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Estimation of Concrete Strength Using Improved Probabilistic Neural Network Method

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ABSTRACT

The compressive strength of concrete is commonly used criterion in producing concrete. However, the tests on the compressive strength are complicated and time-consuming. More importantly, it is too late to make improvement even if the test result does not satisfy the required strength, since the test is usually performed at the 28th day after the placement of concrete at the construction site. Therefore, accurate and realistic strength estimation before the placement of concrete is being highly required. In this study, the estimation of the compressive strength of concrete was performed by probabilistic neural network(PNN) on the basis of concrete mix proportions. The estimation performance of PNN was improved by considering the correlation between input data and targeted output value. Improved probabilistic neural network was proposed to automatically calculate the smoothing parameter in the conventional PNN by using the scheme of dynamic decay adjustment (DDA) algorithm. The conventional PNN and the PNN with DDA algorithm(IPNN) were applied to predict the compressive strength of concrete using actual test data of two concrete companies. IPNN showed better results than the conventional PNN in predicting the compressive strength of concrete.

Keywords *: concrete compressive strength, strength prediction, correlation, dynamic decay adjustment algorithm (DDA), probabilistic neural network(PNN)*

1. Introduction

Concrete is one of the most widely used construction materials in the world. Traditionally, concrete has been fabricated from a few well-defined components: cement, water, fine and coarse aggregates, etc. In concrete mix design and quality control, the strength of concrete is a very important property. Many properties of concrete such as elastic modulus, water-tightness or impermeability, resistance to weathering agents, etc. are directly related to the strength. The strengths of concrete include compressive strength, tensile strength, flexural strength, shear strength, bond strength, and so on. A majority of concrete elements are designed to take advantage of the higher compressive strength of the material, since the compressive strength of concrete is usually many times greater than other types of strength. The mixture design of concrete targets its 28-day compressive strength. The 28-day compressive strength is determined based on a standard uni-axial compression test and is accepted conventionally as a general index of concrete strength. Generally, concrete testing procedures are very complicated and time-consuming. Furthermore, experimental errors are inevitable. A typical test performed 28 days after concrete placement may be too late to make improvements if the test results do not satisfy the required criterion. Therefore, accurate and realistic strength estimation before the placement of concrete is highly required.

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

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been constructed to model such prediction problems[1,2]. If we consider the 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 network. A standard multi-layer feed-forward neural network with a back propagation algorithm has been used to predict the compressive strength of concrete[3-5]. Back propagation neural network(BPNN) has the advantage that it can effectively consider various inputs without using complicated equations, in contrast to conventional regression analyses. Also, it can easily adapt a new data through a re-training process. However, BPNN needs more efforts to determine the architecture of network and more computational time in training the network. Moreover, the estimated results from BPNN are not probabilistic but deterministic, even though the test results for 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) is basically a forward process not requiring back-propagation for error correction. Therefore, PNN can be an effective alternative, because PNN needs less time to determine the network's architecture and to train the network.[19,26] Moreover PNN provides the probabilistic viewpoints as well as deterministic classification results.

Probabilistic neural network has been widely used for pattern recognition problems such as texture recognition[6,7], image recognition[8,9], medical/biochemical field[10,11], signal processing[12], finance[13], civil/geotechnical engineering[14-16], etc. In this study, the estimation of the compressive strength of concrete is carried out by PNN on the basis of concrete mix proportions. Training and test patterns for PNN are prepared using the data sets on the mix proportions of two concrete companies. The predicted strengths are compared with those tested in the laboratory. The estimation performance of PNN is improved by considering the correlation between input data and targeted output values in training samples. Improved probabilistic neural network (IPNN) is proposed to automatically calculate the smoothing parameter, which is the only user-defined variable in the conventional PNN, by using the scheme of dynamic decay adjustment(DDA) algorithm. DDA algorithm has been utilized to determine the architecture of networks as well as the required number of neurons through training process[17,18]. In this study, the smoothing parameter is calculated based on the threshold scheme of DDA algorithm under the fixed number of training samples.

The proposed methods are verified using the actual test data of two concrete companies. The estimated results are compared with the results of the actual compression tests. The comparison results have shown that the presented method can effectively predict the concrete strength in spite of data complexity, incompleteness, and incoherence, and it can be an effective tool for concrete mix designers to support their decision process and to improve design efficiency.

2. Estimation of concrete strength using improved probabilistic neural network

2.1 Overview of probabilistic neural network

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[19]. 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.

