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A neuro-fuzzy model for estimating electromyographical activity of trunk muscles due to manual lifting

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The main objective of this study was to develop a hybrid neuro-fuzzy system for estimating the magnitude of EMG responses of 10 trunk muscles based on two lifting task variables (trunk velocity and trunk moment) as model inputs. The input and output variables were represented using the fuzzy membership functions. The initial fuzzy rules were generated by the neural network using true EMG data. Two different laboratory-derived EMG data sets were used for model development and validation, respectively. The mean absolute error (MAE) between the actual and model-estimated normalized EMG values was calculated. Across all muscles, the average value of MAE was 8.43% (SD = 2.87%) of the normalized EMG data. The larger absolute errors occurred in the left side of the trunk, which exhibited higher levels of muscular activity. Overall, the developed model was capable of estimating the normalized EMG values with average value of the mean absolute differences of 6.4%. It was hypothesized that model performance could be improved by increasing the number of inputs, including additional task variables as well as the subjects' characteristics.

1. Introduction

Many real-world problems are so complex that they allow only for imprecise description of the relationships between system elements and system behaviours (Karwowski *et al.* 1999a). For this reason, many of the current intelligent engineering design approaches are heuristic. According to Wang and Mendel (1992), this kind of approach has two weak points: 1) it is problem dependent, i.e., a method may work well for one problem but may not be suited for another problem; and 2) there is no common framework for modelling and representing different aspects of control, which makes the analyses difficult. Furthermore, as the system structures become larger and more complex, they also become nonlinear in nature.

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Consequently, it is not easy to understand the relationships between the task conditions and human performance.

The general modelling method for the complex human-machine system can be developed by incorporating some standard measures with the additional human knowledge defined specifically for a given problem. Evaluation of body stresses in manual material handling (MMH) activities is such a complex problem that requires combination of several approaches (Karwowski and Ayoub 1984, Karwowski *et al.* 1999b, Karwowski and Rodrick 2001). The biomechanical approach is one of the analytical approaches for investigating the relationships between human responses and the lifting task environment. The low back biomechanical models attempt to estimate the loads on the lumbar spine under different (occupational) task conditions. Figure 1 show how the human body is viewed under the low back biomechanical model, and what variables are needed for building such models. These variables include both the human and workplace characteristics variables. Trunk motion description includes such factors as trunk flexion angle, angular velocity, etc. Electromyography (EMG) has been also widely for estimating muscular activities due to lifting tasks.

1.1. *Biomechanical modelling of manual lifting tasks*

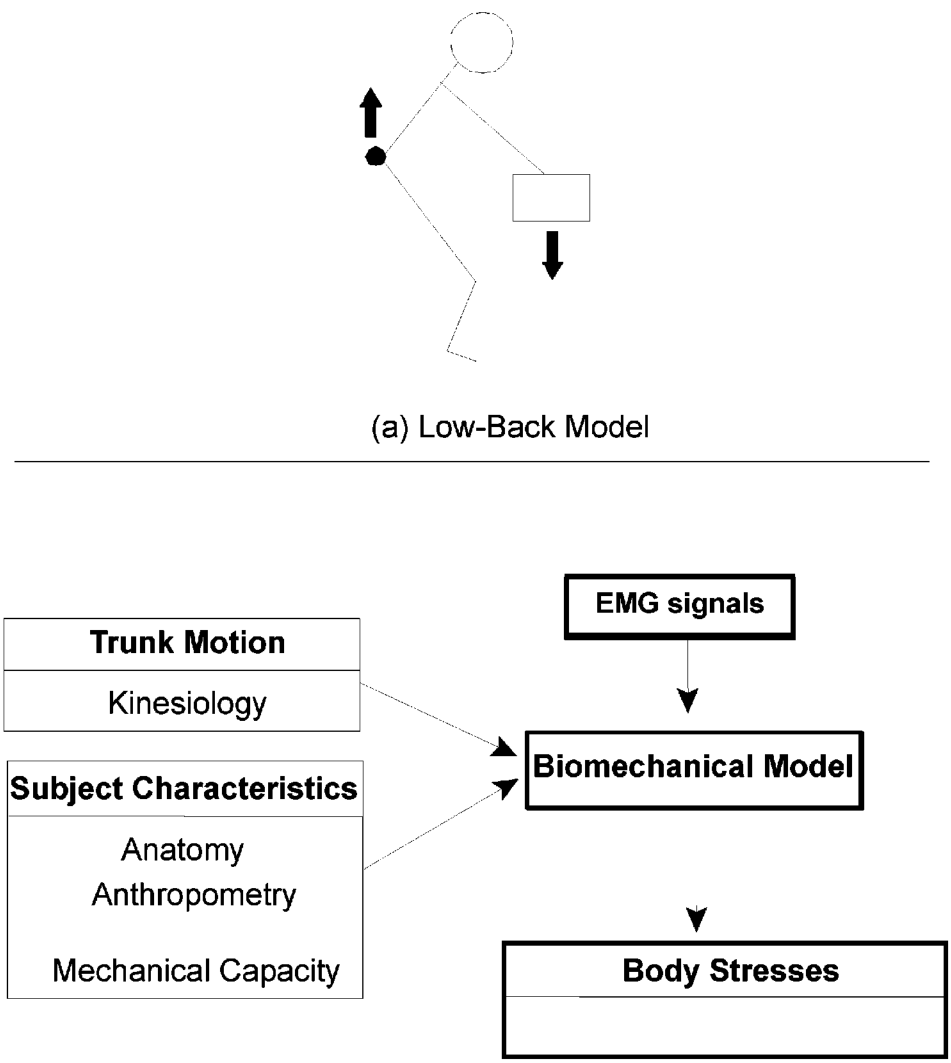
Biomechanical models employ variety of the human- and environment-related variables. The need for utilizing such variables is motivated by different types of inquires (Chaffin 1988). First is the matter of correct interpretation of complex data now available from the very sophisticated bio-instrumentation. For instance, if one accepts that low-back pain originates at mechanical disruption of normal tissue function, then the electromyography (EMG) data and other types of data can be combined into biomechanical models in order to interpret the meaning of each measurement. A second motivation for building biomechanical models is practicality. Under a new work situation it may be necessary to simulate manual activity in order to estimate whether a given lifting task would be safe.

The biomechanical models have many practical limitations:

1. the number of control variables considered at one time in a model are restricted due to time constraints,
2. many proceeding steps are needed to develop the relationship between control variables and the EMG activities (mathematical functions) which might be nonlinear,
3. most estimation models are seldom capable of accounting for individual variability because mathematical models use objective functions to optimize the spine loading in the most efficient manner (Marras and Sommerich 1991).

Compared to typical estimation models which produce average muscle loading, the variability in the spine loading is meaningful for identification of the peak loading. This allows for more accurate assessment of the risk injury risk attributable to workplace design. The individual variability could be accounted for by evaluating the spine loading at points in normalized time throughout the exertion in the three-dimensional motion model (Marras and Sommerich 1991).

Muscle activity featuring the internal behaviour of the body is usually described with EMG data. Thus, most biomechanical models heavily rely on the EMG inputs to 'drive' them (Mirka *et al.* 1996). However, it is often impractical to collect EMG



(b) Model Elements

Figure 1. A typical low-back model and its elements.

activity in industry due to hostility (such as presence of the magnetic field) of work environments. Laboratory experiments are, therefore, performed under precisely controlled conditions to measure muscle activity during the specific trunk motions (Marras and Sommerich 1991).

The manual lifting activities are influenced by multiple work environmental factors. The environment faced by the human is so complex that no adequate mathematical model can be developed using traditional design methods. The human expert can provide certain amount of information for modelling the workplace. On the other hand, the numerical input-output EMG data are measured under controlled conditions. Therefore, we can have two kinds of information for evaluating manual lifting tasks: 1) numerical information of the EMG data obtained from the experiment (i.e., laboratory-based measurements), and 2) system behaviour information (described with linguistic terms) obtained from the human observers. The human expert knowledge associated with the risk factors of LBDs can be represented as a set of IF-THEN rules. These rules state the levels of responses (outputs) function of certain input conditions. They are based on the subjective perception of the environment. The sampled input-output EMG data pairs are numerical data that give the specific values of inputs and the corresponding outputs for the given lifting tasks. In this study, a proposed EMG estimation model design is based on combining these two types of information.

