Analysis of the Effects of Obesity Classes on Manual Lifting Using Fuzzy Differential Modeling

Bulanık Diferansiyel Modelleme ile Obezite Sınıflarının Manuel Kaldırma Üzerindeki Etkisinin Analizi

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ABSTRACT

Obesity has emerged as a major global public health challenge, while musculoskeletal disorders (MSDs) remain the leading cause of injury, disability, and work-related absenteeism worldwide. Increased body mass amplifies the mechanical load exerted on the musculoskeletal system during lifting tasks. In this study, a fuzzy differential equation-based model was developed to evaluate the biomechanical impact of manual material handling across varying body weights. The model quantifies the joint forces and moments at the lower back, explicitly accounting for uncertainties inherent in the model parameters.

In biomechanical modeling, obesity introduces inherent uncertainties, primarily due to inter-individual variations in body composition, particularly the relative amounts and distribution of adipose and muscle tissue, which differentially affect mechanical responses to load and movement. To address these uncertainties, fuzzy differential equations (FDEs) offer a structured approach by incorporating imprecise parameters, initial conditions, and biological variability using fuzzy logic. Unlike classical methods, FDEs represent variables as fuzzy numbers, enabling simulations to better capture the imprecision of the real world.

The results showed that with increasing obesity levels, both the forces and moments acting on the lower back during lifting tasks was increased noticeably. This pattern was observed consistently across different load weights and body heights, indicating that higher BMI leads to more greater biomechanical stress on the musculoskeletal system. The FDE model was successful in capturing the uncertainties caused by variations in body composition and changes in balance due to obesity. This approach provides a more realistic understanding of mechanical loads compared to traditional models.

Keywords: Obesity, Manual Material Handling, Biomechanical Modelling, Fuzzy Differential Equations, Musculoskeletal Disorders.

ÖZ

Obezite, küresel ölçekte önemli bir halk sağlığı sorunu haline gelirken, kas-iskelet sistemi bozuklukları (KİSB) dünya genelinde yaralanma, engellilik ve işe devamsızlığın başlıca nedenleri arasında yer almaktadır. Artan vücut ağırlığı, kaldırma sırasında kas-iskelet sistemine binen mekanik yükü artırır. Bu çalışmada, farklı vücut ağırlıklarında elle malzeme taşımanın biyomekanik etkisini değerlendirmek için bulanık diferansiyel denklemlere (BDD) dayalı bir model geliştirilmiştir. Model, alt sırttaki eklem kuvvetlerini ve momentleri nicel olarak değerlendirirken, parametrelerdeki belirsizlikleri de dikkate alır.

Biyomekanik modellemede, obezite doğası gereği bazı belirsizlikler barındırır; bunun başlıca nedeni, bireyler arasındaki vücut kompozisyonundaki farklılıklar, özellikle de yağ ve kas dokusunun miktarı ve dağılımıdır. Bu farklılıklar, yük ve harekete verilen mekanik tepkileri farklı şekillerde etkiler. Bu belirsizlikler, bulanık mantık temelli BDD yaklaşımıyla ele alınmıştır. Klasik yöntemlerden farklı olarak, BDD'ler değişkenleri bulanık sayılarla temsil ederek gerçek dünyadaki belirsizliği daha iyi yansıtır.

Sonuçlar, obezite düzeyi arttıkça kaldırma sırasında alt sırt bölgesine binen kuvvet ve momentlerin belirgin şekilde yükseldiğini gösterdi. Bu durum, farklı yük ağırlıkları ve vücut boylarında da tutarlı olup daha yüksek Vücut Kitle İndeksi seviyelerinin kas-iskelet sistemi üzerinde daha fazla biyomekanik stres oluşturduğunu ortaya koymuştur. Model, vücut bileşimi değişimlerinin neden olduğu belirsizlikleri başarıyla yakalayarak geleneksel modellere kıyasla daha gerçekçi sonuçlar sunmuştur.

Anahtar Kelimeler: Obezite, Elle Yük Kaldırma, Biyomekanik Modelleme, Bulanık Diferansiyel Denklemler, Kas-İskelet Sistemi Hastalıkları

There is no need for ethics committee approval for the study.