Consider the two-category situation in which the state of nature θ is known to be either θ_A or θ_B. If it is desired to decide whether $\theta=\theta_A$ or $\theta=\theta_B$ based on a set of measurements represented by the p-dimensional vector $X^T=[X_1 \cdots X_j \cdots X_p]$, the Bayes decision rule becomes

$$d(X)=\theta_A \quad \text{if } h_A l_A f_A(X)>h_B l_B f_B(X) \tag{1a}$$

$$d(X)=\theta_B \quad \text{if } h_A l_A f_A(X)<h_B l_B f_B(X) \tag{1b}$$

where $f_A(X)$ and $f_B(X)$ are the probability density functions (PDFs) for categories A and B, respectively; l_A is the loss function associated with the decision $d(X)=\theta_B$ when $\theta=\theta_A$; l_B is the loss associated with the decision $d(X)=\theta_A$ when $\theta=\theta_B$ (the losses associated with correct decisions are taken to be equal to zero); h_A is the priori probability of occurrence of patterns from category A; and $h_B=1-h_A$ is the priori probability that $\theta=\theta_B$.

In the simplified case that assumes both loss function and a priori probability are equal to each other, the Bayes rule classifies an input pattern to the class that has its PDF greater than the PDF of the other class. Therefore, the accuracy of the decision boundaries depends on the accuracy with which the underlying PDFs are estimated. Parzen showed how one may construct a family of estimates of $f(X)$[20], and Cacoullos has also extended Parzen's results to estimates in the special case that the multivariate kernel is a product of univariate kernels[21]. In the particular case of the Gaussian kernel, the multivariate estimates can be expressed as

$$f_A(X)=\frac{1}{(2\pi)^{p/2}\sigma^p}\frac{1}{m}\sum_{i=1}^{m}\exp\left[-\frac{(X-X_{Ai})^T(X-X_{Ai})}{2\sigma^2}\right] \quad (2)$$

where X is the test vector to be classified; $f_A(X)$ is the value of the PDF of category A at point X ; m is the number of training vectors in category A; p is the dimensionality of the training vectors; X_{Ai} is the ith training vector for category A; and σ is the smoothing parameter. Note that $f_A(X)$ is simply the sum of small multivariate Gaussian distributions centered at each training sample. However, the sum is not limited to being Gaussian.

2.2 Improved probabilistic neural network

In this study, improved probabilistic neural network (IPNN) is proposed to automatically calculate the smoothing parameter in the conventional PNN by using the scheme of dynamic decay adjustment (DDA) algorithm. DDA algorithm determines automatically the architecture of networks and the required number of neurons through training process[16,17)]. The basic idea of DDA algorithm is to distinguish between matching and conflicting neighbors in an area of conflict, which is illustrated in Fig. 1. It uses two thresholds; upper and lower limits. Upper limit (θ^+) determines the minimum correct-classification probability for the training patterns of the correct class, and lower limit (θ^-) is used to avoid misclassification. In other words, the algorithm trains the network in such a way that for a given training pattern, the probability density for the correct class has to be less than or equal to lower limit (θ^-). The area left in-between θ^+ and θ^- is called the area of conflict that neither matching nor conflicting training pattern is allowed to lie. The two thresholds, θ^+ and θ^-, are user-defined training parameters which control the classification accuracy of the resulting neural network. The smoothing parameter for jth sample in class k is determined by satisfying the following equation. The values of 0.4 and 0.2 are generally accepted for θ^+ and θ^- in the DDA algorithm[20,21)].

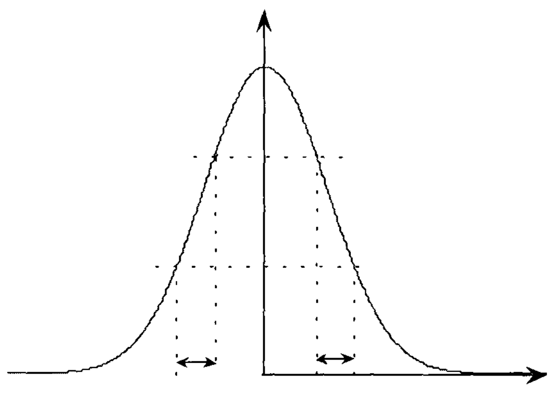


Fig. 1 The area of conflict in DDA algorithm[23)]

