study. None of the subjects had a history of low back disorder. Basic subject anthropometry is listed in Table 1. Each of these subjects had participated in similar studies in the past so each was somewhat familiar with the experimental protocol and the apparatus, thus limiting the learning artifact.

The bending motions examined in this study included isometric, isokinetic and isoinertial (constant acceleration) exertions. The levels of torque exerted by the subjects were set at 40 and 80 Nm. Two trunk positions were used in the isometric trials: 5 and 40° of forward flexion. In the isokinetic trials, the angular velocity of the lumbar spine was 20 deg/sec. The angular acceleration of the trunk during the isoinertial experiments was set at 40 deg/sec^2. Each of these combinations was repeated ten times for each subject, yielding 100 trials per subject. The order of presentation of the various combinations of the above independent variables was randomized.

The dependent variables were the normalized processed EMG values of the ten trunk muscles identified by the transverse cutting plane technique described by Schultz and Andersson.[64] These muscles included the right and left erector spinae, right and left latissimus dorsi, right and left rectus abdominis, right and left external obliques, and the right and left internal oblique muscles. The muscle sampling locations were as follows: 1) right erector spinae, left erector spinae—location of largest muscle mass (found by palpation, approximately 4 cm from midline of spine) at the level of L3; 2) right latissimus dorsi, left latissimus dorsi—most lateral portion of the muscle at the level of T9; 3) right rectus abdominus, left rectus abdominis—3 cm from the midline of the abdomen, 2 cm above the umbilicus; 4) right external obliques, left external obliques—10 cm from the midline of the abdomen and 4 cm above the ilium at an angle of 45° to the midline of the abdomen; and 5) right internal oblique, left internal oblique—4 cm above ilium in the lumbar triangle (dorsal side of trunk) at an angle of 45° to the midline of the spine. The inter-electrode distance for each pair was 3 cm.

Table 1. Basic Anthropometry of Subject Population

Dimension	Mean	Standard Deviation
Age	22.6 (years)	2.72 (years)
Height	185.7 (cm)	8.91 (cm)
Weight	765 (N)	85.1 (N)
Spine length (S1-C1)	59.1 (cm)	5.00 (cm)
Max strength (at 5°)	240 (Nm)	42 (Nm)

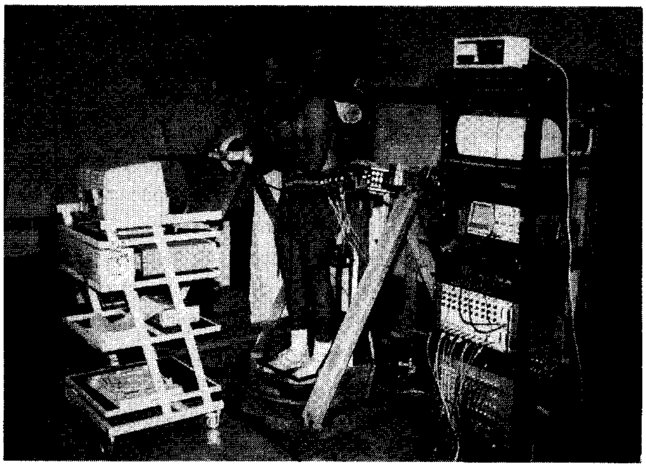

Figure 1. Experimental apparatus used to control the position, motion, and torque of each experimental trial.

The equipment used for this experiment consisted of a Kin/Com (Chatanooga Group, Inc., Hixson, TN) dynamometer, a trunk motion reference frame, an EMG data processing system and a data collection system. The dynamometer was connected to the reference frame to permit precise control of the angular trunk position, velocity, acceleration, and the external torque (about the L5/S1 joint) exerted by the subject (Figure 1).[46] It was necessary to precisely control and document trunk motions with this device so that the trunk muscle EMG activity could be adjusted as a function of muscle length and trunk motion characteristics in the EMG-assisted model.

The EMG signals collected by the electrodes were amplified 1000× by miniature preamplifiers located at the muscle site. The electrode leads to the preamplifiers were kept short to reduce the movement noise and the external electrical noise from the surrounding environment. The signal was amplified 52,000× and high and low pass filtered at 80 and 1000 Hz, respectively. This filtered signal was rectified and processed using a 20 msec moving average window. These processed EMG data along with torque, angle, and velocity (measured by the dynamometer) were collected at 100 Hz by the data collection system.

On arrival the subjects had surface electrodes applied to their skin through standard preparation procedures.[44] The subject was then asked to enter the reference frame so the adjustable base could be set for the subject's leg length to ensure that their L5/S1 joint was aligned with the rotating axis of the Kin/Com dynamometer. Once the subject was secured in the reference frame they performed maximum voluntary contractions at two positions (5° and 40° of sagittal bend). Both maximum static extensions and flexions were collected as well as the resting values in each of these postures.