1.2. *Fuzzy modelling*

Fuzzy methodology (Zadeh, 1965, 1973, 1975, 1978, Zimmermann 1978, Karwowski and Mital 1986, Karwowski 1992, Karwowski *et al.* 1999a) has been effective as an approach which allows utilization of vague linguistic information obtained from the human experts, whereas artificial neural networks are suited for numerical data pair's analysis. The neuro-fuzzy approach is an alternative methodology, compared to the traditional systems modelling approaches. Fuzzy systems can represent imprecise human knowledge, while neural networks have an ability of generalizing nonlinear properties of the data. The rationale for using both technologies is that both are free of numerical model estimators. They do not require mathematical functions in modelling of complex and presumably nonlinear systems, but also show good performance when the model is made. They can also share their respective abilities by working efficiently in uncertain, imprecise, and noisy environments. The effects of such integration can be found in many other engineering applications (Sugeno and Kang 1988, Kosko 1992, Kasabov 1996).

Fuzzy and neural systems can be applied to treat the numerical EMG data (figure 2) and interact with the low back biomechanical models. There are two possible neuro-fuzzy approaches. First, a neuro-fuzzy model for estimating the EMG activity can be a basis for the EMG-based models for estimating the biomechanical stresses on the spine. Second, a neuro-fuzzy model can be directly used to estimate the compressive and shear forces on the spine, without the EMG data. This study is related to the first approach. Since the information about system behaviour is based on human judgment, the available knowledge can be described with imprecise linguistic terms such as {low, medium, high}. The basic premise of this research is to build a neuro-fuzzy model for estimating the EMG values of trunk muscles due to manual lifting tasks. Fuzzy variables are used to capture the knowledge, while fuzzy EMG-estimation rules are generated by the neural network, based on numerical EMG data.

2. Objectives

Low back biomechanical models attempt to estimate loads on the lumbar spine under different occupational conditions in order to allow for estimating allowable loads held in various postures, the least stressful configuration of workplaces, etc. These models can help to rationally interpolate and extrapolate musculoskeletal capacity data from different sources to provide specific design guides. When applied at the design stage, this approach appears to help prevent musculoskeletal injury and reduce organizational costs (Chaffin and Andersson 1991).

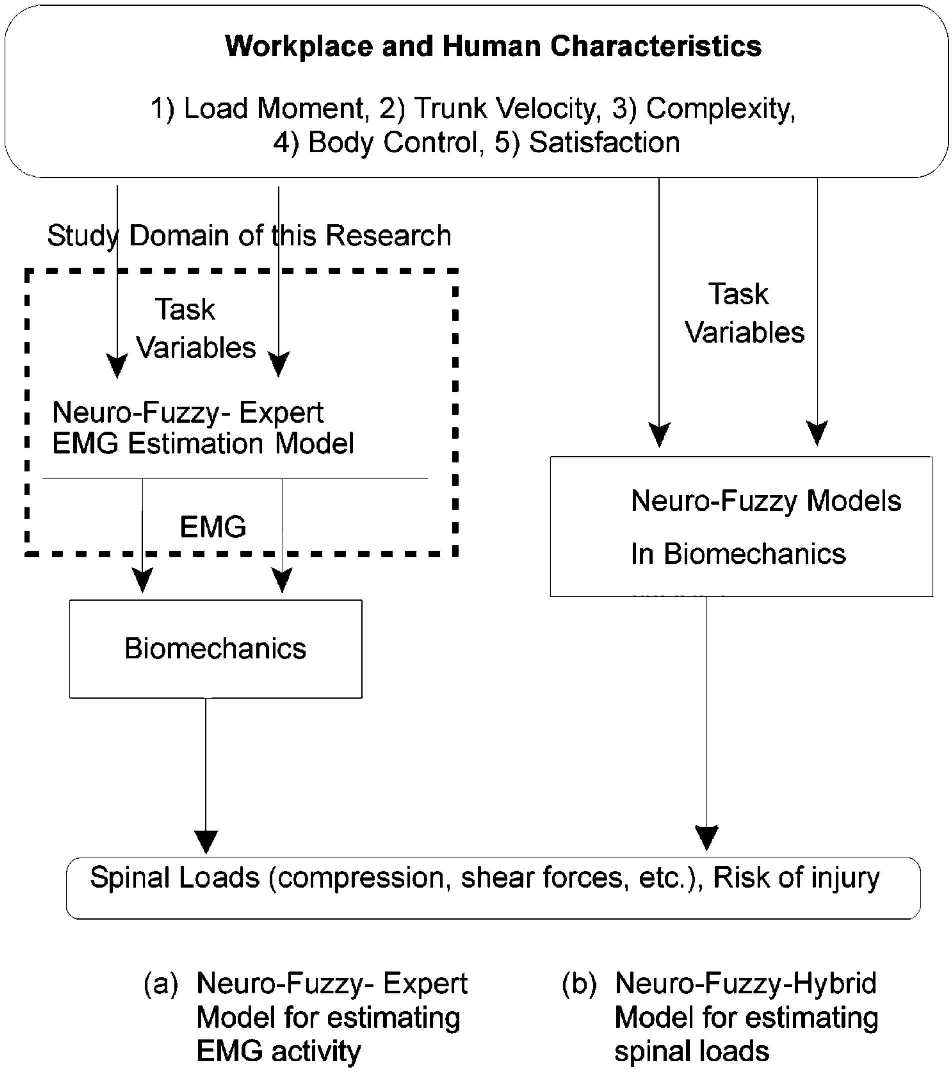


Figure 2. Applications of neuro-fuzzy expert approach in biomechanical modelling.

The EMG data are often needed as inputs for the ‘EMG-driven’ and ‘optimization-based’ biomechanics models. However, such measurements are often impractical to perform in real industrial environments. The present study aims to develop a hybrid neuro-fuzzy system for estimating the EMG magnitude of 10 trunk muscles due to lifting tasks, based on two physical variables (trunk velocity and trunk moment) as model inputs. The proposed neuro-fuzzy model is a fuzzy logic-based model which uses a neural network as a tool to generate the fuzzy rule bases. It was hypothesized that such a model can lead to acceptable performance in estimating the EMG activity, based on the synergistic effects of combining a fuzzy system and a neural network.

3. Biomechanical modelling

3.1. *Low back models*

Electromyography (EMG) has been employed as a measure of muscle tension for estimating the amount of muscle activity and evaluating system performance. Generally, four types of information can be provided through the EMG data (Marras 1990):

1. knowledge about whether the muscle is in use (on/off) during an exertion;
2. a relative activity level, indicating muscle effort, can be determined by comparing the exertion level of the processed signal under various conditions;
3. quantitative information regarding force generation of the muscle under static and constant velocity of the muscle; and
4. muscle fatigue as indicated by the shift of frequency spectrum to lower levels (Basmajian and DeLuca 1985).

In general, the relationships between the EMG activity of muscles and several task-related factors appear to be monotonic. However, this relationship is non-linear under many circumstances. Thus, clear understanding of the EMG signals in MMH-related studies plays an important role for guiding the reduction of body loading in heavy work situations. Quantitative evaluation is available throughout the analysis of EMG activity patterns. Based on their functional roles and measurability, typically five primary human muscles are used in the biomechanical models: erector spinae (ES), latissimus dorsi (LD), rectus abdominis (RA), external obliques (EO), and internal obliques (IO) (see figure 3).

The EMG data used in biomechanical models can be used to validate the optimization-based models (Bean *et al.* 1988, Schultz and Andersson 1981), or as input to the EMG-driven models (Marras and Sommerich 1991, McGill and Norman 1986). For model validation, the measured EMG data are compared with the estimated EMG data obtained from the optimization-based model. The external moment is compared with the internal moment obtained from the EMG-driven model. The model uses the measured EMG data as input to produce loads on the lumbar spine.

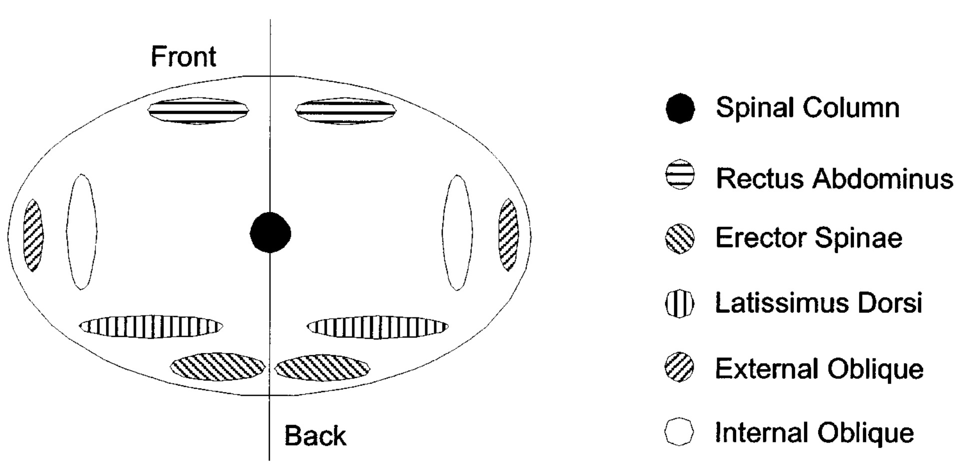


Figure 3. Trunk muscles used in the study.

