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Some Studies on Noise and Its Effects on Industrial/Cognitive Task Performance and Modeling

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1. Introduction

Present industrial environment is quite different than past. Globalization and market driven forces has made the working environment quite competitive. It is quite obvious that these factors when combined with environmental factors, lead to poor operators/workers performance. Therefore, ergonomists has new challenges in terms of predicting workers efficiency as well as workers health protection and well being.

High noise level exposure leads to psychological as well physiological problems. It results in deteriorated cognitive task efficiency, although the exact nature of work performance is still unknown. To predict cognitive task efficiency deterioration, neuro-fuzzy tools were used. It has been established that a neuro-fuzzy computing system helps in identification and analysis of fuzzy models. The last decade has seen substantial growth in development of various neuro-fuzzy systems. Among them, adaptive neuro-fuzzy inference system provides a systematic and directed approach for model building and gives the best possible design parameters in minimum possible time.

Input variables were noise level, cognitive task type, and age of workers. Out-put variable was predicted in terms of reduction in cognitive task efficiency. The cause-effect relationships of these parameters are complex, uncertain, and non-linear in nature therefore, it is quite difficult to properly examine it by conventional methods. Hence, an attempt is made in present study to develop a neuro-fuzzy model to predict the effects of noise pollution on human work efficiency as a function of noise level, cognitive task type, and age of the workers practicing cognitive type of task at (I.T.O power plant station, centrifugal pump industry WPIL India Limited, and Shriram Piston & Rings limited) industries. Categorization of noise and its levels (high, medium, and low) was based on a survey conducted for this purpose.

A total of 155 questionnaires were distributed among the workers of industries under reference. Likert scale has been used to evaluate the answers densities which ranges between “strongly disagree” to “strongly agree”. Cognitive workers performance was evaluated based on self administrated questionnaire survey, which consisted of 55-questions, covering all possible reported effects of cognitive task on cognitive task performance.

The model was implemented on neural Fuzzy Logic Toolbox of MATLAB using Sugeno technique. The modeling technique was based on the concept of neural Fuzzy Logic, which offers a convenient means of representing the relationship between the inputs and outputs of a system in the form of IF-THEN rules. Model has been built under The Recommended Exposure Limit (REL) for workers engaged in occupation such as engineering controls, administrative controls, and/or work practices is 90 dB(A) for 8 hr duration OSHA. In order to validate the model 20% data sets were used for testing purpose.

2. Literature review

Since the last one-decade or so extensive research work has been in progress in the field of affects of noise on the health, comfort and performance of people under the banner of the discipline environmental Ergonomics. The matter content available on the topic is found to be highly scattered in literature. An attempt has been made in this chapter to present the matter content in a systematic manner under different chapters as given below:

2.1 Studies on Industrial/cognitive task performance

Rasmussen (2000) [1] Society is becoming increasingly dynamic and integrated owing to the extensive use of information technology. This has several implications that pose new challenges to the human factors profession. In an integrated society, changes and disturbances propagate rapidly and widely and the increasing scale of operations requires also that rare events and circumstances are considered during systems design. In this situation, human factors contributions should be increasingly proactive, not only responding to observed problems, but also, they should be based on models of adaptive human behavior in complex, dynamic systems.

Murata, et al. (2000) [2] To clarify whether job stressors affecting injury due to labor accidents differ between Japanese male and female blue-collar workers, the Job Content Questionnaire (JCQ), assessing dimensions of job stressors based on the demand-control-support model, was applied to 139 blue collar workers in a manufacturing factory. Of them, 24 male and 15 female workers suffered from injuries at work. In the female workers with the experience of work injury, the job demand score and job strain index (i.e., the ratio of job demand to job control) of the JCQ were significantly higher and the score of coworker support was significantly lower, than those in the female workers without the experience. High job demand (or, high job strain and low coworker support) was significantly related to work injury in all the female workers. Between the male workers with and without work injury, however, there was no significant difference in any job stressors. This pilot study suggests that high job strain (specifically, high job demand), as well as low coworker support, are important factors affecting work injury in Japanese female blue-collar workers. Further research with a large number of male blue-collar workers will be required to seek other factors that may be associated with work injury.

Genaidy (2005) [3] Advances in human-based systems have progressed at a slower pace than those for technological systems. This is largely attributed to the complex web of variables that jointly influence work outcomes, making it more difficult to develop a quantitative methodology to solve this problem. Thus, the objective of this study was to develop and validate work compatibility as a diagnostic tool to evaluate musculoskeletal

and stress outcomes. Work compatibility is defined as a latent variable integrating the positive and negative impact characteristics of work variables in the human-at-work system in the form of a prescribed relationship. The theoretical basis of work compatibility is described at length in terms of concepts and models. In addition, approximate reasoning solutions for the compatibility variables are presented in terms of three models, namely, linear, ratio, and expert. A test case of 55 service workers in a hospital setting has been used to validate work compatibility with respect to severe musculoskeletal and high stress outcomes. The results have demonstrated that the expert compatibility model provided the stronger and more significant associations with work outcomes in comparison to the linear and ratio compatibility models. In conclusion, although the work compatibility validation is limited by both the cross-sectional design and sample size, the promising findings of this exploratory investigation suggest that further studies are warranted to investigate work compatibility as a diagnostic tool to evaluate musculoskeletal and stress outcomes in the workplace.

Genaidy, et al. (2007) [4] Although researchers traditionally examined the 'risk' characteristics of work settings in health studies, few work models, such as the 'demand-control' and 'motivation-hygiene theory', advocated the study of the positive and the negative aspects of work for the ultimate improvement of work performance. The objectives of the current study were: (a) to examine the positive and negative characteristics of work in the machining department in a small manufacturing plant in the Midwest USA, and, (b) to report the prevalence of musculoskeletal and stress outcomes. A focus group consisting of worker experts from the different job categories in the machining department confirmed the management's concerns. Accordingly, 56 male and female workers, employed in three shifts, were surveyed on the demand/energizer profiles of work characteristics and self-reported musculoskeletal/stress symptoms. On average, one-fourth to one-third of the workers reported 'high' demand, and over 50% of the workers documented 'low' energizers for certain work domains/sub-domains, such as 'physical task content'/'organizational' work domains and 'upper body postural loading'/'time organization' work sub-domains. The prevalence of workers who reported 'high' musculoskeletal/stress disorder cases, was in the range of 25-35% and was consistent with the results of 'high' demands and 'low' energizers. The results of this case study confirm the importance of adopting a comprehensive view for work improvement and sustainable growth opportunities. It is paramount to consider the negative and positive aspects of work characteristics to ensure optimum organizational performance. The Work Compatibility Improvement Framework, proposed in the reported research, is an important endeavor toward the ultimate improvement and sustainable growth of human and organizational performance.

John, et al. (2009) [5] The main objective of this study was to test the research question that human performance in manufacturing environments depends on the cognitive demands of the operator and the perceived quality of work life attributes. The second research question was that this relationship is related to the operator's specific task and time exposure. Two manufacturing companies, with a combined population of seventy-four multi-skilled, cross-trained workers who fabricated and assembled mechanical and electrical equipment, participated in an eight month, four-wave pseudo panel study. Structural equation modeling and invariance analysis techniques were conducted on the data collected during cognitive task analysis and the administration of questionnaires. Human performance was

indicated to be a causal result of the combined, and uncorrelated, effect of cognitive demands and quality of work attributes experienced by workers. This causal relationship was found to be dependent on the context of, but not necessarily the time exposed to, the particular task the operator was involved with.

2.2 Studies on age related noise effects

As age effects, sensitivity to the high frequencies is lost first and the loss is irreversible. In audiometry, such loss is described as a permanent threshold shift. Audiometric testing consists of determination of the minimum intensity (the threshold) at which a person can detect sound at a particular frequency. As sensitivity to particular frequencies is lost as a result of age or damage, the intensity at which a stimulus can be detected increases. It is in this sense that hearing loss can be described as a threshold shift. Studies have shown age decrements in performance of sustained attention tasks.

Parasuraman, et al. (1990) [6] Thirty-six young (19-27 years), middle-aged (40-55 years), and old (70-80 years) adults performed a 30-min vigilance task at low (15 per min) and high (40 per min) event rates for 20 sessions. Skill-acquisition curves modeled on power, hyperbolic, and exponential functions were predicted. With extensive practice, hit rates increased and false-alarm rates decreased to virtually asymptotic levels. Skill development was best described by the hyperbolic function. Practice reduced but did not eliminate the vigilance decrement in all subjects. The event-rate effect-the decrease in hit rate at high event rates-was reduced with practice and eliminated in young subjects. Hit rates decreased and false-alarm rates increased with age, but there was little attenuation of age differences with practice. Implications for theories of vigilance, skill development, and cognitive aging are discussed.

Hale (1990) [7] Children respond more slowly than young adults on a variety of information-processing tasks. The global trend hypothesis posits that processing speed changes as a function of age, and that all component processes change at the same rate. A unique prediction of this hypothesis is that the overall response latencies of children of a particular age should be predictable from the latencies of young adults performing the same tasks-without regard to the specific componential makeup of the task. The current effort tested this prediction by examining the performance of 4 age groups (10-, 12-, 15-, and 19-year-olds) on 4 different tasks (choice reaction time, letter matching, mental rotation, and abstract matching). An analysis that simultaneously examined performance on all 4 tasks provided strong support for the global trend hypothesis. By plotting each child group's performance on all 4 tasks as a function of the young adult group's performance in the corresponding task conditions, precise linear functions were revealed: 10-year-olds were approximately 1.8 times slower than young adults on all tasks, and 12-year-olds were approximately 1.5 times slower, whereas 15-year-olds appeared to process information as fast as young adults.

Madden (1992) [8] Examined in three experiments a revised version of the Eriksen and Yeh (C. W. Eriksen and Y.-Y. Yeh, 1985) model of attentional allocation during visual search. Results confirmed the assumption of the model that performance represents a weighted combination of focused-and distributed-attention trials, although they were relied on focused attention more than was predicted. Consistent with the model, predictions on the basis of the assumption of a terminating search fit the data better than predictions on the

basis of an exhaustive search. The effects of varying cue validity favored an interpretation of focused attention in terms of a processing gradient rather than a zoom lens. Although the allocation of attention across trials was similar for young and older adults, there was an age-related increase in the time required to allocate attention within individual trials.

Carayon, et al. (2000) [9] There have been several recent reports on the potential risk to hearing from various types of social noise exposure. However, there are few population-based data to substantiate a case for concern. During the last 10-20 years use of personal cassette players (PCPs) has become very much more prevalent, and sound levels in public nightclubs and discotheques are reported to have increased. This study investigated the prevalence and types of significant social noise exposure in a representative population sample of 356 18-25 year olds in Nottingham. Subjects were interviewed in detail about all types of lifetime noise exposure. Noise measurements were also made for both nightclubs and PCPs. In the present sample, 18.8% of young adults had been exposed to significant noise from social activities, compared with 3.5% from occupational noise and 2.9% from gunfire noise. This indicates that social noise exposure has tripled since the early 1980s in the UK. Most of the present day exposure, measured in terms of sound energy, comes from nightclubs rather than PCPs. Moreover, 66% of subjects attending nightclubs or rock concerts reported temporary effects on their hearing or tinnitus. As will be reported in a later publication, any persistent effect of significant noise exposure on 18-25 year olds is difficult to show, however these data suggest that further work is indicated to study the possibility of sub-clinical damage, and also to consider the implications for employees of nightclubs.

Boman, et al. (2005) [10] The objectives in this paper were to analyze noise effects on episodic and semantic memory performance in different age groups, and to see whether age interacted with noise in their effects on memory. Data were taken from three separate previous experiments that were performed with the same design, procedure and dependent measures with participants from four age groups (13-14, 18-20, 35-45 and 55-65 years). Participants were randomly assigned to one of three conditions: (a) meaningful irrelevant speech, (b) road traffic noise, and (c) quiet. The results showed effects of both noise sources on a majority of the dependent measures, both when taken alone and aggregated according to the nature of the material to be memorized. However, the noise effects for episodic memory tasks were stronger than for semantic memory tasks. Further, in the reading comprehension task, cued recall and recognition were more impaired by meaningful irrelevant speech than by road traffic noise. Contrary to predictions, there was no interaction between noise and age group, indicating that the obtained noise effects were not related to the capacity to perform the task. The results from the three experiments taken together throw more light on the relative effects of road traffic noise and meaningful irrelevant speech on memory performance in different age groups.

2.3 Studies on noise effects related to task performance

Suter (1991) [11] The effects of noise are seldom catastrophic, and are often only transitory, but adverse effects can be cumulative with prolonged or repeated exposure. Although it often causes discomfort and sometimes pain, noise does not cause ears to bleed and noise-induced hearing loss usually takes years to develop. Noise-induced hearing loss can indeed impair the quality of life, through a reduction in the ability to hear important sounds and to

communicate with family and friends. Some of the other effects of noise, such as sleep disruption, the masking of speech and television, and the inability to enjoy one's property or leisure time also impair the quality of life. In addition, noise can interfere with the teaching and learning process, disrupt the performance of certain tasks, and increase the incidence of antisocial behavior.

Evans, et al. (1993) [12] Large numbers of children both in the United States and throughout the economically developing world are chronically exposed to high levels of ambient noise. Although a great deal is known about chronic noise exposures and hearing damage, much less is known about the non-auditory effects of chronic ambient noise exposure on children, to estimate the risk of ambient noise exposure to healthy human development, more information. About and attention to non-auditory effects such as psycho-physiological functioning, motivation, and cognitive processes is needed. This article critically reviews existing research on the non-auditory effects of noise on children; develops several preliminary models of how noise may adversely affect children; and advocates an ecological perspective for a future research agenda.

Evans, et al. (1997) [13] In the short term, noise induced arousal, may produce better performance of simple tasks, but cognitive performance deteriorates substantially for more complex tasks (i.e. tasks that require sustained attention to details or to multiple cues; or tasks that demand a large capacity of working memory, such as complex analytical processes). Some of the effects are related to loss in auditory Comprehension and language acquisition, but others are not, among the cognitive effects, reading, attention, problem solving and memory are most strongly affected by noise. The observed effects on motivation, as measured by persistence with a difficult cognitive task, may either be independent or secondary to the aforementioned cognitive impairments. For aircraft noise, the most important effects are interference with rest, recreation and watching television. This is in contrast to road traffic noise, where sleep disturbance is the predominant effect. The primary sleep disturbance effects are: difficulty in falling asleep (increased sleep latency time); awakenings; and alterations of sleep stages or depth, especially a reduction in the proportion of REM-sleep (REM = rapid eye movement). Other primary physiological effects can also be induced by noise during sleep, including Noise sources 7 increased blood pressure; increased heart rate; increased finger pulse amplitude; vasoconstriction; changes in respiration; cardiac arrhythmia; and an increase in body movements.