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Geliş Tarihi / Received: 28.06.2025
Kabul Tarihi/Accepted: 02.09.2025

INTRODUCTION

Obesity is a complex, chronic, and multifactorial medical condition characterized by abnormal or excessive accumulation of body fat (adiposity), which adversely affects health. It is commonly defined using the body mass index (BMI), with individuals having a BMI of 30 or higher classified as obese. As a metabolic disease, obesity increases the risk of long-term health complications and reduces the overall quality of life.[1–3] The World Health Organization (WHO) classifies obesity into three main classes based on the Body Mass Index (BMI), which is calculated by dividing body weight in kilograms by the square of height in meters (kg/m²). Class I obesity (moderate) corresponds to a BMI of 30.0–34.9 kg/m², Class II obesity (severe) to 35.0–39.9 kg/m², and Class III obesity (morbid or extreme) to 40.0 kg/m² or greater.[4–6]

Obesity increases the risk and severity of musculoskeletal disorders (MSDs) during manual lifting tasks by imposing additional mechanical loads on the musculoskeletal system. Individuals with a higher body mass index (BMI) experience elevated stress on muscles, joints, and ligaments, which not only intensifies biomechanical strain during physical activities but also increases the prevalence of conditions such as postural alterations in the knees and feet, arthritis, and pain in the spine and lower limbs.[7–9]

The impact of obesity on musculoskeletal disorders during manual load handling in industrial settings has been investigated. Using surface electromyography (EMG), researchers examined muscle activation in individuals with varying obesity levels under different loads and task styles. The results demonstrated that obesity increases musculoskeletal risk and that muscle responses vary according to load magnitude. Notably, muscle activation significantly increased from 5 kg to 10 kg loads, followed by a slight decrease at 15 kg, though activation remained higher than at the lowest load. These findings highlight that the combined effect of obesity and manual load handling on the musculoskeletal system differs depending on the load applied.[10]

L5/S1 disc compression forces during moderate lifting in severely obese individuals (BMI ≥ 35 kg/m²) were quantitatively evaluated compared to normal-weight controls.[1] Significantly higher compression forces ranging from 3000N to 8500N were found in the obese group, with 99.5% exceeding the 3400N action limit recommended by the National Institute for Occupational Safety and Health (NIOSH), while none of the normal-weight participants surpassed this threshold.[11] Using subject-specific musculoskeletal modeling based on motion capture data, L5-S1 compression loads in obese and normal-weight individuals during static load-reaching tasks were assessed. Results showed that obese participants experienced significantly higher compression forces (2305 ± 468N) compared to normal-weight individuals (1674 ± 337N), representing an average increase of approximately 38% .[12]

A study using a subject-specific finite element musculoskeletal model was conducted. They examined the effects of obesity and obesity shape on spinal loads, trunk stability, and vertebral fatigue risk. The study analyzed anthropometric data from 5,852 obese individuals. Three obesity shapes were considered: mean, apple-shaped (high waist circumference), and pear-shaped (low waist circumference). These shapes were evaluated at three body weights (86, 98, and 109 kg) with a constant height. The results showed that adding 12 kg of body weight increased spinal loads by about 11.8%. A larger waist circumference at the same weight increased spinal loads equivalent to an extra 20 kg.[13]

Classification of individuals as obese based on Body Mass Index (BMI) may lead to misleading conclusions due to variations in body composition; for instance, an elevated BMI may result from increased lean muscle mass rather than excess adipose tissue, particularly in individuals with an athletic build. BMI may not be an accurate indicator of adiposity in athletes, as it often misclassifies individuals with high muscle mass as overweight or obese.[1] The importance of assessing body composition by distinguishing between fat mass and lean body mass to avoid misclassification was also highlighted.[14]

BMI is a commonly used measure to classify obesity but has significant limitations. Since BMI is based only on height and weight, it cannot distinguish between fat and muscle mass. Therefore, muscular individuals may be misclassified as obese despite not having excess fat. Additionally, BMI does not accurately reflect changes in body composition with age, where fat increases and muscle decreases. Gender differences also affect the relationship between BMI and actual body fat percentage. Self-reported height and weight data can introduce further errors in BMI calculation. Due to these factors, BMI has low sensitivity and specificity for measuring true obesity, leading to misclassification and potential bias in assessing obesity-related health risks.[15] These limitations introduce significant uncertainties in modeling obesity-related outcomes, as inaccurate classification affects the reliability of risk assessments and biomechanical analyses.