3.2. *Optimization-based models*

The optimization-based models are another class of models that permit evaluation of human performance in industrial tasks. These models assume that muscle forces are exerted in the way that can minimize the risk level, based on spinal compression and sum of muscle forces on the spine. Such models are usually validated by comparing the estimated EMG data with the measured EMG data obtained from experiments or other sources. Therefore, the possessions of accurate normalized EMG (NEMG) data are necessary to evaluate the accuracy of any estimation model. Although the requirement for the EMG data can be satisfied at least to some extent under careful experimental control, the acquisition of pure EMG data can be an additional burden for system designers (Aaras *et al.* 1996).

The optimization-based models have some limitations in keeping model performance consistent. For example, these models could not find solutions for the particular postures when the maximum muscle force exceeds the defined ranges. Also, most optimization models cannot estimate co-contraction of musculature, while significant co-contraction has been demonstrated experimentally in many EMG studies (Lavender *et al.* 1991, Lavender *et al.* 1992). Hughes (1995) tested four different optimization-based models for estimating torso muscle force in order to investigate the practical effect of optimization models. The objective was to determine the degree to which the choice of model formulation affects spinal compression force estimates when analysing industrial tasks. The results showed that the choice of low-back model formulation can significantly affect the magnitude of spinal compression force estimations. For example, the greatest difference between model estimations of compression force was 3625N for the task selected. This difference could be due to the way in which the four models penalized large muscle stresses. In some cases, there was no solution for any posture selected because the 100 N/cm^2 bound of model constraint was too restrictive, and some of the computed muscle stresses exceeded physiological limits. In another example, the Minimum Compression model could not find solutions for the selected postures when a muscle stress bound of 100 N/cm^2 was used. Hughes (1995) also found none of the four models could be used to estimate contraction of the extensor musculature.

3.2. *EMG-driven biomechanical models*

The EMG-driven biomechanical models, using the EMG data as inputs, have been known to provide better performance (e.g., with respect to accuracy and consistency) than that of optimization-based models in many laboratory studies of manual handling tasks. The EMG-driven models basically assume that trunk moment is directly related to spine loading. So the equilibrium between internal and external moments is pursued for balancing the body posture. The internal forces which act to resist the external moments are created by the muscle forces, while the external forces are created by two task effects: the weights and moment of the object lifted; and the weight of the body segments and the distance from the spine. Based on these assumptions, the validation of the model can be tested by comparing directly the measured joint moment with the joint moment estimated by the model.

The EMG-driven models differ from the optimization-based models in that the EMG-driven models can account for individual variability. The variability of spine loading has the useful meaning of identifying peak spine loading due to the movement that allows more accurate assessment of the risk of injury attributable to workplace design. Most estimation models are seldom capable of accounting for individual variability because they use objective functions that aim to optimize spine loading in the most efficient manner.

Marras and Sommerich (1991) developed an EMG-driven dynamic three-dimensional motion model to examine trunk muscle activity patterns and to quantify biomechanical stresses on the spine during the isokinetic trunk lifting exertion. This model included three types of model inputs: 1) subject characteristics (such as subject anthropometry), 2) EMG signals (such as EMG amplitude), and 3) trunk kinematics and kinetics (such as trunk flexion angle, angular velocity and torque). In addition, individual variability in the amount of loads on the spine could be observed in a way of evaluating the spine loading at points in normalized time throughout the exertion under symmetric and asymmetric constant velocity lifting conditions. However, the EMG-driven models are not general-purpose models. Rather, they are intended for the use under laboratory conditions, and to interface with common laboratory instruments (EMG, dynamometers, etc.) which can assess the influence of motion-related biomechanical factors. In this respect, Mirka *et al*. (1996) developed a simulation-based model which can generate the EMG signals, given a set of environmental conditions such as weight, moment, and trunk posture and trunk dynamics. The shapes of best fit distributions were developed with multiple runs of the simulation, and then the estimated EMG values were generated for bending and lifting activities by the multivariate Johnson distribution method. The model had the capability of generating muscle activities during bending and lifting activities.

3.3. *Risk factors associated with LBDs in lifting tasks*

Both epidemiologic and biomechanical studies have indicated that there is a link between the risk of the LBDs and occupational conditions. Specifically, the MMH is associated with greater risk of the LBDs. Marras (1992) documented workplace and individual characteristics to be highly related to LBDs risk from over 400 industrial lifting jobs in 48 varied industries. These factors included lifting frequency, load moment, trunk lateral velocity, trunk twisting velocity and the trunk sagittal angle. A lumbar motion monitor was employed in his study to assess the contribution of three-dimensional dynamic trunk motions to the risk of LBD during occupational lifting in industry.

One of the most important factors affecting trunk moment is the external load being lifted. For example, a greater weight produces a greater trunk moment, and in turn influences the compressive force on the spine. Marras and Mirka (1992) found that all muscles increased their activities when trunk moment increased. As trunk moment increases, the agonist and antagonist muscles increase their activities dramatically. Thus, additional spinal loading is expected due to the mechanical disadvantage in antagonist muscles when these muscles are activated to counter-balance the external moments. Trunk velocity is another major factor that modifies activity of the trunk muscles. Higher the trunk velocity results in greater muscle activities needed to maintain the same level of torque production by the trunk. This indicates there is an internal musculoskeletal cost associated with trunk motion (Marras 1992).

3.4. *Relationships between EMG and task factors*

The EMG data includes useful information which describes the synergistic effects of muscle activities on joint loadings due to lifting task design. Accurate description of the relationships between the EMG data and task factors (workplace and human characteristics) can help to logically trace possible causes and effects of excessive biomechanical stresses. However, the causal relations between EMG data and lifting task factors are not easily formulated with the mathematical forms because they are often too complex to define. For example, it is known that human muscles behave indeterminately (Basmajian and DeLuca, 1985). An infinite number of sets of muscles are organically recruited to generate the required reaction moments during a given exertion and posture of the body. The antagonistic muscles also contribute to the exertion for the required reaction moment. Such indeterminate characteristics of muscle recruitment cause the relationships between task factors and body stresses to be nonlinear and uncertain.

Most EMG estimation models take a deterministic approach to estimating muscular forces, and muscle activation levels are expressed as one constant value. These data are also fed into the biomechanical models for estimating spinal loading due to lifting task. Therefore, the EMG data largely affect the estimation of spinal loads, such as compressive force and shear force. Furthermore, there is always uncertainty that arises from the inability to perform adequate measurements. The EMG data may be physically affected by the measurement itself regardless of the task characteristics. Although some factors can be controlled (to some extent) with a precise setup of instrumentation and careful selection of electrode location, it may be hard to guarantee the acceptable level of accuracy of the measured EMG signals, particularly in field environments. Furthermore, the error sources tend to be multiplicative in varying their effects on the EMG data due to their interaction (Marras 1990).

The specific characteristics of a biomechanical model itself may be another uncertainty source. Different estimation models have to be used for the analysis of different types of body motions (e.g., static and dynamic motion). For example, the static models can overestimate the population's capabilities when fast movements are required with the combination of maximum strength exertions, and will also overestimate when older populations are employed. Most optimization-based models may underestimate the muscle-induced compression and shear forces on the spinal motion segments by as much as 30%, especially during sudden (i.e., jerking) motions, or lateral, asymmetric exertions (Chaffin 1997). In this sense, most biomechanical models are neither complete nor accurate for all types of exertions that may occur during manual lifting. In this study, two types of information sources were combined for evaluating lifting tasks: numerical information of the EMG data measured with precise control, and human expert evaluations which can provide a certain amount of information related to overall workplace characteristics.

