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DEVELOPMENT OF A NEURO FUZZY MODEL FOR NOISE PREDICTION IN OPENCAST MINES

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The need of developing appropriate noise prediction models for finding out the accurate status of noise levels (>90 dBA) generated from various opencast mining machineries is overdue. The measured sound pressure levels (SPL) of equipments are not accurate due to instrumental error, attenuation due to geometrical aberration, atmospheric attenuation etc. Some of the popular noise prediction models e.g. VDI and ENM have been applied in mining and allied industries. Among these models, VDI2714 is simple and less complex model. In this paper, a neuro-fuzzy model is proposed to predict the machinery noise in an opencast coal mine. The proposed model is trained with VDI2714 and the model output is seen very closely to matching with VDI2714 output. The model proposed has a mean square error of 2.73%. This model takes CPU time of nearly 0.0625 sec where as it takes 0.5 sec for VDI2714 i.e. approximately twelve times faster.

Keywords: Noise prediction models; opencast mines, VDI2714; fuzzy system; neuro-fuzzy model.

1. Introduction

Noise is generated from all most all the opencast mining operations from different fixed, mobile and impulsive sources; thereby becoming an integral part of the mining environment. With increased mechanization, the problem of noise has got accentuated in opencast mines. Prolonged exposure of miners to the high levels of noise can cause noise induced hearing loss besides several non-auditory health effects. The impact of noise in opencast mines depends upon the sound power level of the noise generators, prevailing geo-mining conditions and the meteorological parameters of the mines. The noise levels need to be studied as an integrated effect of the above parameters. In mining conditions the equipment conditions and environment continuously changes as the mining activity progresses. Depending on their placement, the overall mining noise emanating from the mines varies in quality and level. Thus for environmental noise prediction models, the noise level at any receiver point needs to be the resultant sound pressure level of all the noise sources.

The need for accurately predicting the level of sound emitted in opencast mines is well established. Some of the noise forecasting models used extensively in Europe are those of the German Draft Standard VDI-2714 Outdoor Sound Propagation and Environmental Noise Model (ENM). These models are generally used to predict noise in petrochemical complexes and mines. The algorithm used in these models rely for a greater part on interpolation of experimental data which is a valid and useful technique, but their applications are limited to sites which are more or less similar to those for which the experimental data were assimilated.

A number of models were developed and were extensively used for the assessment of sound pressure level and their attenuation around industrial complexes. Generally in Indian mining industry, ENM (Environmental Noise Model) developed by RTA group, Australia is mostly used to predict noise. Pal *et al.* (1997) applied ENM model to predict sound pressure level in mining complexes at Moonidih Project in Jharia Coalfield (Dhanbad, Inida).[1] The applied model output was represented as noise contours.

Tonin (1985) studied the applications of different noise prediction models including VDI2714 for various mines and petrochemical complexes and discussed that VDI2714 model is the simplest and least complex as compared to other models.[2] Rabeiy *et al.* (2004) used VDI2714 and ISO (1996) noise prediction models in Assiut cement plant, Assiut cement quarry and El-Gedida mine at El-Baharia oasis of Egypt to predict noise. They concluded that the prediction models can be used to identify the safe zones with respect to the noise level in mining and industrial plants. They also inferred that the VDI2714 model is the simplest model for prediction of noise in mining complexes and workplace.[3] Pathak et al. (2000) developed air attenuation model for noise prediction in limestone quarry and mines of Ireland.[5] They developed the model to predict attenuation in air due to absorption in air considering temperature and relative humidity.

All the noise models treat noise as a function of distance, sound power level, different form of attenuations such as geometrical absorptions, barrier effects, ground topography etc. Generally these parameters are measured in the mines and best fitting models are applied to predict noise. Mathematical models are generally complex and cannot be implemented in real time systems. Additionally they fail to predict the future parameters from current and past measurements. It has been seen that noise prediction is a non-stationary process and soft-computing techniques like Fuzzy system, Adaptive network based fuzzy inference system (ANFIS) or (Neuro-Fuzzy), Neural Network etc. have been tested for non-stationary timeseries prediction nearly for two decades. Fuzzy logic was introduced by Zadeh (1965) as a mathematical way to represent vagueness in linguistics and can be considered as a generalization of classical set theory.[6] This great innovation had supplemented conventional technologies in many scientific applications and engineering applications.There is a scope of using soft-computing techniques viz. Fuzzy system, Artificial neural networks, Radial basis function etc. for noise prediction in mining industry. The authors had earlier investigated the use of fuzzy model for predicting noise induced hearing loss in mining industry.[4] The results have encouraged them to investigate noise prediction in opencast mine using Neuro-Fuzzy model.

In this paper, an attempt has been made to develop a neuro-fuzzy model for noise prediction in Balaram opencast mine of Talcher, Orissa, India. The data assembled through surveys, measurement or knowledge to predict sound pressure level in mines is often imprecise or speculative. Since fuzzy system is a good predicted tool for imprecise and uncertainty information, hence fuzzy approach would be the most appropriate technique for modeling the prediction of sound pressure level in opencast mines.

2. VDI-2714 Noise Prediction Model

In 1976, the VDI (Verein Deutscher Ingenieur) draft code 2714 on Outdoor Sound Propagation was issued by the VDI Committee on Noise Reduction.[2] The sound pressure level at an environmental point is calculated form the following equation:

$$\begin{aligned} L_p dB(A) = \Sigma^{\log}_{\text{all sources}}[&L_W + K_1 - 10\log(4\Pi R^2) \\ &+ 3dB - K_2 - K_3 - K_4 - K_5 - K_6 - K_7] \end{aligned} \tag{1}$$

where

$$\begin{aligned} L_w &= \text{source power level re } 10^{-12} \text{ watts} \\ K_1 &= \text{source directivity index} \\ -10\log(4\Pi R^2) + 3dB &= \text{geometric spreading term including infinite hard plane} \\ & \text{coinciding with the source} \\ R &= \text{source to receiver distance} \\ K_2 &= \text{atmospheric attenuation} = 10\log(1 + 0.0015R)dB(A) \\ K_3 &= \text{attenuation due to meteorological conditions} \\ &= [(12.5/R^2) + 0.2]^{-1} \text{ dB(A)} \\ K_4 &= \text{ground effects} = 10\log[3 + (R/160)] - K_2 - K_3 dB(A) \\ K_5 &= \text{barrier value (0-10)} = 10\log(3 + 20d) \text{ dB(A)} \\ d &= \text{barrier path difference} \\ K_6 &= \text{attenuation due to woodland areas} \\ K_7 &= \text{attenuation due to built-up areas.} \end{aligned}$$