Fuzzy logic-based methods are effective in modeling systems that involve uncertainty.[16] Obesity in Malaysian adults has been highlighted as a multifactorial issue, and a fuzzy logic-based DEMATEL approach was employed to prioritize key risk factors such as physical inactivity, poor diet, and stress for targeted interventions.[17] Fuzzy set theory, particularly Zadeh's Extension Principle, has been concluded to be a valuable tool for evaluating abdominal obesity and cardiometabolic risks.[18] They highlighted the importance of population-specific correlation functions in constructing accurate fuzzy models and proposed this approach as a foundation for more complex fuzzy inference systems to assess global cardiovascular and cardiometabolic risk amid the growing prevalence of obesity-related health issues worldwide. The risk of childhood obesity was predicted by analyzing various contributing factors using type-2 fuzzy logic.[19]

Fuzzy differantial equations (FDEs) are particularly useful in biomechanics for modeling systems where there is uncertainty in initial conditions or parameters. This is crucial in biomechanics, where precise measurements are often difficult to obtain due to biological variability.[20,21] A diabetes model using FDE is studied to address uncertainty in medical data. By applying the generalized Hukuhara derivative, the fuzzy model is transformed into a system of ordinary differential equations, enabling classical stability analysis despite imprecise parameters.[22] Fuzzy difference equations help improve early diagnosis of heart problems by handling uncertainty and detecting small changes in heart rhythms.[23]

In this study, the kinetic parameters acting on the lower back during manual load-lifting tasks were examined in individuals belonging to different obesity classes. As the obesity class increased, a significant rise was observed in the joint force and moment values exerted on the lower back due to the increase in body mass. However, various sources of uncertainty may affect the accuracy of the model outcomes. For instance, although classifying individuals based solely on Body Mass Index (BMI) is a common approach, high muscle mass may be misinterpreted as fat mass, leading to ambiguity in obesity classification.

Additionally, the free-form nature of the lifting task, especially in obese individuals with postural deviations, may result in deviations from standard lifting mechanics. Factors such as fatigue level, muscular response time, and balance composition also introduce dynamic uncertainties during the motion.

Classical differential equation-based models operate with fixed and well-defined parameters, which tend to generalize individual physical capacities and thus limit the realism of the model. In contrast, for a more accurate representation of such biomechanical systems, it is essential to systematically incorporate uncertainty into the modeling process. Therefore, instead of classical differential equations, fuzzy differential equations were utilized in this study to enable the model to function under uncertain conditions.

Furthermore, a Genetic Algorithm (GA)-based optimization strategy was employed during the modeling process. The model was executed separately for each combination of obesity class, loading condition, and BMI level. Accordingly, the genetic algorithm performed the optimization procedure independently for each case. Notably, during the determination of the lower and upper bounds of the fuzzy intervals, some contradictory results were obtained. Initially considered as a limitation of the model, these outliers were later interpreted as an advantage, especially when considering the dynamic nature of real-world problems, as they highlighted the model's flexibility and adaptability.

MATERIALS AND METHODS

Fuzzy Numbers

A fuzzy set $\tilde{S} \in R$ is called a fuzzy number $\tilde{s}$ if it satisfies the following conditions:[24]

1. $\tilde{S}$ is normal, there exists at least one element $x_0 \in \mathcal{R}$, the membership function $\mu_{\tilde{s}}(x_0) = 1$.
2. $\tilde{S}$ is convex, for any $x_1, x_2 \in \mathcal{R}$ and, $\lambda \in [0,1]$ the membership function satisfies $\mu_{\tilde{s}}(\lambda x_1 + (1-\lambda)x_2) \geq min(\mu_{\tilde{s}}(x_1), \mu_{\tilde{s}}(x_2))$.
3. The membership function $\mu_{\tilde{s}}$ is upper semi-continuous.
4. The support of the fuzzy number $\tilde{s}$ is bounded and closed.