$$f_j^k(X)=\frac{1}{(2\pi)^{p/2}(\sigma_j^k)^p}\exp\left(-\frac{(X-\mu_j^k)^T(X-\mu_j^k)}{2(\sigma_j^k)^2}\right)\geq\theta^+ \ \text{if}\ X\in C_k \quad (3a)$$

$$f_j^k(X)=\frac{1}{(2\pi)^{p/2}(\sigma_j^k)^p}\exp\left(-\frac{(X-\mu_j^k)^T(X-\mu_j^k)}{2(\sigma_j^k)^2}\right)<\theta^- \ \text{if}\ X\notin C_k \quad (3b)$$

where f_j^k is the probability density function; k is the class; j is the training pattern; X is the input data; p is the dimensionality of the training vectors; μ_j^k is the i^{th} training vector; $\sigma_{m_k}^k$ is the smoothing parameter; C_k is the k^{th} class space.

2.3 Strength estimation using probabilistic neural network

Concrete structures are generally required to have safety, strength, durability, and serviceability. In order to produce high-quality concrete to satisfy these needs, code information, specifications, and experience of experts in determining the concrete mix proportions play vital roles. The concrete used at construction sites is mostly produced in a ready-mixed concrete company according to specified concrete mix proportions. In general, slump tests are performed before the placing of concrete, but the compression tests of specimens are carried out at the 28th day after the placing. Therefore, it is difficult to estimate the compressive strength at construction sites. Ready-mixed concrete companies use their own mix proportions based on codes, previous experience, and experiments. In this study, the probabilistic neural network for estimating the concrete compressive strength was incorporated using actual mix proportion data provided by two companies, A and B. The material properties of concrete from the two companies are shown in Table 1. Normal Portland cement was used. The maximum size of aggregate was 25mm, the range of compressive strengths was from 9.8 to 39.2MPa, and slump values were 5, 8, 10, 12, 15, 18, and 21cm.

Table 1 Material properties of concrete

Properties of material		Experiment data	
		Company A	Company B
Specific gravity	Cement	3.14	3.15
	Natural sand (s1)	2.59	2.58
	Crushed sand (s2)	2.51	-
	Coarse aggregate	2.64	2.63
Fineness modulus	Natural sand (s1)	3.30	2.70
	Crushed sand (s2)	2.25	-
	Coarse aggregate	6.53	6.60
Admixtures	Air-entraining admixtures	AE water-reducing (standard)	AE water-reducing (standard)

Verifications on the applicability of the PNN to the problem of strength estimation were performed using actual mix proportion data provided by two companies. At first, eight (for Company B) or nine (for Company A) parameters including water-cement ratio, fine aggregate percentage, unit water content, unit cement content, unit fine aggregate content, unit coarse aggregate content, admixtures, and slump were used as the input set for PNN, while the specified compressive strength, is required average strength, was defined as the output (class) to be estimated.

The mixture of natural sand (s1) and crushed sand (s2) was used in Company A as a fine aggregate, so Company A has an additional unit fine aggregate content parameter. Then five(for Company B) or six(for Company A) parameters including water-cement ratio, fine aggregate percentage, unit cement content, natural sand(s1), admixtures which showed close correlation to output values as shown in Fig. 2 were selected using the following equation and utilized as input data for PNN to improve the estimation performance.

$$R_{xy} = \frac{(x-\mu_x)^T (x-\mu_y)}{\sqrt{\| x-\mu_x \| \| y-\mu_y \|}} \tag{4}$$

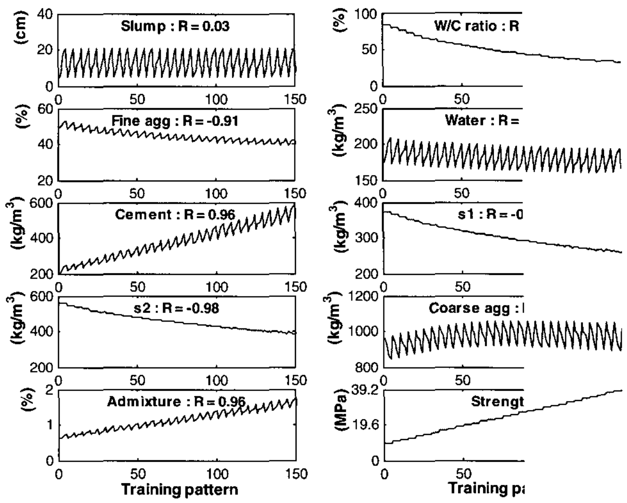
where x, y denote the input and output data, respectively, and μ_x and μ_y are their mean values. All the input data are normalized to 0.1~0.9 to give an equal weighting factor before implementing the data to the network.