3. Fuzzy Expert System — An Introduction

This section provides an introduction to fuzzy systems. Detailed analysis on fuzzy system can be found in numerous literature [6–9]. Block diagram of a typical fuzzy logic system is presented in Fig. 1. As outlined in Fig. 1, a fuzzy rule based system

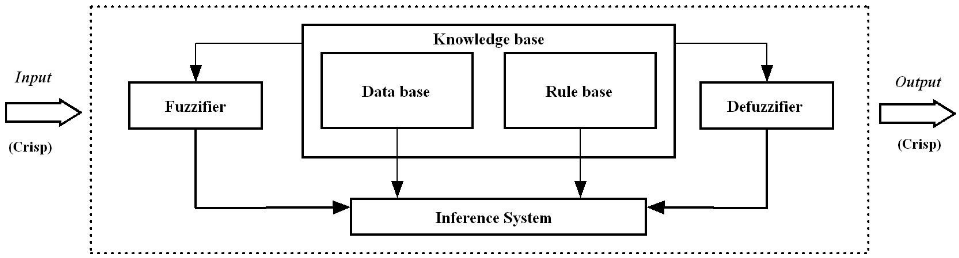

Fig. 1. Structure of fuzzy rule based system.

consists of four parts: fuzzifier, knowledge base, inference engine and defuzzifier. These four parts are described below:

- Fuzzifier: The real world input to the fuzzy system is applied to the fuzzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier converts this precise quantity to the form of imprecise quantity like 'large', 'medium', 'high' etc. with a degree of belongingness to it. Typically, the value ranges between 0 to 1.
- Knowledge base: The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules where as the rule base contains a number of fuzzy if-then rules.
- Inference engine: The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined.
- Defuzzifier: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

The above description shows the behavior of a fuzzy expert system. Let X be the universe of discourse and x is the elements of X. A fuzzy set A in a universe of discourse X is characterized by a membership function $\mu_A(x)$ which has a value ranging from 0 to 1. If there are n fuzzy sets associated with a given input x, then fuzzifier would produce n fuzzy sets as $A_1(x), A_2(x) \ldots A_n(x)$ with n number of membership function $\mu_{A_i}(x), i = 1, 2 \ldots n$. This process is called the fuzzification. After fuzzification the information goes to knowledge base which comprises a database and rule base. Membership functions of the fuzzy sets are contained in the data base. The rule base is a set of linguistic statements in the appearance of

IF-THEN rules with antecedents and consequents, correspondingly, with AND or OR operators. Fuzzy rule based system with multi-inputs single-output(MISO)can be represented in the following manner:[10]

IF X_1 is B_{11} **AND** X_2 is B_{12} **AND** .. **AND** X_r is B_{1r} **THEN** Y_1 is D_1
ALSO ... **ALSO**
IF X_1 is B_{m1} **AND** X_2 is B_{m2} **AND** ... **AND** X_r is B_{mr} **THEN** Y_s is D_s

Where $X_1, X_2 \ldots X_r$ are the input variables and $Y_1, Y_2 \ldots Y_s$ are the output variables, $B_{ij}(i = 1, ..m; j = 1, ..r)$ and $Di(i = 1, ..s)$ are the linguistic labels defined as reference fuzzy sets over the input space $X_1, X_2 \ldots X_r$ and output space $Y_1, Y_2..Y_s$ of the MISO system. After formation of rule base the last unit block defuzzifier converts the fuzzy output obtained by inference engine into a non-fuzzy output real number domain and this process is called defuzzification. Among several methods of defuzzification, the Center of Area (COA) is the most widely used method.

In general two most popular fuzzy inference systems are available i.e. Mamdani fuzzy model and Sugeno fuzzy model depending on the fuzzy reasoning and formulation of fuzzy IF-THEN rules. Mamdani fuzzy model[11] is based on the collections of IF-THEN rules with both fuzzy antecedent and consequent predicts. The benefit of this model is that the rule base is generally provided by an expert and hence to a certain degree it is translucent to explanation and study. Because of its ease, Mamdani model is still most commonly used technique for solving many real world problems. Sugeno fuzzy model was proposed by Takagi and Sugeno[12] ; Sugeno and Kang[13] in an attempt to build up a methodical approach to generate fuzzy rules from a given input-output data. These models are build up with the help of if-then rules that have fuzzy antecedent and functional consequent. Typically the consequent is a polynomial function of the desired input variables. When the order of the polynomial function is first order, then the resulting fuzzy expert system is called the first order Sugeno or TSK fuzzy model, which was originally, proposed by Takagi and Sugeno;[12] Sugeno and Kang.[13] When the order of the polynomial function of zero or the consequent part is totally constant, then the system is called zero order Sugeno and TSK fuzzy model, in which each rule's consequent, is specified by a fuzzy singleton. To represent this constant output, a single spike is used which also known as singleton output membership function. The main advantage of the TSK model is its computational efficiency.

In general fuzzy systems work with a set of heuristic rules. Sometimes if, a set of training data (prototype output for given inputs) is available, fuzzy system can be updated iteratively by training. These systems are generally termed as ANFIS (adaptive network based fuzzy inference system) or Neuro-Fuzzy systems [15–17]. Here the fuzzy parameters consisting of rule base, defuzzification and fuzzy inference rules are iteratively updated to provide optimal performance.