4. Fuzzy and neural modelling

4.1. *Fuzzy methodology*

Fuzzy logic can be used to model human imprecise reasoning and control complex and ill-defined processes without precise knowledge of their underlying dynamics (Zadeh, 1965, 1973, 1978; Zimmermann, 1985; Karwowski and Mital, 1986; Klir and Yuan, 1995; Ross 1995). In general, a fuzzy logic controller consists of three modules: fuzzification/defuzzification module, fuzzy inference engine, and fuzzy rule base allowing to process uncertainty in human thinking (figure 4). The following are the main phases of a fuzzy system development (Kasabov 1996):

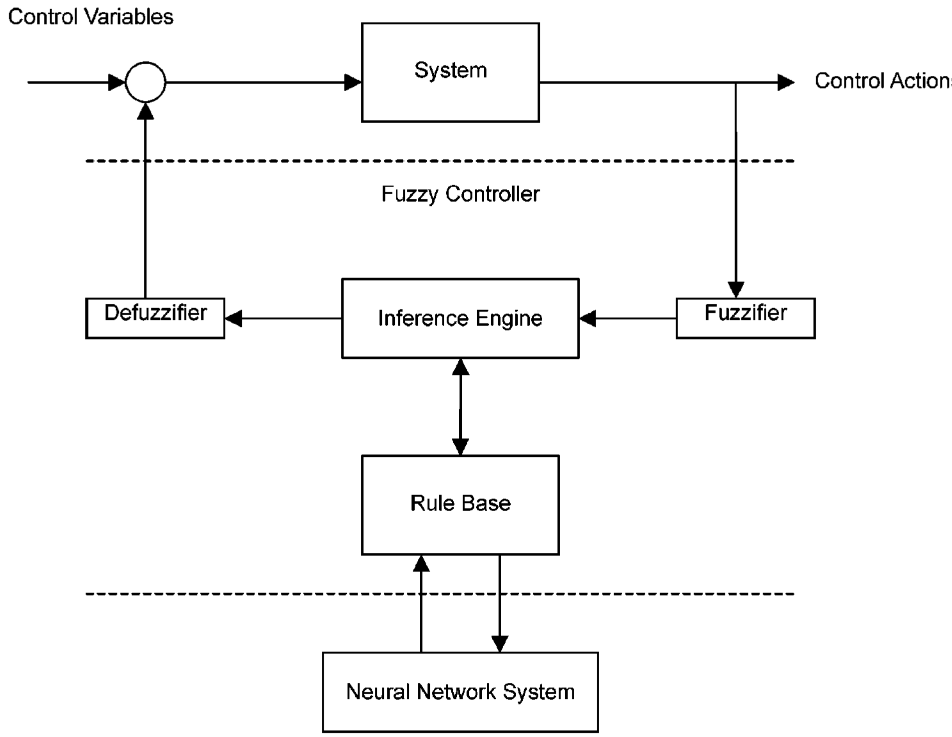


Figure 4. Diagram of the neuro-fuzzy system.

1. identifying the current problem,
2. defining the input and output variables, their fuzzy variables and their membership functions,
3. gathering the set of fuzzy rules,
4. selecting fuzzification and defuzzification methods,
5. tuning the fuzzy system: changing membership functions and fuzzy rules if necessary: validation of the results.

When evaluating MMH activities, human experts can observe the lifting workplaces, and then document the information about the relationships between task variables and system outputs based on their judgments (Karwowski and Ayoub 1984, Karwowski *et al.* 1995, Karwowski *et al.* 1999b). Such information can be expressed with imprecise linguistic forms such as 'low', 'medium' and 'high'. In a fuzzy system, the subjective judgments can be formulated through fuzzification module which transforms them into appropriate fuzzy linguistic variables characterized by membership functions in a specified universe of discourse.

A fuzzy inference engine is a decision-making logic based on fuzzy rules that determine fuzzy outputs corresponding to fuzzified inputs. Fuzzy inference engine allows for simulation of the human decision making procedures to evaluate the fuzzified variables. The evaluation of fuzzy rules fired depends on the fuzzy implication in fuzzy logic. For example, assume that two task variables are selected to analyse a lifting task, and the EMG values are outputs in the corresponding workplace. The inputs are: M (trunk moment imposed on L5/S1 level of the human spine) and V (lateral bending velocity of upper trunk). An output N is the normalized EMG of muscle activity. In this example, fuzzy rules have the form shown below:

R_1: If M is A_1 and V is B_1, then N is C_1,
R_2: If M is A_2 and V is B_2, then N is C_2.

Fuzzy implication, 'and' operator, in the rule expression generates common parts for the linguistic variables A_i and B_i, such as 'low', 'medium', and 'high'. Then the firing strengths of the first and second rules are expressed in terms of the degrees of partial match between the user-supplied data and the data in the fuzzy rule base. Once all of the fuzzy output sets have been computed, they are combined through their sum or union together to produce the combined fuzzy output set.

4.2. *Neural network systems*

A neural network, also called a connectionist system, is a biologically inspired computational model that consists of processing elements (neurons) and connections between them, as well as training and recalling algorithms (Kasabo 1996). Neural networks can be used for rapid pattern recognition, complex data classification, and learning from complex numerical data.

In general, a neural network consists of three basic entities: 1) a set of neurons, 2) pattern of connectivity, and 3) learning rules. Neurons can be organized into several layers, called hidden layers, depending on the network architecture used that function as stations able to send and receive signals from the outside environment or other neurons in the network. Network can be completely operated when neurons are linked with each other, partially or fully, depending on the network topology. The most attractive characteristic of neural network is its ability to learn, which makes it possible modification of system behaviour in response to the environment, and involves a process of changing the pattern and strength of connectivity among neurons.

The efficient and effective replication of the human's ability to classify patterns allows the neural network to solve real world problems inherent to complex and nonlinear systems (Wasserman 1993). Neural networks have been proven effective for performing variety of tasks, including:

1. pattern mapping, one can input a written text to receive a spoken word;
2. pattern completion, in which one can input a partially obscured object to recall a stored complete pattern;
3. pattern classification, by which one can sort different patterns into categories; and
4. optimization, in which one can efficiently solve a complicated combinatorial problem (Neuralware 1989, Chu 1993).

The neural network self-organizes the presented data to discover common properties. Most general learning schemes are either supervised or unsupervised. Supervised learning incorporates desired outputs and information regarding when to turn off the learning, and how long and how often to present each data set for training. Unsupervised learning, which relies only upon local information and internal control to derive the results, is considered to be psychologically more plausible. This may be because humans tend to learn more about nature and life through their own experience, rather than by listening to a teacher (Kasabov 1996). One of the network learning algorithms is differential competitive learning (DCL) that provides a form of unsupervised adaptive vector quantization (Kong and Kosko 1991). The DCL systems learn only if the competing neurons change their competitive signal.

4.4. *Applications of Neural Networks in Biomechanics*

A few studies have utilized the neural networks in the biomechanics area. Nussbaum and Chaffin (1996) developed a neural network model to evaluate the capability of generating estimations of muscular activity averaged across subjects performing moderate levels of static exertions. Three sets of data from other studies containing EMG patterns were employed for the evaluation in the neural network consisting of three layers. With multiple evaluations, neural networks estimated muscle activity within 3% accuracy across a range of experiments and a high degree of consistency in the averaged muscle activity measured in several different experiments.

In the medical application of the EMG pattern analysis (Pattichis and Schizas 1995), neural network models were combined with the parametric pattern recognition algorithm to provide an integrated system for the diagnosis of neuromuscular disorders. Parametric pattern recognition algorithm automatically extracts motor unit action potential (MUAP) feature. In a routine clinical application of EMG, the MUAP morphology is subjectively evaluated by the examiner. Such a manual analysis is time-consuming and introduces variable sources of error in the subjective measurement of MUAP parameters. The neural networks approach was used for automated classification of the EMG features recorded from normal individuals and patients suffering from neuromuscular diseases. From the medical standpoint, this study showed great potential for solving the nonlinearity problems by way of eliminating the need to solve difficult nonlinear mathematical models. Instead, the networks learned from experience (examples) to optimize performance despite of the system nonlinearity characteristics.

4.5. *Integration of fuzzy systems and neural networks*

The purpose of integrating the fuzzy logic with the neural network approach is to take advantage of their synergistic effects based on the features of both technologies in a particular domain problem. Neural networks, with their highly interconnected systems, pertain to trainable dynamic structures whose learning, noise-tolerance, and, generalization abilities grow organically out of their connectionist structures (Lin and Lee 1996). This dynamic structure works well for the low-level data set obtained from both the linear or nonlinear systems, and produce highly reliable results. Fuzzy logic provides a way to handle the linguistic statements in order to model complex systems. The ability of representing behaviour inherent to imprecise, inconsistent and ill-defined systems helps one to visually explain system functions using the linguistic structures (variables, e.g., low, medium, high, etc.) that are used to describe the state of objects and processes confronting human.