Smith (1998) [14] This paper examines the operation of urban bus transport systems based upon exclusive bus roadways (bus ways) in three cities in Brazil. The historic, economic, political, regulatory and operating context for these services is discussed. The strengths and weaknesses of bus way systems in Curitiba, Porto Alegre and São Paulo are compared, with particular reference to the operating capacity of the bus ways. The paper concludes with an assessment of the importance of operations techniques, infrastructure development, land use planning, political stability and regulation to the success or failure of these systems.

Berglund, et al. (1999) [15] Two types of memory deficits have been identified under experimental noise exposure: incidental memory and memory for materials that the observer was not explicitly instructed to focus on during a learning phase. For example, when presenting semantic information to subjects in the presence of noise, recall of the information content was unaffected, but the subjects were significantly less able to recall, for example, in which corner of the slide a word had been located. There is also some evidence

that the lack of “helping behavior” that was noted under experimental noise exposure may be related to inattention to incidental cues.

Birgitta, et al. (1999) [16] Exposure to night-time noise also induces secondary effects, or so-called after effects. These are effects that can be measured the day following the night-time exposure, while the individual is awake. The secondary effects include reduced perceived sleep quality; increased fatigue; depressed mood or well-being; and decreased performance.

Stansfeld (2000) [17] Noise, including noise from transport, industry, and neighbors, is a prominent feature of the urban environment. This paper reviews the effects of environmental noise on the non-auditory aspects of health in urban settings. Exposure to transport noise disturbs sleep in the laboratory, but generally not in field studies, where adaptation occurs. Noise interferes with complex task performance, modifies social behavior, and causes annoyance. Studies of occupational noise exposure suggest an association with hypertension, whereas community studies show only weak relations between noise and cardiovascular disease. Aircraft and road-traffic noise exposure are associated with psychological symptoms and with the use of psychotropic medication, but not with the onset of clinically defined psychiatric disorders. In carefully controlled studies, noise exposure does not seem to be related to low birth weight or to congenital birth defects. In both industrial studies and community studies, noise exposure is related to increased catecholamine secretion. In children, chronic aircraft noise exposure impairs reading comprehension and long-term memory and may be associated with increased blood pressure. Noise from neighbors causes annoyance and sleep and activity interference health effects have been little studied. Further research is needed for examining coping strategies and the possible health consequences of adaptation to noise.

WHO (2002) [18] It has been documented in both laboratory subjects and in workers exposed to occupational noise, that noise adversely affects cognitive task performance. In children, too, environmental noise impairs a number of cognitive and motivational parameters.

Harris, et al. (2005) [19] Studies from our lab show that noise exposure initiates cell death by multiple pathways, therefore, protection against noise may be most effective with a multifaceted approach. The Src protein tyrosine kinase (PTK) signaling cascade may be involved in both metabolic and mechanically induced initiation of apoptosis in sensory cells of the cochlea. The current study compares three Src-PTK inhibitors, KX1-004, KX1-005 and KX1-174 as potential protective drugs for NIHL. Chinchillas were used as subjects. A 30 microl drop of one of the Src inhibitors was placed on the round window membrane of the anesthetized chinchilla; the vehicle (DMSO and buffered saline) alone was placed on the other ear. After the drug application, the middle ear was sutured and the subjects were exposed to noise. Hearing was measured before and several times after the noise exposure and treatment using evoked responses. At 20 days post-exposure, the animals were anesthetized their cochleae extracted and cochleograms were constructed. All three Src inhibitors provided protection from a 4 h, 4 kHz octave band noise at 106 dB. The most effective drug, KX1-004 was further evaluated by repeating the exposure with different doses, as well as, substituting an impulse noise exposure. For all conditions, the results suggest a role for Src-PTK activation in noise-induced hearing loss (NIHL), and that therapeutic intervention with a Src-PTK inhibitor may offer a novel approach in the treatment of NIHL.

2.4 Studies on the fuzzy logic and their application

Lah, et al. (2005) [20] Developed an experimental model for found that the controlled dynamic thermal and illumination response of human-built environment in real-time conditions. He was designing an experimental test chamber for thermal and illumination response on a human performance. The time-dependent outside conditions as external system disturbances, the air temperatures and the solar radiation oscillation are also included as input data, this input data controlled by fuzzy logic toolbox. After the many experiments they were found that outside conditions as sun light & temperature was highly effects on human performance.

Zaheeruddin, et al. (2006) [21] Developed a model (system) for predicting the effects of sleep disturbance by noise on humans as a function of noise level, age, and duration of its occurrence. The modeling technique is based on the concept of fuzzy logic, which offers a convenient way of representing the relationships between the inputs and outputs of a system in the form of IF-THEN rules. They were taken the three input variables; such as noise level, duration of sleep and age of the person and one output variable is noise effect (sleep disturbance). In this model they was decided the range of the variables & fluctuated these ranges in fuzzy logic model. After fluctuation they were found the many output variables. They were concluded that the middle-aged people have more probability of sleep disruption than the young people at the same noise levels. However, very little difference is found in sleep disturbance due to noise between young and old people. In addition, the duration of occurrence of noise is an important factor in determining the sleep disturbance over the limited range from few seconds to few minutes. Finally, authors have compared our model results with some of the findings of researchers reported in International Journals.

Zaheeruddin (2006) [22] Studied that noise effects on industrial worker performance. From the literature survey, they observed that the three most important factors influencing human work efficiency are noise level, type of task, and exposure time. Therefore they was developed a model on neuro-fuzzy system. According his model they were taken three input variables (noise level, type of task & exposure time) and one output variables (reduction in work efficiency). All variables apply in neuro-fuzzy models and collect the results. He was concluded that the main thrust of the present work has been to develop a neuro-fuzzy model for the prediction of work efficiency as a function of noise level, type of tasks and exposure times. It is evident from the graph that the work efficiency, for the same exposure time, depends to a large extent upon the noise level and type of task. It has also been verified that simple tasks are not affected even at very high noise level while complex tasks get significantly affected at much lower noise level.

Aluclu, et al. (2008) [23] They described noise-human response and a fuzzy logic model developed by comprehensive field studies on noise measurements (including atmospheric parameters) and control measures. The model has two subsystems constructed on noise reduction quantity in dB. The first subsystem of the fuzzy model depending on 549 linguistic rules comprises acoustical features of all materials used in any workplace. Totally 984 patterns were used, 503 patterns for model development and the rest 481 patterns for testing the model. The second subsystem deals with atmospheric parameter interactions with noise and has 52 linguistic rules. Similarly, 94 field patterns were obtained; 68 patterns were used for training stage of the model and the rest 26 patterns for testing the model.

These rules were determined by taking into consideration formal standards, experiences of specialists and the measurements patterns. They were found that the model was compared with various statistics (correlation coefficients, max-min, standard deviation, average and coefficient of skewers) and error modes (root mean square Error and relative error). The correlation coefficients were significantly high, error modes were quite low and the other statistics were very close to the data.

Zaheeruddin, et al. (2008) [24] They developed an expert system using fuzzy approach to investigate the effects of noise pollution on speech interference. The speech interference measured in terms of speech intelligibility is considered to be a function of noise level, distance between speaker and listener, and the age of the listener. The main source of model development is the reports of World Health Organization (WHO) and field surveys conducted by various researchers. It is implemented on Fuzzy Logic Toolbox of MATLAB using both Mamdani and Sugeno techniques. They were found his result from fuzzy logic model & comparison of the results from World Health Organization (WHO) and U.S. Environmental Protection Agency (EPA). After comparison they were concluded that the model has been implemented on Fuzzy Logic Toolbox of MATLAB the results obtained from the proposed model are in good agreement with the findings of field surveys conducted in different parts of the world. The present effort also establishes the usefulness of the Fuzzy technique in studying the environmental problems where the cause-effect relationships are inherently fuzzy in nature.

Mamdani, et al. (1975) [25] Studied after an experiment on the “linguistic” synthesis of a controller for a model industrial plant (a steam engine). Fuzzy logic is used to convert heuristic control rules stated by a human operator into an automatic control strategy. They developed 24 rules for controlling stem engine. The experiment was initiated to investigate the possibility of human interaction with a learning controller. However, the control strategy set up linguistically proved to be far better than expected in its own right, and the basic experiment of linguistic control synthesis in a non-learning controller is reported here.

Ross (2009) [26] Presented their approach to introduce some applications of fuzzy logic, introduced the basic concept of fuzziness and distinguish uncertainty from other form of uncertainty. It also introduce the fundamental idea of set membership, thereby laying the foundation for all material that follows, and presents membership functions as the format used from expressing set membership. Chapters discussed the fuzzification of scalar and the defuzzification of membership functions & various forms of the implication operation and the composition operation provided.

2.5 Studies on the noise survey

Nanthavanij, et al. (1999) [27] Developed noise contours by two procedures: 1) Analytical and 2) Graphical. The graphical procedure requires input data: ambient noise level, noise levels generated by individual machines, and the (x, y) coordinates of the machine locations. When draw the noise contours in work shop floor, a set of mathematical formulae is also developed to estimate the combined noise levels at predetermined locations (or points) of the workplace floor. Contour lines are then drawn to connect points having an equal noise level. The analytical nature of the procedure also enables engineers to quickly construct the noise contour map and revise the map when changes occur in noise levels due to a workplace re-layout or an addition of a new noise source.

Kumar (2008) [28] Studied the case of high level of noise in rice mills and to examine the response of the workers towards noise. They was done a noise survey was conducted in eight renowned rice mills of the north-eastern region of India. They were following the guidelines of CCOHS for noise survey. Their model as same like above author model. But they was taking the size of grid is 1m X 1m.

3. Problem statement

Based on the literature surveyed as presented in the previous section, it was observed that noise as a pollutant produces contaminated environment, which affects adversely the health of a person and produces ill effects on living, as well as on non-living things. The prominent adverse effects of noise pollution on human beings include noise-induced hearing loss, work efficiency, annoyance responses, interference with communication, the effects on sleep, and social behavior. The effects on work efficiency may have serious implications for industrial workers and other occupations. The effects of noise on human performance have also been investigated by researchers based on sex, laterality, age and extrovert introvert characteristics. However, these factors do not affect human performance significantly. Therefore, depending on the nature of the task, human performance gets affected differently under the impact of different levels of noise and cognitive task type.

After the literature review, we are now much better able to understand why the benefits of low noise level at workplace, taking into account the nature of cognitive task performed, are also important. A part from the health and well-being advantages for the workers themselves, low noise level also leads to better work performance (speed), fewer errors and rejects, better safety, fewer accidents, and lower absenteeism. The overall effect of all this is better productivity. For an industrial environment (moderately type of cognitive task), total productivity increase as a result of reducing noise level, the indirect correlation between worker's age and the increase in production, improvement in attitude, the availability of workers, and working efficiency. There have been several studies to demonstrate the effect of either ages or noise on the performance of various tasks of industrial relevance. It was shown that increasing cognitive work difficulty was predisposed to increased reduction in cognitive work efficiency in industries. But second site we have already discussed that, when level of noise increase then this reduces the efficiency of the worker.

In the present study an attempt has been made to develop a neural fuzzy expert system to predict human cognitive task efficiency as a function of noise level, age of the worker and cognitive task type. We have observed that cognitive task type affects the efficiency of worker in various level of noise in industries. The model is implemented on Fuzzy Logic Toolbox @ MATLAB 2007.

4. Methodology

4.1 Introduction

Noise is one of the physical environmental factors affecting our health in today's world. Noise is generally defined as the unpleasant sounds, which disturb the human being physically and physiologically and cause environmental pollution by destroying environmental properties. The general effect of noise on the hearing of workers has been a topic of debate among scientists for a number of years. Regulations limiting noise exposure

of industrial workers have been instituted in many places. For example, in the U.S., the Occupational Noise Exposure Regulation states that industrial employers must limit noise exposure of their employees to 85 dB (A) for 8 hr period.

Based on the literature surveyed as presented in previous section, it was observed that a great majority of people working in industry are exposed to noise with different cognitive task type. In this study, attempt has been made to find out the combined effects of noise level and cognitive task type on industrial worker’s performance. Attempt has also been made in present study to identify the noisy industries located in Delhi and around Delhi. Different industries with or without noise were categorized based on measured sound pressure level.

Sound pressure level for industries clearly shown in Appendix-A. In this context, measurement the sound pressure level and cognitive task type, questionnaire studies have been conducted at automobile, power plant and steel textile industries in and around Delhi and also noise counters has been drawn for noisy industries. Assuming that the working environment (Temperature, Humidity, illumination level, other facilities), are same in the industries under reference; categorization has been made as presented in the Table 4.1(a) and 4.1(b).

S.No.	Industry	Noise level (dB (A))	Category	workers number
1.	Shriram Piston and Rings Limited, Ghaziabad	45 - 95	Low noise level	44
2.	WPIL India Limited, Ghaziabad	63 - 102	Medium noise level	38
3.	I.T.O power plant station New Delhi	75-116	High noise level	73

Table 4.1. (a) Industries name & their category with reference to noise level.

S.No.	Industry	Old age 46 up	Medium age 31-45	Young age 15-30
1.	Shriram Piston and Rings Limited, Ghaziabad	8	18	18
2.	WPIL India Limited, Ghaziabad	10	12	16
3.	I.T.O power plant station New Delhi	14	22	37

Table 4.1. (b) Industries name with reference to workers age groups.

In addition to this, the questionnaire data was segregated based on various sections of above-mentioned industries. Performance rating was obtained based on questionnaire survey for different noise levels and type of cognitive task (simple, moderate, and complex). On the collected performance rating data, we have implemented our model using Sugeno technique (Fuzzy Logic Tool box) of MATLAB. It is a three input-one output system. The input variables are noise level, Age of the worker or operator, and cognitive task type and the reduction in cognitive task efficiency is taken as the output variable. The whole methodology shown in Figure 4.1

4.2 Material and methods

In the present study industrial noise measurement technique carried out at three different industries (ITO power plant station, centrifugal pump industry WPIL India Limited, and Shriram Piston & Rings Limited). Selection of industry was based on requirement of study i.e., worker working under different noise levels as well as cognitive task type (simple, moderate, and complex). Questionnaire established with a group of questions refer to parameters will be effected by the noise levels as well as type of cognitive task. Questionnaire asked questions about the age, skill discretion, psychological job demands, etc. Likert scale is used to evaluate the answers density from strongly disagree to strongly agree. Operators and supervisor fulfils the questionnaire on the working day after 8 hrs continuous working, Questionnaire form contains 55 questions. Only workers doing cognitive task were taken in this study. To check the reliability of the survey, the cronbach's alpha value was calculated. Similar sets of items of the questionnaire were identified and cronbach's alpha was calculated [2]. If the value is more than 0.7, then the survey was considered to be reliable. Present model include three inputs and one output, first input is noise level measured by sound level meter, second and third inputs were age and cognitive task type, assessed by questionnaire, and one output was reduction on cognitive task efficiency assessed by using the questionnaire also.