After these maximal exertions, the experiment began with the subject performing completely randomized trials. Each of these trials dictated that the subjects perform a controlled exertion with very specific parameters (torque, position, or velocity or acceleration). During these trials the angular position, velocity and acceleration was controlled by the dynamometer. The exerted torque was controlled by the subject within a tolerance of 3 Nm using a video feedback system that displayed their instantaneous torque output as well as the torque designated for the particular trial.

The EMG data collected during the experiment were preprocessed by employing a Hanning smoothing function (band width of 17 and repeated 3 times). This process served as a low pass filter of 3 Hz for the integrated signal. This technique has been shown to minimize noise present in the EMG signal and enhances the EMG/muscle force relationship.[22] The EMG values associated with the data were normalized with respect to the maximum and resting EMG values that occurred at a particular trunk angle. Dynamic trials were normalized with respect to the interpolated maximum and resting values. This normalization was performed to eliminate the length–tension artifacts present in the EMG signal.[56] The data was further normalized across subjects. This data set was used to describe the distribution of muscle activities.

■ Model Structure

The fundamental concept of the model is that during a specific lifting motion each trunk muscle behaves according to a probabilistic process. Furthermore, this process describes the various states of activation that can be assumed by a muscle throughout a range of motion. The data from the experimental portion of this study provided key information about the basic nature of trunk muscle activity and variability that could be expected over repeated trials given a set of trunk bending specifications. These data became the foundation on which the stochastic simulation model was based.

The database development involved two steps. These steps were intended to put the data into a form such that it could be accessed by the model. First, the collected data were used to develop empirical distributions (histograms) for each muscle. These histograms indicated how often a specific range of muscle activity occurred given specific components of trunk bending motion. An example of this type of histogram is shown in Figure 2 for the right erector spinae muscle under one specific exertion condition. However, these histograms do not capture the inherent coactivity of the system.

In an effort to model the coactive nature of the trunk's multiple muscle system, conditional histograms of the various muscle combinations were determined as a function of the various trunk bending conditions. A conditional histogram describes the probabilistic activity of one muscle given knowledge of another's activation level. This process assumed that the primary drivers of the trunk's multiple muscle system were the erector spinae muscles. Knowledge of their collective activities could indicate how balanced and forceful an exertion might be and would dictate how much peripheral coactivity would be likely. This type of control mechanism has been hypothesized previously.[6,77]

The conditional influence of the erector spinae muscles on the coactivation of the other muscles was governed in the model through the creation of two new variables: SES and DES. SES describes the sum of the erector spinae normalized EMG values (right erector spinae + left erector spinae) whereas DES describes the difference between the two erector spinae values (right erector spinae - left erector spinae). The mean and standard deviation for SES and DES activities were calculated for each experimental condition. These distributions (SES and DES) collectively represent the muscles' activation magnitude and asymmetry and drive the probability of coactivation of the remaining muscles in the muscle prediction model.

The mean and standard deviation values of SES and DES were used to drive this coactivation concept by partitioning the possible combinations of SES and DES into the matrix shown in Figure 3. Once this matrix was developed the values of SES and DES explicitly defined a position in the matrix (CELL) to which each experimental value was assigned. Associated with each of these cells are ten conditional histograms that represent the activity range (distribution) of each of the ten trunk muscles.

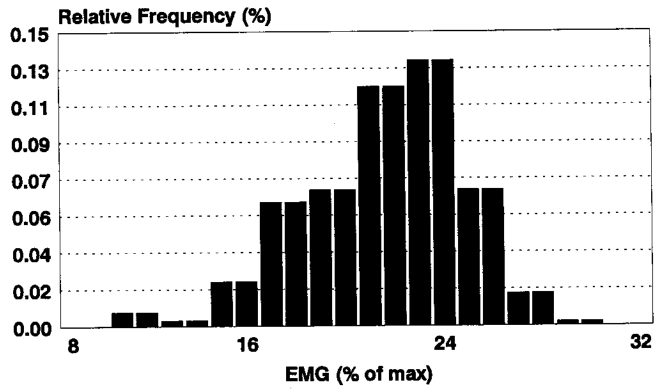

Figure 2. Histogram of right erector spinae muscle activities resulting from repetitive performance of a specific bending motion (isometric, torque = 80 Nm, trunk angle = 40°. This illustrates the spread of the electromyographic data.