Gaussian Fuzzy Number

A Gaussian fuzzy number is defined as a fuzzy number $\tilde{s}$, where the membership function is characterized by a normalized and, in general, asymmetrically parameterized Gaussian function.[25]

$$\tilde{s} = gfn(\bar{z}, \sigma_l, \sigma_r) \quad (1)$$

Membership function of $\tilde{s}$ is,

$$\mu_{\tilde{s}}(z) = \begin{cases} exp[-(z-\bar{z})^2/(2\sigma_l^2)] \; for \; z < \bar{z} \\ exp[-(z-\bar{z})^2/(2\sigma_r^2)] \; for \; z \geq \bar{z} \end{cases} \quad (2)$$

Fuzzy number $\tilde{s}$ is represented with its $\alpha - cut$ levels $\widetilde{s^{\alpha}} = [a^{\alpha}, b^{\alpha}]$,

It is assumed that $\sigma_l = \sigma_r =$, so the membership function gets,

$$\mu_{\tilde{s}}(z) = exp[-(z-\bar{z})^2/(2\sigma^2)] \quad (3)$$

Then we get a^{α}, b^{α} ,

$$a^{\alpha} = \bar{z} - \sqrt{-log_e(\mu_{\tilde{s}}(z))(2\sigma^2)} \quad (4)$$

$$b^{\alpha} = \bar{z} + \sqrt{-log_e(\mu_{\tilde{s}}(z))(2\sigma^2)} \quad (5)$$

Fuzzy Differential Equations

A fuzzy differential equation can be generally describes as[26]

$$\left[\frac{d\tilde{y}(t)}{dt} = \tilde{f}(t, \tilde{y}(t)),\right] [\tilde{y}(t_0) = \widetilde{y_0}] \quad (6)$$

We will concentrate on the second order, linear, constant coefficient ordinary differential equation,

$$\begin{gathered} y'' + a_1 y' + a_2 y = f(x), \\ x \in [0, +\infty) \\ y(0) = b_0, \quad y'(0) = b_1, \quad b_0, b_1 \in R \end{gathered} \quad (7)$$

We turn the problem into a fuzzy problem by fuzzifying the initial conditions by replacing b_0, b_1 with the Gaussian fuzzy number $\widetilde{b_0}, \widetilde{b_1}$; thus, we have a differential equation with crisp coefficients but fuzzy initial conditions. Then, the solution of the initial value problem is a Gaussian fuzzy number $\tilde{y} = [y_1(x,\alpha), y_2(x,\alpha)]$, $\alpha \in [0,1]$, with $y_1(x,\alpha), y_2(x,\alpha)$ differentiable functions at least up to second order. The substitution of $\tilde{y}$ into the equation (7) yields[27,28]

$$\begin{gathered} [y_1''(x,\alpha), y_2''(x,\alpha)] + \\ a_1[y_1'(x,\alpha), y_2'(x,\alpha)] + \\ a_2[y_1(x,\alpha), y_2(x,\alpha)] = [f(x), f(x)] \end{gathered} \quad (8)$$

Initial conditions are,

$$y_1(0,\alpha) = \widetilde{b_{01}}(\alpha), \quad y_1'(0,\alpha) = \widetilde{b_{11}}(\alpha)$$
$$y_2(0,\alpha) = \widetilde{b_{02}}(\alpha), \quad y_2'(0,\alpha) = \widetilde{b_{12}}(\alpha)$$

Indeed, we can write,

$$\widetilde{b_0} = [b_{01}(\alpha), b_{02}(\alpha)], \quad \widetilde{b_1} = [b_{11}(\alpha), b_{12}(\alpha)] \tag{9}$$

Nonlinear Fuzzy Differential Equations

In addition to linear models, we consider second-order nonlinear fuzzy differential equations of the following general form:

$$\widetilde{y''}(x) + \tilde{p}(x, \tilde{y}, \widetilde{y'}) + \tilde{q}(x, \tilde{y}) = \tilde{f}(x), \tag{10}$$

where $\tilde{y}(x)$ is a fuzzy-valued function, and $\tilde{p}, \tilde{q}, \tilde{f}$ are fuzzy functions that may depend nonlinearly on x, $\tilde{y}$, and their derivatives. The initial conditions are expressed as fuzzy numbers as follows:

$$\tilde{y}(0) = \widetilde{b_0}, \quad \widetilde{y'}(0) = \widetilde{b_1}, \tag{11}$$

where $\widetilde{b_0}$ and $\widetilde{b_1}$ are typically represented as Gaussian fuzzy numbers.

