1. INTRODUCTION

Ergonomics, which focuses on the design of human–machine systems with respect to requisite compatibility between the users, products, systems, and environments, is often faced with the complex and uncertain relationships between human characteristics, various artifacts, and human activity requirements (Karwowski 1991). Investigation of such relationships must take into consideration the natural fuzziness in human and system performance, which can be expressed in terms of degrees of vagueness, and which formally can be modeled through gradation (Karwowski 1991; Karwowski and Mital 1986). As fuzziness occurs at all levels of perception processes (Smithson 1982). Uncertainty due to fuzziness is inherent to any complex system and to the human thought and perception processes (Smithson 1982). It should be noted that fuzziness, which measures the degree to which an event occurs, and not whether it occurs, differs from randomness, which describes the uncertainty of event occurrence. (Kosko 1992). Furthermore, fuzziness, i.e. a type of deterministic uncertainty, also models ambiguity as a property of physical phenomena.

In order to study complex human–machine systems it is necessary to use modeling approaches that are approximate in nature (Zadeh 1973; Karwowski 1983). Fuzzy systems methodologies allow accounting for human and human–artifact fuzziness, and, therefore, provide the necessary framework for successful modeling efforts in the ergonomics (Karwowski 1991; Karwowski and Mital 1986). As fuzziness occurs at all levels of human interactions with the outside environments, ranging from physical to cognitive tasks, it can be used as the model for human–artifact interactions. It can also help to explain the complex phenomena of human sensation, information processing, decision-making and communication and functioning (Karwowski 1991, 1992; Karwowski and Salvendy 1992).

2. HUMAN–MACHINE FUZZINESS

Contemporary models used in ergonomics utilize formal structures to represent the human–artifact–environment reality as perceived by the human operator (Karwowski et al. 1999). However, the process of human perception is intrinsically governed by the natural fuzziness due to the human (human fuzziness), and by complexity and related uncertainty of the system under observation (human–machine fuzziness). Fuzziness is a useful model for human language and categorizing processes, and fuzzy mathematics can be used to augment conventional statistical techniques in the analysis of fuzzy data, reliability analysis and regressions, and structurally oriented methods such as hierarchical clustering and multidimensional scaling (Smithson 1982). In view of the above, fuzzy systems provide a useful framework for modeling variety of complex tasks, situations, systems, artifacts and environments, and their interactions with people.

For example, an assessment of resource demand or mental workload imposed on human operators in human–machine systems is of great importance to assure acceptable levels of performance (Wickens 1987). The measures of mental workload, such as those of perceptual–cognitive effort or response loading, are fuzzy phenomena, by the very nature of the underlying processes (Karwowski 1992). Therefore, the assessment methods must exhibit fuzzy properties of the investigated systems. As fuzziness occurs at many levels of cognitive processes, people have the unique ability to understand and apply vague and uncertain concepts (Hersh and Caramazza 1976). Research in semantic memory showed that people perceive natural categories as sets with no clear boundaries separating members from non-members (McCloskey and Glucksberg 1978). People are also able to comprehend vague concepts of the natural language, as if fuzzy labels represented them, and manipulate them according to rules of fuzzy logic (Oden 1977).

2.1. Human Performance

Human functioning can be described in terms of perception, information processing and decision-making, memory, attention, feedback, and human-response processes. Any task requires processing of information that is gathered based on perceived and interpreted relationships between the system elements. According to the model of human information processing (Wickens 1984), the sensory information coming from the sensor organs is compared to some internal representation of the recognized object stored in the permanent (long-term) memory. After the stimulus is identified, a decision can be made regarding the appropriate course of action. The decision process may require some transformations of the available information in the working memory, information storing in the long-term memory, and generating a response. The response can be realized through a process of coordinated muscular control actions, which effects are perceived through the feedback system. An inherent fuzziness of these natural processes is discussed below.

2.2. Perception and Memory

The purpose of the human perceptual system is to provide sufficient conditions for adaptive behavior (Foley and Moray 1987). Perception is constructed by the observer rather than determined by parameters of physical signals received from the receptors. The process of conscious perception is a fuzzy one, with uncertainties as to the physiological thresholds for physical stimuli, pattern recognition, and judgment requirements. For example, a question of “At what frequency will an intermittent light be perceived as just flickering?” is an ambiguous one, and hence the eye flicker frequency is a fuzzy, not random, phenomenon, as it refers to the degree of noticeable flickering rather than the question of whether it occurs (Karwowski 1992).