All the classes are defined using the compressive strength of 9.8~39.2MPa with the step size of 0.98MPa. Consequently, the compressive strength to be estimated is divided into 31 classes in total. There are 7 independent training patterns with the slump values of 5, 8, 10, 12, 15, 18, and 21cm in each class. 5 samples which are randomly selected among 7 samples in a class are used for training patterns and the others are used for testing, that is, the numbers of training and test patterns are 155 and 62, respectively. Examples of specified concrete mix proportions of two companies for training are shown in Tables 2 and 3.

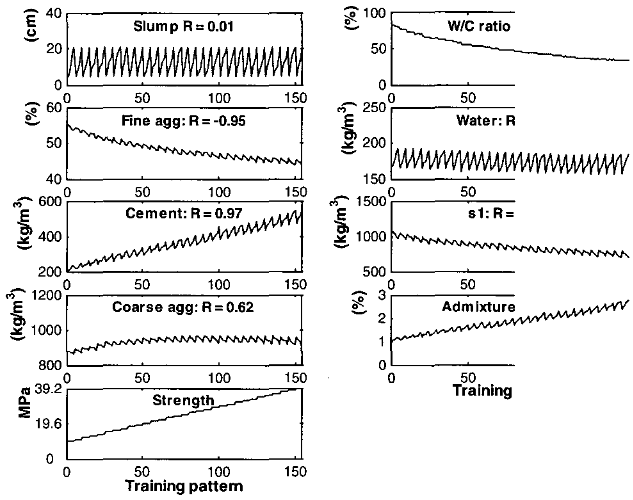
Table 4 shows the estimation results for the 62 test patterns along with RMS error defined by

$$e = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(f-\overline{f}\right)^2} \tag{5}$$

where N is the number of test patterns; f and $\overline{f}$ denote the actual and predicted concrete strength, respectively. Three different smoothing parameters (σ =1.0, 0.5, 0.1) are investigated to find a better reflection of the actual distribution of the test results. The estimation error was



(a) Company A



(b) Company B

Fig. 2 Correlation between mix proportion and compressive strength

decreased when five and six input parameters with high correlation to output target values were utilized as the inputs to PNN. It has been found that the smoothing parameter σ =0.1 provided the smallest estimation error. The user-defined smoothing parameter σ affects largely the estimation accuracy in PNN as shown in Table 4. Table 5 illustrates some typical examples of estimation results for $\sigma = 0.1$.

2.4 Strength estimation using improved probabilistic neural network

An empirical method has been incorporated to specify σ in the conventional PNN technique, which causes significant uncertainty in the estimation results as shown in Table 4. In this study, therefore, improved probabilistic neural network(IPNN) was proposed to automatically calculate the smoothing parameter in the PNN by using the scheme of dynamic decay adjustment algorithm. The smoothing parameters are determined by equation (3) using two thresholds.

Table 2 Samples of specified concrete mix proportions of company A for training

Specified strength (MPa)	Slump (cm)	W/C weight ratio(%)**	Fine aggregate percentage (%)**	Unit water content (kg/m^3)	Unit cement content (kg/m^3)**	Unit fine aggregate content (kg/m^3)		Unit coarse aggregate content(kg/m^3)	Admixture (%)**
						Natural sand(s1)**	Crushed sand(s2)**		
9.8	8	84.9	50.4	181	213	372	558	941	0.64
11.76	10	76.9	49.2	183	238	358	538	951	0.72
13.72	12	69.9	48.2	185	266	346	518	954	0.80
13.72	21	69.9	50.0	204	293	344	517	885	0.88
15.68	10	64.2	46.6	179	279	335	503	987	0.84
15.68	15	64.2	47.6	190	296	334	502	945	0.89
17.64	5	59.4	44.7	167	281	326	490	1038	0.84
17.64*	12	59.4	46.1	182	306	326	489	979	0.92
17.64	18	59.4	47.3	195	328	325	487	930	0.98
20.58*	12	53.5	44.9	180	336	314	471	990	1.01
20.58	18	53.5	46.1	193	361	313	469	938	1.08
23.52	8	48.6	43.1	170	350	304	456	1030	1.05
23.52*	12	48.5	43.9	179	368	303	455	995	1.10
26.46	10	44.2	42.7	173	391	294	441	1014	1.17
26.46	18	44.3	44.3	190	429	292	438	942	1.29
29.4	10	40.9	42.0	172	421	286	428	1013	1.26
29.4	15	40.9	43.0	183	447	284	426	966	1.34
34.3	10	35.7	40.9	171	479	271	406	1005	1.44
34.3	18	35.7	42.5	187	524	268	402	931	1.57
37.24	18	33.4	42.1	187	557	261	392	922	167
39.2	15	32.1	41.2	180	561	258	387	945	1.68