To solve such equations, we employ the α-cut representation of the fuzzy numbers. For each $\alpha \in [0,1]$, the fuzzy solution $\tilde{y}(x)$ is represented as an interval

$$\tilde{y}(x) = [y_1(x,\alpha), y_2(x,\alpha)], \tag{12}$$

where $y_1(x,\alpha)$ and $y_2(x,\alpha)$ denote the lower and upper bounds of the α-cut of $\tilde{y}(x)$, respectively. Substituting this representation into the nonlinear fuzzy differential equation yields a system of coupled nonlinear differential equations:

$$y_1''(x,\alpha) + p_1(x, y_1, y_1') + q_1(x, y_1) = f_1(x), \tag{13}$$

$$y_2''(x,\alpha) + p_2(x, y_2, y_2') + q_2(x, y_2) = f_2(x), \tag{14}$$

subject to the initial conditions:

$$y_1(0,\alpha) = b_{01}(\alpha), \quad y_1'(0,\alpha) = b_{11}(\alpha),$$
$$y_2(0,\alpha) = b_{02}(\alpha), \quad y_2'(0,\alpha) = b_{12}(\alpha),$$

where $[b_{01}(\alpha), b_{02}(\alpha)]$ and $[b_{11}(\alpha), b_{12}(\alpha)]$ are the α-cut intervals of the fuzzy initial conditions $\widetilde{b_0}$ and $\widetilde{b_1}$, respectively.

The resulting system is solved numerically for a discrete set of α levels using standard ODE solvers. The fuzzy solution is then reconstructed from the family of interval solutions $\{[y_1(x,\alpha), y_2(x,\alpha)]\}_{\alpha\in[0,1]}$. This approach ensures that the uncertainty propagation through the nonlinear dynamics is captured accurately within the fuzzy framework.

Genetic Algorithm

Genetic Algorithm (GA) is one of the most known algorithm in the class of metaheuristic algorithms and it has been inspired by the process of biological evolution. Metaheuristic algorithms are used to solve complex and hard problems which comes from areas like economy, engineering, politics and management. These algorithms are usually developed by inspiring from biological evolution processes, swarm behaviours or physical laws.[29]

Genetic algorithms belongs to the population-based metaheuristic algorithms. Such algorithms use multiple candidate solutions during the search process, helping to keep diversity and prevent getting stuck in local optimum. In GA, a population is randomly created at the beginning and genetic operations are applied to it. These operations includes selection, crossover and mutation, and they works similar to the formation of chromosomes in biology.

The success of each individual is measured with the fitness of the solution it represents. Individuals with higher fitness have more chance to be selected for next generations. This leads to improvement in solution quality over generations. The process ends when the most optimal solution is found for the problem that should be optimized by the GA. John Holland is accepted as the founder of the original genetic algorithm and it dates back to 1970s.[30] In this study, genetic algorithm was used to optimize two unknown parameters inside a 7th degree polynomial by considering the minimum objective function.

Biomechanical Model

A two-dimensional, sagittally symmetric human body model (Figure 1) was designed as a five-rigid-link mechanism for the biomechanical simulation of manual lifting tasks. These links were modeled to reflect the estimated length, mass, and inertia properties of their human counterparts. Thus, any movement or configuration within the system can be described using five generalized coordinates, which define the relative orientation of each link with respect to its parent link.[31]

In the model, the ankle, knee, hip, shoulder, and elbow joints were considered as one-degree-of-freedom revolute joints. The spinal column was represented as a single rigid link that includes the mass of the head and neck. The hands were modeled as part of the forearms, and their relative motion with respect to the forearms was neglected.

The equations of motion of the model consist of five second-order nonlinear fuzzy differential equations, and the system is treated as an inverse dynamics problem. Since inverse dynamics problems allow for infinitely many joint configurations that can produce the same motion trajectory, trajectory optimization becomes necessary.

The model based on experiments which were conducted at the Ohio State University Biodynamics Laboratory, where markers were placed on the subjects' feet, knees, waist, shoulders, and elbows (Figure 1), and angular displacements were analyzed during the lifting motion. Angular velocity and angular acceleration were obtained by numerically differentiating the angular displacement data. These data were then integrated into the equations of motion, along with polynomials having unknown coefficients and their analytical derivatives.