Many of the psychophysical laws that relate the magnitude of change in physical stimuli (DI) that will just be noticed by an observer, also exhibit requisite fuzziness. In the Weber-Fechner Law, the magnitude of change in a physical stimulus that will be just noticed by an observer is a constant proportion of the
stimulus. Referring to the magnitude of DI that will result in a judgment of a difference in the levels of physical stimuli 50% of the time (so called just noticeable difference or jnd), this law is not a probabilistic statement of whether the perception of change will occur. Rather, it concerns the question at what level (degree) of the difference in physical stimuli such a change will be observed.

Human ability to process information from different stimulus objects at one time is limited. However, several dimensions of a single object can be processed in parallel (Wickens 1987). The degree to which many sources of object the human brain can process stimuli and different dimensions of the same objects exemplifies the fuzzy nature of human perceptual and central processing processes (Karwowski 1992). In the human–computer system, information displayed on the screen can be arranged along a continuum that defines the degree to which that information is spatial-analog in nature (i.e. information about relative location, transformation or continuous motion), linguistic-symbolic or verbal. The two end points of this verbal–spatial continuum distinguish the verbal and spatial memory systems (Wickens 1987). The border between these two systems, however, is subject to fuzzy interpretation. For example, the capacity of working memory is limited to 7 (+/-) 2 of the unrelated items (Miller 1956). The important question is to what degree one can recall and operate on a given number of items. The degree to which the memory is short or long is also a fuzzy category (Karwowski 1992).

2.3. Attention and Decision-making
Attention is the ability to process information in parallel or time-sharing fashion (Wickens 1987), which can be measured by the graded (fuzzy) categories of success. The selective allocation of human attention is determined by the human operator’s internal model of the statistical properties of the environment (Moray 1984). Decision-making and diagnosis in human–machine systems are also of uncertain nature. Decisions are typically followed by responses, many of which are intrinsically fuzzy. It should be noted here that the prevalent definition of the relationship between choice reaction time and degree of choice (the Hick-Hyman law) is based upon the information content of a stimulus (S) in bits as follows: \( RT = a + b S \). The presence of human fuzziness cannot be overlooked in the paradigm of stimulus—response compatibility (Wickens 1987), which described the physical relationship between a set of stimuli and the speed of human response. The spatial relations in arrangements of signals and response devices with respect to direction of movement and logic of adjustments, often exhibit high levels of uncertainty regarding the effects of intended and unintended control actions (Karwowski 1992).

2.4. Human Sensations
Traditional methods for quantification of the relationships between human sensations and physical characteristics affecting them are based on multivariate analysis techniques such as multiple regression analysis and quantification theory. With higher order data, however, it is more difficult to find an adequate formula that would represent the non-linearity factor. In addition, conventional methods have typically excluded the ambiguities that can arise in the process of recognizing and making subjective evaluations of the physical characteristics. Shimizu and Jindo (1995) developed a model accounting for non-linearity property of information processing. The benefits of the fuzzy approach is that uncertainties and non-linearity of human sensations can be accounted for and quantified in order to derive correlations with the considered physical characteristics of the product.

2.5. Mental Workload
Mental workload is the amount of mental effort necessary to perform a given task. Mental workload assessment can be used to maintain a workload level allowing acceptable performance (Proctor and Zandt 1994). Subjective assessment techniques are based on empirical methods that measure workload directly in an operational system or a simulated environment through the use of human operators’ judgments. The operators are asked to rate the perceived mental effort, time load, and stress load of particular tasks. Therefore, workload is not as a scalar quantity, but rather a vector quantity associated with multiple dimensions (Moray 1982). The subjective measures of mental workload utilize the scale method, which calls for the subjects to express their feelings through rating scales or questionnaires. Unfortunately, a precise scale often cannot represent the human feelings adequately. Using the linguistic quantifiers can help to overcome this difficulty, as evidenced by recent applications of fuzzy methodologies to risk analysis with mental workload assessment (Liou and Wang 1994; Chen 1996).