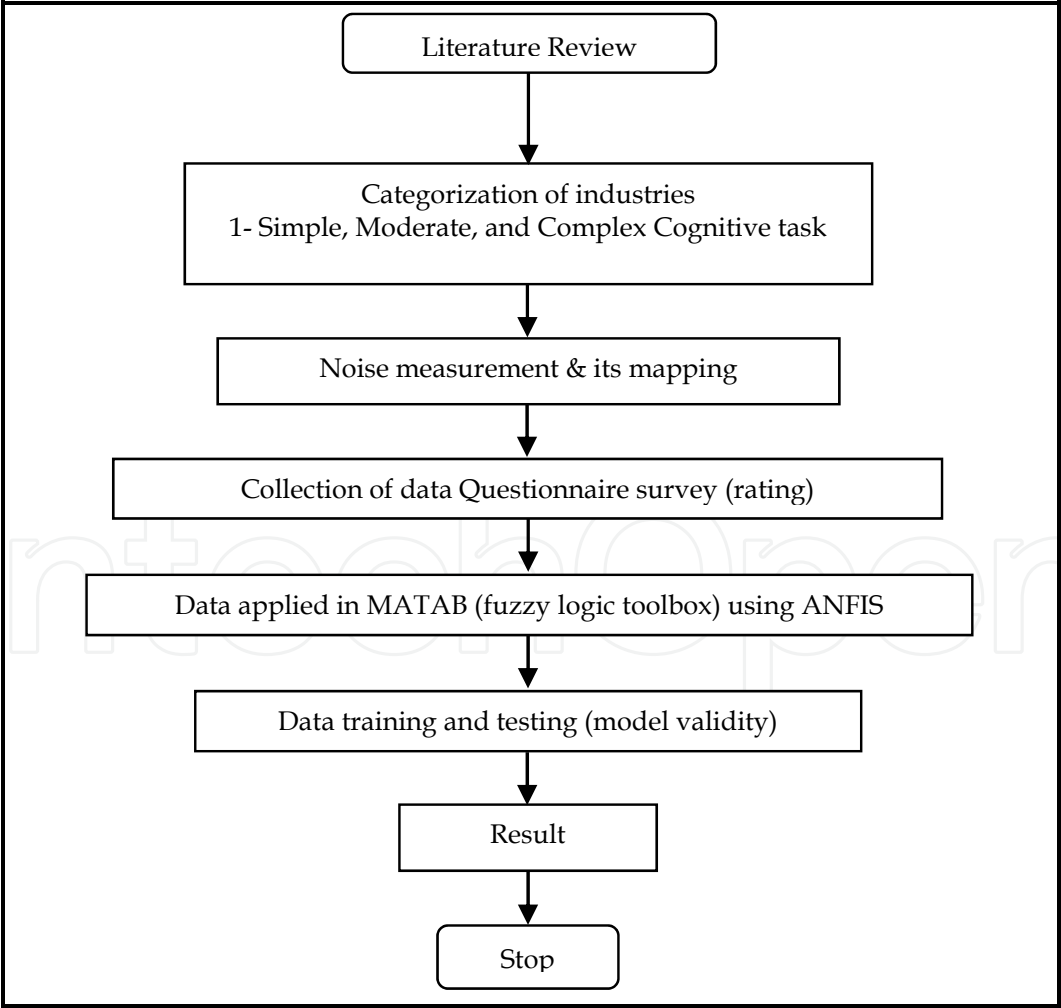


Fig. 4.1. Flow diagram for methodology

4.2.1 Description of study area

A 330 MW Pragati power station is located in New Delhi, latitude (28°37 ' -28°38 ') at longitude (77°14 ' -77°15 ') near (Income Tax Office) ITO beside the highway at 0.3 Km from World Health Organization (WHO) building as shown in Figure 4.2. A centrifugal pumps WPIL India Limited, located in Ghaziabad, latitude (28°40 '57) at longitude (77°25'41) as shown in Figure 4.3.



Fig. 4.2. Geographical location of I.T.O power plant (New Delhi).



Fig. 4.3. Geographical location of centrifugal pumps WPIL India Limited (Ghaziabad).



Fig. 4.4. Geographical location of Shriram Piston & Rings Ltd (Ghaziabad).

Shriram Piston & Rings Ltd. is located at Ghaziabad, latitude (28°41'07) at longitude (77°26'06) as shown in Figure 4.4.

4.2.2 Description of cognitive task factors

Cognitive task (CT) questionnaire is prepared to assess the cognitive task among the workers in (I.T.O power plant station, centrifugal pump industry WPIL India Limited ,and Shriram Piston & Rings Lt.) Industries. This is self-administered questionnaire consists of 55-items. The operators were asked to respond to each and every item of questionnaire by giving subjective opinions from strongly disagrees to strongly agree. The items of the questionnaire were classified into the following factors.

The first factor is skill discretion, described by (possibility of learning new things, repetitive nature of the work, creative thinking at work, and high level of skill, time span of activities and developmental nature of job). The second factor is decision authority, described by (lot of say on job, freedom to take own decisions while working, continual dependence on others). Third scale is organizational decision latitude, described by (influence over organizational changes, influence over work team's decisions, regular meeting's of work team, supervising people as a part of job, influence over policies of union). Fourth factor is psychological job demands described by (work hard, work fast, excessive work, enough time to finish the job, conflicting demands). Fifth factor is emotional demands described by (emotional demanding work, negotiation with others, suppressing genuine emotion, ability to take care, constant consultation with others).

Sixth factor is family/work stress, described by (responsibility for taking care of home, inference of family life and work). The seventh factor is perceived support which is the sum of three sub factors namely supervisor support, coworker support, organizational support and procedural justice, supervisor support is described by (concern of supervisor and helpful supervisor). Coworker support is described by (helpful coworkers and friendly coworkers). Organizational support is described by (organizational care about worker's opinions, care about well-being, consideration of goals and values, concern about workers). Procedural justice is described by (collecting accurate information for making decisions, providing opportunities to appeal the decisions, generating standards to take consistent decisions). Eighth factor is job insecurity (steady work, threat to job security, recent layoff, future layoff, valuable skills, hard to keep job for long duration). Ninth factor is physical job demands, described by (requires much physical effort, rapid physical activities, heavy load at work, awkward body positions and awkward upper body positions). The tenth factor is collective control, described by (sharing the hardships of the job, possibility of helping the coworkers and unity among workers).

The eleventh factor is cognitive task type, described by (felt depressed, sleep was restless, enjoyed life, felt nervous while work, exceptionally tired in the morning and exhausted mentally and physically at the end of the day).

After data collections, data was analyzed and scores for each worker (noise level, age, cognitive task type and cognitive task efficiency), input/output parameters were categorized. The values of scores were used to establish the rules for optimum model. Neural fuzzy model under reference used three input and one output parameters. Questionnaire answers graded the cognitive task type into three categories (simple,

moderate, and complex). Noise levels prevalent in the industries were graded as (low, medium, high), while workers were graded into three categories as (young, medium, and old age workers). Then noise levels and age are scaled from 40 dB(A) to 110 dB(A), and 15 to 65 years respectively, and Cognitive task type scaled from (1) strongly disagree to (5) strongly agree. While the output (cognitive task efficiency) classified as questionnaire answers weight (0%=strongly disagree, 25%=disagree, 50%=neutral, 75%=agree, and 100%=strongly agree). Model was constructed according to questionnaire form responses.

4.2.3 Questionnaire studies (surveys) in the industry

Data may be obtained either from the primary source or the secondary source. A primary source is one that itself collects the data; a secondary source is one that makes available data which were collected by some other agency. A primary source usually has more detailed information particularly on the procedures followed in collecting and compiling the data. Many methods for collecting the data such as direct personal interview, Mailed questionnaire method, indirect oral interviews schedule sent through enumerators, Information from correspondents etc.

So our data is direct personal interview method, under this method of collecting data, there is a face to face contact with the persons from whom the information is to be obtained (known as informants).

4.2.4 Purpose of the questionnaire

1. To determine the effects of noise on the workers under different cognitive task type.
2. To determine the effect of the noise level on workers age.
3. For specifying workers comments on protection from noise.
4. To determine what parameters have negative and positive affect to noise level.
5. To find the threshold level of noise on industries for this kind of task.
6. To feed back these data to neural fuzzy logic model.

4.2.5 Why we used the questionnaire survey?

This method suitable for this study, the explanations are following:

- The information obtained by this method is likely to be more accurate because the interviewer can clear up doubts of the informants about certain questions and thus obtain correct information.
- The language of communication can be adjustable to the status and education level of the worker or operator.
- Due to the direct interaction the correct and desired information collected.
- The answers of the questions arranged in ranking order (low, medium, high and very high etc.), because answers easily implemented in Fuzzy logic toolbox. Its detail can be seen in the section 4.6

To obtain occupants opinions on the industrial/cognitive task, questionnaire was administered. This questionnaire was consisting of 55 questions related to cognitive work effects on industrial worker performance in different noise level environment. The objective of the detailed survey was to confirm and clarify the results obtained from the short-form

survey. Questions corresponding to the statements in the short-form questionnaire were used. A total 155 questionnaire were distributed among the workers of automobile industries. Responses were made using likert scale 5-point scales instead of simple choices.

- Along with the questionnaire the demographic data like age, noise level, gender etc. were also collected.
- The operators or workers were asked to respond to the self administered questionnaire by giving their objective opinions.
- These responses were transferred to a five point likert scale by assigning the rating from 1 to 5.
- Not to cause any work loss in the general industry, the questionnaire forms were distributed during the day shift and collected the next day while it has been done on a one-to-one basis during the night shift.
- Each choice filled through the worker or operator at the time of working.
- All responses were collected and calculated the performance rating of the workers.

An example of the procedure used to calculate the value required is shown below:-

Sample survey response shows the procedure adopted for response collection of workers, all responses rating adding and divided by the number of questions to find out the ratio of the performance.

- Addition the input response (answers) = 2+4+2+3+1+3+3+2+2+2+3+2+3+3+2+3+2+3+3+2+2+2+3+1+3+4+3+4+1+3+2+2+4+1+1+2+2+2+4+3+3+3+2+2+3+3+2= 116
- Input Performance ratio (x) = 116/ 47 = 2.4
- Addition the output response (answers) =25%+0%+0%+0%+25%=50%

Output Performance ratio (η) =50%/5=10%

Similarly we have found the output performance ratio at different noise levels. Respectively and see the corresponding value of “reduction in cognitive work efficiency (η)” from Table 4.2, the detailed procedure for calculation has been described in Appendix-B.

Ratio value (η)	Reduction in cognitive task efficiency
0.00%	Strongly disagree (None)
25%	Disagree (Low)
50%	Neutral (moderate)
75%	Agree (High)
100%	Strongly agree (Very high)

Table 4.2. Rating ratio for reduction in cognitive task efficiency.

For Linguistic rules in Fuzzy logic Toolbox @ MATLAB software require 27 rules. Questionnaires were selected randomly from the given set of questionnaire depicted as linguistic rule.

4.3 Noise measurement

No single method or process exists for measuring occupational noise. Hearing safety and health professionals can use a variety of instruments to measure noise and can choose from

a variety of instruments and software to analyze their measurements. The choice of a particular instrument and approach for measuring and analyzing occupational noise depends on many factors, not the least of which will be the purpose for the measurement and the environment in which the measurement will be made. In general, measurement methods should conform to the American National Standard Measurement of Occupational Noise Exposure, ANSI S12.19-1997 [ANSI 1996a].

4.4 Noise mapping

A noise survey or mapping takes noise measurements throughout an entire plant or section to identify noisy areas. Noise surveys provide very useful information which enables us to identify:

- Areas where employees are likely to be exposed to harmful levels of noise and personal dosimeter may be needed,
- Machines and equipment which generate harmful levels of noise,
- Employees who might be exposed to unacceptable noise levels, and
- Noise control options to reduce noise exposure.

Noise survey is conducted in areas where noise exposure is likely to be hazardous. Noise level refers to the level of sound. A noise survey involves measuring noise level at selected locations throughout an entire plant or sections to identify noisy areas. This is usually done with a sound level meter (SLM). A reasonably accurate sketch showing the locations of workers and noisy machines is drawn. Noise level measurements are taken at a suitable number of positions around the area and are marked on the sketch. The more measurements taken were more accurate the survey. A noise map can be produced by drawing lines on the sketch between points of equal sound level. Noise survey maps; provide very useful information by clearly identifying areas where there are noise hazards.

The following sections briefly explain the theory of sound and the contours estimation procedure. Theory Two basic formulae play an important role in estimating the noise level. Herein, the terms 'sound' and 'noise' are used interchangeably. These formulae convert sound power to sound intensity, and sound intensity to sound pressure level respectively.

$$I = \frac{P}{4\pi d^2} \quad (4.1)$$

$$L = 10 \log \left[\frac{I}{I_0} \right] \quad (4.2)$$

Where:

P is the sound power (W) of the noise source

I the sound intensity (W/m²),

d the distance (m) from the noise source,

L is the sound pressure level (dB (A)),

I₀ is the reference sound intensity.

By knowing the noise level (L), in dB (A), of a given noise source, its noise level can be estimated at any distance (d) from the source. This can be achieved by initially converting

the noise level (dB (A)) of the noise source into its sound power (watt) using Eq. (4.1) and Eq. (4.2) and by assuming that the noise level is measured at 1 m from the source (i.e., $d=1$). From the inverse square law, the sound intensity at a distance d from the noise source is then attenuated by Eq. (4.1). In case there are n noise sources, the combined noise level ($\bar{L}$) at any given location can be estimated using the following formula:

$$\bar{L} = 10 \sum_{i=1}^n \log \frac{I}{I_0} \quad (4.3)$$

For the ease of computation, Eq. (4.2) can be rewritten as follows:

$$I = 10^{(L-120)/10} \quad (4.4)$$

Then, the combined sound intensity (I) can be directly computed from

$$\bar{I} = \sum_{i=1}^n 10^{\frac{(L_i-120)}{10}} \quad (4.5)$$

4.4.1 Construction of a noise contour map

The procedure for constructing a noise contour map of the workplace can be described as Follows:

Initialization steps:-

1. Determining (x, y) coordinates of machine locations:

The layout of the factory floor must be obtained and all machines (or noise sources) must be plotted on the layout map. Since the computation requires an assumption of a pointed noise source, the machine location must be represented by a point on the X-Y plane. By selecting one corner of the factory floor as the reference origin (usually the lower left corner), the machine location can be expressed as a pair of X and Y coordinates which are measured from that reference point. That is, the location of machine k is expressed as, (X_k, Y_k)

2. Determining the ambient noise intensity:

The ambient noise level (dB (A)) must be either measured or estimated. For a direct measurement, the ambient noise is measured when none of the machines are operating. To obtain reliable data, several measurements should be taken from different locations and different times. Then the average noise level is calculated and used as the ambient noise level of the factory floor. It must be converted to the ambient noise intensity, I_{ab} , using Eq. (4.4).