Based on the anthropometric data of the subjects, the "minimum total moment" objective function was minimized using genetic algorithms. The resulting polynomial coefficients represent the optimal values that yield the minimum total moment. These coefficients were then reapplied to the equations of motion, and joint reaction forces and moments were computed.[32]

The differential equations of the model were expressed in fuzzy form. Consequently, the model inputs were also defined as fuzzy numbers of Gaussian type. Lifting simulations were performed for three different load values: 6.8 kg, 13.6 kg, and 20.5 kg (corresponding to 15, 30, and 45 pounds, respectively). The model inputs were defined as the individual's body mass (BM), height (H), and lifted load (LL), while the outputs were the joint moments (M) and forces (F).[33]

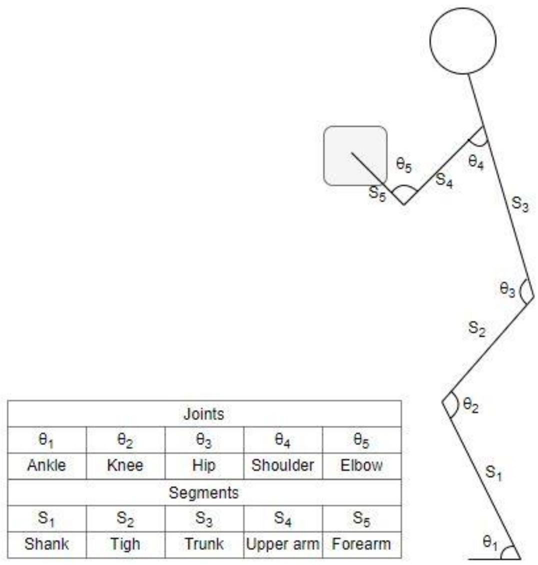

Figure 1. Sagittally symmetric 2D model of lifting motion in an obese subject.

RESULTS AND DISCUSSION

The model was supplied with synthetic data representing BMI ranges covering three obesity classes. Height values ranged from 58 to 76 inches (147.32 cm to 193.04 cm). To reduce computational cost and analyze general trends, four representative heights at 5-inch intervals (58, 64, 70, 76 inches) were selected. Body mass values were calculated for these heights within the BMI subranges of all obesity classes and used as model inputs.

Inputs included individual height, body mass, lifting duration (2 seconds), lifting style (free lifting), and lifted loads (6.8 kg, 13.6 kg, and 20.5 kg). Each obesity class contained 6 BMI values, combined with four heights, resulting in 24 distinct body mass values, representing 24 individuals. Inputs were converted into Gaussian fuzzy numbers for use in fuzzy differential equations. To save computational effort, solutions were calculated for selected alpha-cut levels (0.01, 0.4, 0.7, and 1.0) instead of all. Alpha-cut values indicate uncertainty intervals, narrowing as alpha increases. The model was first run for 6.8 kg loads at all alpha-cut levels, then repeated for 13.6 kg and 20.5 kg. Lifted loads were also modeled as Gaussian fuzzy numbers.

Model outputs, optimized via genetic algorithm minimizing moment objective function, included forces and moments acting on the lumbar region during lifting. Figures 2 through 7 share a common presentation style: graphs divided into three color-coded blocks for obesity classes, with vertical lines marked by four points representing average alpha-cut levels. The spread of these lines shows uncertainty in BMI values within each obesity class.

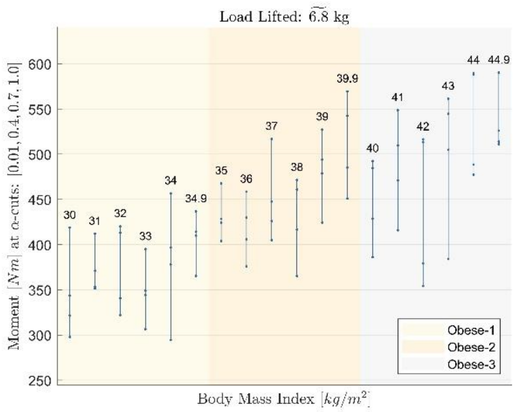

Figure 2. Moment $[Nm]$ values for three obesity classes at four $\alpha - cut$ levels during a $\widetilde{6.8}$ kg lifting motion.

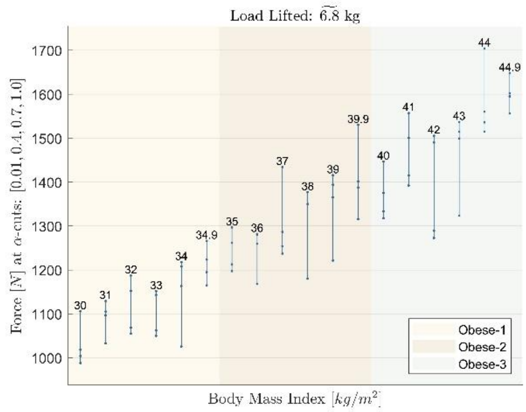

Figure 3. Force $[N]$ values for three obesity classes at four $\alpha - cut$ levels during a $\widetilde{6.8}$ kg lifting motion.

