Research Article

Application of Functional Link Artificial Neural Network for Prediction of Machinery Noise in Opencast Mines

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Functional link-based neural network models were applied to predict opencast mining machineries noise. The paper analyzes the prediction capabilities of functional link neural network based noise prediction models vis-à-vis existing statistical models. In order to find the actual noise status in opencast mines, some of the popular noise prediction models, for example, ISO-9613-2, CONCAWE, VDI, and ENM, have been applied in mining and allied industries to predict the machineries noise by considering various attenuation factors. Functional link artificial neural network (FLANN), polynomial perceptron network (PPN), and Legendre neural network (LeNN) were used to predict the machinery noise in opencast mines. The case study is based on data collected from an opencast coal mine of Orissa, India. From the present investigations, it could be concluded that the FLANN model give better noise prediction than the PPN and LeNN model.

1. Introduction

At the present time, owing to the improvements in technology through superior energy competence, higher labor output, continuous production methods, and operating flexibility, automation has also advanced rapidly in open and underground pits together with mineral processing plants. In parallel to this improvement, sources of noise and ambient noise at work place in the mining industry have increased significantly. In general, 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 nonauditory health effects [1]. The impact of noise in opencast mines depends upon the sound power level of the noise generators, prevailing geomining conditions and the meteorological parameters of the mines [2–4]. The noise levels need to be studied as an integrated effect of the above parameters. In mining conditions the equipment

conditions and environment continuously change 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) of Australia [5]. 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 extensively used for the assessment of sound pressure level and their attenuation around industrial complexes. Generally, in Indian mining industry, environmental noise model developed by

TABLE 1: Simulation study of shovel noise.

Distance from the source (meters)	Measured field data (dBA)	Prediction result (dBA)				Average percentage error (dBA)		
		VDI	PPN	FLANN	LeNN	PPN	FLANN	LeNN
1	102.3000	95.6919	74.1198	88.6731	81.4871			
2	102.1000	95.4828	74.1198	94.3428	81.4871			
3	98.6000	91.9738	74.1198	94.5178	81.4871			
4	98.2000	91.5648	74.1198	89.4572	81.4871			
5	97.5000	90.8559	74.1198	87.9020	81.4871			
6	97.5000	90.8469	85.8609	96.5394	94.5712			
7	96.7000	90.0380	85.8609	90.3449	94.5712			
8	95.2000	88.5291	85.8609	93.3190	94.5712			
9	93.3000	86.6202	85.8609	94.0383	94.5712			
10	92.4000	85.7113	85.8609	94.0383	94.5712			
11	91.5000	84.8025	85.8609	87.6493	94.5712			
12	91.5000	84.7937	85.8609	88.3686	94.5712			
13	91.3000	84.5848	85.8609	85.2195	94.5712			
14	90.4000	83.6760	85.8609	91.4140	94.5712			
15	88.8000	82.0672	76.5756	85.3685	85.3813	7.03	5.68	8.42
16	88.4000	81.6585	76.5756	85.3685	85.3813			
17	87.9000	81.1497	76.5756	88.5889	85.3813			
18	87.1000	80.3410	76.5756	88.4139	85.3813			
19	86.7000	79.9323	76.5756	87.6947	85.3813			
20	86.3000	79.5236	76.5756	87.6947	85.3813			
21	85.7000	78.9149	76.5756	85.1287	85.3813			
22	85.2000	78.4063	74.3142	84.4095	85.3813			
23	85.3000	78.4976	74.3142	84.4095	85.3813			
24	85.5000	78.6890	73.2126	81.1891	85.3813			
25	85.5000	78.6804	73.2126	80.1264	82.0894			
26	85.3000	78.4718	75.3380	81.6816	82.0894			
27	84.7000	77.8632	71.4890	81.4353	82.0894			
28	84.2000	77.3547	72.2342	81.6103	82.7253			
29	83.8000	76.9461	72.2342	82.3295	82.9287			
30	82.7000	75.8376	72.2342	82.3295	82.9287			

RTA group, Australia is mostly used to predict noise [4, 6]. ENM was used to predict sound pressure level in mining complexes at Moonidih Project in Jharia Coalfield, Dhanbad, India [6]. The applied model output was represented as noise contours. The application of different noise prediction models was studied for various mines and petrochemical complexes and it was reported that VDI2714 model was the simplest and least complex model vis-à-vis other models [5]. VDI2714 and ISO (1996) noise prediction models were used in Assiut cement plant, Assiut cement quarry and El-Gedida mine at El-Baharia oasis of Egypt to predict noise. From the study, it was concluded that the prediction models could be used to identify the safe zones with respect to the noise level in mining and industrial plants. It was also inferred that the VDI2714 model is the simplest model for prediction of noise in mining complexes and workplace [7]. Air attenuation model was developed for noise prediction in limestone quarry and mines of Ireland. The model was used to predict attenuation in air due to absorption [8].