In neural network systems, the facilitation of structured knowledge manipulation provides the means for reducing time necessary to obtain the trained network, and for improving its estimation accuracy. In fuzzy systems, the fine tuning of a fuzzy logic controller can be simplified by the use of learning ability and generalization capability of the neural network that systematically extracts fuzzy logic rules from the numerical training data, and tunes fuzzy membership function of the input and output variables (Huang *et al.* 1996). Merging of these two technologies can be accomplished in three ways (Lin and Lee 1996):

1. neuro-fuzzy systems (NFS): use of neural networks as tools in fuzzy models;
2. fuzzy-neural networks (FNN): fuzzification of the conventional neural network models; and
3. hybrid fuzzy-neural systems (HFNS): incorporation of the fuzzy logic technology and neural network into a hybrid system.

Since the neuro-fuzzy systems (NFS) are inherently fuzzy logic-based systems, neural networks can help in augmenting numerical processing by extracting membership functions and generating fuzzy rules throughout the input-output mapping. The fuzzy neural networks (FNN) are based on the neural networks, and still retain the basic functions and structure of neural networks. In a hybrid fuzzy-neural system (HFNS), both fuzzy logic techniques and neural networks are utilized separately to establish two de-coupled subsystems that perform their own tasks in serving different functions in the combined system.

4.6. *Neural network generating fuzzy rules from numerical data*

Fuzzy rules play an important role in a fuzzy system and the associated application systems. They are generally developed by domain experts by observing system behaviour. However, the tuning of such fuzzy rules and membership functions which, is a critical burden of fuzzy models, can be improved by the adjustment of membership function and fuzzy rules based on the model performance. The membership functions for the fuzzy variables can also be derived from appropriate techniques, based on the control actions observed. One of the logical fuzzy rule generation methods is the vector quantization algorithm that utilizes the mapping capability of neural networks. This method finds and allocates quantization vectors of the training data to fuzzy grids on the partitioned input-output product space, and then determines the weight of each fuzzy grid according to the number of quantization vectors falling into it (Kosko 1992). The vector quantization algorithm also includes the differential competitive learning (DCL) rule that combines competitive and differential Hebbian learning.

In order to generate the fuzzy logic rules from numerical data, the DCL method proceeds along two phases for the pattern classification problem: 1) fuzzy partitioning of the input space, and 2) identification of a fuzzy logic rule for each fuzzy subspace. This method assumes that proper fuzzy partitions of input and output spaces and the associated membership functions are given beforehand. A geometric procedure used to extract the fuzzy logic rules adaptively clusters training samples in the input-output product space of a fuzzy system. Each cluster formed in the input-output product space corresponds to one potential fuzzy logic rule. For instance, suppose *n* fuzzy subsets $\{A_1, A_2, A_n\}$ quantize the input universe of discourse X, and the *p* fuzzy subsets $\{B_1, B_2, B_P\}$ quantize the output universe of discourse Y. So, fuzzy rules exist in the fuzzy Cartesian product $A \times B$ where sets $\{A_i\}$ and $\{B_j\}$ define $A \times B$ fuzzy grids F_{ij} in the input-output product space $X \times Y$. The fuzzy rules are identified if any fuzzy grids are satisfied with criterion such as the threshold (the required number) of training samples in the grids. The fuzzy rules (F) to be extracted are in the form of 'If x is A, then y is B, where $x \tilde{\in} X$ and $y \in Y$.

The training data (provided externally) are fed into a differential competitive learning (DCL) algorithm in order to estimate at most one rule per fuzzy grid column: only the highest-weight fuzzy grid per column is picked. If two fuzzy grids have equally high weights, either fuzzy rule can be picked based on the parameter setting of users. At the training stage, the DCL method initializes the n nodes of the network either by spacing the nodes according to a user-defined method in the input-output space, or by using the first n data vectors, where n is a number determined by the number of membership functions in the fuzzy system. The remaining data vectors are then compared with the nodes of the network.

One feature of the DCL algorithm is that it is sensitive to the data used to create the initial states of nodes in a network whose resulting rules are not always guaranteed to match the relationships between the input-output set exactly. However, they will at least provide an initial rule base that may then be refined further. The refinement can be conducted based on the human expert knowledge obtained from the observation of the given workplace. Figure 5 illustrates the rule generation process for simple one input and one output system with three membership functions predefined on each variable, respectively. In this figure, all training data is distributed in a 3x3 fuzzy matrix, where $n = 3$ input subspaces and $p = 3$ output subspaces.

In this study, the initial fuzzy rules are generated by pre-evaluated neural network with the DCL algorithm. The DCL network can be controlled by the threshold parameter per fuzzy grid. For example, in the trained network, if the threshold is set to 3, then the cells which contain more than 3 data will be fired. In figure 5, only one rule, 'If INPUT is Medium, Then OUTPUT is Medium,' would be produced, since only Cell 5 contains three nodes of the network. It should be noted that the number of generated fuzzy rules depends on the value set for the threshold indicating the required number of the data presented in a cell.

5. Methods and procedures

5.1. *Model structure*

The Fuzzy Logic-based EMG Estimation Model aims to estimate the normalized EMG (NEMG) signals of 10 trunk muscles, based on two physical factors: trunk moment and trunk velocity as model inputs (figure 6). Trunk moment is the product of the force imposed on the L5/S1 level of the human spine and the corresponding moment arm. Trunk velocity was defined as the lateral bending velocity of the upper trunk. The authors provided the subjective assessment of task variables in terms of linguistic values as inputs. The fuzzy rules refined in model development were used to estimate the normalized EMG activities of 10 muscles under specific lifting task conditions. The complete model allows one to visually analyse how the changes of contribution of task variables impact the NEMG magnitude of 10 trunk muscles. The implementation of this model aims to demonstrate usability of the fuzzy approach for estimating the EMG data, or ultimately the biomechanical stresses, such as compression and shear forces imposed on the lumbar spine when lifting loads.

The EMG data were fed into the neural network in order to generate the initial fuzzy rules. The performance of neural network is determined by a control parameter of the network (i.e., threshold) which was set to 3 in this study, because this criterion allowed neural networks to generate maximum number of rules. That is, every input-output mapping has each fuzzy rule to estimate EMG magnitude.

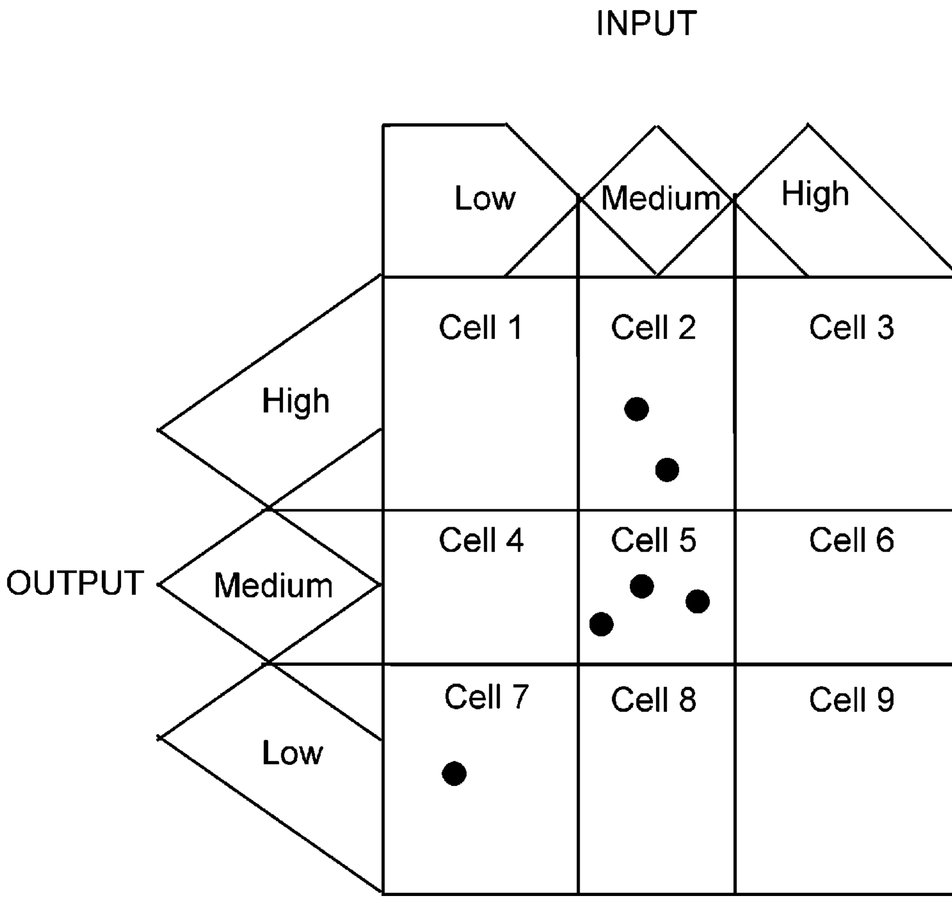


Figure 5. Fuzzy rule generation process for simple one input and one output system: cells indicate product space that can be clustered with differential competitive learning algorithm.

