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Advanced Probabilistic Neural Network for the Prediction of Concrete Strength

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Summary

Accurate and realistic strength estimation before the placement of concrete is highly desirable. In this study, the advanced probabilistic neural network (APNN) was proposed to reflect the global probability density function by summing the heterogeneous local probability density function automatically determined in the individual standard deviation of variables. Currently, the estimation of the compressive strength of concrete is performed by a probabilistic neural network (PNN) on the basis of concrete mix proportions, and the PNN is improved by the iteration method. However, an empirical method has been incorporated to specify the smoothing parameter in the PNN technique, causing significant uncertainty in the estimation results. In addition, the probability density function (PDF) is the sum of homogeneous multivariate Gaussian distribution because only one global smoothing parameter is used. The APNN was applied to predict the compressive strength of concrete using actual test data from two concrete companies, and the estimated results of APNN were compared with those of PNN. APNN showed better results than PNN in predicting the compressive strength of concrete and provided the promising probabilistic viewpoints by using the individual standard deviation in a variable.

Introduction

Over a period of many years, researchers have proposed various methods for predicting concrete strength. Conventional methods for predicting 28-day compressive strength of concrete are basically based upon statistical analyses, by which many linear and nonlinear regression equations have been constructed to model such prediction problems [1]. If we consider strength prediction as a mapping from the various influencing factors to the 28-day compressive strength, then a mapping model can be created by using artificial neural networks. Standard multi-layer feed-forward neural networks with a back propagation algorithm have been used to predict the strength of concrete [2]. Back propagation neural networks (BPNN) have the advantage of being able to effectively consider various inputs without using complicated equations, in contrast to conventional regression analyses. In addition, they can easily adapt to new data through a re-training process. However, BPNN needs more effort to determine the architecture of networks and more computational time in training the networks. Moreover, the estimated results from BPNN are not probabilistic but deterministic, even though the test results for the

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compressive strength of concrete specimens under the same conditions, such as mix proportions, curing conditions, methods of transporting, placing, testing, etc., show distributed characteristics in nature. Probabilistic neural network (PNN), therefore, is effective alternative because PNN needs less time to determine the networks' architecture and to train the networks. Moreover, PNN provides probabilistic viewpoints as well as deterministic classification results.

PNN has been widely used for pattern recognition problems, such as texture recognition [3], image recognition [4], medical/biochemical field [5], signal processing [6], civil/geotechnical engineering [7], and so on.

Kim et al. [2] proposed PNN to predict the estimation of the compressive strength of concrete on the basis of concrete mix proportions and verified performance of PNN through comparison with the results of the actual compression tests; the estimation performance of PNN is improved by the iteration method. It is that the prediction of the concrete strength (i.e. classification) was performed iteratively. However, an empirical method has been incorporated to specify (smoothing parameter) in the PNN technique, causing significant uncertainty in the estimation results. In addition, the probability density function (PDF) is the sum of homogeneous multivariate Gaussian distribution because only one global smoothing parameter is used.

In this paper, the advanced probabilistic neural network (APNN) was proposed to reflect the global probability density function by summing the heterogeneous local probability density function. The heterogeneous local probability density function of APNN is automatically determined to use the individual standard deviation of variables. Training and test patterns for APNN are prepared using the data sets on the mix proportions of two concrete companies. The proposed methods are verified using the actual test data from two concrete companies. The estimated results of APNN are compared with those of PNN.

PNN and APNN

PNN is basically a pattern classifier that combines the well-known Bayes decision strategy with the Parzen non-parametric estimator of the probability density functions of different classes [8]. PNN has gained interest because it offers a way to interpret the network's structure in the form of a probability density function and it is easy to implement. An accepted norm for decision rules or strategies used to classify patterns is that they do so in a way that minimizes the "expected risk." Such strategies are called "Bayes strategies" and can be applied to problems containing any number of classes.

Figure 1 shows the neural network organization for classification of input patterns **X** into two categories. In Figure 1, the input layer is the merely distribution units that supply the same input values to all of the pattern units. The second layer consists of a number of pattern units. In PNN, each pattern unit (shown in more detail in Figure 2) forms a dot product of the input pattern vector $\mathbf{X}$ with a weight vector$\mathbf{W}_i$,$Z_i = \mathbf{X} \cdot \mathbf{W}_i$, and then performs a nonlinear operation on $Z_i$before outputting its activation level to the summation unit. Instead of the sigmoid activation function commonly used for back-propagation neural network, the nonlinear operation used here is$\exp[(Z_i - 1)/\sigma^2]$. Assuming that both $\mathbf{X}$ and $\mathbf{W}_i$ are normalized to unit length, this is equivalent to using

$$\exp[-\frac{(\mathbf{X} - \mathbf{W}_i)^T(\mathbf{X} - \mathbf{W}_i)}{2\sigma^2}] \tag{1}$$

Each variable, such as slump, water/cement ratio, unit water, fine aggregate, unit cement content, natural sand (s_1), crushed sand (s_2), unit coarse aggregate content, and admixture, has an individual standard deviation and different probabilistic property. However, the probability density function did not consider the individual probabilistic property of variables in PNN because only one global smoothing parameter was used. Therefore, in this paper, the advanced probabilistic neural network (APNN) was proposed to reflect the global probability density function by summing the heterogeneous local probability density function automatically determined to use the individual standard deviation of variables. The basic idea is to individually use the heterogeneous local probability density function in a variable because the probabilistic property of variables is not homogenous but heterogeneous. The individual probability density function was derived from the standard deviation of variables. The probability density function for i^{th}sample is determined to sum different standard deviations of the training vector with j^{th}variables (Figure 3). Therefore, the nonlinear operation of APNN can be expressed as

$$\exp\left\{-\sum_{j=1}^{p}\left(\frac{(X_j - W_{i,j})^2}{2\sigma_j^2}\right)\right\} \tag{2}$$

where i and j are indices for the i^{th} training pattern and j^{th} variable; p is the number of variables; X_j is the j^{th} variable of input data; $W_{i,j}$ is the j^{th} variable of the i^{th} training vector; σ_j is the standard deviation with the j^{th} variable.