Based on the results, moments on the lower back during lifting of fuzzy 6.8 kg loads ranged from 295 Nm to 590 Nm across all obesity classes (Figure 2). A general trend showed moments tending to grow with obesity class, following a non-linear pattern. Within the Obese-1 class, individuals with BMI 30 and 34 showed a wider moment range, reflecting variation within and between classes. Additional lumbar loading due to obesity is suggested by variations in moments between BMI 30 and 34.9. Comparing BMI 30, 35, and 40, lower and upper moment bounds also trended upward, especially near class upper limits. This reflects body mass distribution changes and forward shifts in the center of mass, which lengthen the lever arm and increase moments.

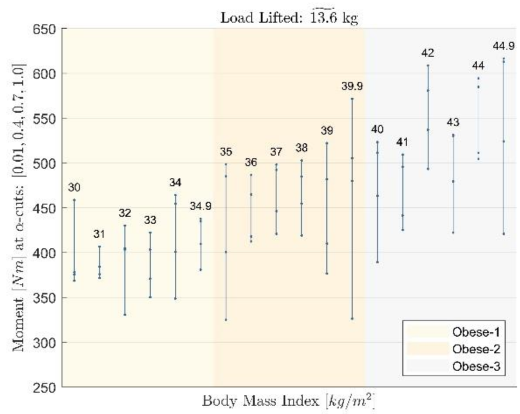

Figure 4. Moment $[Nm]$ values for three obesity classes at four $\alpha - cut$ levels during a $\widetilde{13.6}$ kg lifting motion.

For forces on the lumbar region under fuzzy 6.8 kg loads (Figure 3), values ranged between 988 N and 1704 N across obesity classes. Transitions between classes corresponded with force increases.

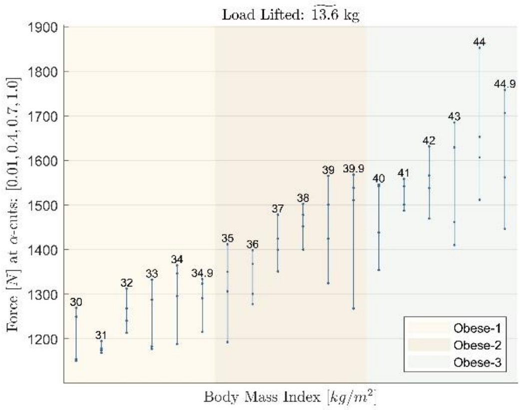

Figure 5. Force $[N]$ values for three obesity classes at four $\alpha - cut$ levels during a $\widetilde{13.6}$ kg lifting motion.

As BMI rose, total body weight and its distribution shifted, often concentrating in the abdomen, increasing lumbar load. Within Obese-1, force bounds for BMI 30 to 34.9 showed clear growth. Across classes, force bounds rose progressively with BMI increases. Forces acting on the lumbar region include both the lifted load and the individual's body weight; hence, even with a constant external load, total lumbar force grows with BMI due to higher body mass and altered weight center.

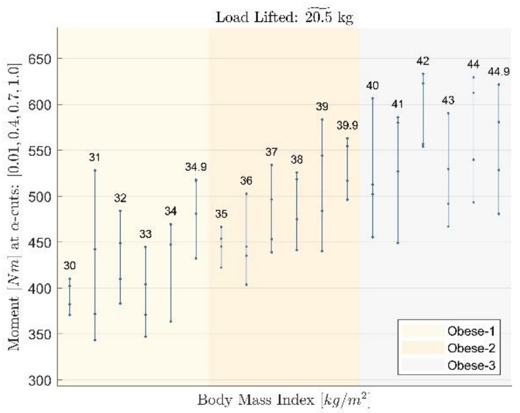

Figure 6. Moment $[Nm]$ values for three obesity classes at four $\alpha - cut$ levels during a $\widetilde{20.5}$ kg lifting motion.