Then, the initial rules were verified (modified) based on the authors' knowledge of the lifting tasks and associated EMG activities. It should be stressed that this was done only at the learning stage in order to correct the initial rules generated by the network.

5.2. *EMG data acquisition*

The real EMG data was collected at the Ohio State University (OSU) Biomechanics Lab (Marras and Sommerich 1991, Marras and Granata 1997). In summary, in the OSU experiments, 12 subjects were asked to exert two types of lateral upper trunk moments (30 ft-lb and 60 ft-lb), at three (sagittal) dynamic trunk velocities (15, 30, 45 degrees/second). For example, a subject was asked to laterally bend at 30 degrees/second of trunk velocity from 15 degree to the left to 15 degree to the right. Demographics of the subject population are provided elsewhere (Marras and Granata 1997). The EMG signals were measured for five pairs of muscles in the experiment: right/left latissimus dorsi (RLD and LLD), right/left erector spinae (RES and LES), right/left rectus abdominus (RRA and LRA), right/left external

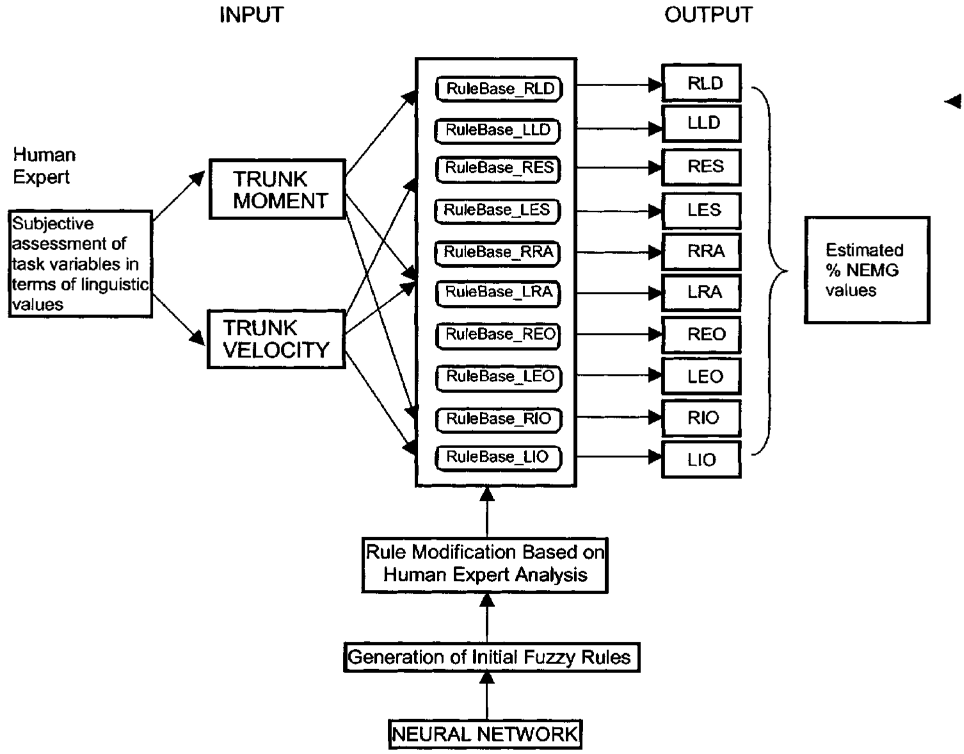


Figure 6. Overall model structure.

obliques (REO and LEO), and right/left internal obliques (RIO and LIO). All the EMG data were normalized by myoelectric maxima recorded from each muscle during a series of six static calibration exertions for the purpose of magnitude comparison and data uncertainty reduction.

$$\text{Normalized EMG} = (\text{EMG} \,/\, \text{EMG}_{max}) \times 100$$

where normalized EMG (NEMG) indicates the relative muscle magnitude ranging from 0% to 100%. EMG is the recorded value at a particular time, and EMG_{max} is the maximum EMG value recorded for the particular muscle at the particular angle of orientation. The NEMG data points per muscle were plotted as a function of normalized time. A peak NEMG value (maximum value) was chosen and used as the 'representative NEMG' (RNEMG) of muscle for the particular task condition. Data for eight subjects (total of 480 RNEMG data sets) were used to develop the estimation model, i.e., to build the respective membership functions, and to train neural networks for producing the appropriate fuzzy rule bases. Another data set for four subjects (total of 240 RNEMG data sets) was used to validate the developed model.

5.3. *Fuzzification of the input-output space*

Fuzzification is defined as a mapping from an observed input space to labels of fuzzy sets in a specified universe of discourse. The NUFEMG has two inputs, trunk moment and trunk velocity. Trunk moment was fuzzified into two fuzzy linguistic variables: 1) 'About30' degrees and 2) 'About60' degrees, since the physical setting for trunk moments were at 30 ft-lb and 60 ft-lb when the EMG signals were measured. Trunk velocity was fuzzified into three fuzzy linguistic variables: 1) 'About15', 2) 'About30', and 3) 'About60' degrees, since the physical settings for trunk velocity were at 15, 30, and 60 degrees/second when the EMG signals were measured. The linguistic term of 'About30' in trunk moment variable represents the moment value of about 30 ft-lb.

Although different system designers can assign different categories of membership functions for task variables when the experimental settings are unknown, the system designer in this study had the information about the true EMG signals. Therefore, the membership functions of the trunk moment variable were defined to have the maximum degree of 1.0 at moments equal to 30ft $\times$ lbs and 60 ft-lb. The membership functions of trunk velocity were defined to have their maximum membership value of 1.0 at 15, 30, 45 degree/second. In order to assign membership functions for the ten muscles' EMG activity as model outputs, the 480 RNEMG data points were plotted in two dimensional space that consist of the combination of two task conditions along the X axis, and the RNEMG magnitude along the Y axis. Then, the triangular-shape membership functions were assigned in such a manner where the whole range of the data was covered with the adequate number (and width) of these membership functions.

5.4. *Neural network generating fuzzy rule bases*

Forty eight data per muscle (total of 480 data points) were fed into the pre-evaluated neural network for the purpose of training and generating the fuzzy rules for a fuzzy system (Togai Infralogic Inc. 1993). The neural network includes the differential competitive learning (DCL) algorithm for the network learning which generates at most one rule per fuzzy grid according to the control parameter. The neural network developed in this research is a general two-layer feed-forward unsupervised network (Zurada 1992) trained with the DCL algorithm (figure 7). Two processing elements in an input layer receive the information about trunk moment and trunk velocity. The processing elements in an output layer consist of the membership functions for the muscles. The number of processing elements in an output layer is dependent on the number of membership functions for the particular muscle.

The number of fuzzy rules depends not only on the number of input and output membership functions, but also on the control parameter provided in the neural network (i.e., the level of threshold to space the initial quantization vectors). The control parameter was set up to three levels of threshold that allows for generation of fuzzy rules at all possible combinations of membership functions of two input variables. Therefore, at least three data points were needed to initiate a cell which generates a fuzzy rule. Since the DCL learning method adaptively moves vectors to pattern-class centroids, the generated fuzzy rules could refer to the centroid value of the applied data presumably believed to be the same data group.

A total of 60 fuzzy rules were generated by the neural network for all trunk muscles. These rules were also verified with the human expert knowledge obtained from the graphical data analysis. Among the generated rules, eight fuzzy rules were further modified by the human expert. These are two rules for the left latissimus dorsi (LLD) muscles, three rules for the left external obliques (LEO) muscles, and three rules for the left internal obliques (LIO) muscles. The set of fuzzy rules utilized in this model is shown in table 1.

5.5. *The inference mechanism*

In order to illustrate the inference mechanism applied in the system, assume the following fuzzy rule is activated:

> If Trunk Moment is 'About30' and Trunk Velocity is 'About15', then NEMG of RLD is 'About_10.'