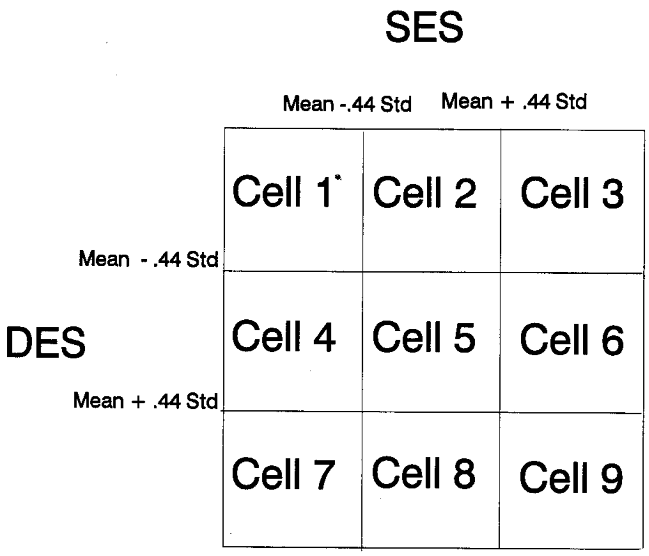

Figure 3. Scheme used to partition the SES/DES sample space. Each experimental data point was placed into one of the nine bins or "CELLs" shown. The resulting nine histograms of for each muscle described the co-activity of the muscular system.

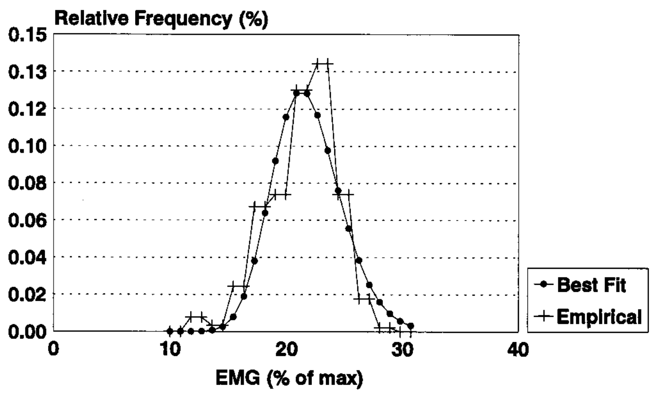

Figure 4. Example of the fitted vs empirical distribution: right erector spinae, torque = 80 Nm, trunk angle = 40°.

The second step in this process was to parameterize each of the resulting conditional histograms using a software package called FITTR1,[78] which fit the empirical data into a distribution function using Johnson's translation system. The Johnson translation system is a four-parameter model that converts a standard normal distribution into a wide variety of distributions. The four parameters are xi (a location parameter), lambda (a scale parameter), gamma (a shape parameter), and delta (a shape parameter). The resulting probability density functions (PDFs) represent the conditional probabilities of trunk muscle activation. An example of the fitted empirical distributions is shown in Figure 4, where the normalized EMG is plotted against relative frequency that is indirectly related to probability. A sample of the parameters describing these best-fit distributions are shown in Tables 2 and 3.

The actual simulation model flow is shown in Figure 5 that indicates the process followed by the simulation model and the point at which the experimental databases (developed in the experimental portion of this research and refined in the database development) were accessed. The model process contains several key components. First, the characteristics of a specific trunk bending exertion must be precisely identified in terms of trunk torque, position, velocity, and acceleration. Second, this information is used to calculate the four distribution parameters (xi, lambda, gamma, and delta) for the SES and DES distributions. These parameters are often interpolated and/or extrapolated from the experimental values associated with the experimental database. Third, once the appropriate SES and DES distributions are defined the model randomly samples values from these two distributions. Based on this random sampling a cell in the SES/DES probability matrix (Figure 3) is selected. The cell selection further refines the probability distribution associated with each muscle of the trunk thereby identifying feasible activity levels. At this point the four parameters that describe each individual muscle probability distribution are also interpolated/extrapolated to meet the specifications of the individual exertion. Finally, the model randomly selects a point from each of these refined EMG distributions for each muscle. The model then considers the next time point and starts the process again using updated information about the characteristics of the exertion. The differences between subjects were modeled in this process using linear translations of the distributions based on subject maximum strength data.[46] The output from the simulation model are time-dependent traces of possible EMG activity that could occur during the specified lift. When the simulation model is run multiple times an appreciation for muscle variability can be gained.

Table 2. Distribution Parameters for the Sum of the Erector Spinae

Torque (Nm)	Trunk Angle (deg)	Gamma	Delta	Lambda	Chi
40	5	0.0378	2.402	0.0808	-0.0213
40	40	-0.1596	2.224	0.1022	-0.0297
80	5	0.0000	13.960	0.7453	-0.043
80	40	0.0868	3.390	0.2387	-0.0293

Table 3. Distribution Parameters for the Latissimus Dorsi Muscle

CELL	Torque (Nm)	Trunk Angle (deg)	Gamma	Delta	Lambda	Chi
1	40	5	-5.341	2.849	0.0200	0.0555
2	40	5	-2.849	8.072	0.1189	0.1143
3	40	5	-0.1691	3.154	0.0638	0.1892
4	40	5	-5.011	2.507	0.0138	0.0906
5	40	5	0.000	13.600	0.1614	0.1766
6	40	5	0.000	8.772	0.2303	0.2153
7	40	5	-5.775	5.023	0.0831	0.0394
8	40	5	-5.159	2.802	0.0118	0.1506
9	40	5	-4.583	2.001	0.0098	0.1877

To quantify the spinal loading effects of the potential muscle activity variability multiple runs of the simulation model were performed. These simulated EMG values were then used as inputs to an EMG-assisted biomechanical model[22,48] so an understanding of the cost of this variability at the spinal level could also be determined.