A comparison between APNN with PNN

In this section, we compared the estimation capability of the APNN and conventional PNN. Table 1 shows the estimation errors for 62 test patterns of each company using eight (for Company B) or nine (for Company A) parameters as input to APNN. Table 2 shows the estimation results of the concrete compressive strength using conventional PNN with empirical smoothing parameters $(\sigma = 0.1)$. The estimation errors are defined by the root mean square (RMS) errors.

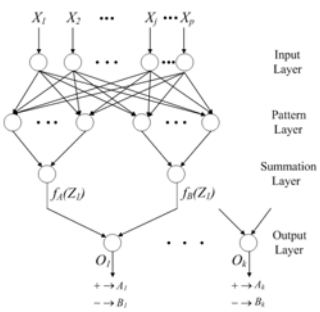


Figure 1: Structure of PNN

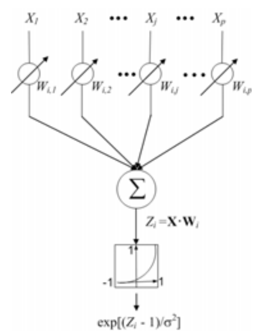


Figure 2: Pattern layer of PNN

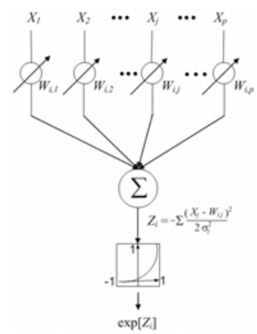


Figure 3: Pattern layer of APNN

Table 1: Estimation results of APNN

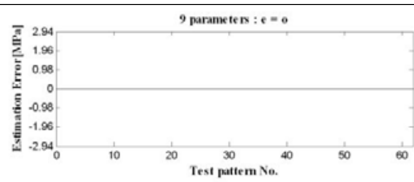
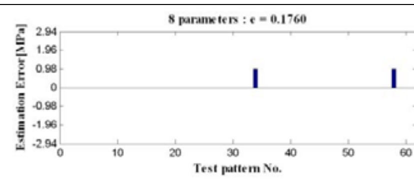
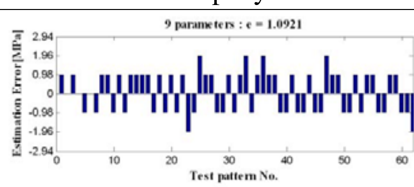
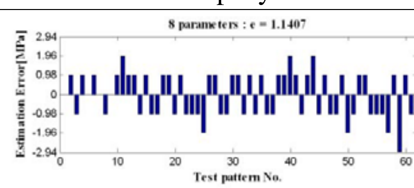
Company A	Company B
	

Table 2: Estimation results of PNN

Company A	Company B
	

Comparison of predictions and test results

Figures 4 and 5 show the estimated results obtained by PNN and APNN compared with the test results of two concrete companies A and B. The training patterns are the same as in the previous section and the test patterns for specified compressive strengths of 23.52MPa with a slump of 12cm. The estimated results can be represented from the viewpoint of probability.

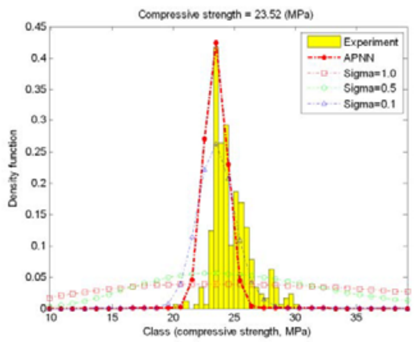


Figure 4: Results for company A

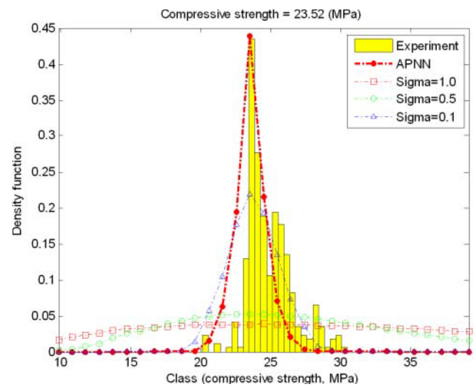


Figure 5: Results for company B

Conclusions

Advanced probability neural network (APNN) was proposed and incorporated to predict the compressive strength of concrete. The concrete mix proportions and the slump values of two ready-mixed concrete companies are used as inputs to the APNN, and the compressive strength of concrete is defined as classes to be predicted by the networks. The conclusions of this paper are as follows.

(1) From the results in the RMS errors, it has been found that the estimation performance of the proposed method is more effective than that of the conventional PNN.

(2) The validity of the proposed method was proven by comparing the predicted strength with the test results of the concrete. The estimation results using the individual standard deviation of input patterns in APNN showed the best agreement with the distribution of the test results compared with user defined smoothing parameters.

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