2.6. Human Cognitive Processes in Industrial Tasks
Ukita et al. (1996) described a fuzzy-based system to model the decision-making process of the human operators involved in tuning of microwave circuits in a real-time environment. The process was automated through the application of a fuzzy knowledge-based system. In a complex tuning process, multiple circuit specification criteria have to be simultaneously satisfied by several trimmers. To reduce the number of trial-and-error steps required to meet specific circuit tuning criteria, and, consequently, the tuning process time, the order of subsequent trimmer adjustments in the tuning process, as well as the extent of each individual trimmer tuning magnitude, must be chosen very carefully. In the past, experienced workers, who would skillfully adjust a set of trimmers by hand, performed the circuit tuning process. The quality of the adjustment process was primarily based on the human operator’s mental model of the circuit tuning behavior formulated from the long practice and requires specific cognitive skills of the human operator. Ukita et al. (1994) proposed to account for the effect of each trimmer on each of the tuning criterion by a grade of fuzzy membership related to the circuit output. The overall effect of each trimmer on the circuit tuning performance was modeled by an aggregation of the fuzzy grades used for trimmer selection. The model simulation showed that the geometrical average operator was the best method for evidence aggregation of fuzzy evidence in modeling of the human cognitive processes underlying manual circuit tuning tasks.

3. HUMAN–MACHINE RELIABILITY
Human reliability is typically defined as a probability that a person correctly performs some system-related activity in a required time period, or as the probability of a successful performance of a
task. However, given the natural fuzziness of human interactions with the outside world, both probabilistic and possibilistic approaches to human reliability are needed (Terano et al. 1983). Since the human operator characteristics which affect the reliability include such fuzzy processes as sensory perception, motor control, cognitive functions (information processing and decision-making), and meta-cognitive functions (intuition and abstract processing), human reliability models must allow for qualitative reasoning through human error possibility measures, and should account for natural vagueness of higher cognitive functions. Onisawa (1988) proposed the concept of human error based on the possibility measure that is affected by several human performance-shaping factors. Pedrycz (1990) also discussed cognitive aspects of information processing and proposed a fuzzy framework for development of human perception perspective as opposed to machine perspective.

4. FUZZINESS IN HUMAN–COMPUTER
INTERACTION

The interactions between people and computers often reflect the cognitive fuzziness of the data, as well as users’ uncertainty exhibited in perception of the computing environment. The field of human–computer interaction (HCI) focuses on developing effective models of such inter-relationships, including the fuzzy-based communication tools. Karwowski et al. (1990) discussed the problems of fuzziness due to high complexity of human–computer systems and the nature of user’s perception and information processing.

4.1. Fuzzy GOMS Model

According to GOMS model (Card et al. 1983), the user’s cognitive structure consists of the following four components: (1) a set of Goals, (2) a set of Operators, (3) a set of Methods for achieving the goals, (4) a set of Selection Rules for choosing among competing methods for goals. Karwowski et al. (1990) proposed extensions to GOMS to account for uncertainty within selection rules and to generalize the Goals, Operators and Methods components as either precise or fuzzy. The Selection Rules were also expressed in either probabilistic or fuzzy variables. A variation of the manuscript editing experiment by Card et al. (1983), with the subject verbalizing five different cursor placement rules, was used. The fuzzy GOMS model utilized the sets of Goals and Operators that were precisely defined, while the (predicted) Methods used by subjects, as well as specific Selection Rules applied to accomplish the editing task included application of linguistic descriptors, fuzzy logic, and possibilistic measures of uncertainty. The rules, methods, and corresponding membership functions were elicited from the subjects, and theory of possibility was used to model the subject’s rule selection process. Each of the potential rules was assigned a possibility measure equal to the membership value(s) associated with it during the elicitation phase of experiment. The non-fuzzy GOMS model successfully predicted 58.7% of the responses, while the fuzzy GOMS model predicted significantly more correct responses, i.e. 82.3% of all decisions (Karwowski et al. 1990).