All the noise prediction models treat noise as a function of distance, sound power level, different form of attenuations such as geometrical absorptions, barrier effects, ground topography. 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 nonstationary process and soft-computing techniques like fuzzy system, adaptive neural network-based fuzzy inference system (ANFIS), neural network, and so forth, have been tested for nonstationary time-series prediction nearly for two decades. There is a scope of using different soft computing techniques: fuzzy logic, artificial neural networks, radial basis function (RBF) and so forth, for noise prediction in mines. In comparison to other soft computing techniques, functional link artificial neural network (FLANN) and Legendre Neural Network (LeNN) has less computational cost and easily implemented in hardware applications. This is the motivation on which the present research work is based.
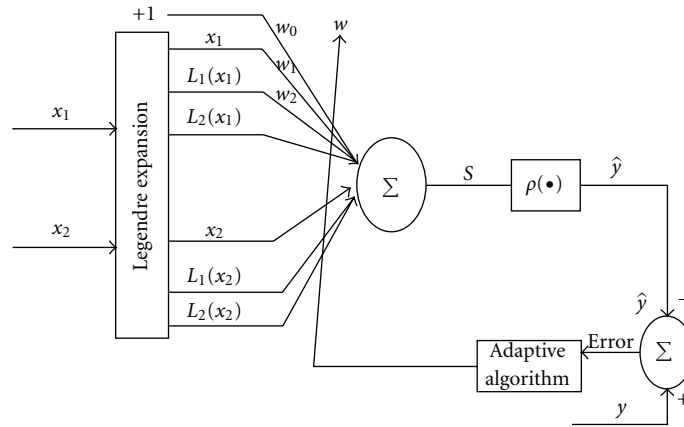
In this paper, an attempt has been made to develop three types of functional link artificial neural network models
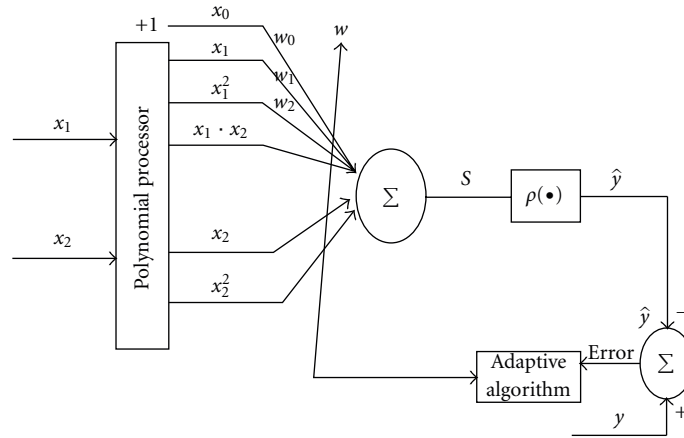
(a) PPN structure
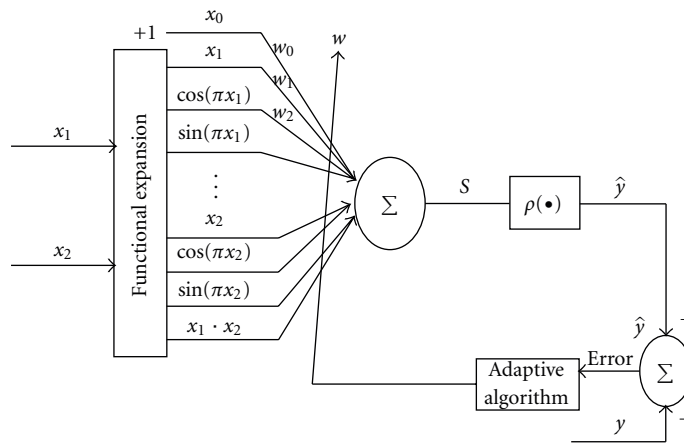
(b) FLANN structure

(c) Legendre neural network structure

FIGURE 1: System architecture of function link based artificial neural networks.

(FLANN, PPN, and LeNN) for noise prediction of machineries used in Balaram opencast coal 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 neural network-based systems are good predictive tools for imprecise and uncertainty information; therefore, the proposed approach would be the most appropriate technique for modeling the prediction of sound pressure level in opencast coal mines.

2. VDI-2714 Noise Prediction Model

In 1976, the VDI draft code 2714 "outdoor sound propagation" was issued by the VDI committee on noise reduction

TABLE 2: Simulation study of dumper noise.