This fuzzy rule is characterized by a fuzzy IF-THEN statement in which the preconditions and consequents involve the linguistic variables. The two preconditions are evaluated by the fuzzy implication process (AND operator), while the two fuzzy linguistic variables associated with input task variables are fired to induce the

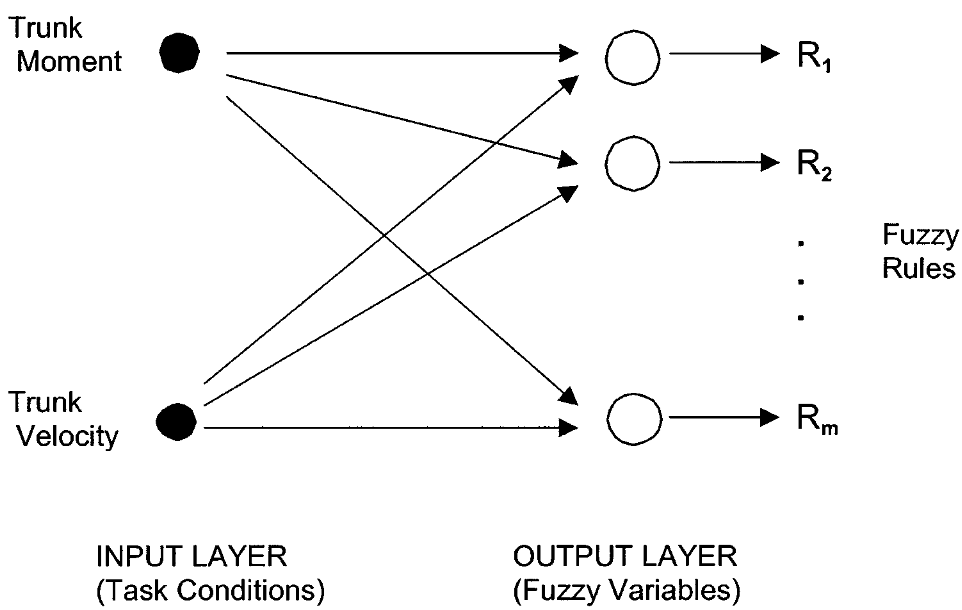


Figure 7. Structure of the Neural Network Used for Generation of Fuzzy Rules.

Table 1. The fuzzy rules used in model development.

RLD			Trunk Velocity	
		About15	About30	About45
Trunk	About30	About_10	About_15	About_10
Moment	About60	About_15	About_15	About_15
LLD			Trunk Velocity	
		About15	About30	About45
Trunk	About30	About_55	About_50	About_55
Moment	About60	About_85	About_90 (About_65)	About_90 (About_85)
RES			Trunk Velocity	
		About15	About30	About45
Trunk	About30	About_5	About_10	About_10
Moment	About60	About_15	About_15	About_15

expected EMG activity. This conjunction rule of fuzzy implication is analogous to the Boolean logic 'AND' operator, thus it takes the minimum of the fuzzy membership values of these conditions to produce a fuzzy outcome (Klir and Yuan 1995).

The 'AND' fuzzy operator evaluates the fuzzy relation between two fuzzy predicates, based on the firing strength of the rule:

$$. \alpha = f_M \text{ (About30) } \Lambda \; f_V \text{ (About15)}$$

where f_M (About30) and f_V (About15) indicate the degrees of membership function at the given input condition, 'About30' of trunk moment and 'About15' of trunk velocity, respectively. The firing strength takes the smaller degree value of the two. It should be noted that the above outcome is still a fuzzy value, while it has to be defuzzified into a crisp value defining the muscle activity (a normalized EMG) of interest. In this study, the Max-dot defuzzification method was used to quantify the fuzzy outcome. According to this method, the rule that has the higher activation level will contribute more to the final output.

6. Results and discussion

6.1. *Analysis of the raw EMG data*

The normalized EMG (NEMG) signals were measured under 30 degrees/second of trunk velocity and 60 ft-lb of the trunk moment. Owing to the lifting task characteristics, the left side muscles of trunk were clearly more active than the right side muscles, and muscular activity increased slightly as the trunk velocity increased. The 480 RNEMG data sets used for building the NUFEMG were averaged at task conditions in the combination of task velocity and trunk moment (table 2). These values are defined as 'averaged NEMG' (ANEMG) of muscle for the particular task condition.

$$\text{Averaged NEMG} = \Sigma(\text{ RNEMG }) \, / \, \text{number of subjects}$$

At the trunk moment of 30 ft-lb condition, the left internal obliques (LIO) muscles showed the highest muscle activity of 63.10% ANEMG under 45 degrees/second of trunk velocity. All right trunk side muscles exerted less than 20% ANEMG regardless

Table 2. Average values of real NEMG signals of 480 data sets used for model development.

	Trunk Velocity / Trunk Moment					
Muscles	15/30	30/30	45/30	15/60	30/60	45/60
RLD	11.08	10.37	9.24	19.35	18.01	16.39
LLD	59.32	54.02	52.36	82.85	92.42	92.79
RES	7.87	10.46	8.33	13.58	12.55	12.76
LES	42.01	46.57	45.49	56.32	59.98	59.54
RRA	5.97	6.86	6.27	13.05	12.12	13.35
LRA	16	18.06	15.59	34.4	32.46	38.45
REO	6.63	8.33	7.64	14.96	13.75	13.33
LEO	39.38	42.05	41.94	82.62	91.01	90.97
RIO	18.09	13.45	13.81	19.81	16.49	16.11
LIO	57.64	58.66	63.1	83.36	92.68	96.42

of the level of trunk velocity. At the trunk moment of 60 ft-lb condition, the left internal obliques (LIO) muscles also showed activation of 96.42% ANEMG magnitude under 45 degrees/second of trunk velocity, while all the right side muscles exerted less than 20% ANEMG, regardless of the trunk velocity levels. Similar results were reported by Marras and Granata study (1997) that describes how spine loading changes as a function of lateral trunk velocity in a load-supporting task. They found that activity of the external oblique and internal oblique muscles were significantly greater than the activities of the erector spinae and rectus abdominus muscles.

6.2. *Model validations*

The developed model was validated by comparing the estimated ANEMG values from the model with the representative RNEMG data of four subjects (a total of 240 data points) which were not used in the model development. Since the model estimate was a continuum in the NUFEMG, the discrete points were taken at the combinations of task conditions for evaluation purposes.

6.2.1. *Mean absolute error (MAE)*: The absolute errors between 24 evaluation data sets per muscle and the model estimates for six task conditions were calculated, and then the absolute errors for each muscle were averaged, resulting in the mean absolute error (MAE). A value of the MAE indicates the errors between the representative NEMG (RNEMG) values and the model EMG estimates (ENEMG).

$$\text{MAE} = (\Sigma \mid \text{RNEMG} - \text{ENEMG} \mid) \,/\, \text{number of evaluation data}$$

where ENEMG indicates the value estimated by NUFEMG.

The mean absolute error (MAE) ranges from 4.97% for the right latissimus dorsi (RLD) to 13.16% for the left rectus abdominus (LRA). Overall, across all muscles, the average value of MAE was 8.43% (SD = 2.87%) of the normalized EMG data. The larger MAE occurred for the left erector spinae (LES), left rectus abdominus (LRA), and left external obliques (LEO) muscles (12.79%, 13.16%, and 13.00%, respectively). The smaller MAE occurred for the right latissimus dorsi (RLD) and right rectus abdominus (RRA) muscles (4.97% and 5.12%, respectively). The larger absolute errors, presumably, occurred in the left side muscles which exhibited the higher levels of muscular activity.

6.2.2. *The average method*: In the traditional modelling approaches, the averaged EMG value is often taken as the representative value for the muscle activity due to a given lifting task. The real signals are averaged over all subjects, and then put into the biomechanical model (e.g., EMG-driven model or optimization-based model) to evaluate spine loads. Hence, it is useful to analyse the differences between the model estimates provided by the NUFEMG and the average NEMG of real EMG signals. These differences between the averaged NEMG values (ANEMG) and the model estimates (ENEMG), defined as mean absolute difference or MAD were calculated. The MAD was defined as:

$$\text{MAD} = (\Sigma \mid \text{ANEMG} - \text{ENEMG} \mid) \,/\, \text{number of task conditions}$$

where ANEMG indicates the average value of the representative RNEMG values, estimated NEMG (ENEMG) is the value estimated by NUFEMG.