4.2. Computer Screen Design

Effectiveness of the human interactions with computer systems depends to a large extent on computer screen design (Tullis 1981). Among well-defined relationships between screen formats, there are many rules of thumb, which are based on subjective views and anecdotal knowledge (Grobelny et al. 1995). Limited empirical data and lack of consistent measures and quantitative criteria for assessment of screen quality makes the evaluation of system efficiency and comparison of different screen designs difficult. Fuzzy-based linguistic patterns for assessment of the computer screen design quality have been proposed. The linguistic patterns are based on intuitive expressions closely related to natural language and truth-values. The proposed system of concepts, relations and definitions, includes: (1) the implication and definition of linguistic variables, (2) a degree of truth of an implication, (3) intensity levels of implication variables, (4) degree of truth of the consistency of two expressions, (5) definitions of linguistic relationships, and (6) definitions of modifiers for linguistic expressions and connectors.

For example, searching times for desired information can be reduced if the information presented on the screen is organized in groups of closely related items. Furthermore, the amount of presented information greatly influences the searching times. If groups are significantly larger than optimal, the mean group size becomes the main factor that can be used to predict searching times. The study demonstrated that it is possible to achieve rational and relatively easy to interpret assessment of different screen designs in the form of the degrees of truth (Grobelny et al. 1994).

5. PHYSICAL WORKLOAD

5.1. Modeling of Manual Lifting Tasks

Application of the psychophysical approach to setting limits in manual lifting tasks requires the subject to adjust the weight of load according to his or her perception of effort in order to minimize the potential for over-exertion or excessive fatigue. Karwowski (1983) and Karwowski and Ayoub (1984) applied fuzzy sets to model and assess the acceptability of stresses involved in manual lifting task. They hypothesized that a combination of acceptability measures of the biomechanical and physiological stresses leads to an overall (psychophysical) measure of lifting task acceptability.

Fuzzy modeling was also used to investigate the relationships between physical weight, its perceived heaviness, and size of load. Luczak and Ge (1989) noted that it is not clear why the handling of a small box with a certain weight is sometimes perceived heavier than handling a bigger box with the same weight (size-weight illusion). They asked the subjects to express the relationships between physical weight and its perceived heaviness. Load heaviness levels were expressed using fuzzy sets, including “very light,” “light, moderate,” “heavy” and “very heavy.” The derived relationships illustrate how fuzzy measures can be used to quantify natural fuzziness underlying human cognitive processes. Recently, Yang et al. (1998) extended the study by Luczak and Ge (1989) to Asian population of workers, focusing on load heaviness in relation to perceived weight lifted.

Following the 1982 study, Karwowski and his co-workers performed variety of research projects focusing on understanding of human perception of load heaviness, and fuzzy modeling of acceptable and safe weights for lifting tasks (see Yang et al. 1998; Karwowski et al. 1999). Recently, Karwowski et al. (1999) demonstrated experimentally that perception of load heaviness...
is subject to fuzziness of human cognitive processes, and concluded that this phenomenon should be taken into account when setting limits in manual lifting tasks. Examples of other important studies in this area include development of the model of ergonomic workload stress index (Chen et al. 1994), and fuzzy knowledge-based decision support system for recommending the maximum acceptable weights of lift, based on data generated from the job severity index (Ngo et al. 1996).

5.2. WORK-RELATED MUSCULOSKELETAL DISORDERS

Work-related musculoskeletal disorders (WRMDs), such as carpal tunnel disorders, tendinitis, chronic muscle strain, and degenerative joint diseases, are a major occupational health problem (Karwowski and Marras 1997). These cumulative trauma disorders (CTDs) may occur when a force is applied repeatedly over a prolonged period to the same muscle group, joints, or tendons, and are linked to jobs that exhibit repeated or awkward postures. In order to implement adequate prevention and health program, it is necessary to document the relationships between work exposure (prevalence of job related risk factors in a production environment) and specific musculoskeletal disorders. From the perspective of CTDs prevention, a desirable situation is to predict the possibility of occurrence of CTDs in a given occupational setting. A fuzzy system methodology can be used to determine the possibility of occurrence of CTDs, given the available relationships between CTDs, risk factors and their severity level. It should also be noted that in many cases, the human-expert is the only available “measurement device” for observing, coding and classifying interesting data. Therefore, the linguistic expressions are more adequate and reliable tools for human analyses than precise numerical measurements in many real life situations. Zadeh (1978) introduced a concept of the linguistic variable, which enables an application of linguistic, expert-defined expressions. The main point of this approach is that natural language expressions describing level or intensity of a given value can be defined in appropriate spaces as fuzzy sets.