Distance from the source (meters)	Measured field data (dBA)	Prediction result (dBA)				Average percentage error (dBA)		
		VDI	PPN	FLANN	LeNN	PPN	FLANN	LeNN
1	102.4000	95.7919	74.1198	88.6731	81.4871			
2	101.3000	94.6828	74.1198	93.0404	81.4871			
3	98.2000	91.5738	74.1198	94.5178	81.4871			
4	97.7000	91.0648	74.1198	89.4572	81.4871			
5	97.2000	90.5559	74.1198	87.9020	81.4871			
6	96.8000	90.1469	85.8609	96.5394	94.5712			
7	94.2000	87.5380	74.1198	82.7701	81.4871			
8	94.1000	87.4291	85.8609	93.3190	94.5712			
9	93.6000	86.9202	85.8609	94.0383	94.5712			
10	93.2000	86.5113	85.8609	94.0383	94.5712			
11	93.2000	86.5025	85.8609	84.6752	94.5712			
12	92.5000	85.7937	85.8609	85.3944	94.5712			
13	92.2000	85.4848	85.8609	86.3534	94.5712			
14	90.6000	83.8760	85.8609	88.4398	94.5712			
15	89.7000	82.9672	76.5756	85.3685	85.3813	7.27	5.77	8.20
16	88.3000	81.5585	76.5756	85.3685	85.3813			
17	88.2000	81.4497	76.5756	88.5889	85.3813			
18	87.6000	80.8410	76.5756	88.4139	85.3813			
19	87.1000	80.3323	76.5756	87.6947	85.3813			
20	86.8000	80.0236	76.5756	87.6947	85.3813			
21	86.5000	79.7149	76.5756	85.1287	85.3813			
22	86.2000	79.4063	74.3142	84.4095	85.3813			
23	85.8000	78.9976	74.3142	84.4095	85.3813			
24	85.6000	78.7890	73.2126	81.1891	85.3813			
25	84.8000	77.9804	73.2126	83.1006	82.0894			
26	84.2000	77.3718	75.3380	84.6557	82.0894			
27	84.2000	77.3632	71.4890	81.4353	82.0894			
28	83.7000	76.8547	72.0592	81.6103	82.7253			
29	83.4000	76.5461	72.2342	82.3295	82.9287			
30	82.8000	75.9376	72.2342	82.3295	82.9287			

[5]. The sound pressure level at an environmental point is calculated from the following equation (1)

$$L_P \, \text{dB(A)} = \sum_{\text{all sources}}^{\log} \left[L_W + K_1 - 10 \log(4\pi R^2) + 3 \, \text{dB} - K_2 - K_3 - K_4 - K_5 - K_6 - K_7 \right],$$

(1)

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

3. Introduction to Functional Link-Based Artificial Neural Network

Neural network (NN) represents an important paradigm for classifying patterns or approximating complex nonlinear process dynamics. These properties clearly indicate that NN exhibit some intelligent behavior, and are good candidate models for nonlinear processes, for which no perfect mathematical model is available. Neural networks have been a powerful tool for their applications for more than last two decades [9–13]. Multilayer perceptron (MLP), radial basis function (RBF), Support vector machine (SVM) and so forth, are the types of Neural Network Model, where these models have better prediction competence with high computational cost. Generally, these models have high computational cost due to the availability of hidden layer. To minimize the computational cost, structures like, polynomial perceptron network (PPN) [14], functional link artificial neural network (FLANN) [15–18], Legendre neural

TABLE 3: Simulation study of grader noise.

Distance from the source (meters)	Measured field data (dBA)	Prediction result (dBA)				Average percentage error (dBA)		
		VDI	PPN	FLANN	LeNN	PPN	FLANN	LeNN
1	105.3000	98.6919	74.1198	89.9755	81.4871			
2	103.4000	96.7828	74.1198	95.4768	81.4871			
3	101.2000	94.5738	74.1198	92.6776	81.4871			
4	98.7000	92.0648	74.1198	89.4572	81.4871			
5	97.2000	90.5559	74.1198	87.9020	81.4871			
6	95.5000	88.8469	74.1198	85.9905	81.4871			
7	94.3000	87.6380	74.1198	82.7701	81.4871			
8	94.1000	87.4291	85.8609	93.3190	94.5712			
9	93.7000	87.0202	85.8609	94.0383	94.5712			
10	93.2000	86.5113	85.8609	94.0383	94.5712			
11	92.6000	85.9025	85.8609	87.6493	94.5712			
12	91.8000	85.0937	85.8609	88.3686	94.5712			
13	90.4000	83.6848	85.8609	88.1936	94.5712			
14	88.6000	81.8760	85.8609	91.4140	94.5712			
15	88.5000	81.7672	76.5756	85.3685	85.3813	9.56	6.15	9.76
16	88.2000	81.4585	76.5756	85.3685	85.3813			
17	87.9000	81.1497	76.5756	88.5889	85.3813			
18	87.3000	80.5410	76.5756	88.4139	85.3813			
19	86.5000	79.7323	76.5756	87.6947	85.3813			
20	85.8000	79.0236	76.5756	87.6947	85.3813			
21	85.4000	78.6149	76.5756	85.1287	85.3813			
22	85.1000	78.3063	74.3142	84.4095	85.3813			
23	84.6000	77.7976	74.3142	84.4095	85.3813			
24	84.2000	77.3890	73.2126	81.1891	85.3813			
25	83.8000	76.9804	73.2126	83.1006	82.0894			
26	83.2000	76.3718	63.5968	74.1068	66.3679			
27	82.9000	76.0632	71.4890	81.4353	82.0894			
28	82.5000	75.6547	60.3181	71.0614	67.0982			
29	82.1000	75.2461	60.3181	71.7806	67.3327			
30	81.8000	74.9376	60.3181	71.7806	67.3327			

network (LeNN) [19, 20] were proposed. In this paper, three types of functional based artificial neural networks have been applied to predict mining machinery noise. These include polynomial perceptron network (PPN), functional link artificial neural network (FLANN), and Legendre neural network (LeNN).