The negative sign (−) under the 'Difference' column indicates that the averaged NEMG value (ANEMG) is less than the model estimate (ENEMG). The ANEMG magnitude of the right erector spinae (RES), right rectus abdominus (RRA), and right internal obliques (RIO) muscles were overestimated for all (six) task conditions, while the NUFEMG underestimated the ANEMG magnitude of the left external obliques (LEO) for all (six) task conditions.

Table 3 shows the mean absolute differences of NEMG values of all the muscles between average method and the study model.

The larger MAD occurred for the left erector spinae (LES), left rectus abdominus (LRA), and left external obliques (LEO) muscles (11.59%, 11.31%, and 10.18%, respectively). The smaller MAD was 2.71% for the right external obliques (REO) muscles. The ANEMG values for the left side trunk muscles had larger MAD values compared to right side trunk muscles. It should be noted that a similar tendency was found in the MAE analysis.

In the analysis of the Pearson product correlation between the averaged EMG (ANEMG) values and the model estimates (table 4), the r values ranged from 0.16 for the left erector spinae (LES) to 0.99 for the left latissimus dorsi (LLD). The coefficient of correlation for the left erector spinae was 0.16, and for the left rectus abdominus was 0.41, with the corresponding mean absolute differences of 11.59% and 11.31%, respectively. The right internal obliques (RIO) muscles had a coefficient of correlation value of 0.29, despite comparatively lower MAD of 6.28%.

6.3. *Comparison of the EMG model estimation quality with other studies*

The estimation quality of NUFEMG was compared with that of a neural network model (Nussbaum and Chaffin 1996) and optimization models (Schultz *et al.* 1983,

Table 3. Mean absolute difference (MAD) between averaged NEMG (ANEMG) of real signals and the model estimates (ENEMG) for all the muscles.

Trunk Velocity/ Moment	RLD	LLD	RES	LES	RRA	LRA	REO	LEO	RIO	LIO
15/30	0.95	0.94	1.77	6.44	1.27	7.79	3.58	16.60	1.05	2.08
15/60	6.32	3.76	7.90	12.51	1.71	19.40	2.05	7.25	1.74	6.79
30/30	4.92	1.98	4.52	15.14	5.72	3.71	2.14	17.37	9.95	1.55
30/60	2.16	1.44	5.79	6.89	6.88	19.51	0.06	8.31	9.03	6.68
45/30	0.37	3.85	4.64	15.46	6.45	0.57	3.59	11.05	9.97	9.70
45/60	7.16	5.32	7.55	13.12	7.12	16.90	4.83	0.52	5.94	4.51
Mean	3.65	2.88	5.36	11.59	4.86	11.31	2.71	10.18	6.28	5.22
STD	2.88	1.69	2.26	3.98	2.66	8.36	1.66	6.31	4.07	3.12

RLD = Right Latissimus Dorsi
LLD = Left Latissimus Dorsi
RES = Right Erector Spinae
LES = Left Erector Spinae
RRA = Right Rectus Abdominus
LRA = Left Rectus Abdominus
REO = Right External Oblique
LEO = Left External Oblique
RIO = Right Internal Oblique
LIO = Left Internal Oblique.

Hughes and Chaffin 1985). The comparisons were based on mean absolute difference and coefficient of determination scores (table 4). The neural network model developed by Nussbaum and Chaffin (1996) could estimate NEMG values. Model inputs were the crisp values of four task variables including magnitudes of applied flexion, extension, right lateral and left lateral moments at L3/L4. The optimization model developed by Hughes and Chaffin (1987) was used to evaluate the effect of adding shear constraints in the original Schultz *et al.* (1983) torso optimization model. The original Schultz model had no constraint on the motion segment shear force. The coefficient of determination data used in this study were taken from Chaffin's study (1988) for the purpose of comparison. Overall, the MAD of NUFEMG (6.40%NEMG) was less than that of the neural network model (9.34 %NEMG), but the coefficient of determination of NUFEMG (0.59) showed worse correlation than that of the neural network model (0.95). However, as shown in table 5, NUFEMG showed better performance in the comparison of coefficient of determination than the two optimization models (0.47 of Schultz *et al.* model, 0.57 of Hughes and Chaffin model). Unfortunately, no statistical comparison of the above results was possible.

Table 4. Coefficients of Pearson product correlation (r) and mean absolute difference (MAD) between averaged NEMG of real signals (ANEMG) and the model estimates (ENEMG).

Muscle	*r*	MAD	MAE
Right Latissimus Dorsi	0.69*	3.65	4.97
Left Latissimus Dorsi	0.99	2.88	6.62
Right Erector Spinae	0.93	5.36	5.45
Left Erector Spinae	0.16*	11.59	12.79
Right Rectus Abdominus	0.71*	4.86	5.12
Left Rectus Abdominus	0.41*	11.31	13.16
Right External Obliques	0.96	2.71	6.50
Left External Obliques	0.98	10.18	13.00
Right Internal Oblique	0.29*	6.28	6.76
Left Internal Oblique	0.98	5.22	9.94

* $p > 0.05$, N = 6 observations. The unit of MAD is %ANEMG.

Table 5. Comparison of results with other studies.

	Mean Absolute Difference (MAD: %NEMG)				Coefficient of Determination (R^2)			
Range	Mean	S.D	N	Range	Mean	S.D	N	Range
FLHEPM	6.40	3.39	10	[2.88 ~ 11.59]	0.59	0.39	10	[0.02 ~ 0.98]
Neural Network Model for NEMG prediction								
Nussbaum & Chaffin (1996)	9.34	4.72	6	[2.16 ~ 16.01]	0.95	0.01	6	[0.93 ~ 0.96]
Optimization Models								
Schultz *et al.* (1983 model)	Not Available				0.47	0.14	8	[0.25 ~ 0.65]
Hughes & Chaffin (1987 model)	Not Available				0.57	0.17	8	[0.30 ~ 0.73]

*N indicates the number of observations (muscles).

7. Conclusions

The proposed modelling approach combines fuzzy methodology with the neural network to model estimating the EMG magnitude of 10 trunk muscles based on two lifting task variables. This approach utilizes linguistic values as model inputs in order to estimate EMG values, instead of numerical input data as required by other approaches. Since most of the biomechanical models for estimating loads on the lumbar spine rely heavily on the EMG inputs to derive the desired model outputs, the developed neuro-fuzzy- model makes a significant contribution by allowing for estimating the EMG activity (under limited task conditions), without the actual measurement of the EMG signals of the considered trunk muscles. In the development of NUFEMG system, the initial fuzzy rules were generated by the neural network using the differential competitive learning (DCL) algorithm. The suitability of these preliminary rules was then validated by the authors. Eight of the sixty rules were modified for the sole purpose of improving the quality of the network learning process. These included two rules for the left latissimus dorsi (LLD) muscles, three rules for the left external obliques (LEO) muscles, and three rules for the left internal obliques (LIO) muscles. It should be noted that no rule modification was used during the actual EMG prediction phase that utilized different set of experimental data. It is believed that the rule modification will not be needed when the set of input variables is increased beyond two, as the network performance will be significantly increased. Future studies will focused on fully automated network learning and estimating of the EMG values based on the larger number of task variables.

Several advantages of the developed system were found. The lifting task variables could be represented with the fuzzy membership functions. This provides flexibility to combine different scales of model variables in order to design the EMG estimation system. The NEMG signals could be estimated with reasonable accuracy (as average value of the mean absolute difference of 6.4%) by the model without using complex mathematical formulations. In model development, it was possible to generate the initial fuzzy rules using the neural network, but not all of the initial rules were appropriate (87% correct). The larger mean absolute error (MAE) occurred, presumably, for the left side (trunk) muscles which exhibited higher levels of the activity on the lateral bending task used in this study. A comparison of performance of the EMG-driven biomechanical model with the NUFEMG-based EMG input and the real EMG data input is needed for future model development and validation. The present model accuracy is limited by use of only two task variables which were available for this study (out of five proposed task variables: load moment, trunk velocity, trunk motion complexity, body control, and work satisfaction). According to the Marras (1992), a multiple logistic regression model indicated that a combination of these five trunk motions and workplace factors were related to the LBD risk. Ultimately, the neuro-fuzzy approach utilizing all five variables to estimate either the EMG activities or the spinal loading due to dynamic lifting tasks should be developed. The advantages of the proposed method originate from the fact that fuzzy logic and neural networks are flexible model-free estimators, as they allow for modelling a system with a large number of inputs, and require less effort in adding a new task variable. Future research should focus on developing fully automated hybrid neuro-fuzzy models for estimating the spinal loads without involvement of the human expert. Improved model performance could be achieved by introducing more input task variables and employing a larger subject population.

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