* Samples used as test patterns to compare with test results in sec. 3

** Input data considering the correlation between input data and targeted output data

Table 3 Samples of specified concrete mix proportions of company B for training

Specified strength (MPa)	Slump (cm)	W/C weight ratio (%)**	Fine aggregate percentage (%)**	Unit water content (kg/m^3)	Unit cement content (kg/m^3)**	Unit fine aggregate content (kg/m^3)		Unit coarse aggregate content (kg/m^3)	Admixture (%)**
						Natural sand (s1)**	Crushed sand (s2)		
9.8	8	82.0	54.8	172	211	1040	-	875	1.06
11.76	10	73.8	53.1	174	238	995	-	895	1.19
13.72	12	66.3	51.4	175	263	951	-	915	1.32
13.72	21	66.9	50.6	190	286	907	-	902	1.43
15.68	10	63.0	50.9	171	271	942	-	927	1.36
15.68	15	63.0	50.4	180	285	916	-	919	1.43
17.64	5	59.0	50.5	162	277	944	-	944	1.39
17.64*	12	59.0	49.8	174	297	908	-	933	1.49
17.64	18	58.0	49.2	184	315	877	-	923	1.58
20.58*	12	53.0	48.6	173	329	874	-	943	1.65
20.58	18	53.0	48.0	182	346	846	-	934	1.73
23.52	8	49.0	48.2	165	339	873	-	956	1.7
23.52*	12	49.0	47.8	172	353	852	-	948	1.77
26.46	10	45.0	47.3	168	372	840	-	954	1.86
26.46	18	45.0	46.5	181	400	800	-	938	2.00
29.4	10	42.0	46.6	167	400	818	-	956	2.00
29.4	15	42.0	46.1	175	420	792	-	944	2.10
34.3	10	37.0	45.7	166	449	785	-	951	2.25
34.3	18	37.0	44.9	179	484	744	-	930	2.42
37.24	18	34.7	44.4	179	518	723	-	923	2.59
39.2	15	33.0	44.4	174	524	726	-	927	2.62