In general, the functional link-based neural network models were single-layer ANN structure possessing higher rate of convergence and lesser computational load than those of an MLP structure. The behavior and mapping ability of a PPN and its application to channel equalization is reported by Xiang et al. (1994) [14]. The mathematical expression and computational calculation is evaluated as per MLP. Figure 1(a) represents the structure of PPN. Patra originally proposed functional link artificial neural network (FLANN), and it is a novel single-layer ANN structure capable of forming arbitrarily complex decision regions by generating nonlinear decision boundaries [15–18]. In

FLANN, the hidden layers are removed. Further, the FLANN structure offers less computational complexity and higher convergence speed than those of an MLP because of its single-layer structure. The FLANN structure is depicted in Figure 1(b). Here, the functional expansion block makes use of a functional model comprising a subset of orthogonal sin and cos basis functions and the original pattern along with its outer products. For example, considering a two-dimensional input pattern $X = [x_1 x_2]^T$. The enhanced pattern is obtained by using the trigonometric functions as $X^* = [x_1 \cos(\pi x_1) \sin(\pi x_1) \cdots x_2 \cos(\pi x_2) \sin(\pi x_2) \cdots x_1 x_2]^T$ which is then used by the network for the equalization purpose. The BP algorithm, which is used to train the network, becomes very simple because of absence of any hidden layer. Justification for the use of the trigonometric functions in the FLANN model is provided in [15–18].

Structure of the Legendre neural network [19, 20] (LeNN) (Figure 1(c)) is similar to FLANN. In contrast

TABLE 4: Simulation study of tipper noise.

Distance from the source (meters)	Measured field data (dBA)	Prediction result (dBA)				Average percentage error (dBA)		
		VDI	PPN	FLANN	LeNN	PPN	FLANN	LeNN
1	100.9000	94.2919	74.1198	85.6989	81.4871			
2	99.7000	93.0828	74.1198	93.0404	81.4871			
3	98.6000	91.9738	74.1198	94.5178	81.4871			
4	97.5000	90.8648	74.1198	92.4313	81.4871			
5	96.5000	89.8559	74.1198	87.9020	81.4871			
6	96.2000	89.5469	85.8609	96.5394	94.5712			
7	95.8000	89.1380	85.8609	93.3190	94.5712			
8	94.8000	88.1291	85.8609	93.3190	94.5712			
9	94.3000	87.6202	85.8609	94.0383	94.5712			
10	93.7000	87.0113	85.8609	91.0641	94.5712			
11	92.8000	86.1025	85.8609	84.6752	94.5712			
12	90.6000	83.8937	85.8609	88.3686	94.5712			
13	89.5000	82.8848	85.8609	88.1936	94.5712			
14	88.4000	81.6760	74.1198	80.8651	81.4871			
15	86.8000	80.0672	64.8344	74.8196	70.1930	13.59	4.36	10.03
16	86.2000	79.4585	64.8344	74.8196	70.1930			
17	85.8000	79.0497	64.8344	78.0400	70.1930			
18	85.2000	78.4410	64.8344	77.8650	70.1930			
19	85.2000	78.4323	64.8344	77.1458	70.1930			
20	84.7000	77.9236	64.8344	77.1458	70.1930			
21	84.5000	77.7149	64.8344	74.5798	70.1930			
22	83.8000	77.0063	62.5730	73.8606	70.1930			
23	83.5000	76.6976	62.5730	73.8606	70.1930			
24	83.5000	76.6890	61.4715	70.6402	70.1930			
25	83.2000	76.3804	61.4715	72.5517	66.3679			
26	82.8000	75.9718	63.5968	74.1068	66.3679			
27	82.6000	75.7632	59.7479	70.8864	66.3679			
28	82.2000	75.3547	60.3181	71.0614	67.0982			
29	82.2000	75.3461	60.3181	71.7806	67.3327			
30	82.2000	75.3376	72.2342	82.3295	82.9287			

to FLANN, in which trigonometric functions are used in the functional expansion, LeNN uses Legendre orthogonal functions. LeNN offers faster training compared to FLANN. The performance of this model may vary from problem to problem. The Legendre polynomials are denoted by $L_n(X)$, where n is the order and $-1 < x < 1$ is the argument of the polynomial. The zero and the first-order Legendre polynomials are, respectively, given by $L_0(x) = 1$ and $L_1(x) = x$. The higher order polynomials are given by $L_2(x) = 1/2(3x^2 - 1)$, $L_3(x) = 1/2(5x^3 - 3x)$ and so forth. Polynomials are generated by using the following mathematical expression:

$$L_{n+1}(x) = \frac{1}{n+1}[(2n+1)xL_n(x) - nL_{n-1}(x)]. \quad (2)$$

Similar to FLANN, the two-dimensional input pattern $X = [x_1 x_2]^T$ is enhanced to a seven dimensional pattern by Legendre functional expansion $X^e = [1, L_1(x_1), L_2(x_1), L_3(x_1), L_1(x_2), L_2(x_2), L_3(x_2)]$. For Legendre neural network, the training is carried out in the same manner as FLANN and PPN. In all models, supervised learning is used. As in normal artificial neural network techniques, the presence of hidden layers increases the complexity in the real-time system, therefore, FLANN and LeNN is suitably used at here due to less computational cost.