Results

The goal of this analysis was to use the simulation model to generate distributions describing muscle activations and determine how these distributions changed as a function of the trunk bending motion specifications. The method used to generate the empirical distributions was to input a single value for each parameter (torque, position, velocity, and acceleration) repetitively and then create histograms from the resulting simulation output. Two examples of these distributions developed as a function of the experimental conditions are shown in Figures 6 and 7. They illustrate how the experimental conditions tested in the experiment, as well as those developed by interpolating the values of the four distribution parameters, influence the SES distributions.

The sampling distributions were used to generate continuous muscle activities. Time-dependent input data sets that consisted of 500 discrete values of torque, position, velocity, and acceleration were used for this purpose. These values were input into the simulation model and time-dependent traces for each of the ten trunk muscles served as the output. An example of these time-dependent results are shown in Figure 8. This figure illustrate the mean and a ± 3 standard deviation range of the simulated muscular activity as determined by 50 runs of the simulation model.

The time-dependent muscle activities were used to predict spinal loading using an EMG-assisted biomechanical model[22,48] The spinal reaction forces represent the components of the resultant vector force derived from the summation of all of the muscle forces. Figure 9 shows the reaction forces resulting from the predicted EMG values for one experimental condition. An average for all of the isometric conditions reveals that there is a range of 220 N of com-

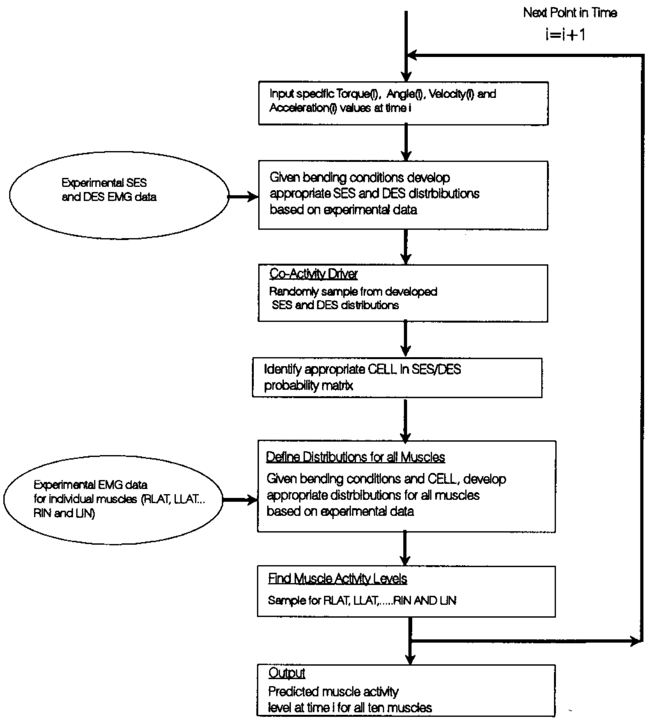

Figure 5. Flow chart describing the mechanics of the simulation model.

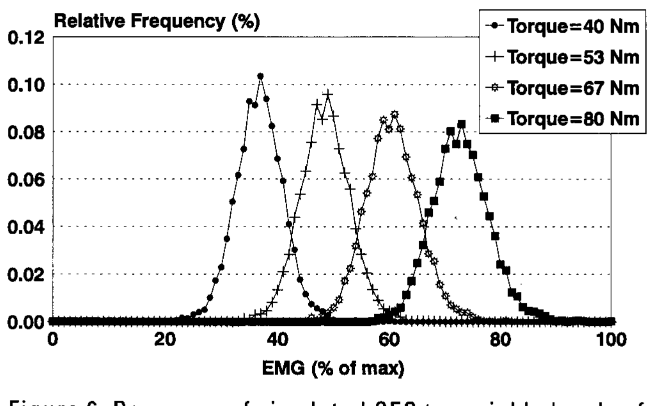

Figure 6. Response of simulated SES to variable levels of trunk torque (trunk angle = 5°), which illustrates the shift of the mean as well and the increased variability of the erector spinae muscles at greater torque levels.