3. Determining the sound power of the machine:

The machine noise level may be difficult to determine since it is impossible to isolate the machine and measure its noise level without any noise interference from others. If applicable, each machine can be operated and measurement taken correspondingly. Otherwise, the machine manufacturer can be contacted to obtain information (specifications) about the noise level generated by the machine. Similarly, the noise level of machine (k) must be expressed as the sound power (P_k), using the following conversion.

From the noise level in dB (A) of machine k , L_k , convert it to its sound power, P_k , using Equations (4.1) and (4.2), and by assuming that $d = 1$ m.

$$P_k = 4\pi 10^{(L_k - 120)/10} \quad (4.6)$$

Repeat Equation (4.8) for $k=1$ to m ; Where m denotes the number of machines

4. Determining the locations where the combined noise levels will be estimated:

Next, a set of locations (points of interest) on the floor must be identified where the combined noise levels will be estimated. These points are expressed as (X_i, Y_i) , $i = 1$ to n , where n is the number of points. Conventionally, the factory floor layout is divided into grids. The grid dimension depends on the size of the factory floor and the required degree of accuracy of the noise contours. If the size of the factory is large and/or high degree of accuracy is required, the number of grids will be large (i.e., the grid size will be small). However, the larger the number of grids implies the longer time to construct the noise contours.

4.4.2 Computation steps

1. Computing the machine noise intensity at the specified location:

The noise intensity of machine k at location i , $I_{i,k}$, can be estimated using the following steps. Initially, the Euclidean distance, d_{ik} , between points i and k must be determined.

$$d_{ik} = [(x_i - x_k)^2 + (y_i - y_k)^2]^{1/2} \quad (4.7)$$

Then, the machine noise intensity at location i is computed using Equation (4.3).

$$I = P_k / 4\pi d_{ik}^2 \quad (4.8)$$

2. Combining all machine noise intensities:

The combined machine noise intensity at location i , $I_{i,k}$, can be determined by adding all machine noise intensities $I_{i,k}$, $k=1$ to m .

$$\bar{I} = \sum_{k=1}^m \frac{P_k}{4\pi d_{ik}^2} \quad (4.9)$$

3. Adding the ambient noise intensity:

The effect of the ambient noise level must be accounted for by adding I_{ab} to Equation (4.9). The combined noise intensity at location i now become:

$$\bar{I}_i = I_{ab} + \sum_{k=1}^m \frac{P_k}{4\pi d_{ik}^2} \quad (4.10)$$

By substituting Equation (4.8) into Equation (4.10), both the terms P_k and 4π disappear. Thus, Equation (4.10) can be written as:

$$\bar{I}_i = I_{ab} + \sum_{k=1}^m \frac{(L_k - 120) / 10}{d_{ik}^2} \quad (4.11)$$

4. Converting the combined noise intensity into its noise level (dB (A)):

Finally, the combined noise intensity at location i is converted into the combined Noise level in dB (A), L_i , using Equation (4.2).

4.5 Industrial noise surveys

4.5.1 NoiseAtWorkV1.31

Software for mapping and analysis of noise at workplaces for health and safety representatives (NoiseAtWorkV1.31) [29] is software for mapping and analysis of noise levels at places where people work. Based on measured noise levels and working times of employees, noise contours and L_{eq} 8hr values are calculated by the software. The software is used by health and safety representatives for the management of occupational noise risks.

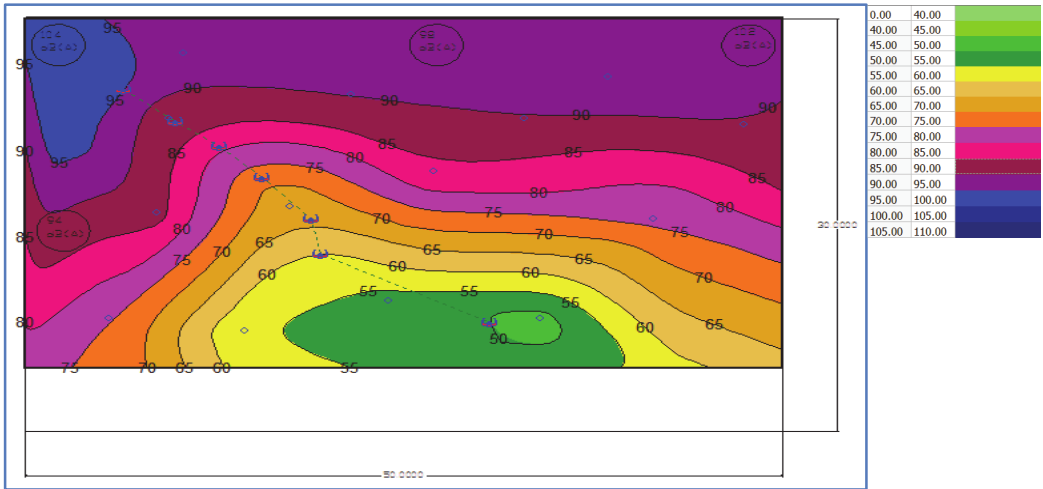


Fig. 4.5. Shriram Piston & Rings Lt. Ghaziabad Noise map (noiseatwork V1.31).

No. 	X	Y	Leq
1	2.00	26.00	100.00
2	10.00	32.00	93.00
3	21.00	28.00	90.00
4	33.00	26.00	90.00
5	47.00	20.00	90.00
6	6.00	10.00	75.00
7	9.00	20.00	87.00
8	10.00	25.00	85.00
9	25.00	22.00	85.00
10	37.00	30.00	95.00
11	41.00	18.00	75.00
12	34.00	10.00	48.00
13	24.00	11.00	53.00
14	17.00	19.00	65.00
15	15.00	9.00	55.00

Table 4.3. (a) (X, Y) Coordinates of noise measurement and noise levels.

Loc	T [h]	Red [dB]	Leq [dB]	Dose [%]
1	8.00	—	95.47	213
2	8.00	—	84.33	46
3	8.00	—	78.69	21
4	8.00	—	71.63	8
5	8.00	—	64.20	3
6	8.00	—	59.60	1
7	8.00	—	49.92	—
Total	56.00		87.45	491

Table 4.3. (b) Employees location and dosage calculation.

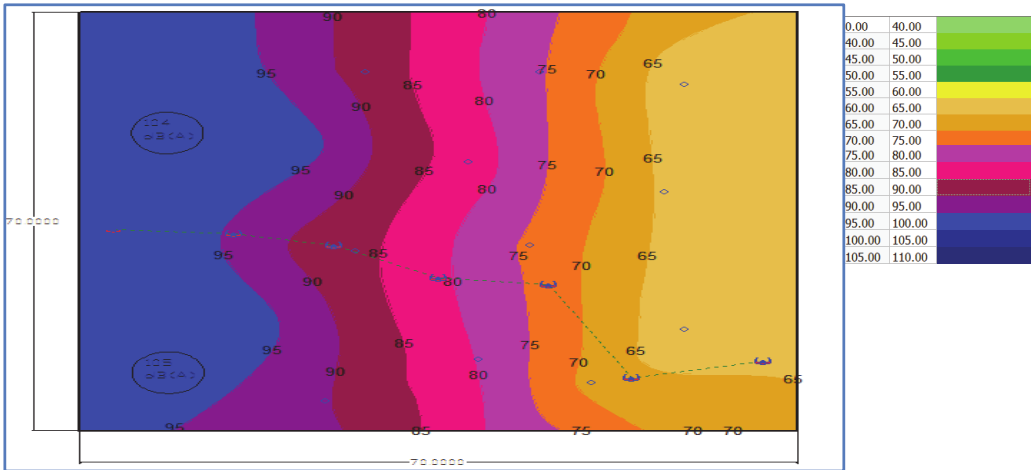


Fig. 4.6. WPIL India Limited, Ghaziabad Noise map (noiseatwork V1.31).

No. 	X	Y	Leq
1	5.00	30.00	100.00
2	10.00	24.00	98.00
3	4.00	16.00	96.00
4	8.00	10.00	99.00
5	12.00	2.00	90.00
6	14.00	30.00	88.00
7	18.00	22.00	83.00
8	13.00	15.00	85.00
9	20.00	6.00	80.00
10	21.00	30.00	75.00
11	22.00	16.00	74.00
12	25.00	4.00	68.00
13	30.00	29.00	60.00
14	28.00	20.00	65.00
15	29.00	9.00	61.00

Table 4.4. (a) (X, Y) Coordinates of noise measurement and noise levels.

Loc	T [h]	Red [dB]	Leq [dB]	Dose [%]
1	8.00	—	97.69	290
2	8.00	—	92.81	148
3	8.00	—	86.68	63
4	8.00	—	80.51	27
5	8.00	—	72.80	9
6	8.00	—	66.32	4
7	8.00	—	64.03	3
Total	56.00		90.79	781

Table 4.4. (b) Employees location and dosage calculation.

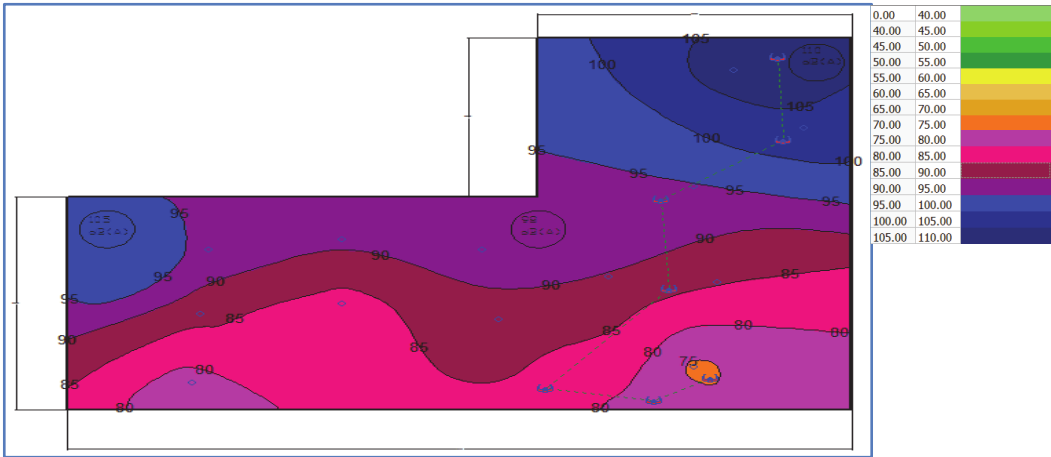


Fig. 4.7. (I.T.O) power plant station New Delhi Noise map (noiseatwork V1.31).

No. ↑	X	Y	Leq
1	85.00	64.00	108.00
2	94.00	53.00	104.00
3	70.00	60.00	100.00
4	80.00	42.00	95.00
5	69.00	25.00	90.00
6	53.00	30.00	94.00
7	55.00	17.00	88.00
8	83.00	24.00	85.00
9	7.00	25.00	100.00
10	18.00	30.00	94.00
11	17.00	18.00	86.00
12	35.00	32.00	90.00
13	35.00	20.00	83.00
14	16.00	5.00	77.00
15	80.00	8.00	74.00

Table 4.5. (a) (X, Y) Coordinates of noise measurement and noise levels.

Loc	T [h]	Red [dB]	Leq [dB]	Dose [%]
1	8.00	—	107.50	1131
2	8.00	—	102.20	543
3	8.00	—	94.10	177
4	8.00	—	85.93	57
5	8.00	—	83.32	40
6	8.00	—	77.39	17
7	8.00	—	74.61	12
Total	56.00		100.36	2944

Table 4.5. (b) Employees location and dosage calculation.

4.6 Building systems with fuzzy logic toolbox

While fuzzy system are shown to be universal approximations to algebraic functions, it is not attribute that actually makes them valuable to us in understanding new or evolving problems. Rather, the primary benefit of fuzzy system theory is to approximate system behavior where analytical functions or numerical relations do not exist. Hence, fuzzy systems have a high potential to understand the very system that red void of analytic formulations: complex system. Complex system can be new systems that have not been tested, they can be system involved with the human condition such as biological or medical system, or they can be social, economic, or political systems, where the vast arrays of input and output could not all possibly be captured analytically or controlled in any conventional sense. Moreover the relationship between the cause and effects of these systems is generally not understood, but often can be observed.

Alternatively, fuzzy system theory can have utility in assessing some of our more conventional, less complex system. For example, for some problems exact solutions are not always necessary. An approximate but fast, solution can be useful in making preliminary design decisions or as an initial estimation in a more accurate numerical technique to save computational costs or in the myriad of situations where the inputs to a problem are vague, ambiguous, or not known at all.

Fuzzy models in a broad sense are of two types. The first category of the model proposed by Mamdani is based on the collections of IF-THEN rules with both fuzzy-antecedent and consequent predicates. The advantage of this model is that the rule base is generally provided by an expert, and hence, to a certain degree, it is transparent to interpretation and analysis. The second category of the fuzzy model is based on the Takagi-Sugeno-Kang (TSK) method of reasoning.

For this study we have establishment of the Sugeno type Fuzzy models under the recommendations of Occupational Safety and Health Administration (OSHA)[30], 90 dB (A) for 8 hr. duration, as shown in Figure 4.8, because of the adaptive data Surgeon’s model is the proper method to build the model. Fuzzy Logic Toolbox is a collection of functions built on the MATLAB® numeric computing environment. Fuzzy logic has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multi valued logic. However, in a wider sense fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with unsharp boundaries in which membership is a matter of degree.