4. Adaptive Fuzzy Model for Predicting Sound Pressure Level

In this present study, an attempt has been made to use adaptive fuzzy model to predict sound pressure level by using sound power level and distance as input parameters. This model can be treated as a MISO (multi inputs and single output) system. Figure 2 shows the general architecture of the adaptive fuzzy system for this application. Here the fuzzy model is designed so as to predict the output as given by VDI2714. The system adapts itself during the training period using a set of training samples. As per Fig. 2, the primary model is VDI2714 and secondary model is ANFIS (Adaptive network based fuzzy inference system) model. Sound power level (L_W) and distance (R) are the two input parameters to the system. The output of the VDI-2714 is Sound pressure level,denoted as (y) where as ($\hat{y}$) denotes the predicted output of the system.

The architecture of the fuzzy prediction model is analyzed here and represented in Fig. 3. The methodology for the development of the adaptive fuzzy noise prediction model involves the following steps:

(1) Selection of input and output variables;
(2) Selection of membership functions;
(3) Formation of linguistic rule base;
(4) Defuzzification and
(5) Training of parameters of the fuzzy model.

4.1. *Selection of input and output variables*

The first step in system modelling is the identification of input and output variables called the system's variables. Here, sound power level and distance from the source are used as the input parameters. These parameters are also inputs to the VDI-2714 model. The output of the system is denoted as ($\hat{y}$). This output is expected to match the output (y) of VDI-2714 model.

4.2. *Selection of membership functions for inputs*

Linguistic values are expressed in the form of fuzzy sets. A fuzzy set is usually defined by its membership functions. In general, triangular membership function is used to normalize the crisp inputs because of its simplicity, mathematically described in the following manner:[14]

$$triangle(x\ ;\ a,\ b,\ c) = \begin{pmatrix} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{pmatrix} \tag{2}$$

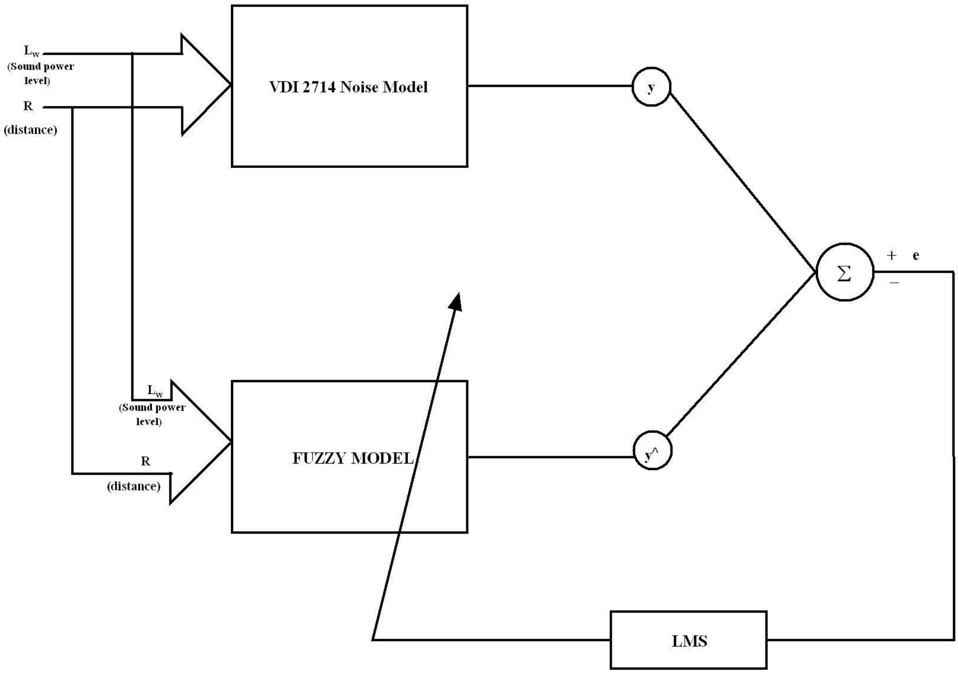

Fig. 2. Block diagram for adaptive fuzzy system of noise prediction model.

$$triangle(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right), \tag{3}$$

where a, b, c are the parameters of the linguistic value and x is the range of the input parameters. This triangular membership function as described in the above expressions (2) and (3) convert the linguistic values in a range of 0 to 1.

In the proposed model, shown in Fig. 3, the two inputs are sound power level L_W and distance from the source (R) respectively. Each input has five membership functions e.g. $L_W^{(1)}, L_W^{(2)} \ldots L_W^{(5)}$ corresponding to (L_W) and $R^{(1)}, R^{(2)} \ldots R^{(5)}$ for R. The process of fuzzification of input (L_W) and R is done with triangular membership function. This is shown in Figs. 4 and 5 for input L_W and R respectively. The membership functions are represented as "$L_W^{(1)} = low$ (80–100 dB)", "$L_W^{(2)} = medium$ (90–110 dB)" … "$L_W^{(5)} = very\ high$ (120–140 dB)" for the input L_W. The membership functions corresponding to this input variables are $\mu_{L_1}, \mu_{L_2}, \ldots \mu_{L_5}$. Similarly the membership functions for R are represented as "$R^{(1)} = medium\ low$ (0–10 *meter*)", "$R^{(2)} = low$ (1–15 *meter*)" … "$R^{(5)} = high$ (20–30 *meter*)" for the input R and the membership corresponding to these input variables are $\mu_{R_1}, \mu_{R_2}, \ldots \mu_{R_5}$ respectively.