4. Development of Functional Link Artificial Neural Network Based-Noise Prediction Model

The functional link artificial neural network-based noise prediction models consist of two input parameters: sound power level (^1x_k) and distance (^2x_k). The inputs patterns are $^1x_1(k)$, $^1x_2(k)$, $^1x_3(k) \cdots ^1x_n(k) \in R$, $^2x_1(k)$, $^2x_2(k)$,
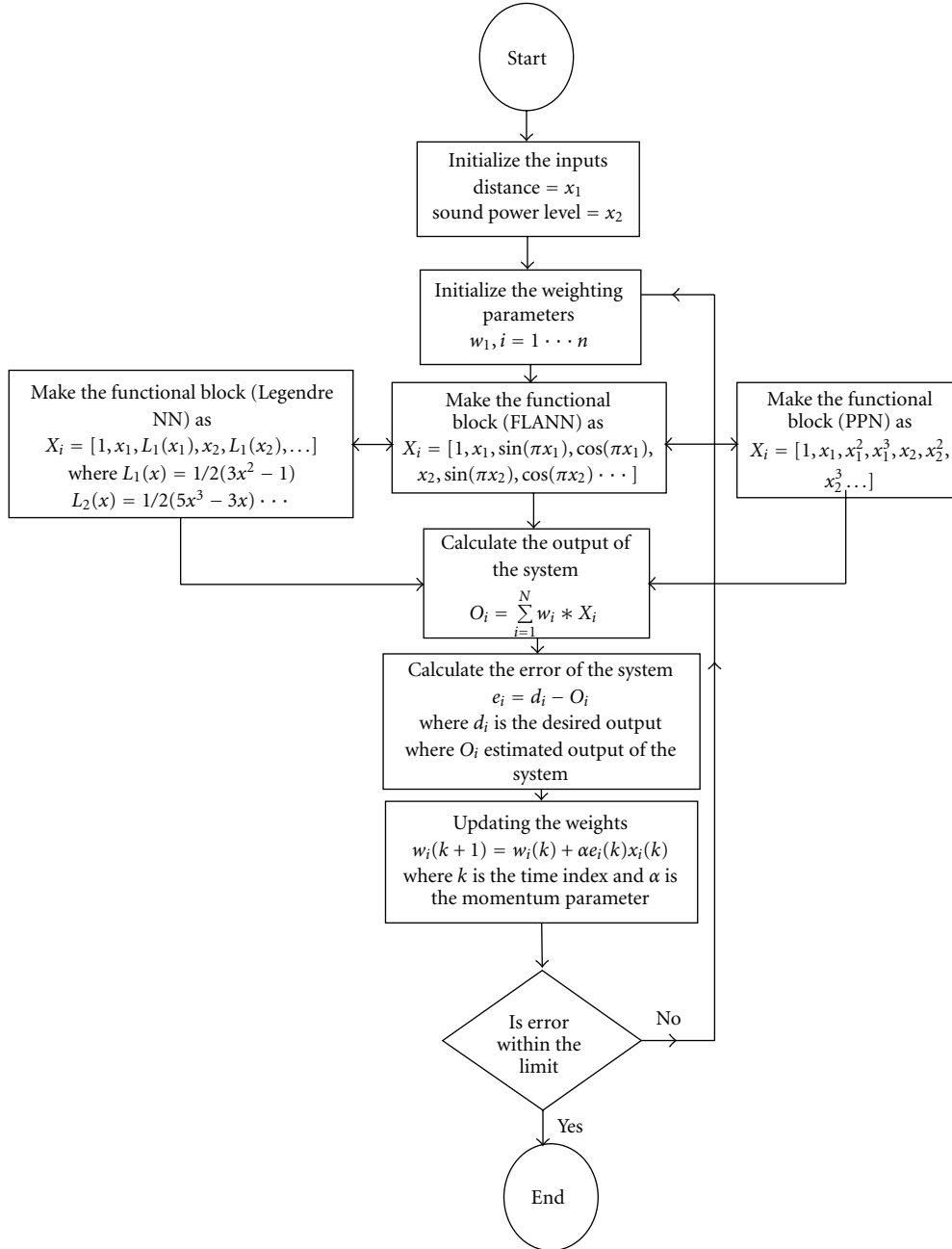
Start

Initialize the inputs
distance = x_1
sound power level = x_2

Initialize the weighting
parameters
$w_1, i = 1 \cdots n$

Make the functional block (Legendre
NN) as
$X_i = [1, x_1, L_1(x_1), x_2, L_1(x_2), \ldots]$
where $L_1(x) = 1/2(3x^2 - 1)$
$L_2(x) = 1/2(5x^3 - 3x) \cdots$

Make the functional
block (FLANN) as
$X_i = [1, x_1, \sin(\pi x_1), \cos(\pi x_1),$
$x_2, \sin(\pi x_2), \cos(\pi x_2) \cdots]$

Make the functional
block (PPN) as
$X_i = [1, x_1, x_1^2, x_1^3, x_2, x_2^2,$
$x_2^3 \ldots]$

Calculate the output of
the system
$$O_i = \sum_{i=1}^{N} w_i * X_i$$

Calculate the error of the system
$e_i = d_i - O_i$
where d_i is the desired output
where O_i estimated output of the
system

Updating the weights
$w_i(k + 1) = w_i(k) + \alpha e_i(k) x_i(k)$
where k is the time index and α is
the momentum parameter

Is error
within the
limit

No

Yes

End

FIGURE 2: Systematic algorithm of functional based neural network based noise prediction models.