* Samples used as test patterns to compare with test results in sec. 3

** Input data considering the correlation between input data and targeted output data

Table 4 Estimation results of PNN

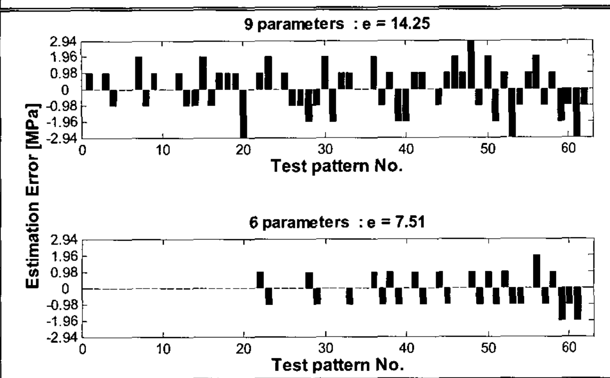
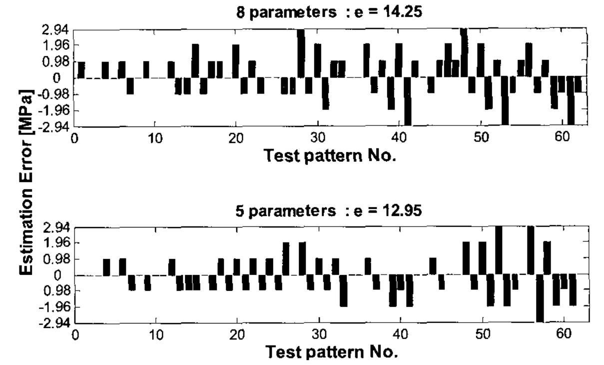
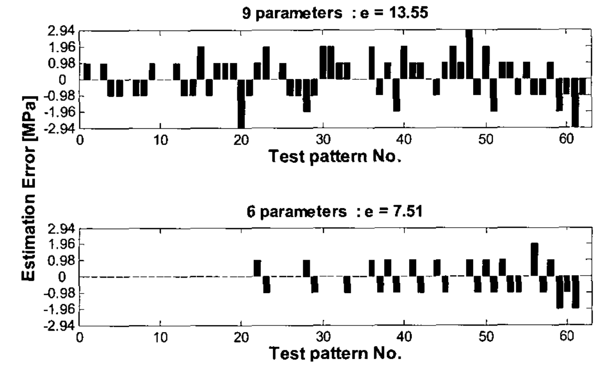
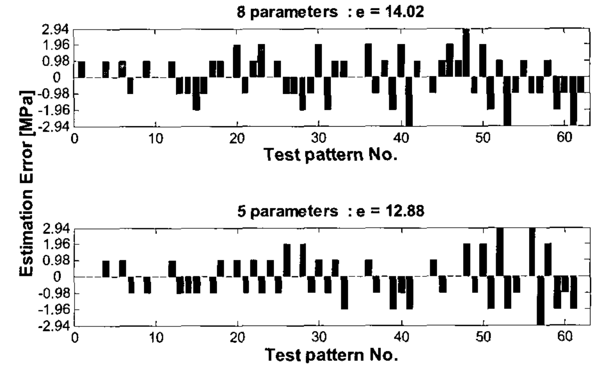
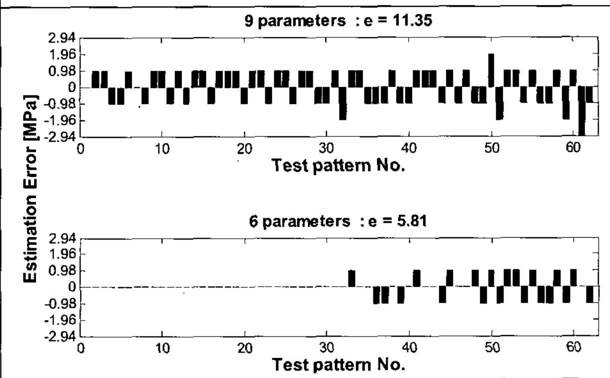
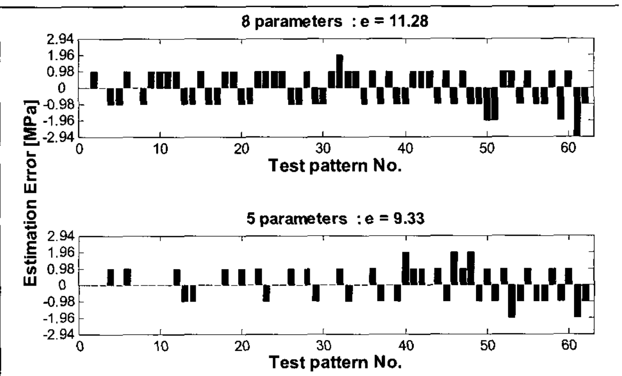
	Company A	Company B
$\sigma = 1.0$		
$\sigma = 0.5$		
$\sigma = 0.1$		

Fig. 3 shows the smoothing parameters implemented for 155 training samples and the estimation errors for 62 test patterns of each company using five(for Company B) or six (for Company A) parameters as input to IPNN. The estimated results of IPNN showed the smallest RMS errors than the best result of the conventional PNN using the constant smoothing parameter (i.e., the case σ =0.1). From these results, it has been found that the proposed method is very effective to predict the compressive strength of concrete by automatically calculating the smoothing parameters, not using user-defined values, based on the concrete mix proportions.

To enhance the estimation accuracy, the prediction of the concrete strength(i.e. classification) was performed iteratively; 62 test patterns(arbitrary 2 test patterns per each class) were selected exclusively from the concrete mix proportions of each company, and the remaining 155 patterns(5 patterns per each class) were utilized as training patterns. Classification was performed iteratively three times decreasing the number of classes, 31-5-3; at the first step, the whole possible classes(31 classes) were examined, and then the number of class to be examined was reduced based on the estimated results at the previous step. At the second step, 5 classes per each test pattern were selected comparing distances between the test pattern and estimated 31 classes at the first step, and then the prediction of compressive strength was performed using normalized training patterns for 5 classes. Finally, 3 classes per each test pattern were chosen by distance between the test pattern and estimated 5 classes at the second step, and then the prediction of compressive strength was performed using normalized training patterns for 3 classes. An iterative classification was incorporated since the number of possible classes is too large to estimate the concrete strength by using only 5 samples per each class. This scheme reduces the effects of the training samples far from test patterns and also increases the weighting effects of the training samples near the test patterns.