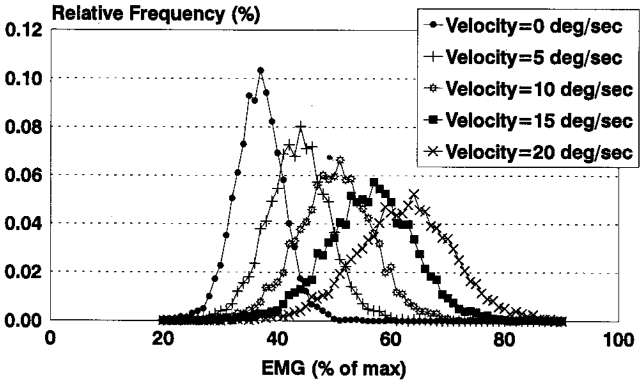

Figure 7. Response of simulated SES to variable levels of trunk velocity (trunk torque = 40 Nm). As in Figure 6, this figure shows that with increased velocity comes increased variability.

pression across the three standard deviation range of the data, a range of 53.7 N of anteroposterior shear and a range of lateral shear of 10.3 N. In relative terms, this means that when the mean data (that would have resulted from a deterministic model) is compared with that at three standard deviations above the mean, compressive forces can be under-estimated by about 6%, anteroposterior shear by about 25%, and lateral shear by about 50%. These values increased significantly under isokinetic (8%, 30%, and 95%) and isoinertial (9%, 50%, and 90%) conditions. It should also be emphasized that these results relate to sagittally symmetric exertions only. The lateral shear values and variability would be expected to increase significantly during asymmetric exertions.

■ Validation Study

The objectives of the validation study were to see how well this new simulation model actually predicts muscle activities under conditions different from those used to develop the model. These new conditions included different levels of the bending motion variables as well as different subjects. For this simulation model to be useful in ergonomic settings, it must be robust in both the population on which it can be used as well as the conditions under which it is applied. Two different male subjects were used in this study. Their anthropometric characteristics are shown in Table 4. These subjects were chosen specifically to see how the model would predict EMG values from two different sections of the population. Subject 1 was similar in anthropometry and strength to the five subjects studied in the development phase of the model. Subject 2 was significantly larger and stronger than those in the original group. This subject was

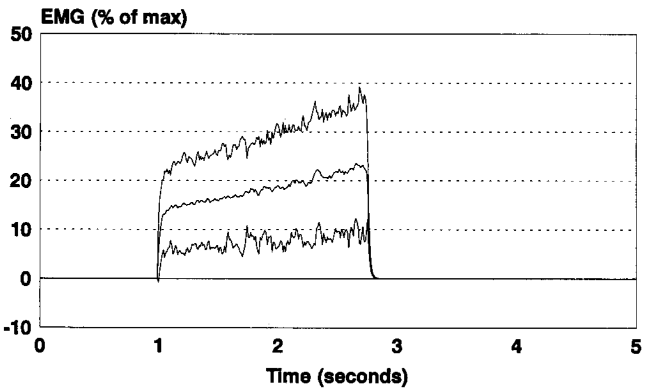

Figure 8. Time-dependent output of the electromyographic generator for the right erector spinae, trunk torque = 40 Nm, trunk acceleration = 40°. Note the spreading of the signal toward the end of the trial, indicating greater variability in the simulated values due to greater velocity at this point.

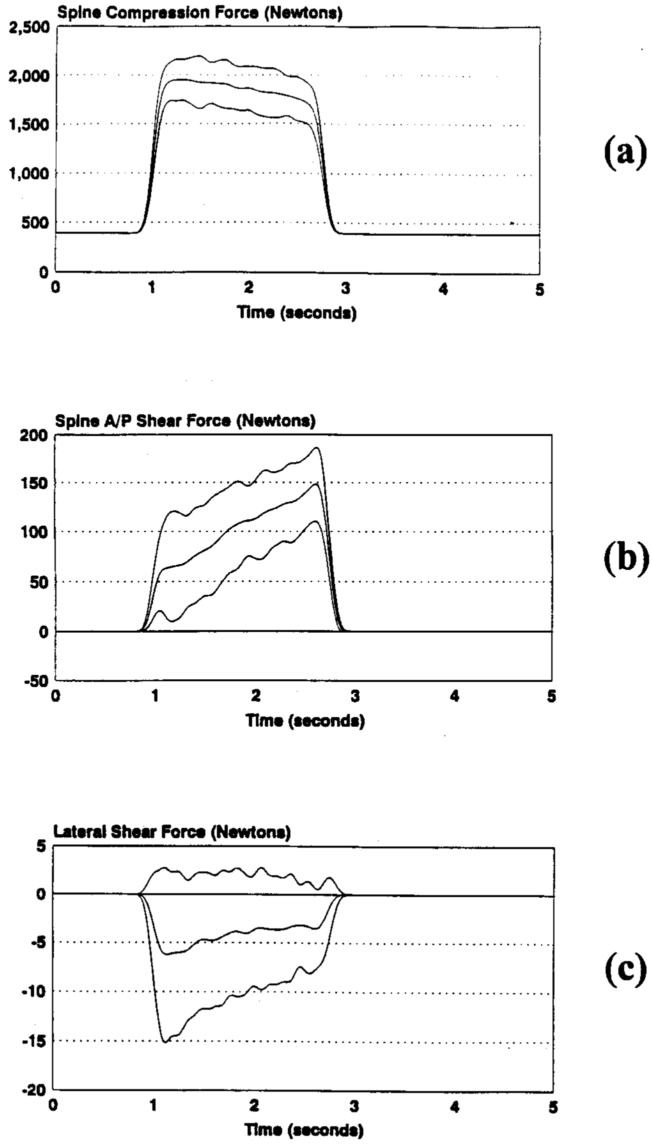

Figure 9. Model predictions of (**A**) time-dependent spinal compression, (**B**) time-dependent anteroposterior shear forces, and (**C**) time-dependent lateral shear forces. Trunk torque = 40 Nm, trunk velocity = 20 deg/sec.