To assess load effects, moments and forces during lifting of fuzzy loads 6.8 kg, 13.6 kg, and 20.5 kg were compared in Figures 2, 4, 6 and 3, 5, 7 respectively. Statistical analyses via Friedman tests for lower and upper bounds revealed significant differences in moments for Obese-1 at lower bounds (p=0.0421), indicating moment sensitivity to load. Upper bounds showed no significance (p=0.0695). For Obese-2, significance appeared at upper bounds (p=0.0094) but not at lower bounds, while Obese-3 showed significance only at lower bounds. Forces exhibited significant differences across all obesity classes and bounds, with p-values well below 0.05.

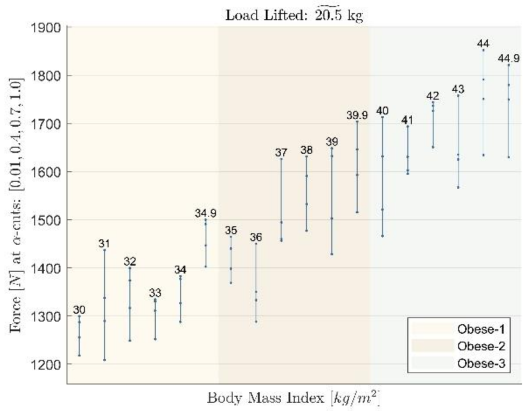

Figure 7. Force $[N]$ values for three obesity classes at four $\alpha - cut$ levels during a $\widetilde{20.5}$ kg lifting motion.

Due to inherent uncertainties, fuzzy differential equations were used to better represent real-world conditions. Force values generally rose with load, while moment increases appeared selectively at either lower or upper bounds. Spearman correlation tests confirmed positive relations between BMI and moments across all loads and bounds, with strong correlations especially at higher alpha levels. Force correlations were even stronger, indicating that higher obesity classes are associated with greater lumbar forces and moments during manual lifting. Statistical results also showed significant load-dependent increases within obesity classes.

CONCLUSION AND RECOMMENDATIONS

The fuzzy differential equation-based model developed in this study effectively evaluated the impact of obesity on forces and moments acting on the lower back during manual lifting tasks. The model results revealed significant increases on mechanical loads on the lumbar region depend on obesity classes and lifted load amounts. Especially with increasing BMI values, the forces and moments affecting the back was found to increase, indicating the strong loading effect of obesity on musculoskeletal system.

Obesity causes considerable changes in body composition such as increased fat tissue and alterations in muscle mass. This leads to biomechanical shifts like forward displacement of the body's center of gravity and new balance strategies. These changes create high levels of biological and structural uncertainties, which are hard to fully represent in classical deterministic models. The fuzzy differential equations used in this study allowed comprehensively to model these uncertainties both parametrically and structurally; especially factors like fat accumulation, muscle distribution, and center of gravity shifts are expressed through smooth transitions and different alpha-cut levels. Thus, the model better reflects inter-individual variability and biological diversity which is seen in real-world individuals.

Statistical analyses showed that both the amount of lifted load and obesity level caused significant increases on forces and moments acting on the back. These results support that obesity not only increases body weight but also affect mechanical load distribution and balance control, causing additional stress on the musculoskeletal system. The non-linear increasing trends observed in the model outputs demonstrate that the biomechanical complexities brought by obesity are well captured.

In this context, the developed model successfully represented the new balance conditions and related uncertainties caused by obesity mathematically and conceptually. This capability of the model can provide important contributions for risk assessment and preventive planning for obese individuals in occupational health and ergonomics. Future studies extending the model with different lifting techniques, dynamic movement scenarios, and validation with real subject data will increase the applicability of results in practical settings.

Acknowledgments

I would like to express my sincere gratitude to Prof. Dr. Mohamad Parnianpour and his team for their valuable contributions by allowing us to use a portion of the experimental data obtained at the Biodynamics Laboratory of The Ohio State University. This data was extremely helpful during my doctoral research, particularly in the development of the original biomechanical model using fuzzy differential equations. I deeply appreciate their support and collaboration.

Conflict Of Interest

The authors declare that they have no conflict of interest regarding the publication of this article.

Contributions By Authors

The **first author** conducted the doctoral research on which this article is based and was responsible for the conceptual design, modeling, analysis, interpretation of results, and manuscript writing. The **second and third authors** (supervisors) provided scientific guidance throughout the research, contributed to the methodology, and supported the writing process through academic supervision.

All authors have reviewed and approved the final version of the manuscript for publication.

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