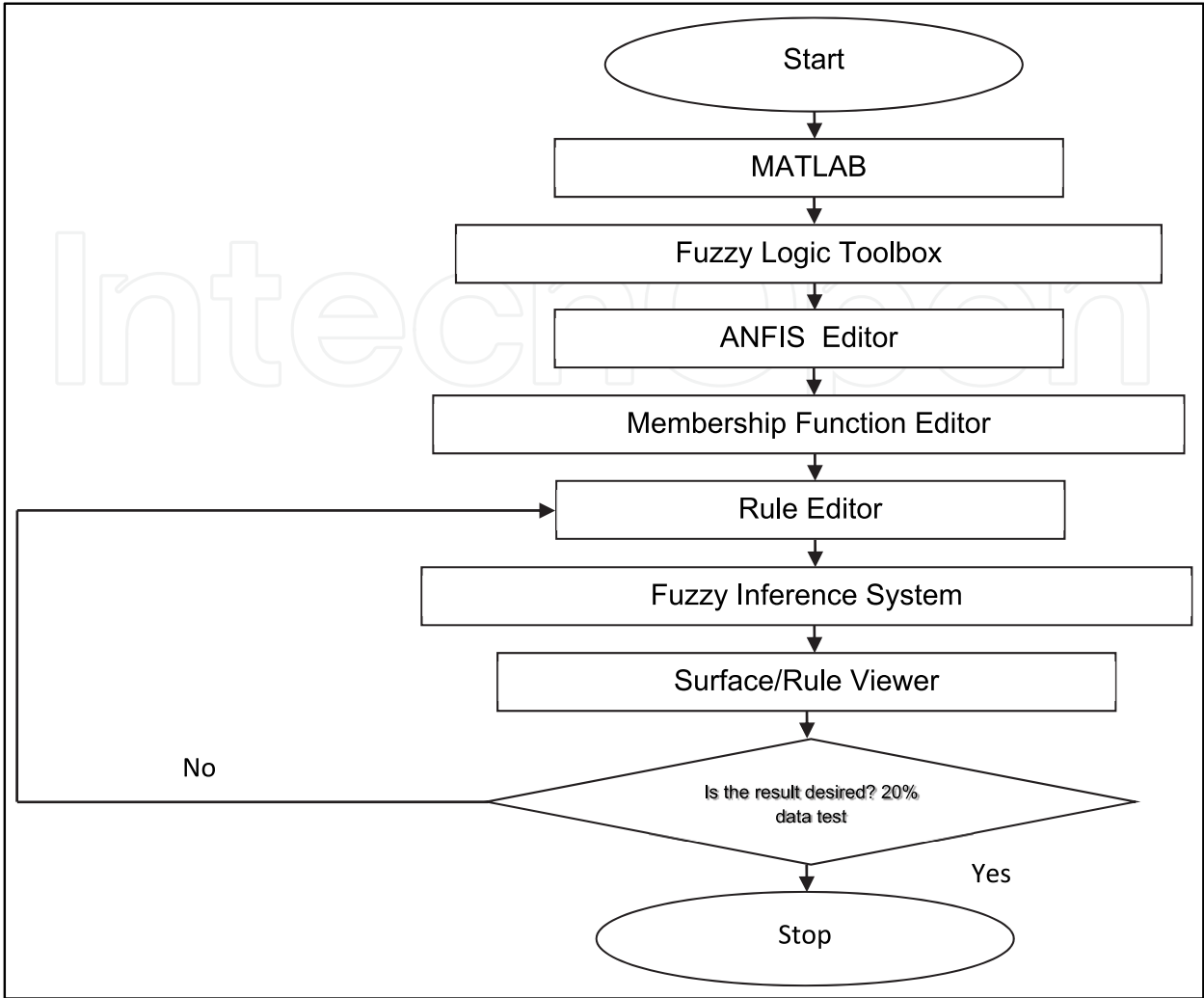


Fig. 4.8. Flow diagram for model structure.

4.6.1 Algorithm

1. Selection of the input and output variables.
2. Determination of the ranges of input and output variables.
3. Determination of the membership functions for various input and output variables.
4. Formation of the set of linguistic rules that represent the relationships between the system variables;
5. Selection of the appropriate reasoning mechanism for the formalization of the neural fuzzy model.
6. Check model validity by using 20% of input/output pairs.
7. Evaluation of the model adequacy;if the model does not produce the desired results, modify the rules in step 4.

4.6.2 Neuro-fuzzy computing

Neuro-fuzzy computing is a judicious integration of the merits of neural and fuzzy approaches. This incorporates the generic advantages of artificial neural networks like massive parallelism, robustness, and learning in data-rich environments into the system.

The modeling of imprecise and qualitative knowledge as well as the transmission of uncertainty is possible though the use of fuzzy logic. Besides these generic advantages, the neuro-fuzzy approach also provides the corresponding application specific merits [31-32] some of the neuro-fuzzy systems are popular by their shorts names. For example ANFIS [33], DENFIS [34], SANFIS [35] and FLEXNFIS [36], etc.

Our present model is based on adaptive neuro-fuzzy interface system (ANFS) an ANFIS is a fuzzy interface system implement in framework of adaptive neural networks. ANFIS either uses input/output data sets to construct a fuzzy interface system whose membership functions are tuned using a learning algorithm or an expert may be specify a fuzzy interface system and then the system is trained with the data pairs by an adaptive network . The conceptual diagram of ANFIS based on latter approach shown in figure 4.9. Is consists of two major components namely fuzzy interface system and adaptive neural network. A fuzzy interface system has five functional blocks. A fuzzifier converts real numbers of input into fuzzy sets. This functional unit essentially transforms the crisp inputs into a degree of match with linguistic values. The database (or dictionary) contains the Membership functions of fuzzy sets. The membership function provide flexibility to the fuzzy sets in modeling commonly used linguistic expressions such as "the noise level is low "or "person is young." A rule base consist of a set of linguistic statements of the form, if x is A then y is B , where A and B are labels of fuzzy sets on universes of discourse characterized by appropriate membership function of database . An interface engine perform s the interface operations on the rules to infer the output by a fuzzy reasoning method. Defuzzifier

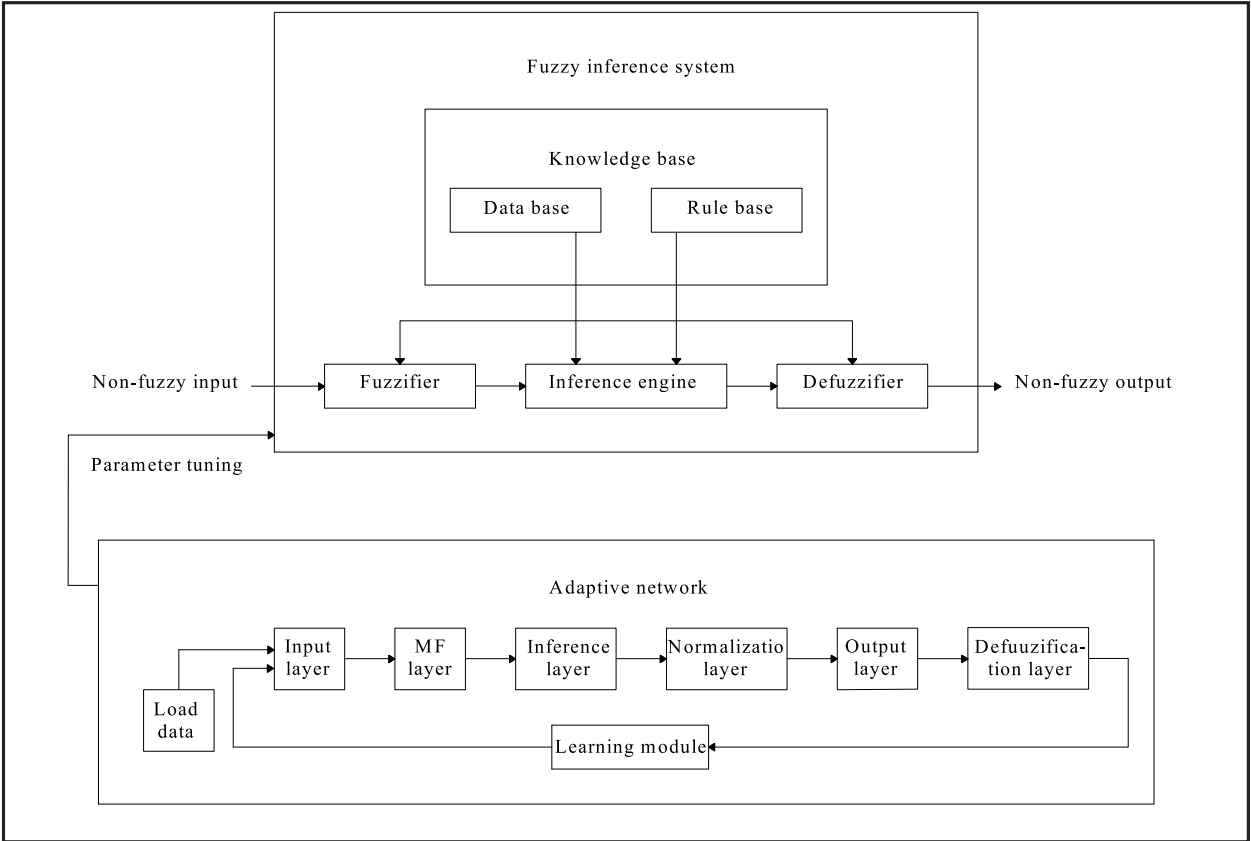


Fig. 4.9. Conceptual diagram of ANFIS.

converts the fuzzy outputs obtained by interface engine into a non-fuzzy output real number domain. In order to incorporate the capability of learning from input/output data sets in fuzzy interface systems, a corresponding adaptive neural network is generated. An adaptive network is a multi-layer feed-forward network consisting of nodes and directional links through which nodes are connected. As shown in Figure 4.10. Layer 1 is the input layer, layer 2 describes the membership functions of each fuzzy input, layer 3 is interface layer and normalizing is performed in layer 4. Layer 5 gives the output and layer 6 is the defuzzification layer. The layers consist of fixed and adaptive nodes, each adaptive node has asset of parameters and performs a particular function (node function) on incoming signals.

The learning model may consist of either back propagation or hybrid learning algorithm, the learning rules specifies how the parameter of adaptive node should be change to minimize a prescribed error measure [37]. The change in values of the parameters results in change in shape of membership functions associated with fuzzy interface system.

4.6.3 System modeling

The modeling process based on ANFIS can broadly be classified in three steps:

Step 1. System identification

The first step in system modeling is the identification inputs and outputs variables called the system's Takagi-Sugeno-Kang (TSK) model [33,34] are formed, where antecedent are defined be a set of non-linear parameters and consequents are either linear combination of input variables and constant terms or may be constants, generally called, singletons.

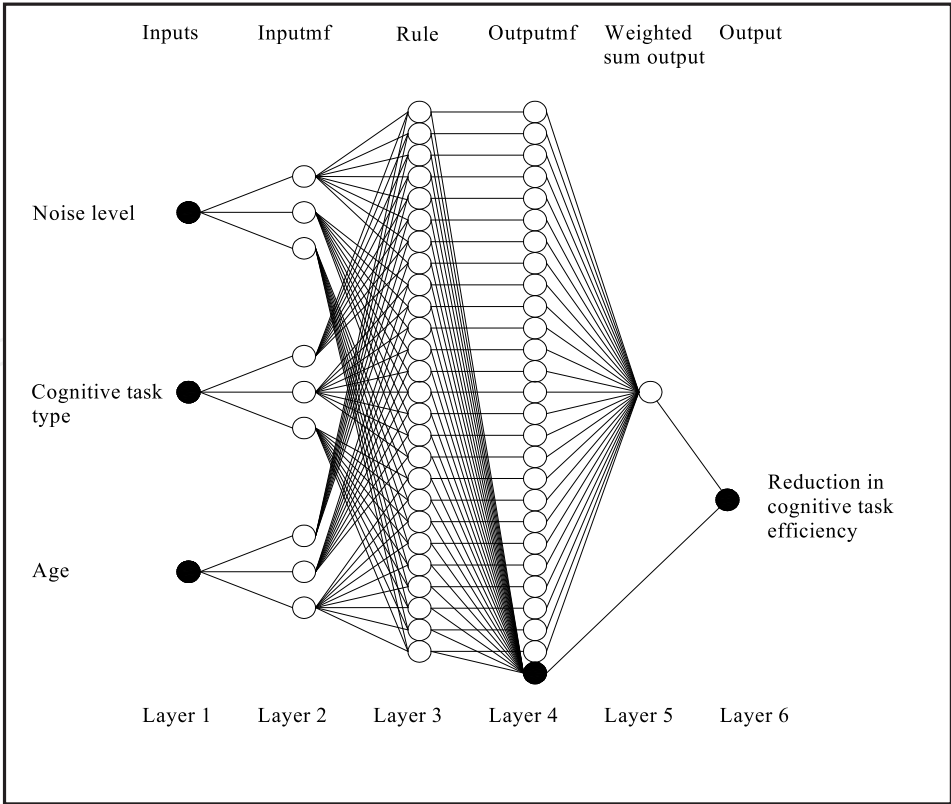


Fig. 4.10. ANFIS structure of the model.

Step 2. Determining the network structure

Once the input and output variables are identified, the neuro-fuzzy system is realized using a six-layered network as shown in Figure 4.10. The input, output and node functions of each layer are explained in the subsequent paragraphs

Layer 1: Input layer

Each node in layer 1 represents the input variables of the model identified in step 1 this layer simply transmits these input variables to the fuzzification layer.

Layer 2: Fuzzification layer

The fuzzification layer describes the membership function of each input fuzzy set, membership functions are used to characterize fuzziness in fuzzy sets, the output of each node i in this layer is given by $\mu_{A_i}(x_i)$ where the symbol $\mu_A(x)$ is the membership function. Its value on the unit interval $(0, 1)$ measure the degree to which elements x belongs to the fuzzy set A , x_i is the input to the node i and A_i is the linguistic label for each input variable associated with this node.

Each node in this layer is an adaptive node that is the output of each node depends on the parameters pertaining to these nodes. Thus the membership function for A can be any appropriate parameterized membership function. The most commonly used membership functions are triangular, trapezoidal, Gaussian, and bell shaped. Any of these choices may be used, the triangular and trapezoidal membership functions have been used extensively especially in real-time implementations due to their simple formulas and computational efficiency.

In our original fuzzy model [40] we have used triangular membership functions however since these membership functions are composed of straight line segments they are not smooth at corner points specified by the parameters though the parameters of these membership functions can be optimized using direct search methods but they are less efficient and more time consuming, also the derivatives of the functions are not continuous so the powerful and more efficient gradient methods cannot be used for optimizing their parameters Gaussian and bell shaped membership functions are becoming increasingly popular for specifying fuzzy sets as they are non-linear and smooth and their derivatives are continuous gradient methods can be used easily for optimizing their design parameters. Thus in this model, we have replaced the triangular fuzzy memberships with bell shapes functions (Table 4.7). The bell or generalized bell (or gbell) shaped membership function is specified by a set of three fitting parameters $\{a, b, c\}$ as:

$$\mu_A(x) = \frac{1}{1 + \left[\left((x - c) / a \right)^2 \right]^b} \quad (4.12)$$

The desired shape of gbell membership function can be obtained by proper selection of the parameters more specifically we can adjust c and a to vary the center and width of membership function, and b to control the slope at the crossover points. The parameter b gives gbell shaped membership function one more degree of freedom than the Gaussian membership function and allows adjusting the steepness at crossover points. The parameters in this layer are referred to as premise parameters.