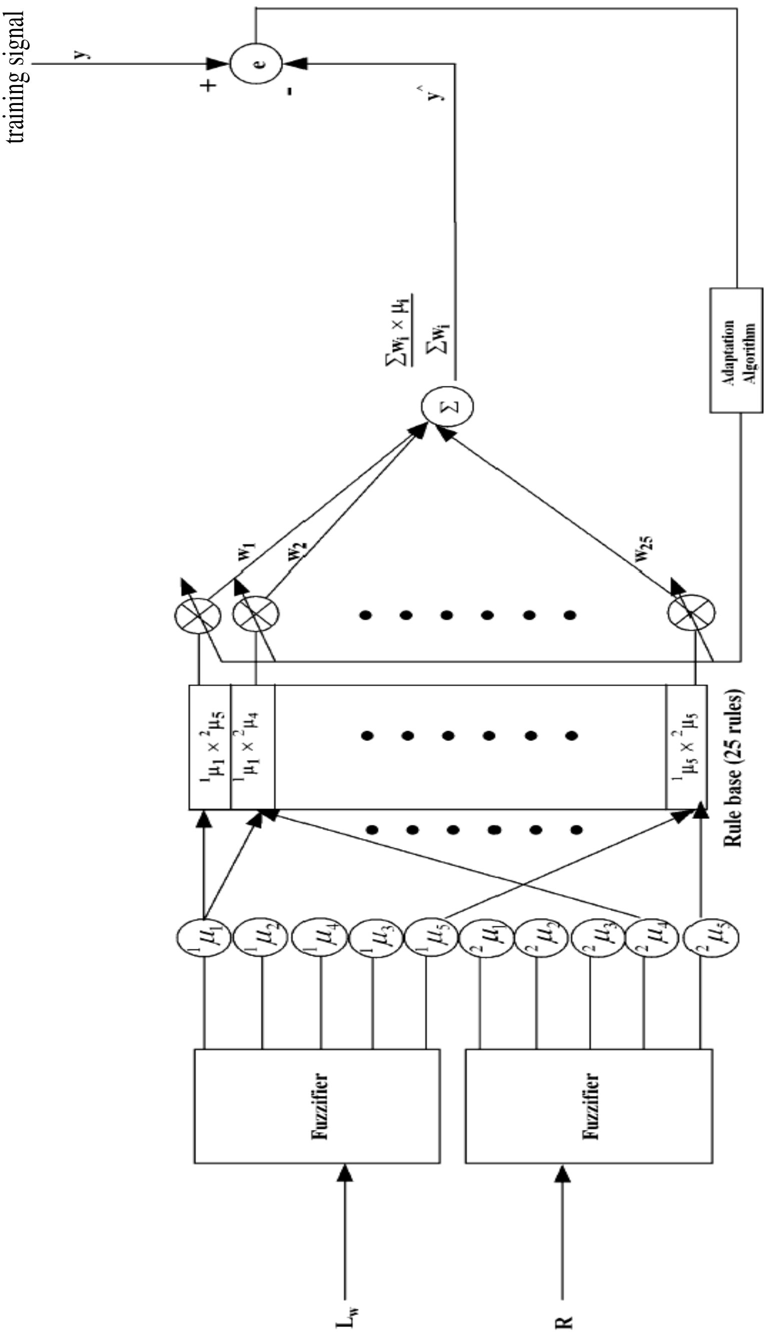

Fig. 3. Adaptive fuzzy system architecture for noise prediction.

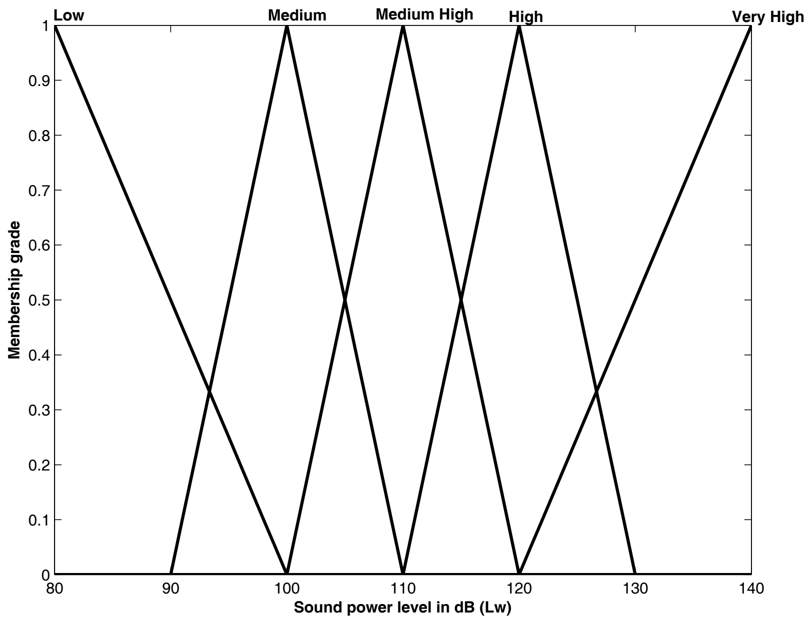

Fig. 4. Membership function of sound power level.

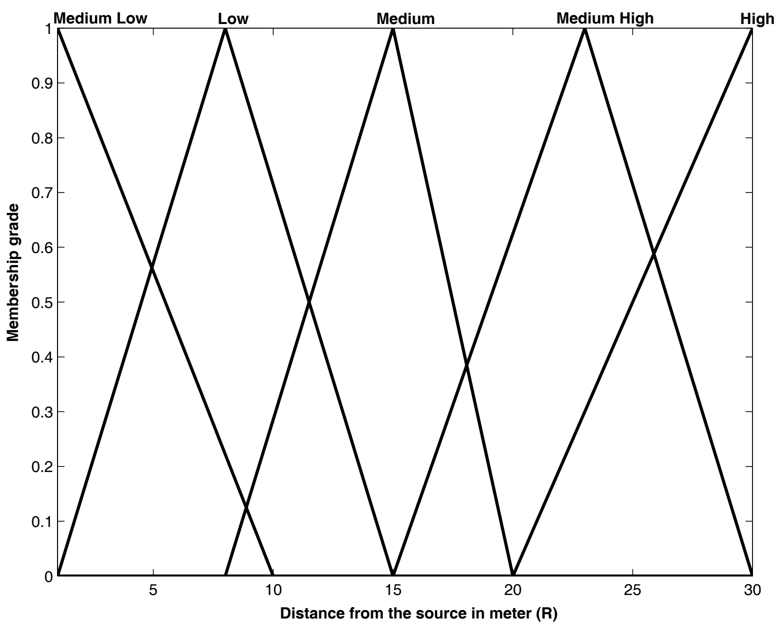

Fig. 5. Membership function of distance.