Table 5 Examples of estimation results for $\sigma = 0.1$

Company	Specified strength (MPa)	Slump (cm)	Water-cement ratio (%)**	Fine aggregate percentage (%)**	Unit water content (kg/m^3)	Unit cement content (kg/m^3)**	Unit fine aggregate content (kg/m^3)**		Unit coarse aggregate content (kg/m^3)	Admixture (%)**	OUTPUT class (9/8 parameters)	OUTPUT class (6/5 parameters)
							Natural sand (s_1)	Crushed sand (s_2)				
A	9.8	10	85	50.8	185	218	372	559	926	0.65	9.8	9.8
	11.76	8	76.9	48.8	179	233	358	538	966	0.69	10.78	11.76
	15.68	8	64.2	46.3	175	273	335	503	1001	0.82	14.7	15.68
	17.64*	12	59.4	46.1	182	306	326	489	979	0.92	18.62	17.64
	19.6	10	55.3	44.9	177	319	318	477	1004	0.96	20.58	19.6
	20.58*	12	53.5	44.9	180	336	314	471	990	1.01	21.56	20.58
	23.52*	12	48.5	43.9	178	368	303	455	994	1.10	24.5	23.52
	25.48	8	45.5	42.5	170	373	297	445	1031	1.11	26.46	26.46
	27.44	10	43.2	42.4	173	401	291	437	1014	1.2	26.46	26.46
	29.4	8	40.9	41.6	168	411	286	429	1031	1.31	30.38	30.38
	33.32	8	36.9	40.8	167	454	275	413	1026	1.38	32.34	32.34
	35.28	8	35.2	40.4	166	475	270	405	1022	1.43	36.26	36.26
	37.24	8	33.6	40.1	166	495	265	398	1019	1.49	36.26	36.26
	39.2	8	32.2	39.8	165	514	261	392	1016	1.54	36.26	39.2
B	10.78	12	77.8	53.7	178	229	1004	-	882	1.15	10.78	10.78
	14.7	18	64.0	50.3	185	290	905	-	912	1.45	15.68	15.68
	17.64*	12	59.0	49.8	174	297	908	-	933	1.49	16.66	17.64
	18.62	8	56.2	49.8	165	296	923	-	944	1.48	19.6	18.62
	20.58*	12	53.0	48.6	173	329	874	-	943	1.65	21.56	21.56
	21.56	18	51.6	47.8	183	353	838	-	934	1.77	20.58	22.54
	23.52*	12	49.0	47.8	172	353	852	-	948	1.77	24.5	23.52
	26.46	12	45.0	47.1	171	378	831	-	951	1.89	25.48	26.46
	28.42	8	42.6	47.0	164	385	836	-	960	1.93	27.44	27.44
	29.4	12	42.0	46.4	171	408	808	-	952	2.04	30.38	30.38
	32.34	18	39.0	45.3	179	462	759	-	933	2.31	31.36	34.3
	34.3	8	37.0	45.9	163	441	795	-	956	2.21	32.34	35.28
	37.24	8	34.6	45.4	162	469	777	-	952	2.35	36.26	36.26
	39.2	8	33.0	45.1	172	488	765	-	949	2.44	36.26	37.24