Layer 3: inference layer

The third layer is inference layer. Each node in this layer is fixed node and represents the IF part of a fuzzy rule. This layer aggregates the membership grades using any fuzzy intersection operator which can perform fuzzy AND operation [35]. The intersection operator is commonly referred to as T-norm operators are min or product operators. For instance

IF x_1 is A_1 AND x_2 is A_2 AND x_3 is A_3 THEN y is $f(x_1, x_2, x_3)$

Where $f(x_1, x_2, x_3)$ is a linear functions of input variables or may be constant, the output of i th node is given as:

$$w_i = \mu_{A_1}(x_1) \times \mu_{A_2}(x_2) \times \mu_{A_3}(x_3) \quad (4.13)$$

Layer 4: normalization layer

The i th node of this layer is also a fixed node and calculates the ratio of the i th 'rules' firing strength in interference layer to the sum of all the rules firing strengths

$$\bar{w}_i = \frac{w_i}{w_1 + w_2 + \dots + w_R} \quad (4.14)$$

Where $i = 1, 2, \dots, R$ and R is total number of rules. The outputs of this layer are called normalized firing strengths.

Layer 5: Output layer

This layer represents the THEN part (i.e., the consequent) of the fuzzy rule. The operation performed by the nodes in this layer is to generate the qualified consequent (either fuzzy or crisp) of each rule depending on firing strength. Every node i in this layer is an adaptive node. The output of the node is computed as:

$$O_i = \bar{w}_i f_i \quad (4.15)$$

Where $\bar{w}_i$ is normalized firing strength from layer 3 and f_i is a linear function of input variables of the form $(p_i x_1 + q_i x_2 + r_i)$ where $\{p_i, q_i, r_i\}$ is the parameter set of the node i , referred to as consequent parameters or f may be a constant if f_i is linear function of input variables then it is called first order Sugeno fuzzy model (as in our present model) and if f_i is a constant then it is called zero order Sugeno fuzzy model. This consequent can be linear function as long as it appropriately describes the output of the model within the fuzzy region specified by the antecedent of the rule. But in the present case, the relationship between input variables (noise level, cognitive task type, and age) and output (reduction in cognitive task efficiency) is highly non-linear. In Sugeno model, consequent can be taken as singleton, i.e. real numbers without losing the performance of the system.

Layer 6: Defuzzification layer

This layer aggregate the qualified consequent to produce a crisp output .the single node in this layer is a fixed node. It computes the weighted average of output signals of the output layer as:

$$O = \sum_i O_i = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (4.16)$$

Step 3. Learning algorithm and parameter tuning

The ANFIS model fine-tunes the parameters of membership functions using either the back propagation learning algorithm is an error-based supervised learning algorithm. It employs an external reference signal, which acts like a teacher and generate an error signal by comparing the reference with the obtained response. Based on error signal, the network modifies the design parameters to improve the system performance. It uses gradient descent method to update the parameters. The input/output data pairs are often called as training data or learning patterns. They are clamped onto the network and functions are propagated to the output unit. The network output is compared with the desired output values. The error measure E^P , for P pattern at the output node in layer 6 may be given as:

$$E^P = \frac{1}{2} (T^P - O_6^P)^2 \quad (4.17)$$

Where T^P are the target or desired output and O_6^P the single node output of defuzzification layer in the network. Further the sum of squared errors for the entire training data set is:

$$E = \sum_P E^P = \frac{1}{2} \sum_P (T^P - O_6^P)^2 \quad (4.18)$$

The error measure with respect to node output in layer 6 is given by delta (δ):

$$\delta = \frac{\partial E}{\partial O_6} = -2(T - O_6) \quad (4.19)$$

This delta value gives the rate at which the output must be changed in order to minimize the error function, since the output of adaptive nodes of the given adaptive network depend on the design parameters so the design parameters must be updated accordingly. Now this delta value of the output unit must be propagated backward to the inner layers in order to distribute the error of output unit to all the layers connected to it and adjust the corresponding parameters the delta value for the layer 5 is given as:

$$\frac{\partial E}{\partial O_5} = \frac{\partial E}{\partial O_6} \frac{\partial O_6}{\partial O_5} \quad (4.20)$$

Similarly for any k th layer, the delta value may be calculated using the chain rule as:

$$\frac{\partial E}{\partial O_K} = \frac{\partial E}{\partial O_{K+1}} \frac{\partial O_{K+1}}{\partial O_K} \quad (4.21)$$

Now if α is a set of design parameters of the given adaptive network then

$$\frac{\partial E}{\partial \alpha} = \sum_{\alpha \in P} \frac{\partial E}{\partial O^I} \frac{\partial O^I}{\partial \alpha} \quad (4.22)$$

Where P is the set of adaptive nodes whose output depends on α thus update for the parameter α is given by:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \quad (4.23)$$

Where η is the learning rate and may be calculated as:

$$\eta = \frac{K}{\sqrt{\sum_{\alpha} (\partial E / \partial \alpha)^2}} \quad (4.24)$$

Where 'k' is the step size. The value of k must be properly chosen as the change in value of k influences the rate of convergence.

Thus the design parameters are tuned according to the real input/output data pairs for the system. the change in value of parameter results in change in shape of membership functions initially defined by an expert. the new membership functions thus obtained after training gives a more realistic model of the system. the back propagation algorithm though widely used for training neural networks may suffer from some problems. The back propagation algorithm is never assured of finding the global minimum. The error surface may have many local minima so it may get stuck during the learning process on flat or near flat regions of the error surface. This makes progress slow and uncertain.

Another efficient learning algorithm, which can be used for training the network, is hybrid-learning rule. Hybrid learning rule is a combination of least square estimator (LSE) and gradient descent method (used in back propagation algorithm). It converges faster and gives more interpretable results. The training is done in two passes. In forward pass, when training data is supplied at the input layer, the functional signals go forward to calculate each node output. The non-linear or premise parameters in layer 2 remain fixed in this pass. Thus the overall output can be expressed as the linear combination of consequents parameters. These consequents parameters can be identified using least square estimator (LSE) method. The output of layer 6 is compared with the actual output and the error measure can be calculated as in eqs.(4-17 and 4-18). In backward pass, error rate prorogates backward from output end toward the input end and non-linear parameters in layer 2 are update using the gradient descent method (eqs.(4-19)-(4-24)) as discussed in back propagation algorithm. Since the consequent parameters are optimally identified using LSE under the condition that the premise parameters are fixed, the hybrid algorithm converges much faster as it reduces the search space dimensions of the original pure back propagation algorithm.

4.6.4 Implementation

We have implemented our model using ANFIS (fuzzy logic tool box) of MATLAB® [39]. The system is first designed using Sugeno fuzzy inference system. It is a three inputs-one output system. The input variables are the noise level, cognitive task type, and age and the reduction in cognitive task efficiency is taken as the output variable. The input parameters are represented by fuzzy sets or linguistic variables Table 4.6. We have chosen gbell shaped membership functions (it is given the minimum error as shown in Table 4.7), to characterize these fuzzy sets. The membership functions for input variables are shown in Figure 4.11(a-c).

System's	Linguistic	Linguistic Values	Fuzzy Intervals
Input	Noise level	Low	40-90
		Medium	80-100
		High	90-110
	Cognitive task type	Simple	1-3
		Moderate	2-4
		Complex	3-5
	Age	Young age	15-35 years
		Medium age	30-50 years
		Old age	45-65 years
Output	Reduction In cognitive task Efficiency	None	0 %
		Low	25 %
		Moderate	50 %
		High	75 %
		Very high	100 %

Table 4.6. Inputs and outputs with their associated neural fuzzy values.

Mf type	Error(linear output)	Error(constant output)	Epoch (iteration)
Tri-mf	8.0327 e-007	2.5532 e-005	190
Trap-mf	1.0955 e-006	0.2886	190
Gbell-mf	6.0788 e-007	2.1502 e-005	190
Gauss-mf	6.1237 e-007	2.2678 e-005	190
Gauss2-mf	1.0014 e-006	2.1687 e-005	190
Pi-mf	1.7942 e-006	0.2886	190
Dsig-mf	2.4415 e-006	2.4847 e-005	190
Psig-mf	1.4882 e-006	2.4847 e-005	190

Table 4.7. Minimum error membership functions.

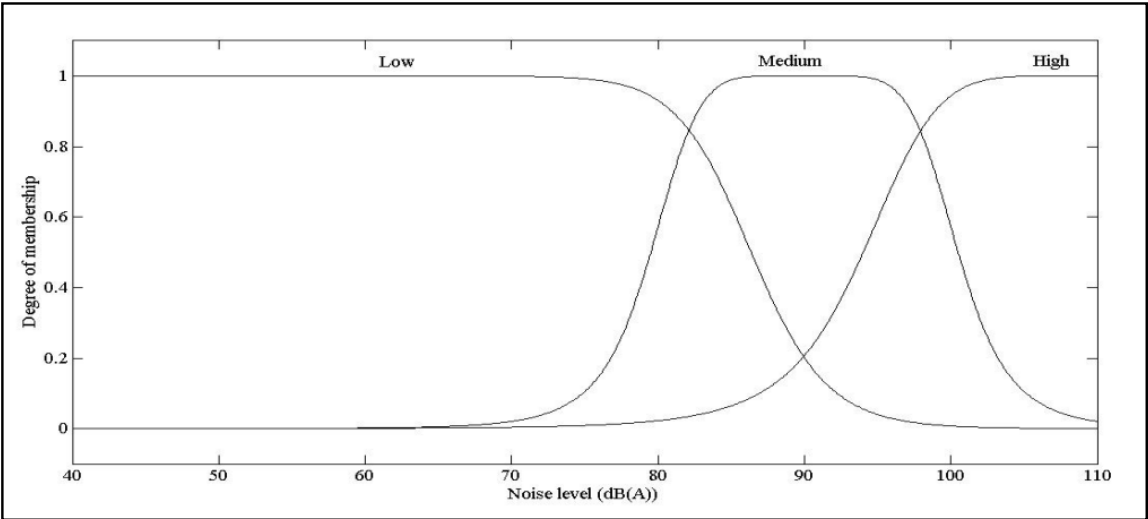


Fig. 4.11. (a) Membership functions of noise level.

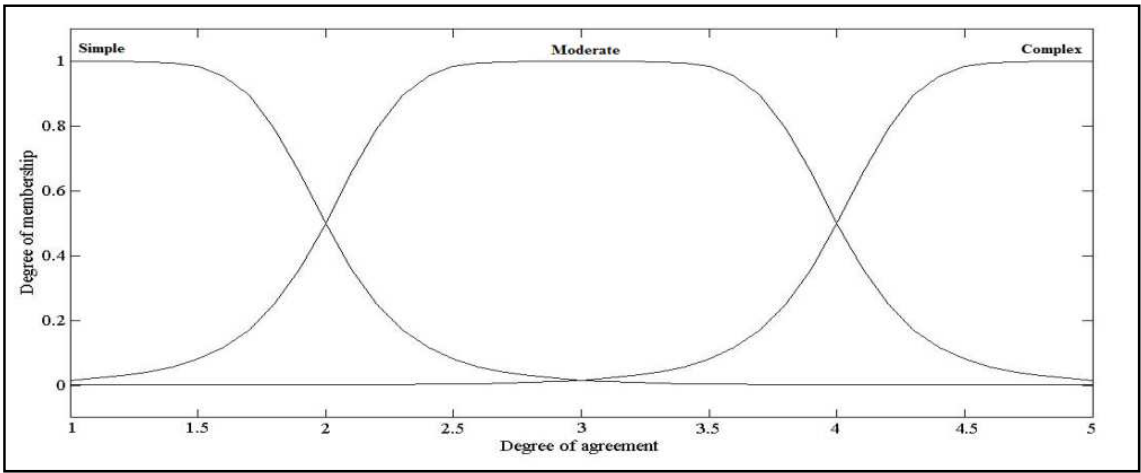


Fig. 4.11. (b) Membership functions of cognitive task type.

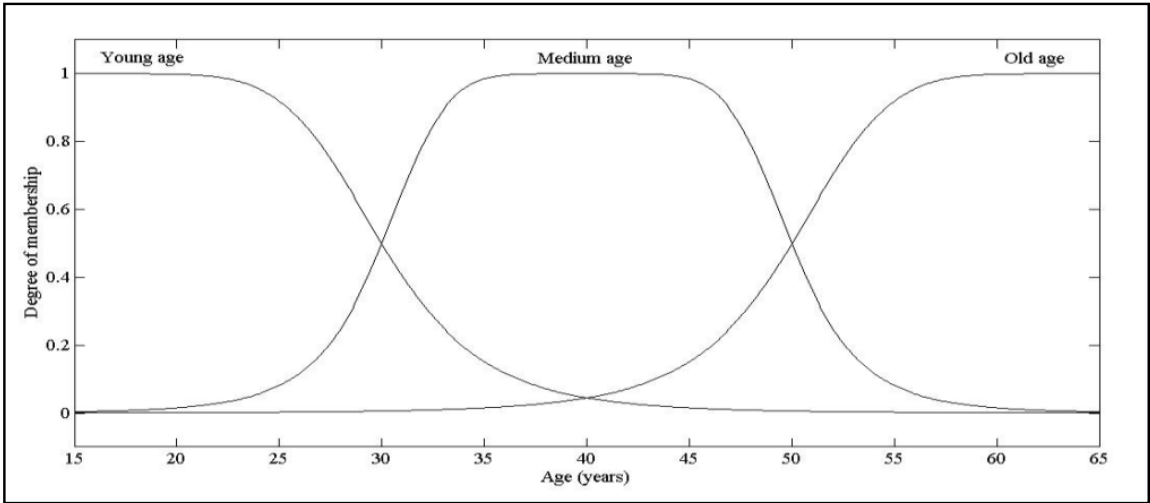


Fig. 4.11. (c) Membership functions of age group.