4.3. *Formation of linguistic rule-base*

The relationship between input and the output are represented in the from of IF-THEN rules. The membership function $L_W^{(1)}, L_W^{(2)} \ldots L_W^{(5)}$ and $R^{(1)}, R^{(2)} \ldots R^{(5)}$ are the inputs to the rule-base. Let the output, Sound pressure level is expressed as Z. Since there are two inputs and each input has five possible fuzzy sets. The system can have at most 5^2 =25 rules. Here in this proposed model, product inference was considered as discussed by Wang and Mendel.[17] Each of these rules receive the membership from each of input variable fuzzy sets. Hence rules are formed in following manner;

R_1 : **IF** L_W *is* $L_W^{(1)}$ **AND** R *is* $R^{(1)}$ **THEN** sound pressure level (Z) is Z = $(\mu_{L_1}(L_W^{(1)})\times\mu_{R_1}(R^{(1)})\times w_1$;

R_2 : **IF** L_W *is* $L_W^{(1)}$ **AND** R *is* $R^{(2)}$ **THEN** sound pressure level (Z) is Z = $(\mu_{L_1}(L_W^{(1)})\times\mu_{R_2}(R^{(2)})\times w_2$;

$\vdots$

R_{25} : **IF** L_W *is* $L_W^{(5)}$ **AND** R *is* $R^{(5)}$ **THEN** sound pressure level (Z) is Z = $(\mu_{L_5}(L_W^{(5)})\times\mu_{R_5}(R^{(5)})\times w_{25}$;

Since the system has 25 rules, each rule is associated with a weight. The rules $R_1, R_2 \ldots R_{25}$ are associated with weights $(w_1, w_2 \ldots w_{25})$ respectively. These weights are initialized to random values at the beginning. Since this model was product inference the fuzzy system can be considered as Takagi-Sugeno-Kang (TSK) fuzzy system.

4.4. *Defuzzification*

In the proposed model, Centroid of area (COA) method of defuzzification has been used for determining the output. Centroid of area (COA) was expressed as (4).[14]

$$Centroid\ of\ \ area^z\ COA = \frac{\int_z \mu A(z) z dz}{\int_z \mu A(z) dz} \tag{4}$$

Here $\mu A(z)$ is the membership value of set A and z is the output variable. In this model (Fig. 3), the estimated output is determined as

$$\hat{y} = \frac{\sum_{i=1}^{25} w_i \times \psi_i}{\sum_{i=1}^{25} w_i} \tag{5}$$

where $\psi_i = \mu_{Lk} \times \mu_{Rm}$. where $k = 1, ..5, m = 1, ..5$ corresponding to number of fuzzy sets in L_w and R.

4.5. *Training of parameters of the fuzzy model*

In the model presented at Fig. 3, weights $w_i, (i = 1, 2, \ldots 25)$ are unknown. These are initialized to random values at the beginning. Subsequently these weights are updated using LMS algorithm which was first proposed by Widrow and McCool in 1976.[18] This is similar to the adaption used by Patra and Mulgrew.[19] The weights can be updated iteratively by;

$$e(k) = y(k) - \hat{y}(k) \tag{6}$$

$$W(k+1) = W(k) + 2\alpha e(k)\psi(k) \tag{7}$$

Where k is the time index, W(k+1)refers to the new weights of the system and W(k) is the existing weight. W=$[(w_1, w_2 \dots w_{25})]^T$ is the weight vector and $\psi = [(\psi_1, \psi_2 \dots \psi_{25})]$ is the output of the inference engine.

5. Simulation Result and Discussion

The proposed model is simulated using MATLAB software. The flowchart for the ANFIS system is shown in Fig. 6.

The training data set was derived from the VDI-2714 noise prediction model (Eq. (1)). A set of 3200 data set was generated for different values of input parameters L_W and R.Using these data in VDI model SPL was determined. This constituted y for training. The fuzzy network was trained with 3000 sets out of the total data generated. Remaining 200 data set was used for testing the model. The performance of training was validated using mean square error(MSE)as performance index. The efficiency and simplicity of the fuzzy system was validated using the CPU time. Figure 7 shows the error update curve during training of the system. Figure 8 shows the performance of the system with 200 samples and it was observed that the mean square error for prediction is 2.73%. The adaptive fuzzy algorithm took CPU time of 0.0625 sec approximately as compared to 0.5 sec for the VDI2714 model.

To test the stability of the model, validation data is essential. The validation data is collected from Balaram Opencast coal mines, Mahanadi Coalfield Limited (MCL), Talcher (Orissa, India). The test data or the field data was measured using Bruel & Kjaer 2239 (Denmark) precession sound level meter. From the measured parameter, VDI-2714 gives prediction by calculating all the sound attenuations in 'dB (A)' not in octave frequency band. In general, numerous machineries are used in opencast mines for production, so it is difficult to show the noise prediction of all the machineries using the proposed model here. The machineries ex. Shovel ($10m^3$ bucket capacity), Dozer (410HP), Tipper (10T-160HP), Grader (220 HP) and Dumper (85T) were selected to predict the sound pressure level (SPL) by using VDI2714 and adaptive fuzzy system. Prediction results of the two models (VDI-2714 and Neuro-Fuzzy) for Dozer machine were graphically represented in Fig. 9(a). These models were compared by using measured distance (R) and sound power level (SWL). The prediction results were also represented in Table 1. Similar plot for other machineries were represented in Figs. 9(b), (c), (d) and (e) respectively. Table 1 shows the measured field data (validation data) and prediction results of

