Research Article

A PLS-Based Weighted Artificial Neural Network Approach for Alpha Radioactivity Prediction inside Contaminated Pipes

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Long-range alpha detection (LRAD) has been used to measure alpha particles emitting contamination inside decommissioned steel pipes. There exists a complex nonlinear relationship between input parameters and measuring results. The input parameters, for example, pipe diameter, pipe length, distance to radioactive source, radioactive source strength, wind speed, and flux, exhibit different contributions to the measuring results. To reflect these characteristics and estimate alpha radioactivity as exactly as possible, a hybrid partial least square back propagation (PLSBP) neural network approach is presented in this paper. In this model, each node in the input layer is weighted, which indicates that different input nodes have different contributions on the system and this finding has been little reported. The weights are determined by the PLS. After this modification, a variety of normal three-layered BP networks are developed. The comparison of computational results of the proposed approach with traditional BP model and experiments confirms its clear advantage for dealing with this complex nonlinear estimation. Thus, an integrated picture of alpha particle activity inside contaminated pipes can be obtained.

1. Introduction

With the rapid development of nuclear industry over the last 50 years, nuclear decommissioning has been paid more attention recently. Most nuclear facility dismantling is involved in contaminated pipe disassembling. The radioactivity of contaminated pipes will be firstly measured to ensure the safety of operators and environment. A long-range alpha detection (LRAD) technique has been presented to measure alpha particles emitting contamination inside pipes [1–7]. The corresponding LRAD instrument has been developed, which consists of five units: (1) detection unit; (2) air drive unit; (3) power supply unit; (4) signal acquisition unit; (5) data processing control and display unit. The basic idea of the LRAD can be described as follows. When air is exposed to alpha radiation, ions are generated. The detector system collects the ions and counts the number of ions produced by the radiation. The number of ions is proportional to the amount of emitting alpha. Thus,

the system can indirectly measure contamination inside pipes. Figure 1 shows the LRAD measuring instrument used in the experiments, which is developed by our own research group.

Normally, the result of a LRAD measurement mainly depends on the following six parameters: pipe diameter, pipe length, distance to radioactive source, radioactive source strength, flux, and wind speed. The statistical analysis to LRAD measurement results indicates that there is a complex nonlinear relationship between the parameter space and measuring results. In particular, it is found that there is an approximate log relation between the distance to the source and the results, while the pipe length exhibits a double-peak relation to the results. That is to say, the multiple parameter effects are quite obvious. Thus, How to distinguish different contributions of different input parameters has been a focus in the system. To the best of our knowledge, this issue has been little studied using a hybrid artificial neural network (ANN) method so far.

FIGURE 1: Illustration of the LRAD experimental installation.

ANN methods especially back propagation (BP) models have been recognized as more efficient models than the conventional statistical forecasting ones for solving nonlinear issues. However, BP models have two main flaws, that is, tendency to overfitting and difficulty to determine the optimal number of the hidden-layer nodes. Recently, a lot of improved BP models based on partial least square (PLS) have been presented and applied to various fields in solving nonlinear issues from natural to man-made systems [8–15]. Medhat presented two methodologies, namely, partial mutual information and self-organizing map, integrated with a genetic algorithm and general regression neural network [12]. Jain and Kumar applied a hybrid neural network model for hydrologic time series forecasting [13]. Research [8] uses the PLS to choose the BP network architecture and initial weights between nodes. In [9], the PLS is added between the hidden layer and the output layer in order to check and remove the correlation among the nonlinear transformed variables in a three-layered BP network. In [10], PLS is used to decrease the abundance of input variables; that is, PLS plays a preprocessing role in a three-layered BP network. In [11], in order to study gas-solid adsorption process, PLS serves for data compression and noise reduction before a normal three-layered BP network is performed.

Although hybrid ANN models have found many applications in a variety of areas, those models normally assumed that contribution of all input nodes is nondiscriminable, that is, homogeneous. In fact, different input nodes could have different contributions on the system. This issue, that is, the weighted input nodes, has been little considered, to the best of our knowledge. Based on excellent ANN research works in the literature and our experimental results obtained from the LRAD, this paper presents a hybrid PLS and BP (PLSBP) model for alpha radioactivity assessment. The weighted input nodes can be described by the PLS. This is a novel of the paper and a difference from other ANN papers. The computational results of the PLSBP approach have shown its clear advantage for dealing with this complex nonlinear problem, compared to traditional ANN models.