The membership functions are then aggregated using T-norm product to construct fuzzy IF-THEN rules that have a fuzzy antecedent part and constant consequent, The total number for rules is 27. Some of the rules are given below:

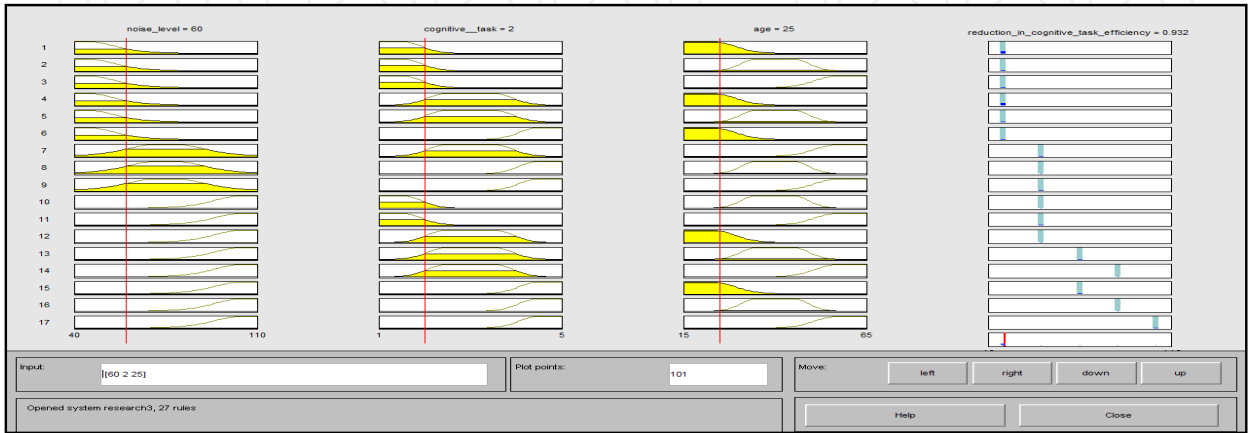


Fig. 4.12. Typical rules and their graphic representations in Sugeno approach.

R1, IF noise level is low AND cognitive task is simple AND age is young THEN reduction in cognitive task efficiency is approximately (none) 0%.

After constructions of fuzzy inference system, the model parameters are optimized using ANFIS. The network structure consists of 78 nodes. The total number of fitting parameters is 54, of which 27 are premise and 27 are consequent parameters. A hybrid learning rule is used to train the model according to input/output data pairs. The data pairs where obtained from questionnaire it was established for this purpose. We designed and developed our model based on conclusions of our studies [40, 41, and 42], out of the total 155 input/output data sets 124 (80%) data pairs were used for training the model. It was trained for 250 epochs with step size of 0.01 and error tolerance 0%. To validate the model 31 (20%) data sets were used testing purpose.

5. Result and discussion

The model was trained for 250 epochs and it was observed that the most of the learning was completed in the first 190 epochs as the root mean square error (RMSE) settles down to almost 0% at 190 th epoch. Figure 5.1(a) shows the training RMSE curve for the model after training the fuzzy inference system. It is found that the shape of membership functions is slightly modified.

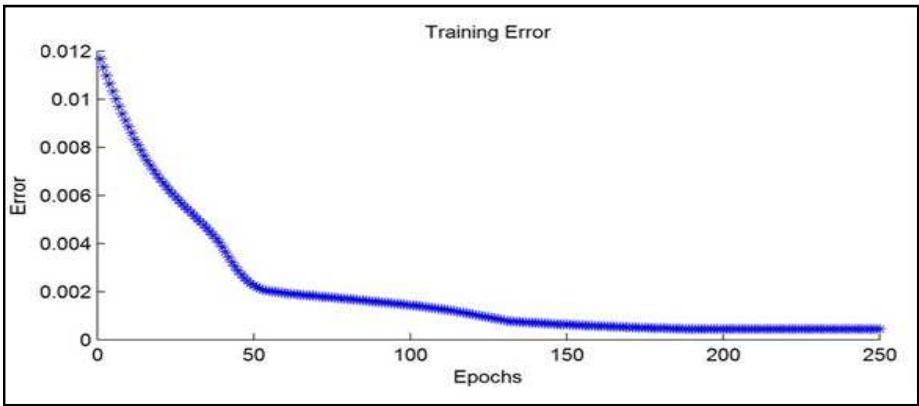


Fig. 5.1. (a) Training root means squared error.

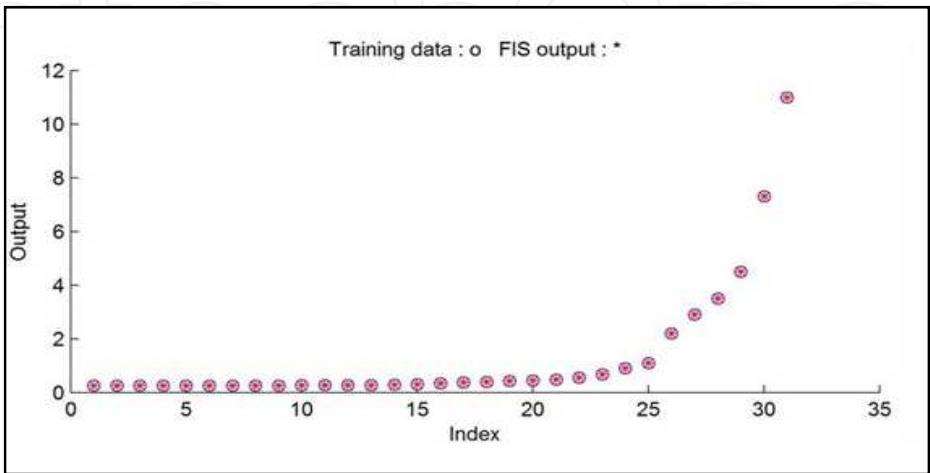


Fig. 5.1. (b) Data testing

This is because of the close agreement between the knowledge provided by the expert and input/output data pairs. While, Figure 5.1(b) shows data testing to check data validity. Hence, the impact of the noise level on cognitive human work efficiency is represented in the form of graphs in Figure 5.2, with the ages as parameters for different cognitive task type. The reduction in cognitive task efficiency up to the noise level of 75 dB (A) is almost negligible for all ages irrespective of cognitive task. Assuming effects of 25% reduction in cognitive work efficiency as low effect Figure 5.2(a) Show the reduction in cognitive task efficiency versus noise level with 'simple' cognitive task for 'young', 'medium', and 'old' ages. The cognitive work efficiency reduce to almost 29.6% at 90 dB (A) and above noise levels for 'old' ages but the 'young' and 'medium' age remain 'unaffected'.

It is to be observed from Figure 5.2(b) that the cognitive task efficiency is low (only 14.8%) at 85 dB (A) for 'young' age whereas for 'medium' and 'old' ages, the reduction in cognitive task efficiency is 26% and 45.9% respectively at the same noise levels for 'moderate' cognitive task . However the reduction in cognitive task efficiency is almost 21.5%, 38.9%, and 60.2% for 'young', 'medium' and 'old' ages, respectively at 90 dB (A) and above noise levels.

Figure 5.2(c) depicts the reduction in cognitive task efficiency with noise level at 'complex' cognitive task for 'young', 'medium', and 'old' ages. It is evident from this figure that the reduction in cognitive task efficiency is negligible up to the noise level of 80 dB (A) for 'young' age while it is about 26.4%, 34.1% for 'medium' and 'old' ages the cognitive task efficiency start reducing after 80 dB (A) even for 'young' and 'medium' ages. At 90 dB (A), cognitive task efficiency reduces to 36% , 56.7% and 75.1% for 'young', 'medium' and 'old' ages, respectively . There is significant reduction in cognitive task efficiency after 95 dB (A) for all ages. When noise level is in the interval of 100-105 dB (A), it is 45.6% for 'young', 68.3% for 'medium', and 91% for 'old' ages, respectively.

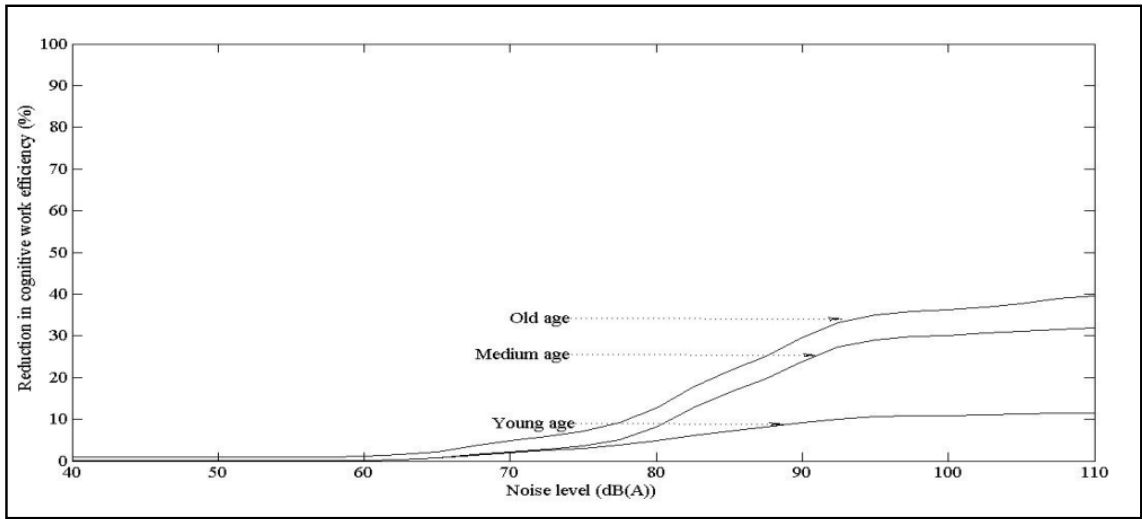


Fig. 5.2. (a) Reduction in cognitive task efficiency as a function of noise level at 'simple' cognitive task for various ages.

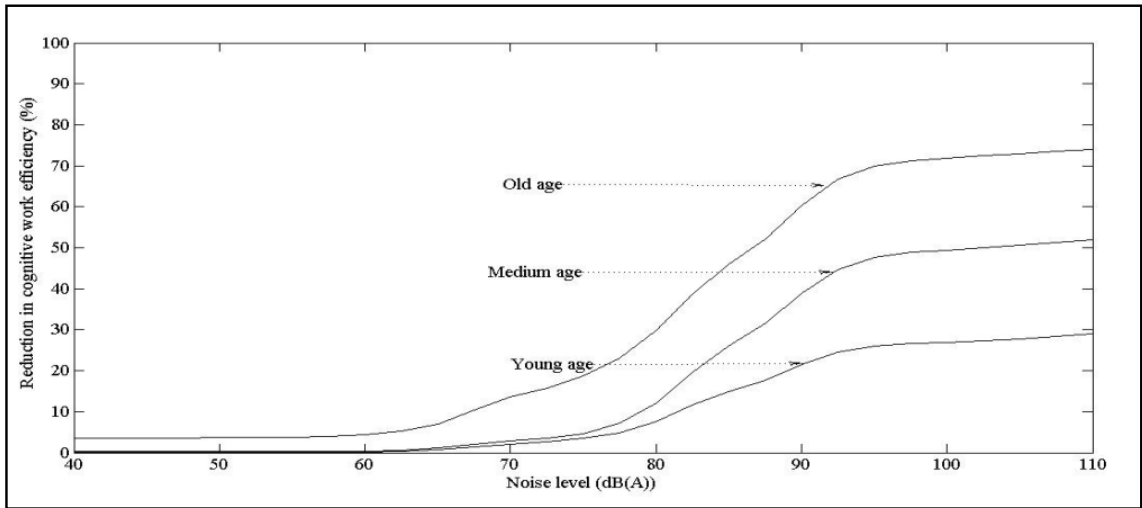


Fig. 5.2. (b) Reduction in cognitive task efficiency as a function of noise level at 'moderate' cognitive task for various ages.

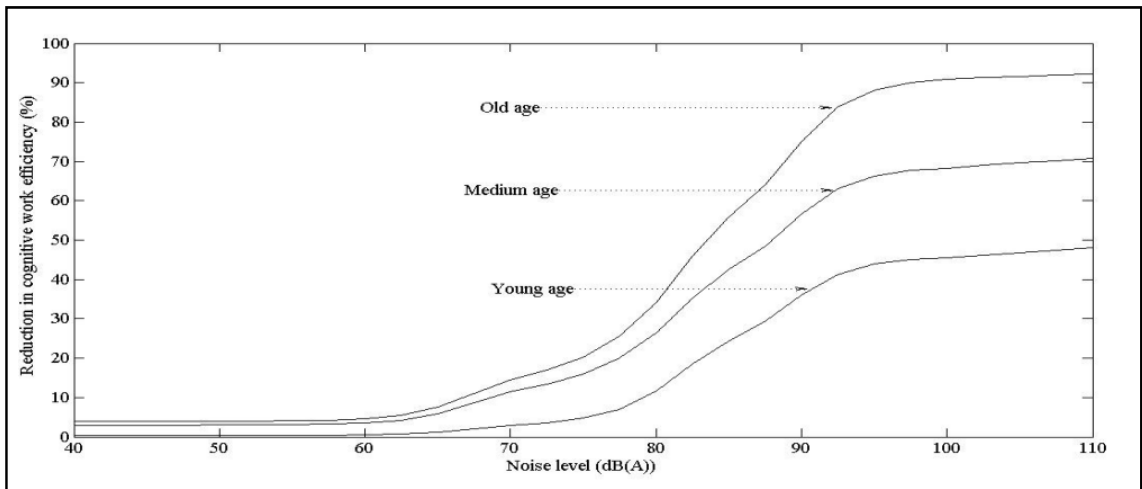


Fig. 5.2. (c) Reduction in cognitive task efficiency as a function of noise level at 'complex' cognitive task for various ages.

An alternative representation to Figure 5.2(a-c) discussed above is shown in Figure 5.3(a-c), in which the reduction in cognitive task efficiency with noise level for 'low', 'medium' and 'high' cognitive task at deferent ages is presented besides this following inference are readily down:

1. If age is 'young' as shown in Figure 5.3(a) the cognitive task efficiency reduces to 21.5% for 'moderate' and 36% for 'complex' cognitive tasks while it reduces 9.22% for 'simple' cognitive task at 90 dB (A) and above noise levels.
2. In case of 'medium' age, the cognitive task efficiency is reduced to 30.1%, 49.4%, and 68.3% at 100 dB (A) for 'simple', 'moderate' and 'complex' cognitive tasks, respectively as is evident from Figure 5.3(b).
3. For 'old' age, the reduction in cognitive task efficiency occurs even at much lower noise levels as can be observed from Figure 5.3(c). It is 36.2%, 71.9%, and 91% at 100 dB (A) for 'simple', 'moderate' and 'complex' cognitive tasks, respectively.