Table 4. Anthropometry of Subjects in Validation Study

Dimension	Subject 1	Subject 2
Age	26 (years)	22 (years)
Height	181 (cm)	193 (cm)
Weight	734 (N)	1223 (N)
Spine length	53.6 (cm)	66.1 (cm)
Max strength (at 5°)	240 (Nm)	427 (Nm)

chosen to see how the model would perform in extrapolation from the original population.

The experimental variables tested in this validation study were the same as those used in the previous studies but the levels were different: torque level 60 and 110 Nm, angular trunk position 20 and 30° of sagittal bend, angular trunk velocity 10 and 40 deg/sec, and angular trunk acceleration 20 and 60 deg/sec^{-2}. These levels were chosen so that an investigation of both the interpolation and extrapolation potential of the model could be evaluated. The rest of the parameters such as muscles sampled, equipment used, data processing techniques used, and protocols followed were identical to those used in the original experiment.

The experimental time-dependent values of torque, trunk angle, trunk velocity, and trunk acceleration from the validation trials were used as trunk bending specifications to generate muscle activities using the stochastic simulation model. The simulation was run 50 times and the simulated muscle activities were summarized as a time-dependent mean and ± 3 standard deviation range. The actual EMG data recorded from each subject were then compared to this model generated range and a percentage of time that the actual EMG value fell within the bounds of the simulation prediction was calculated for each muscle. Figures 10 and 11 show these comparisons for two experimental conditions.

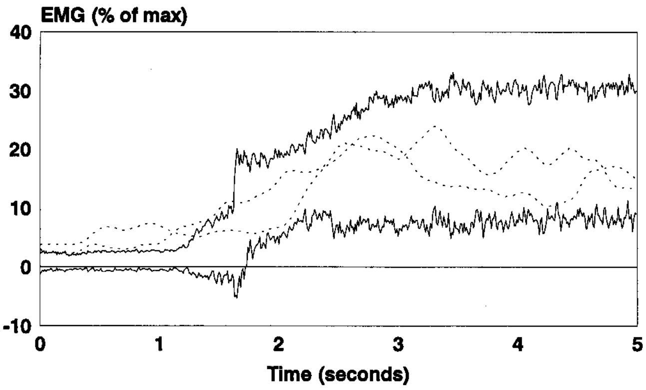

Figure 10. Sample validation result. Simulated range vs actual right erector spinae electromyographic activity. Isometric, trunk torque = 80 Nm, trunk angle = 20°, subject 1. Note the variability between the two experimental electromyographic data traces.

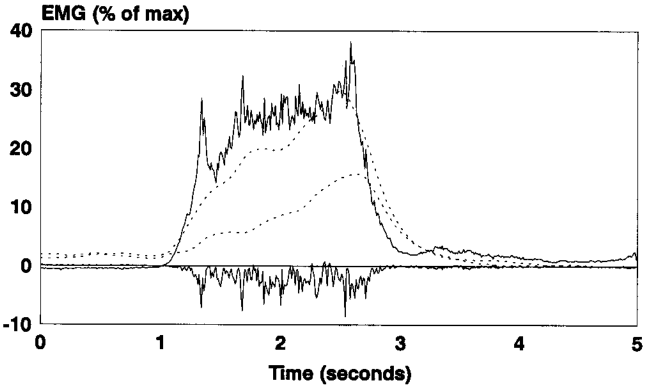

Figure 11. Sample validation result. Simulated range vs actual right latissimus dorsi EMG activity. Isokinetic (trunk velocity = 40 deg/sec), trunk torque = 80 Nm, subject 2. Note the variability between the two experimental electromyographic data traces.

The results of the validation study are summarized in Table 5. The overall predictive ability of the model was 82.4%. This represents the average percentage of data points that were within the ± 3 standard deviation range across all muscles, subjects, and experimental conditions. Table 5 also partitions the model performance as a function of isometric, isokinetic and isoinertial results. This table shows that, in general, the best models are isometric, the second best are isoinertial and isokinetic are the least accurate at predicting the EMG activity of the trunk muscles.

Model sensitivity analyses that assessed model performance as a function of model interpolation and extrapolation revealed that when the model was used to interpolate between original data sets 83.2% of the experimental validation values fell within the predicted range of values, whereas, when the model was used to extrapolate beyond the original data set 79.8% of the experimental data fell within predicted limits. Finally, a mix of extrapolated and interpolated conditions yielded experimental recordings that fell within the model predictions 82.5% of the time. The measures of model sensitivity used here were very conservative. Auto-correlation effects of the simulation model would produce a worst-case evaluation of the model.