This paper is organized as follows. In Section 2, the hybrid PLSBP model is proposed to take different contributions on the input nodes into account. Section 3 analyzes the results of LRAD experiments using the PLSBP model and compares them with measured values. The conclusion is given in Section 4.

2. Hybrid PLSBP Model

The alpha radioactivity estimation can be solved by constructing a model which represents the relationship between the measuring variables and the measuring results. This constructed model can be used to calculate the measuring results from the measured variables of LRAD instrument. In general, the model to be built can be written as

$$y = f(\mathbf{x}), \quad (1)$$

where y is the measuring results and $\mathbf{x}$ is a vector of measured variables of LRAD instrument, particularly, and $\mathbf{x}$ is a vector of $n \times m$ matrix and y consists of a $m \times 1$ matrix in this paper.

2.1. PLS Algorithm. The normal PLS algorithm can be described as follows.

- (a) Preprocess data. Both $\mathbf{x}$ and y variables are normalized by decimal scaling. Consider

$$x_{ij}^* = \frac{x_{ij} - \bar{x}_j}{s_j}, \quad y_i^* = \frac{y_i - \bar{y}}{s_y}, \quad (2)$$

where $\bar{x}_j$ is the average of x_j and s_j is the standard deviation of x_j . Similarly, $\bar{y}$ and s_y are the average and the standard deviation of y , respectively. Then, set $h = 1$, $E_0 = (x_{ij}^*)_{n \times m}$, and $F_0 = (y_i^*)_{m \times 1}$.

- (b) Calculate the weight vectors w_h

$$w_h = E_{h-1}^T F_{h-1}. \quad (3)$$

- (c) Calculate the score vectors t_h

$$t_h = E_{h-1} w_h. \quad (4)$$

- (d) Calculate the loading vectors of x and y

$$p_h = \frac{E_{h-1}^T t_h}{(t_h^T t_h)}, \quad q_h = \frac{F_{h-1}^T t_h}{(t_h^T t_h)}. \quad (5)$$

- (e) Calculate the residuals

$$E_h = E_{h-1} - t_h p_h^T, \quad F_h = F_{h-1} - q_h t_h. \quad (6)$$

- (f) Check the cross validation. If $Q_h^2 \geq 0.0975$, component t_h is extracted. Then, check t_{h+1} .

- (g) Repeat (b)–(f) unless all components $t_1, \dots, t_m$ are obtained.

2.2. PLSBP Algorithm. The PLSBP algorithm is developed as follows.

- (a) Preprocess latent variables. The components $t_1, \dots, t_m$ obtained in the last subsection will be normalized. The minimum-maximum normalization is highly recommended for neural networks and is adopted here.

FIGURE 2: Schematic diagram of PLSBP network structure.

(b) Transfer X space to a new X' space via

$$(x'_{ij})_{n \times m} = (x_{ij})_{n \times m} x(t'_i)_{m \times 1}, \quad (7)$$

where $(x'_{ij})_{n \times m}$ and $(x_{ij})_{n \times m}$ are transferred and original input matrixes, respectively. $(t'_i)_{m \times 1}$ is a minimum-maximum normalized latent variable matrix. Equation (7) reflects the contribution of input nodes.

(c) $(x'_{ij})_{n \times m}$ as a new input matrix is fed into the BP network. The BP network consists of input layer, hidden layer, and output layer. The PLS algorithm is used to get latent variables $(t_1, t_2, \dots, t_m)$ from the source data X space. The latent variables may be viewed as a contribution to the input nodes and fed into the BP network. Figure 2 illustrates the PLSBP network structure.

3. Computational Results

As mentioned above, six LRAD parameters for pipe contamination are involved, that is, pipe diameter, pipe length, distance to radioactive source, radioactive strength, wind speed, and flux. Thus, the network includes 6 inputs and 1 output. In total, 200 sampling data were collected, among which 150 samples were used for model training, 30 samples for model testing, and the rest 20 samples for prediction. We firstly use the PLS algorithm to get the following regression equation:

$$y = 7.8891 - 0.3127t_1 + 0.0668t_2 - 0.1974t_3 + 0.0393t_4 + 2.794t_5 + 1.7111t_6, \quad (8)$$

where t_1, t_2, t_3, t_4, t_5 , and t_6 represent pipe diameter (mm), pipe length (cm), distance to radioactive source (cm), radioactive strength (Bq), wind speed (m/s), and flux (m^3/h), respectively. The corresponding regression coefficients are shown in Figure 3. It can be seen that wind speed and flux dominate the measurement system. These variables are normalized via the minimum-maximum method. And the

FIGURE 3: Illustration of PLS latent variables and values.