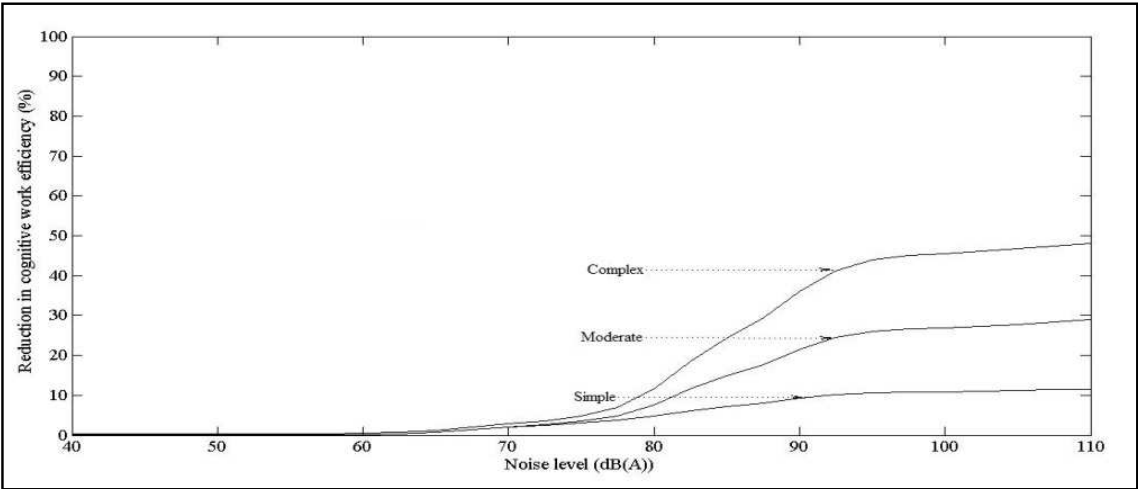


Fig. 5.3. (a) Reduction in cognitive task efficiency as a function of noise level for ‘young’ age for various cognitive tasks.

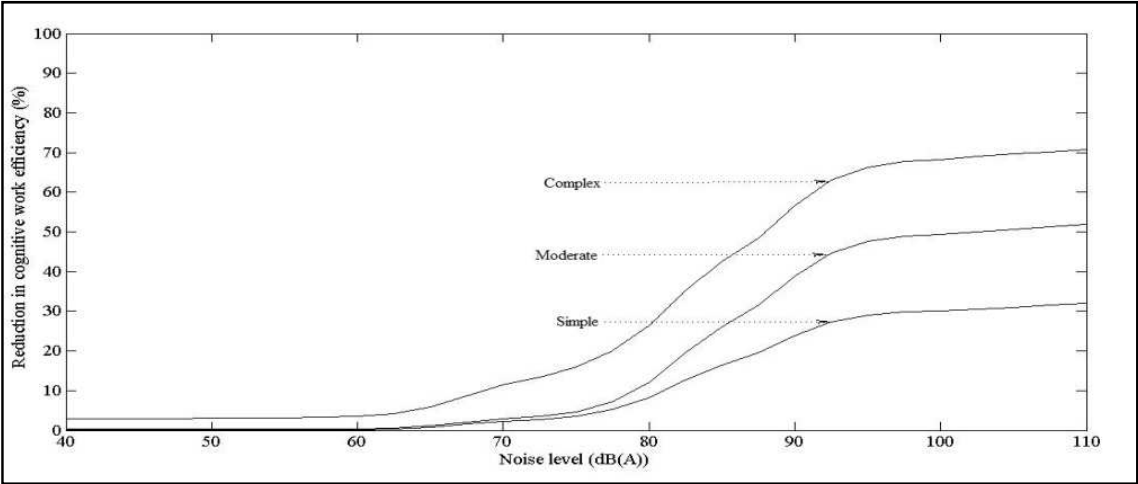


Fig. 5.3. (b) Reduction in cognitive task efficiency as a function of noise level for ‘medium’ age for various cognitive tasks.

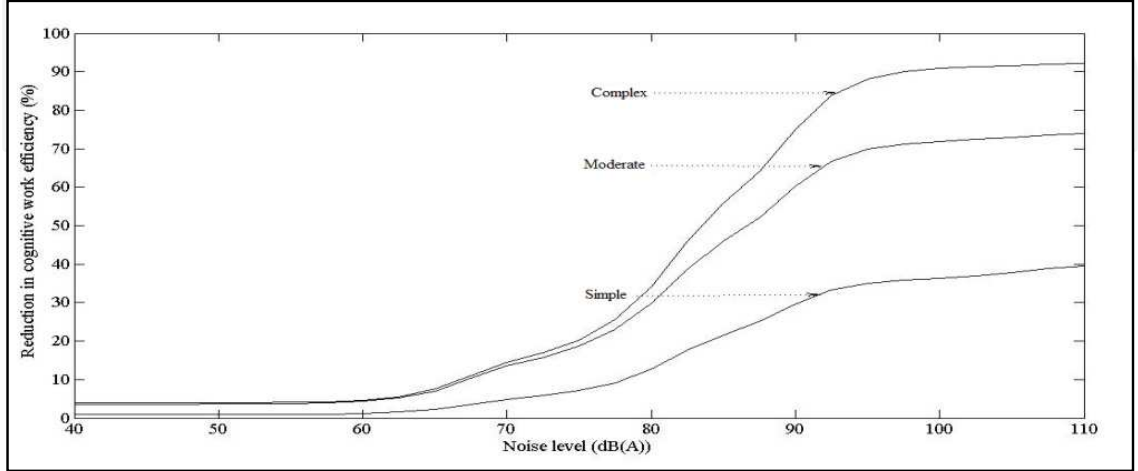


Fig. 5.3. (c) Reduction in cognitive task efficiency as a function of noise level for ‘old’ age for various cognitive tasks.

In order to observe the data behavior, we have compared some of our model results with deduction based on the criterion of Safe Exposure Limited recommended for industrial workers. The Recommended Exposure Limit (REL) for workers engaged in occupation such as engineering controls, administrative controls, and/or work practices is 85 dB (A) for 8 hr duration NIOSH (36), also recommended a ceiling limit of 115 dB(A). Exposures to noise levels greater than 115 dB (A) is not permitted regardless of the duration of the exposure time. There is almost no (0%) reduction in work efficiency when a person is exposed to the maximum permissible limit of 85 dB (A) for 8 hr and maximum (100%) reduction in work efficiency for a noise exposure of 105-115 dB (A) for 8 hr.

		NIOSH		OSHA	
S.No.	Noise levels dB(A)	Acoustic energy Dose(%)	Reduction in work efficiency(%)	model results	
				numerical value (%)	Fuzzy value
1	85	100	0	55.7	moderate
2	90	200	25	75.1	high
4	95	400	50	88.2	high
5	100	800	75	91	Very high
6	105	1600	100	91.6	Very high
7	110	3200	100	92.2	Very high
8	115	6400	100	92.2	Very high

Table 5.1. Data behavior comparison of the Results Based on Recommended Exposure Limit (REL) and the neural fuzzy model for moderate task.

6. Conclusion

The main thrust for the present work has been to develop a neuro-fuzzy model for the prediction of cognitive task efficiency as a function of noise level, cognitive task type and age. It is evident from the graph that the cognitive task efficiency, for the same cognitive task, depends to a large extent upon the noise level and age. It has also been verified that young age are slightly affected even at medium noise level while old ages get significantly affected at much lower noise level. It is to be appreciated that the training done using ANFIS is computationally very efficient as the desired RMSE value is obtained in very less number of epochs. Moreover, minor changes are observed in the shape of the membership functions after training the model. This is because of close agreement between the knowledge provided by expert and input/output data pairs. The present effort also establishes the usefulness of the fuzzy technique in studying the ergonomic environmental problems where the cause-effect relationships are inherently fuzzy in nature.

6.1 Scope for future research

1. The study may also be done by changing the input parameters such as: type of task, gender of the workers, environmental conditions (light, temperature, vibration, humidity) etc.
2. Data should collect from noisy environment for different ages for workers doing cognitive tasks, and the questionnaire form must be filled carefully to simulate high performance model.

- 3. The input & output variables range may also be converted into small ranges such as extremely low, very low, low, medium low, medium etc.
- 4. Input/output data must be categorized and scaled to set the optimum number and shape of membership functions, by increasing the probability (membership functions) model performance will be improved.
- 5. Workers subjected under high cognitive task must be working on low noise level environment to keep their performance.
- 6. This study proved the questionnaire studies it's easy to simulate and programming using neural-fuzzy model to give as approximately solution for several case steadies.
- 7. The problem of noise should be taken into consideration during their establishment phases (construction of the building, allocation of the machinery, etc.).
- 8. It's possible to modify the present model (FIS) to be a part of control system.

7. Appendix

7.1 Appendix-A

Department of labor occupational noise exposure standard

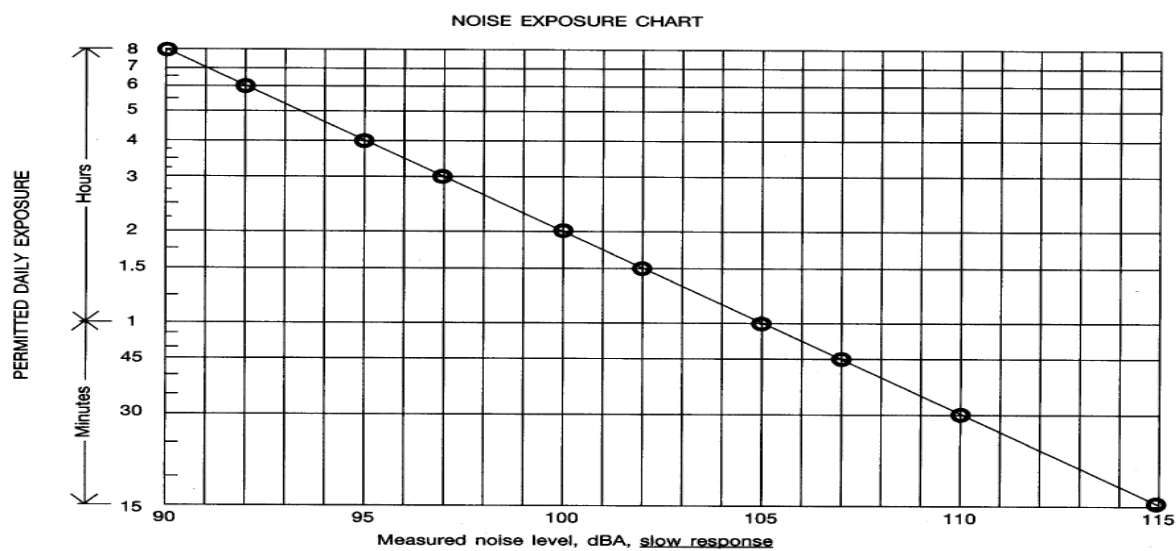


Fig. A.1. Permitted daily exposure time [30]

0	Duration per day (Hrs.)	Sound level dBA, slow response
1	8	90
2	6	92
3	4	95
4	3	97
5	2	100
6	1-1/2	102
7	1	105
8	1/2	110
9	1/4 or less	115

Table A.1. Permissible Noise Exposures

7.2 Appendix-B

1.	Noise level	dB(A)				
2.	age	years				
3.	sex	M or F				
			STRONGLY DISAGREE	DISAGREE	NEUTRAL	AGREE STRONGLY AGREE
4.	Easy to learning new things	A	B	C	D	E
5.	you like repetitive nature of work	A	B	C	D	E
6.	You are creative thinking at work	A	B	C	D	E
7.	Your skill is high	A	B	C	D	E
8.	Care for time span of activities and development nature of job	A	B	C	D	E
9.	Don't Have a lot of say on job	A	B	C	D	E
10.	You are free to take own decision while working	A	B	C	D	E
11.	You are not continual dependence on others	A	B	C	D	E
12.	You are not affected by influence over organization change	A	B	C	D	E
13.	You are not affected by influence of a policies of union	A	B	C	D	E
14.	You are regular meeting of work team	A	B	C	D	E
15.	Doesn't Supervising people at your job	A	B	C	D	E
16.	You effected are not by influence over work team decision	A	B	C	D	E
17.	Have a hard work	A	B	C	D	E
18.	Don't Have a fast work	A	B	C	D	E

19. Have excessive work	A	B	C	D	E
20. Time is enough to finish your work	A	B	C	D	E
21. There is conflicting demands on your job	A	B	C	D	E
22. Have high emotional demands to work	A	B	C	D	E
23. You are negotiation with others	A	B	C	D	E
24. You suppressing genuine emotion	A	B	C	D	E
25. Highly care for your job	A	B	C	D	E
26. Your consultation is constant with others	A	B	C	D	E
27. You don't have high responsibility to taking care for home	A	B	C	D	E
28. You have high interference between family life and your job	A	B	C	D	E
29. You get the concern and the help of your supervisor	A	B	C	D	E
30. Have friendly and helpful coworkers	A	B	C	D	E
31. Have organizational care about workers opinions	A	B	C	D	E
32. You care about we-being	A	B	C	D	E
33. Have high consideration of goals and values	A	B	C	D	E
34. you concern about workers	A	B	C	D	E
35. You need to collect accurate information to make decision	A	B	C	D	E
36. You need providing opportunities to appeal the decision	A	B	C	D	E

37. You need generated standards to take consistent decision	A	B	C	D	E
38. Your work is steady	A	B	C	D	E
39. You are threat to job security	A	B	C	D	E
40. You are lay off recently	A	B	C	D	E
41. You have future lay off	A	B	C	D	E
42. You have valuable skills	A	B	C	D	E
43. Hard to keep job for long duration	A	B	C	D	E
44. Much physical effort is required	A	B	C	D	E
45. Have rapid physical activities	A	B	C	D	E
46. Have heavy loads at work	A	B	C	D	E
47. You feel awkward body position	A	B	C	D	E
48. You feel awkward upper body position	A	B	C	D	E
49. Sharing the hardship of the job	A	B	C	D	E
50 Have possibility to help the coworkers and a unity among workers	A	B	C	D	E
Feeling depressed	A	B	C	D	E
Sleep restless	A	B	C	D	E
Do not Enjoy life	A	B	C	D	E
Feel nervous while working	A	B	C	D	E
Exceptionally tired in the morning and exhausted mentally and physically at end of the day	A	B	C	D	E

Table B.1. Cognitive task (CT) questionnaire form for industrial applications [2]

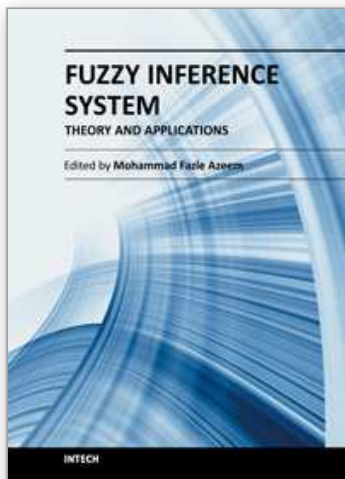
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