5.3. Fuzzy Modeling of CTDs

Theoretical framework for fuzzy modeling of the risk of cumulative trauma disorders (CTDs) was first proposed by Grobelny and Karwowski (1992). The developed conceptual model for quantification of risk for work-related musculoskeletal disorders was based on fuzzy logic, linguistic variables, and knowledge provided by the human experts. For example, the following linguistic proposition was defined with respect to work-related risks of CTD:

PROPOSITION:

B: IF Required force is BIG THEN Exposure time is SHORT
C: IF Deviation from neutral posture is BIG AND Required force is BIG THEN Exposure time is VERY SHORT

The logical expressions (A AND B AND C) were defined using the “General Desired State Patterns” (GDSP), i.e. “natural” descriptions that constitute a basis for a formal assessment of working environment. The GDSP can be compared with risk factors associated with any industrial job to generate the logical truth-values: FALSE or TRUE, respectively, for jobs fulfilling or not fulfilling the above pattern. This was done according to the principle of implication (truth value determination).

For example, using the categorical risk descriptors (HIF — high force, HIR — high repetition), a general pattern of “desired conditions for repetitive work of the hand” was defined as follows:

PROPOSITION:

A: IF Force is HIF THEN Exposure time is SHORT, AND
B: IF Repetition is HIR THEN Exposure time is SHORT, AND
C: IF Force is HIF AND Repetition is HIR THEN Exposure time is VERY SHORT

Assuming the values of measured risk factors for CTD to be:

Force = 8 kg, Repetition = 0.8/sek and Exposure time = 10%, one can set the values: HIF(8) = 0.8, HIR(0.8) = 0.8, SHORT(10) = 0.5, and VERY SHORT (10) = 0.25.

The following formula proposed in multivalued Lukasiewicz logic (Grobelny 1988) can then be used:

If p and q are both truth values of P and Q statements, respectively, then truth value of implication

P => Q can be calculated according to: T (P => Q) = min (1, 1 - p + q)

in order to assess the values of this PROPOSITION as follows:

A: min (1, 1 - 0.8 + 0.5) = 0.7
B: min (1, 1 - 0.8 + 0.5) = 0.7

Also, the “min” operator defined in the Cartesian product of relationship space was used to represent the relationship “AND”. According to this rule, the left side of the sub-pattern C for exemplary data (Force = 8 kg, Repetition = 0.8/sek) can be evaluated as follows:

min(HIF(8 kg), HIR (0.8/sek)) = min (0.8, 0.8) = 0.8, and consequently: C: min (1, 1 - 0.8 + 0.25) = 0.45

Using the “min” operation for evaluation the whole pattern:

(A AND B AND C):

T (PROPOSITION) = min (0.7, 0.7, 0.45) = 0.45.

The “possibility measure” (Zadeh 1978) allows to widen the proposed approach to situations when the input data to PROPOSITION is fuzzy. Assuming that it is possible to obtain a reasonable system of linguistic representations for problems modeled by PROPOSITION, the following expert’s opinions could be possible:

Force is ABOUT 4, Repetition is HIGH, Exposure time is MEDIUM. Having all parameters defined and implemented on a computer model, the user can derive the general “pattern satisfaction index”, as well as the sub-pattern truth-values, expressing quantitatively the relative CTD risk at the workplace.

Recently, Bell and Crumpton (1997) also proposed a fuzzy linguistic model for predicting the risk of carpal tunnel syndrome (CTS). The model utilizes fuzzy sets to quantify the risk associated with development of this neuropathy. The first set of membership functions involved utilizing the linguistic risk level obtained by the expert knowledge acquisition. The second set of membership functions was derived to rate the possibility of the hazard associated with a particular linguistic variable. The membership functions of the two variables were intuitively determined based on graphical representation of the physical data.

6. CONCLUSIONS

Fuzziness represents natural vagueness and uncertainty inherent to any human–artifact–environment systems. Fuzzy systems
methodologies allow accounting for the human and system fuzziness, and provide a useful framework for investigating the requisite human—system compatibility, and for modeling in the human factors and ergonomics discipline in general. Designers should treat the fuzziness in human performance as natural system requirement.

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