TABLE 1: A list of required model parameters.

Name of variables	Value
Training sample φ_{11}	150
Validation sample φ_{12}	30
Testing sample φ_{13}	20
Number of input nodes	6
Number of hidden nodes	6
Number of output nodes	1
Error ε_{11} of sample φ_{11}	0.01
Error ε_{12} of sample φ_{12}	0.05
Error ε_{13} of sample φ_{13}	0.05
Learning	0.05
Training epochs	1000
Training goal	10^{-4}

new input matrix will be obtained by (7) and fed into the BP network.

As the initial connection weights and threshold are randomly chosen, we have carried out this model 20 times. We took its 95% confidence interval as neural network ensemble. The parameters are listed in Table 1.

The most important factor to measure performance of an algorithm is to check its forecasting ability of testing samples. Table 2 listed prediction result comparisons of real data, PLSBP, and normal BP. Figure 4 shows comparisons of relative errors obtained from the PLSBP and normal BP. In the normal BP algorithm, the minimum and maximum of relative errors are 0.000412 and 0.152324, respectively. The averaging relative error is 0.06357. The most relative error is less than 8%. However, in the PLSBP, the minimum and maximum of relative errors are 0.001382 and 0.05925, respectively. The averaging relative error is 0.0329. The most relative error is less than 5%. It can be seen that the proposed PLSBP algorithm has better prediction accuracy than that of normal BP algorithm.

TABLE 2: Prediction result comparisons of the PLS and BP.

Pipe diameter	Pipe length	Distance to source	Radioactive strength	Wind speed	Flux	Measuring results	PLSBP	Normal BP
43	150	50	3200	0.91	4.76	139.83	140.0233	155.7231
43	150	70	3200	0.91	4.76	130.27	135.4798	150.1133
43	150	130	3200	0.91	4.76	113.1	116.2733	121.2121
43	170	30	3200	0.9	4.76	156.28	158.1347	159.1684
48	170	30	3200	0.9	5.93	160.66	162.5901	164.5812
58	170	30	3200	0.9	8.65	197.72	192.5488	172.3124
66	170	30	3200	0.9	11.04	195.28	186.8596	181.8596
78	170	30	3200	0.9	13.07	156.8	163.8596	164.7347
84	170	30	3200	0.9	18.05	167.74	166.8902	167.809
58	40	30	3200	0.91	8.62	152.04	151.2389	150.4819
58	170	130	3200	0.5	4.71	112.38	107.0745	104.0712
58	170	130	3200	0.66	6.25	127.02	120.6906	118.6332
58	170	130	3200	0.8	7.56	133.54	127.905	125.8907
58	170	130	3200	0.93	8.82	141.4	136.5578	130.3024
58	170	130	3200	1.03	9.77	145.98	137.33	133.115
58	170	130	3200	1.15	10.9	146.58	138.7476	135.7476
58	170	130	3200	1.23	11.74	144.32	136.7589	136.7589
58	170	130	3200	1.33	12.6	143.86	138.5632	138.5632
58	170	130	3200	1.42	13.48	142.38	136.99	140.0615

FIGURE 4: Comparison of relative errors between PLSBP and normal BP.

In this paper, we assumed that radioactive source strength and radioactive source position are known to measure ionizing values in order to check the feasibility of the proposed method. In practice, the distance or source strength is normally unknown and should be estimated from the ion current. Therefore, how to estimate the distance or source strength from the ion current is our next step work.

4. Conclusion

This paper introduced a hybrid partial least square back propagation neural network (PLSBP) model to predict alpha radioactivity inside decommissioned pipes during nuclear facility disassembling. The proposed model considers the different contributions of each input node, which has been paid little attention in the literature. The computational results indicate that the PLSBP model has a better prediction performance for alpha radioactivity estimation. Once the six parameters are determined, the PLSBP model will give an approximate output, and thus, an integrated picture of alpha particle activity inside contaminated pipes can be obtained. This approach may give insight into data processing when main and weak component analysis is involved.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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