$^2x_3(k) \cdots {}^2x_n(k)$ and the desired output patterns are: $d_1(k)$, $d_2(k)$, $d_3(k) \cdots d_n(k) \in R$. During training period, the desired network output was calculated with VDI-2714 noise prediction model. Since the procedures of these three models were similar; therefore, one algorithm is presented here to emphasize the development of functional-based neural network-based noise prediction models. Figure 2 graphically represent the algorithm of functional-based neural network-based noise prediction models.

Step 1. Initialize the inputs distance = $x_{1,i}$, $(i = 1, \ldots, n)$, sound power level = $x_{2,j}$ $(j = 1, \ldots, m)$, where n and m are the number of input pattern and an error tolerance parameter $\varepsilon > 0$. The dimension of m and n should be same.

Step 2. Randomly select the initial values of the weight vectors w_i, for $i = 1, 2, \ldots l$, where "i" is the number of functional elements.

Step 3 (Initialization). All the weights w_i were initialized to random number and given as $w_i(0)$

$$w_i \longleftarrow w_i(0). \tag{3}$$

TABLE 5: Simulation study of dozer noise.

Distance from the source (meters)	Measured field data (dBA)	Prediction result (dBA)				Average percentage error (dBA)		
		VDI	PPN	FLANN	LeNN	PPN	FLANN	LeNN
1	100.5000	93.8919	74.1198	85.6989	81.4871			
2	100.2000	93.5828	74.1198	93.0404	81.4871			
3	98.2000	91.5738	74.1198	94.5178	81.4871			
4	97.5000	90.8648	74.1198	92.4313	81.4871			
5	96.7000	90.0559	74.1198	87.9020	81.4871			
6	95.4000	88.7469	74.1198	85.9905	81.4871			
7	94.8000	88.1380	85.8609	93.3190	94.5712			
8	94.2000	87.5291	85.8609	93.3190	94.5712			
9	93.6000	86.9202	85.8609	94.0383	94.5712			
10	92.5000	85.8113	85.8609	94.0383	94.5712			
11	91.8000	85.1025	85.8609	87.6493	94.5712			
12	89.6000	82.8937	74.1198	77.8197	81.4871			
13	89.3000	82.5848	85.8609	88.1936	94.5712			
14	88.8000	82.0760	85.8609	91.4140	94.5712			
15	88.2000	81.4672	76.5756	85.3685	85.3813	10.94	6.32	9.53
16	87.9000	81.1585	76.5756	85.3685	85.3813			
17	87.4000	80.6497	76.5756	88.5889	85.3813			
18	86.6000	79.8410	76.5756	88.4139	85.3813			
19	85.5000	78.7323	64.8344	77.1458	70.1930			
20	85.5000	78.7236	76.5756	87.6947	85.3813			
21	84.8000	78.0149	64.8344	74.5798	70.1930			
22	84.3000	77.5063	62.5730	73.8606	70.1930			
23	84.2000	77.3976	62.5730	73.8606	70.1930			
24	83.8000	76.9890	61.4715	70.6402	70.1930			
25	83.5000	76.6804	61.4715	72.5517	66.3679			
26	83.5000	76.6718	75.3380	84.6557	82.0894			
27	82.8000	75.9632	59.7479	70.8864	66.3679			
28	82.5000	75.6547	60.3181	71.0614	67.0982			
29	82.4000	75.5461	72.0592	82.3295	82.9287			
30	82.4000	75.5376	72.2342	82.3295	82.9287			

Step 4 (Produce functional blocks). For FLANN the functional block is made as follows:

$$X_i = [1, x_1, \sin(\pi x_1), \cos(\pi x_1), x_2, \sin(\pi x_2), \cos(\pi x_2) \ldots], \tag{4}$$

For PPN the functional block is made as follows:

$$X_i = [1, x_1, x_1^2, x_1^3, x_2, x_2^2, x_2^3 \ldots], \tag{5}$$

for LeNN the functional block is made as follows:

$$X_i = [1, x_1, L_1(x_1), x_2, L_1(x_2), \ldots], \tag{6}$$

where $L_1(x) = (1/2)(3x^2 - 1)$, $L_2(x) = (1/2)(5x^3 - 3x)$, and so forth.