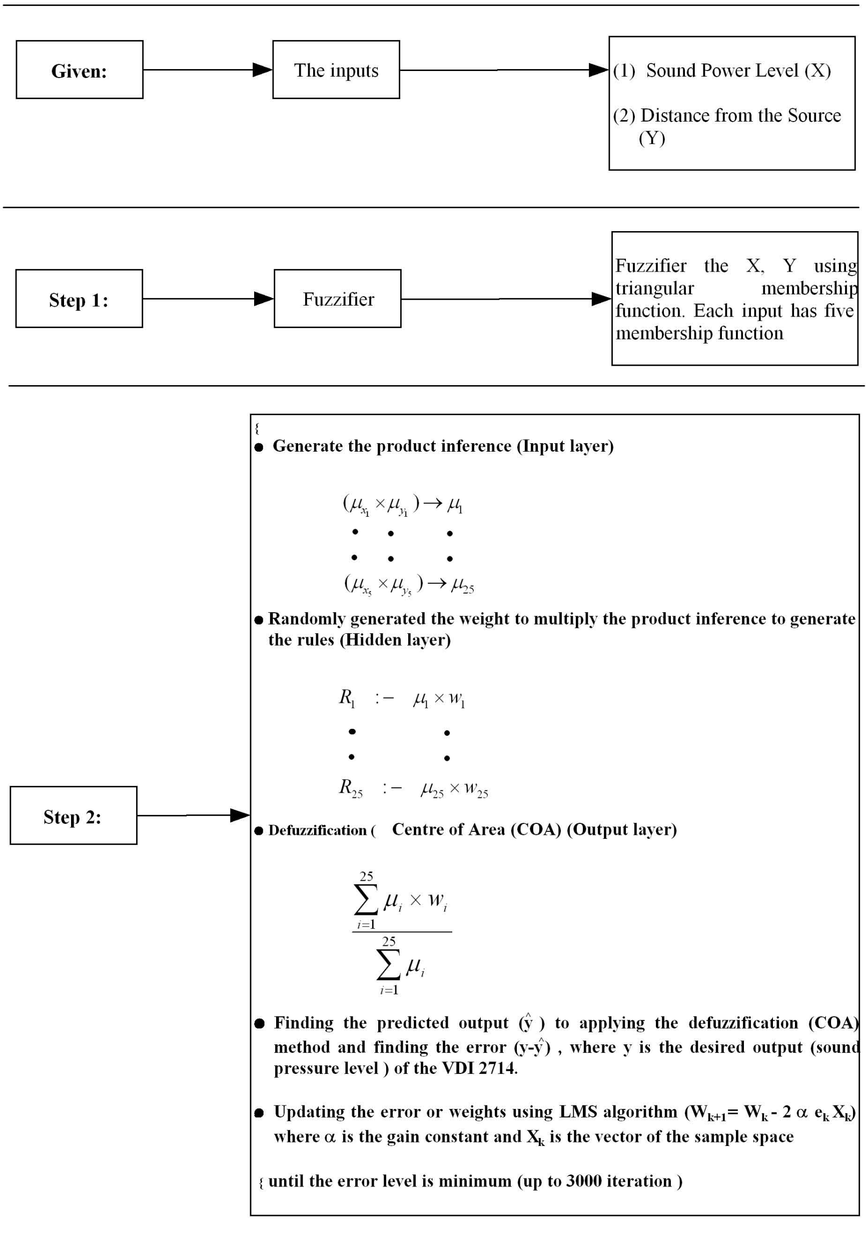

Fig. 6. Flowchart of the neuro-fuzzy noise prediction model.

the two models (VDI-2714 and Neuro Fuzzy) of all the selected machineries. It is seen that the Neuro-Fuzzy noise prediction model closely matches with VDI-2714 model results in noise prediction.

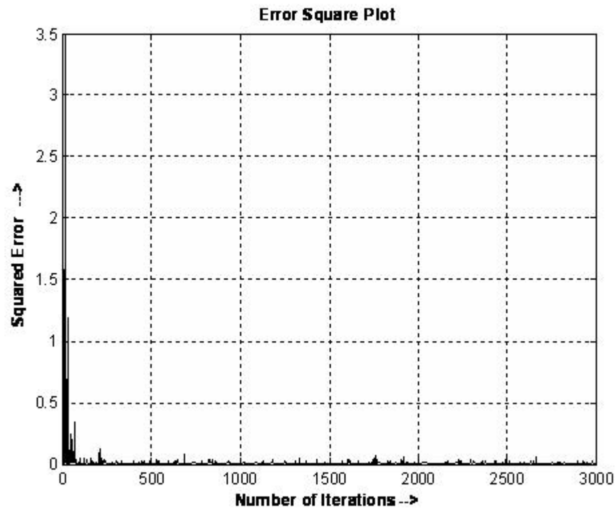

Fig. 7. Square error of the neuro-fuzzy model.

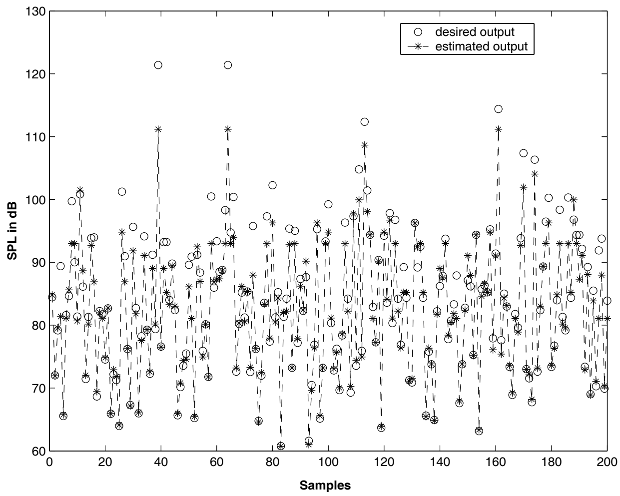

Fig. 8. Matching with 200 samples.