It was also interesting to see how the model responded to a subject who had significantly different anthropometric and strength characteristics than the original subject population. These results showed that the model's predictive power was not diminished significantly by the different subject. The success rate for the subject from the similar population was 83.1% while the success rate for the "extrapolated" subject was 81.8%.

■ Discussion

Biomechanical models of spinal loading are valuable for two reasons. First, they provide insight into the op-

Table 5. Proportion of Actual EMG Data Points Within the Range as Predicted by the Simulation Model, Partitioned by Motion Type

	RLAT	LLAT	RES	LES	RAB	LAB	REX	LEX	RIN	LIN
Isometric	.995	.915	.921	.985	.929	.935	.951	.747	.833	.816
Isokinetic	.945	.991	.539	.910	.763	.855	.717	.729	.581	.644
Isoinertial	.901	.994	.851	.942	.628	.755	.637	.734	.926	.820

eration and behavior of the trunk muscle control system. If the trunk can be successfully modeled then we can further our understanding of how the trunk operates and this information could be used to help evaluate the status of the trunk's musculoskeletal control system. Second, biomechanical models, when accurate, can be used to assess the loading imposed on the spine during the performance of various tasks.

It is imperative that such models predict musculoskeletal behavior and spinal loading as accurately as possible. A key issue associated with model accuracy is the ability to describe the range of muscle activities and spinal loadings associated with a particular motion or activity. Because it has been shown that the extreme, as opposed to average, loadings of the back define the risk of occupationally-related low back disorders[25,50] it is necessary to predict the extreme loadings that would be expected during the performance of a particular task. Unless a model is capable of predicting such extremes via variability predictions one could not accurately assess the probability of injury or risk associated with a particular activity.

Few biomechanical models are capable of accurately assessing three-dimensional spinal loading due to the activity to the trunk muscles during a particular dynamic exertion. EMG-assisted models appear able to achieve such a goal. Traditionally, the problem with EMG-assisted models is that it was necessary to collect EMG recording for every exertion of interest. This study has shown that, for the first time, we are capable of predicting the range of EMG activities that would be expected during a trunk bending task provided that we have an adequate knowledge of the trunk motion and external loading conditions. Thus, we can now use this information to "drive" EMG-assisted models so that we could predict the range of spinal loadings that would be associated with a variety of workers repetitively performing a particular task.

The prediction of EMG activities over repeated trials for a variety of workers has been accomplished in this study through the development of a stochastic model of trunk muscle EMG activity. Stochastic modeling of any system, biomechanical or otherwise, permits one to consider variability in its input and output of the system and thereby creates a more realistic representation of the system. The benefits of modeling the system stochastically arise from ability to account for the varied moment arm, cross-sectional area, and vector force component data across muscles. Because these attributes differ from one muscle group to the next, the spinal reaction forces that result from one combination of muscle forces will differ from those resulting from another combination. This implies that there are ranges of compression, anteroposterior shear, and lateral shear that could occur in the spine during a specified lift. Accounting for this variability would provide a means to more accurately assess the range of spinal loadings expected from a specific task among a population of subjects or workers.

The use of stochastic principles in modeling the EMG signal is not a new idea. There have been several studies that have modeled various magnitude and temporal aspects of the signal in an attempt to understand the basic process of muscle contraction. Some have analyzed single motor unit firings[16,24] whereas others have investigated the summation of a number of motor units.[11,16,55,57] Zajac[80] states that these motor units recordings could be summed to represent activities of whole muscle. The novel feature of the current study is that we have not only applied the stochastic principle to a summation of EMG recordings but we have treated the system of muscles as a stochastic process thereby permitting us to predict coactivations of the trunk muscles accurately for the first time.

The validation study revealed that the simulation model developed renders predictions that are similar to the types of EMG levels that are present during actual lifting activities. Numerically the actual EMG values were within the ± 3 standard deviation range 90% of the time for the trunk extensors. It was also encouraging to see that the model was able to predict EMG values from trials and subjects significantly different from those used to develop the original database used in the EMG generator. These results encourage the further development and future usefulness of this technique.

One of the basic goals of this research was to gain an understanding of the variability that can exist in muscle forces during a simple lifting motion. Figure 6 illustrated this variability at its most basic level and how it was affected by varying levels of extension torque. The probability density functions displayed in this figure were developed for SES and show that not only does the magnitude of the erector spinae muscle force increase with greater torque levels but the variability about the mean increased as well. Further, this increase in variability of the erector spinae will influence the other muscles of the trunk that must stabilize the biomechanical system. The biomechanical significance of this result is increased co-contraction of the peripheral muscles during the exertion thereby increasing the complex, three-dimensional loading of the spine.

The effect of trunk position was also obvious from this study (not shown). There was a shifting of the distributions downward at greater forward trunk angles. This finding was consistent with previous research[46] that illustrated such a shift along the length tension curve of the erector spinae muscle groups. However, there was only a small change in the shape of the distributions at different trunk angles indicating little if any increases in co-contraction as a function of isometric trunk angle.