Step 5 (Calculation of the system outputs). For functional based neural network models, the output was calculated as follows:

$$O_i = \tanh\left(\sum_{i=1}^{N} w_i \times X_i\right). \tag{7}$$

Step 6 (Calculation of the output error). The error was calculated as $e_i = d_i - O_i$. It may be seen that the network produces a scalar output.

Step 7 (Updating the weight vectors). The weight matrixes are updated next using the following relationship:

$$w_i(k+1) = w_i(k) + \alpha e_i(k) X_i(k), \tag{8}$$

where k is the time index and α is the momentum parameter.

Step 8. If error $\leq \varepsilon (0.01)$ then go to Step 8 otherwise, go to Step 3.
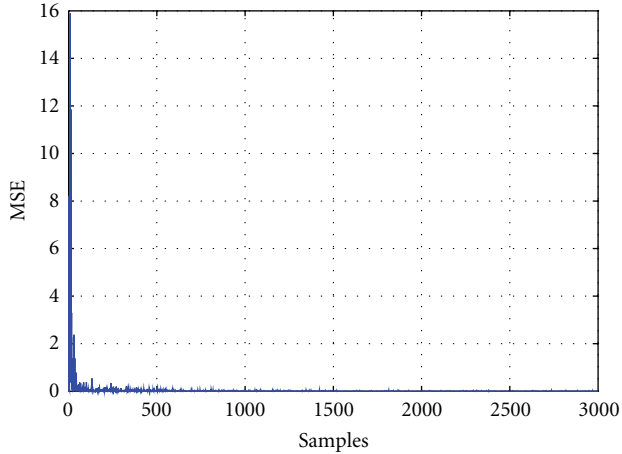
FIGURE 3: Mean square plot of FLANN based noise prediction model for 3000 iteration.
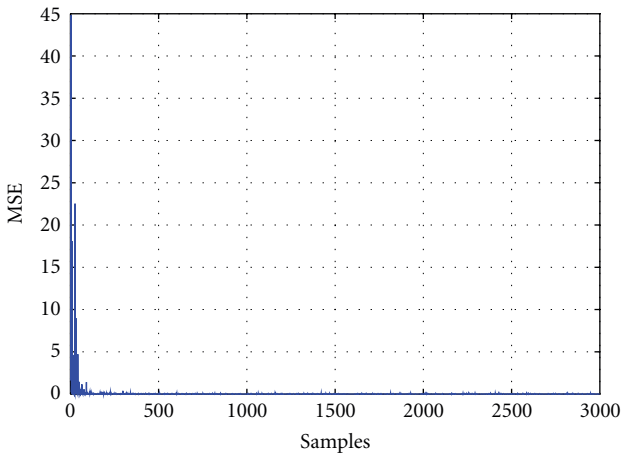

FIGURE 4: Mean square plot of PPN based noise prediction model for 3000 iteration.

Step 9. After the, learning is complete, the weights were fixed, and the network can be used for testing.

5. Simulation Result and Discussion

The proposed system models for noise prediction were validated using simulation studies. The studies were carried out by using MATLAB simulation environment. For validation of the models, the noise data was collected from Balaram opencast coal mine of Mahanadi Coalfields Limited (MCL), Talcher (Orissa, India). The test data was measured using Brüel and Kjaer 2239 (Denmark) precision 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. SPL of the different machineries from the above mine was collected. These machineries include Shovel ($10\,\text{m}^3$ bucket capacity), dozer (410 HP), tipper (10 T-160 HP), grader (220 HP), and dumper (85 T).

According to Figure 2, the stepwise procedures were required to design the model. In this problem, the system
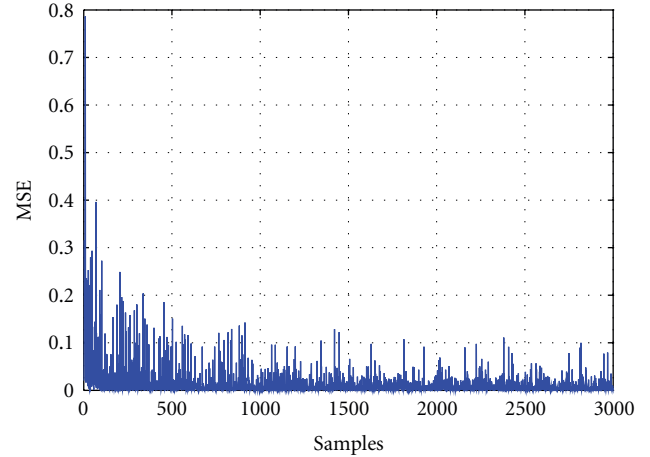
FIGURE 5: Mean square plot of LeNN based noise prediction model for 3000 iteration.

is a MISO (multi input and output system) system. The system architectures of these proposed functional link-based noise prediction models are the same, whereas only the input pattern or functional blocks are different. To design these models, total number of 3200 dataset were selected. Out of 3200, 3000 dataset were selected for training process and 200 data were selected for testing process. In this proposed systems, iteration based training methods were applied. The mean square error (MSE) plot of FLANN-based noise prediction model is represented in Figure 3, where Figures 4 and 5 are represented PPN and LeNN noise prediction models. Performance of these models for 200 testing samples or validation samples was represented from Figures 6, 7, and 8. The average percentage error (APE) was used as the performance index and was calculated as