5.1. *Advantages of neuro-fuzzy model*

From the present research study, it is found that the Neuro-Fuzzy model takes 0.0625 sec CPU time vis-a-vis 0.5 sec CPU time for VDI2714 noise prediction model. Some of the advantages of the model are enumerated below:

- The noise generated from industrial machineries is generally represented by mathematical models. One such model is VDI-2714. In this model, the input

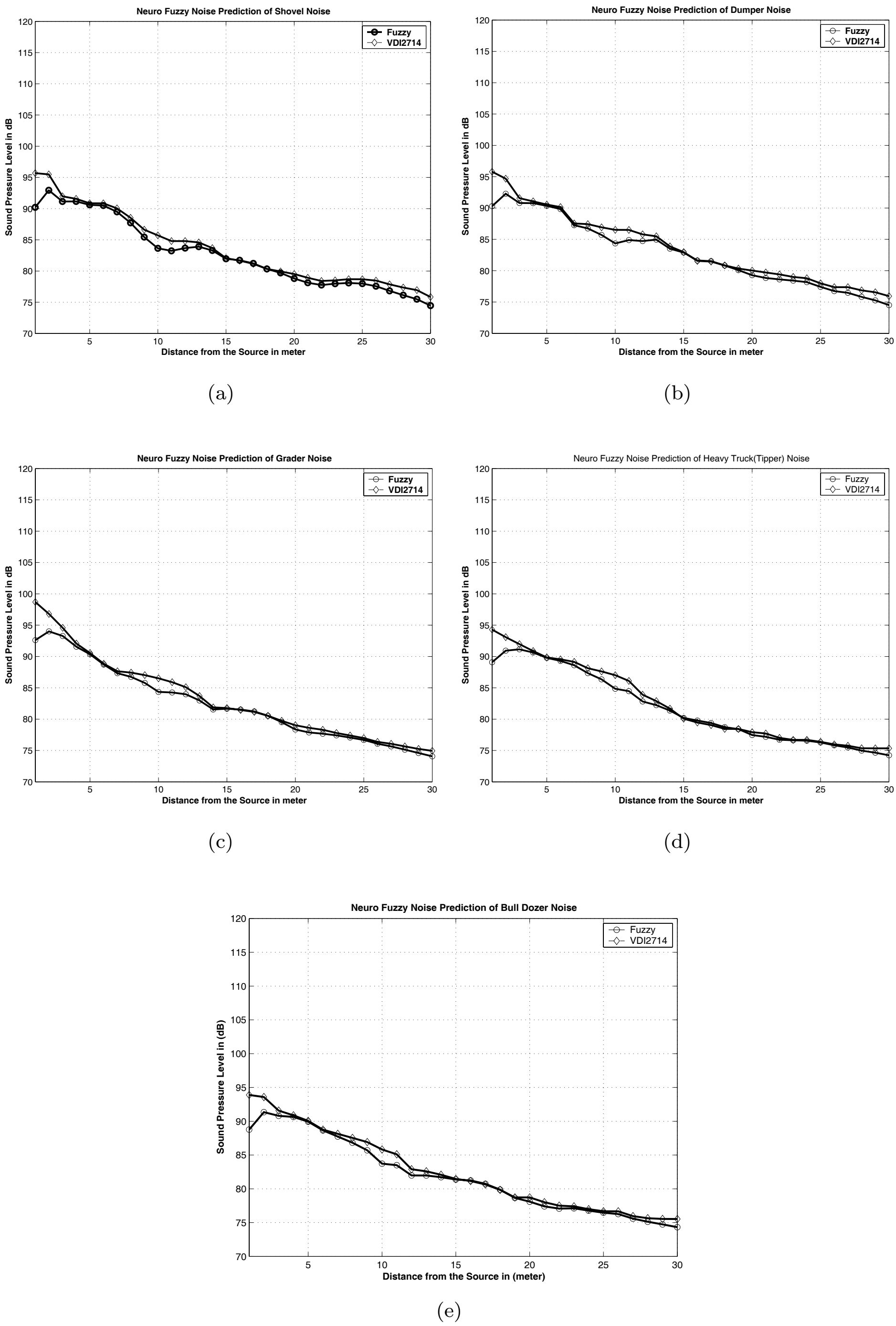

Fig. 9. Neuro-fuzzy noise prediction for machineries in the study area.

Table 1. Neuro-fuzzy noise prediction for different machineries.