These findings add to the body of knowledge regarding co-contraction of a multiple muscle system during bending motions. Recent research has tried to document the role of co-contraction through the experimental findings of EMG studies[34,45,46] or the theoretical development of switching curves[31,33] and co-contraction indices.[12] Generally, these studies have documented the existence of co-contraction of trunk muscles, whereas the current study further quantifies the magnitude of co-contraction as well as offers an explanation as to its origin (erector spinae variability).

The effects of dynamic trunk motion on expected muscle activities were also evaluated in this study. Figure 7 illustrates the dramatic effects of increased velocity on the SES distribution. The change in distribution shape associated with trunk isoinertial activity was similar to that of velocity, but did not exhibit the same amount of translation shift along the horizontal axis. This result is consistent with previous research that showed a slight decrease with greater acceleration.[47] As with increased torque levels, increased dynamic activity during trunk bending tended to increase the amount of co-contraction. This coactivity occurred as a result of erector spinae group variability, thereby requiring the other trunk muscles to increase their activity to maintain three-dimensional equilibrium.

When the aforementioned distributions were employed in the simulation model, time-dependent traces of an individual muscle's activity were generated that were suitable for input into an EMG-assisted biomechanical model. The output from the biomechanical model were estimates of spinal reaction forces. These spinal reaction forces represent a concise means to evaluate the combined effects of multiple muscle system variability.

In this evaluation the output from 50 runs of the EMG generator was input into an EMG-assisted biomechanical model. The results indicated a significant reduction in compressive force variability. This was surprising given the large variability associated with the individual simulated EMGs. The reason for this reduction in compressive force variability relates to a basic attribute of the model that reflects the basic operation of the biomechanical system. Recall that SES was defined as the sum of the right and left erector spinae activities. Because the erector spinae are the primary extensor muscles their sum was closely correlated with the extension torque, especially under the controlled conditions of this experiment. However, torque was maintained at a relative constant as defined by the experiment. Therefore, SES was also well behaved. However, the individual erector spinae muscles were not subject to the same set of constraints. Combinations of activities between these two muscles could supply the required torque and the muscles activities could vary between muscles as long as their sum produced a relatively constant external torque. Therefore, the individual erector spinae muscles were much more variable than the sum and, hence, spinal compression was much more controlled than the individual erector spinae muscle activities. This illustration emphasizes the value of considering the variability associated with trunk muscle activity.

This same reasoning can be used to explain why anteroposterior and lateral shear did not exhibit the same type of focusing effect that occurred with compression. Anteroposterior and lateral shear forces exhibited levels of variability consistent with trunk muscle activity variability. These spinal reaction forces were related to the muscle forces used to stabilize the spine and were also not required to sum to a given value as were the erector spinae muscles. Anteroposterior shear and lateral shear were therefore much more closely related to the variability of the trunk muscle forces than was compression.

These results suggest that, biomechanically, compression was not greatly affected by the variability in muscle forces, whereas variability among shear forces were significantly affected. The variance in shear forces may increase further under greater loading conditions. This is a significant finding since recent research suggests that shear forces may be indicative of risk of injury. In a study assessing risk factors associated with lifting in industry, Marras et al[50] have shown that components outside the sagittal plane discriminate well between high and low risk jobs. They found that three of the five most discriminating factors consisted of trunk motions that increase shear and torsion loading of the spine. Finite element analyses[72] as well as in vitro studies[7,63] have shown that the spine responds in a significantly different manner when compression and shear were simultaneously induced as opposed to pure compression. In fact, a finite element model developed by Shirazi-Adl[71] showed that the anulus fibrosis of the intervertebral disc was capable of resisting very large compressive loads, and potential for failure occurred when there were significant shear and torsional loads applied. When this information is considered in conjunction with the effects found in the current study it becomes apparent that stochastic modeling of the three-dimensional spinal reaction forces holds great promise for understanding the origin of low back disorders.

The stochastic model presented in this article indicates a promising future for this type of biomechanical modeling. Several improvements would further enhance its applicability. First, a wider range of subjects and an expansion of the conditions under which they are tested would broaden the models applicability. These conditions would include the introduction of asymmetry as well as an expansion of the levels of torque, velocity, and acceleration studied.

Second, the model could be expanded to simulate other types of motions such as pulling, pushing, or twisting. This would require that more conditional relationships between the muscle groups be explored and would create a more dynamic coactivity structure.

Finally, a stochastic model of muscle activity can be used to help understand muscle system activities and spinal loadings associated with those with low back disorders. Such a model could be used to quantify how muscle usage changes when patients experience specific low back disorders.

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Address reprint requests to

William S. Marras, PhD
Biodynamics Laboratory
The Ohio State University
210 Baker Systems
1971 Neil Avenue
Columbus, OH 43210-1271