Average Percentage Error

$$= \frac{1}{N} \sum_{i=1}^{N} \frac{(\text{VDI}_i - \text{Estimated}_i)^2}{\text{VDI}_i} \times 100. \tag{9}$$

Tables 1, 2, 3, 4, and 5 summarizes the results for noise prediction by proposed models and compares it with standard VDI-*2714* noise prediction model for all selected opencast machineries. From these tables it can be seen that the proposed PPN, FLANN and LeNN models provided average percentage error of 7.03, 5.68, and 8.42, respectively, for shovel. For dumper, the average percentage errors were 7.27, 5.77, and 8.20; for Grader, the APE were 9.56, 6.15, and 9.76; for Tipper, APE for three systems were 13.59, 4.36, and 10.03, respectively. The average percentage errors of the dozer were found as 10.94, 6.32, and 9.53 respectively. From the simulation studies, it was observed that the average percentage error of FLANN model was lower than the other two models.

6. Conclusion

This paper introduced the idea of designing noise prediction model for opencast mining machineries using functional link
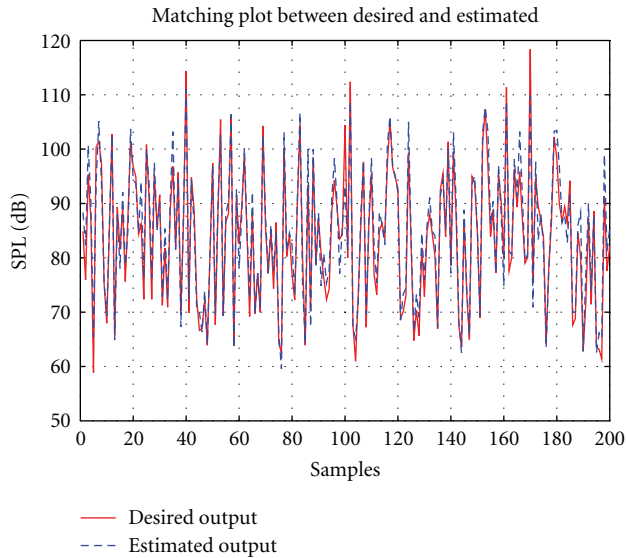
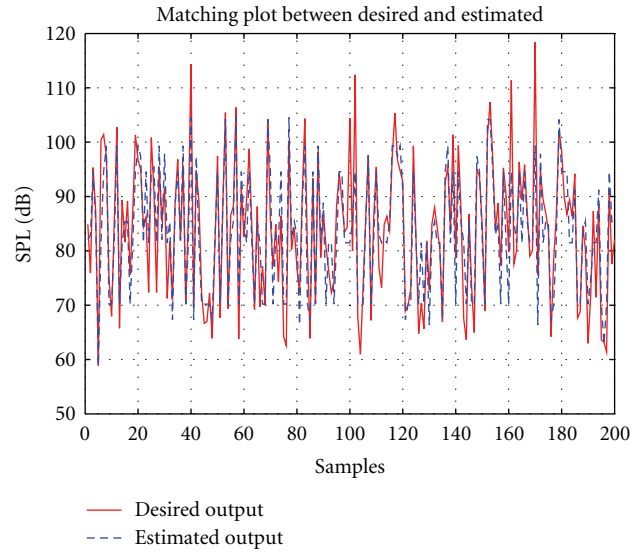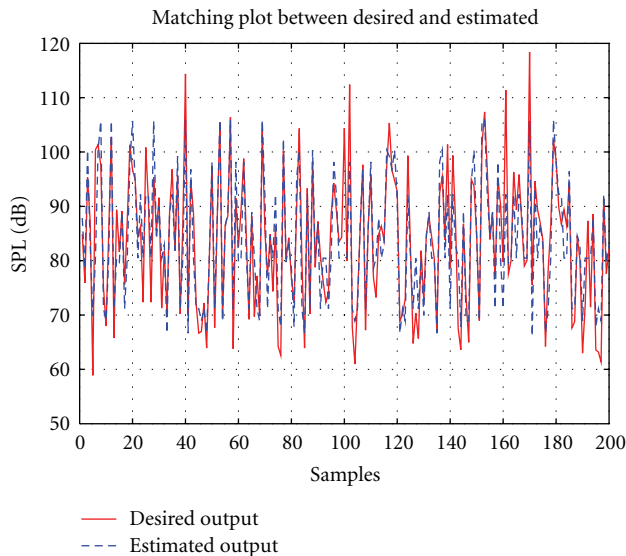FIGURE 6: Prediction performance of FLANN system for 200 samples.

FIGURE 7: Prediction performance of PPN system for 200 samples.

artificial neural network systems. From the present study, it was observed that the average percentage error using FLANN lower than PPN and LeNN systems for all the machineries. These functional link artificial neural network based noise prediction models can be useful tools for mining engineers to estimate the actual noise condition of the machineries accurately.

Acknowledgments

FIGURE 8: Prediction performance of LeNN system for 200 samples.

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