Distance from the source in meter	Shovel noise in dB			Dumper noise in dB			Grader noise in dB			Tipper noise in dB			Dozer noise in dB		
	Measured field data (dBA)	Prediction result (dBA)		Measured field data (dBA)	Prediction result (dBA)		Measured field data (dBA)	Prediction result (dBA)		Measured field data (dBA)	Prediction result (dBA)		Measured field data (dBA)	Prediction result (dBA)	
		N-fuzzy	VDI		N-fuzzy	VDI		N-fuzzy	VDI		N-fuzzy	VDI		N-fuzzy	VDI
1	102.3000	90.2051	95.6919	102.4000	90.2853	95.7919	105.3000	92.6115	98.6919	100.9000	89.0821	94.2919	100.5000	88.7612	93.8919
2	102.1000	92.9455	95.4828	101.3000	92.2722	94.6828	103.4000	94.0081	96.7828	99.7000	90.9254	93.0828	100.2000	91.3463	93.5828
3	98.6000	91.1476	91.9738	98.2000	90.7961	91.5738	101.2000	93.2710	94.5738	98.6000	91.1476	91.9738	98.2000	90.7961	91.5738
4	98.2000	91.1557	91.5648	97.7000	90.7761	91.0648	98.7000	91.5560	92.0648	97.5000	90.6297	90.8648	97.5000	90.6297	90.8648
5	97.5000	90.5989	90.8559	97.2000	90.3440	90.5559	97.2000	90.3440	90.5559	96.5000	89.7812	89.8559	96.7000	89.9376	90.0559
6	97.5000	90.5077	90.8469	96.8000	89.8325	90.1469	95.5000	88.7188	88.8469	96.2000	89.2976	89.5469	95.4000	88.6398	88.7469
7	96.7000	89.4805	90.0380	94.2000	87.2589	87.5380	94.3000	87.3358	87.6380	95.8000	88.6022	89.1380	94.8000	87.7336	88.1380
8	95.2000	87.7212	88.5291	94.1000	86.7376	87.4291	94.1000	86.7376	87.4291	94.8000	87.3480	88.1291	94.2000	86.8217	87.5291
9	93.3000	85.4354	86.6202	93.6000	85.6965	86.9202	93.7000	85.7857	87.0202	94.3000	86.3448	87.6202	93.6000	85.6965	86.9202
10	92.4000	83.6372	85.7113	93.2000	84.3542	86.5113	93.2000	84.3542	86.5113	93.7000	84.8404	87.0113	92.5000	83.7230	85.8113
11	91.5000	83.2331	84.8025	93.2000	84.8830	86.5025	92.6000	84.2596	85.9025	92.8000	84.4620	86.1025	91.8000	83.4994	85.1025
12	91.5000	83.6705	84.7937	92.5000	84.7308	85.7937	91.8000	83.9743	85.0937	90.6000	82.8242	83.8937	89.6000	81.9843	82.8937
13	91.3000	83.9048	84.5848	92.2000	84.9497	85.4848	90.4000	82.9754	83.6848	89.5000	82.2313	82.8848	89.3000	81.9700	82.5848
14	90.4000	83.2946	83.6760	90.6000	83.5142	83.8760	88.6000	81.5435	81.8760	88.4000	81.3709	81.6760	88.8000	81.7200	82.0760
15	88.8000	81.9558	82.0672	89.7000	82.8950	82.9672	88.5000	81.6649	81.7672	86.8000	80.1925	80.0672	88.2000	81.3840	81.4672
16	88.4000	81.7271	81.6585	88.3000	81.6275	81.5585	88.2000	81.5292	81.4585	86.2000	79.7832	79.4585	87.9000	81.2411	81.1585
17	87.9000	81.2228	81.1497	88.2000	81.5252	81.4497	87.9000	81.2228	81.1497	85.8000	79.3791	79.0497	87.4000	80.7425	80.6497
18	87.1000	80.3335	80.3410	87.6000	80.8185	80.8410	87.3000	80.5240	80.5410	85.2000	78.7269	78.4410	86.6000	79.8765	79.8410
19	86.7000	79.7007	79.9323	87.1000	80.0842	80.3323	86.5000	79.5157	79.7323	85.2000	78.4125	78.4323	85.5000	78.6528	78.7323
20	86.3000	78.7986	79.5236	86.8000	79.2704	80.0236	85.8000	78.3542	79.0236	84.7000	77.4620	77.9236	85.5000	78.0998	78.7236
21	85.7000	78.1231	78.9149	86.5000	78.8310	79.7149	85.4000	77.8747	78.6149	84.5000	77.1786	77.7149	84.8000	77.4028	78.0149
22	85.2000	77.7547	78.4063	86.2000	78.6088	79.4063	85.1000	77.6748	78.3063	83.8000	76.7150	77.0063	84.3000	77.0677	77.5063
23	85.3000	77.9729	78.4976	85.8000	78.4024	78.9976	84.6000	77.4136	77.7976	83.5000	76.6210	76.6976	84.2000	77.1139	77.3976
24	85.5000	78.0839	78.6890	85.6000	78.1699	78.7890	84.2000	77.0572	77.3890	83.5000	76.5662	76.6890	83.8000	76.7719	76.9890
25	85.5000	77.9792	78.6804	84.8000	77.4094	77.9804	83.8000	76.6758	76.9804	83.2000	76.2752	76.3804	83.5000	76.4721	76.6804
26	85.3000	77.5712	78.4718	84.2000	76.7400	77.3718	83.2000	76.0750	76.3718	82.8000	75.8299	75.9718	83.5000	76.2664	76.6718
27	84.7000	76.8183	77.8632	84.2000	76.4671	77.3632	82.9000	75.6479	76.0632	82.6000	75.4758	75.7632	82.8000	75.5899	75.9632
28	84.2000	76.1314	77.3547	83.7000	75.8165	76.8547	82.5000	75.1337	75.6547	82.2000	74.9773	75.3547	82.5000	75.1337	75.6547
29	83.8000	75.4846	76.9461	83.4000	75.2580	76.5461	82.1000	74.5923	75.2461	82.2000	74.6400	75.3461	82.4000	74.7371	75.5461
30	82.7000	74.4604	75.8376	82.8000	74.5073	75.9376	81.8000	74.0617	74.9376	82.2000	74.2338	75.3376	82.4000	74.3228	75.5376
Mean square error	0.9738			0.9512			0.9167			0.8236			0.8597		

parameters are distance (R) and sound power level (SWL (L_W)); the model predicts the sound pressure level (SPL (L_P)). Sound pressure level (SPL) was determined for each set of measured distance (R) and Sound power level (SWL). The process has to be repeated for each machinery. The calculation was complex. The fuzzy models need to be trained once for any specific machinery. Once the fuzzy model was trained, SPL can be determined for any input condition. The model predicts SPL with very little CPU time ($\sim$ 12%) compared to VDI-2714. In general, the network can be trained to work for any standard model. The prediction would correspond to the model for which it was trained. In this specific case the authors have considered only VDI-2714.

- The model of Neuro-Fuzzy remains fixed as long as input and output remain the same. This can be implemented as a fixed hardware. The training data is based on actual measurement. This information can be used to train the network. Hence same network with different training sets can provide approximate result for different mines/working conditions.
- Neuro-Fuzzy model can be built using DSP hardware available in market. This can be used in instrument for measurement owing to low CPU time. Higher CPU time of VDI2714 model will prohibit its usage in portable instrument.
- The Neuro-Fuzzy model can be used to predict noise of machineries for other models also. This can be done by using a different training data sheet. In an instrument, this can be implemented easily, where the instrument can provide prediction for different models.

6. Conclusion

The neuro-fuzzy noise prediction model output for five different machineries used in opencast mines such as dozer, shovel, tipper or dumper matches closely with VDI2714 prediction result. This model takes CPU time of nearly 0.0625 sec where as it takes 0.5 sec for VDI2714 i.e. it is approximately twelve times faster. This comparison of CPU time shows the computational stability of the model. It is hoped that the developed model will be quite useful in prediction of machinery noise in opencast mines.

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