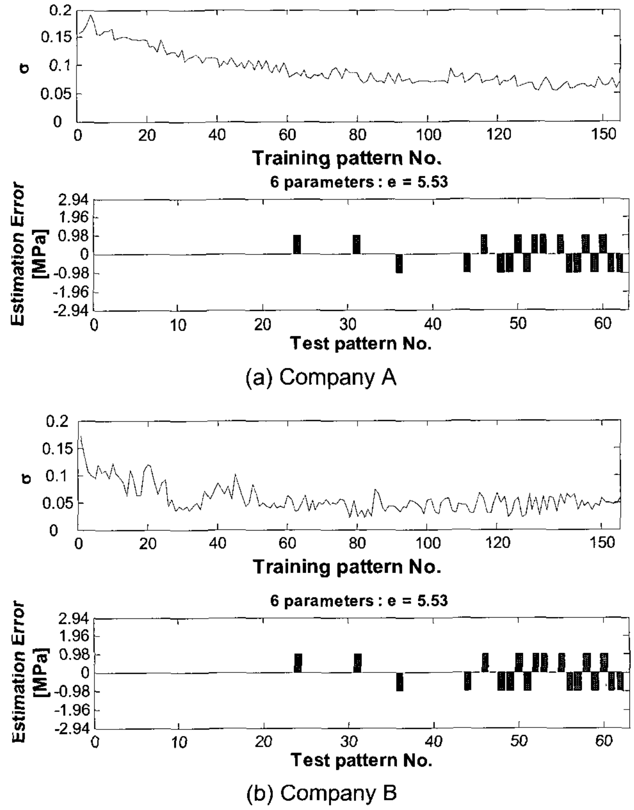


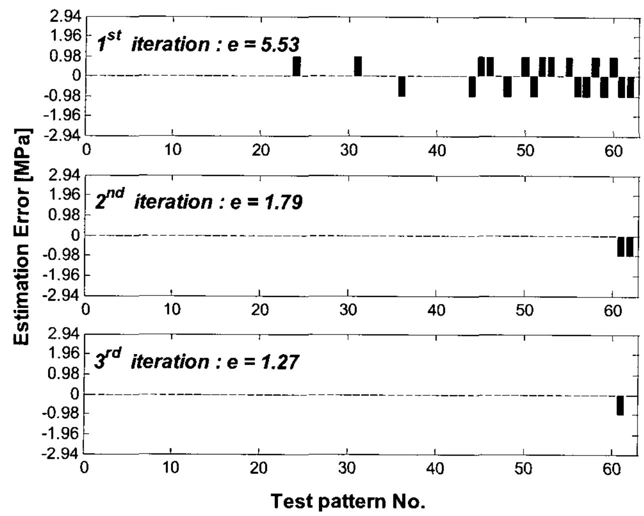
Fig. 3 Estimation results of IPNN

Table 6 shows examples of the results for the iterative classification. For example of specified strength of 23.52MPa in Company B, the whole 31 classes(9.8~39.2MPa) were examined at the first iteration(22.54MPa). Then, 5 classes (classes 12~16) were selected based on the distance between training patterns of 23.52MPa and training patterns of other classes at the first iteration(24.5MPa). Finally, 3 classes (classes 14~16) were selected based on the distance between training patterns of 23.52MPa and training patterns of 5 classes at the second iteration(23.52MPa). Final result for iterative classification was 23.52MPa. Fig. 4 shows the estimation errors for all the test patterns through iteration. Misclassifications occur for all test cases and the level of the misclassifications is quite large at the first iteration step. It is also found that the number and the level of misclassifications are reduced as the classification proceeds iteratively. The estimation errors at the final stage are reduced to 1.27 and 5.08 in RMS level for the cases of two concrete companies A and B, respectively. According to the results shown in Table 6 and Fig. 4, it has been found that the iterative classification scheme is very effective in dealing with fewer training patterns and numerous classes.

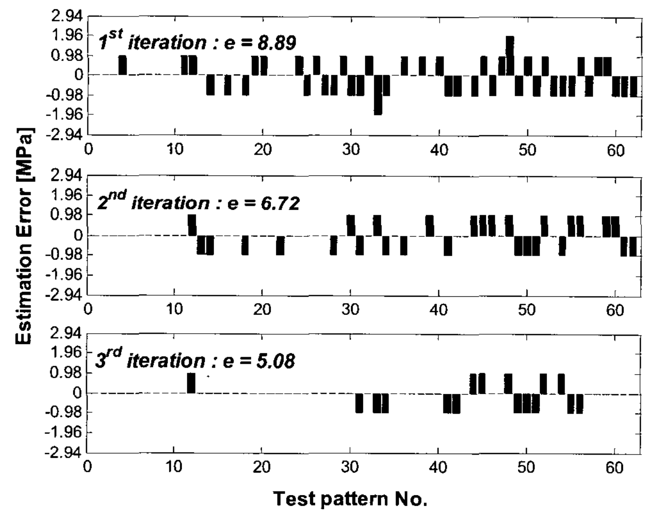
Table 6 Examples of the results for iterative classification

Company	Specified strength (MPa)	Slump (cm)		1st iteration (whole range)	2nd iteration (5class)	3rd iteration (3class)
A	17.64	15	Range	1~31	7~11	8~10
			Est. Value	17.64	17.64	17.64
	20.58	15	Range	1~31	10~14	11~13
			Est. Value	21.56	20.58	20.58
	23.52	15	Range	1~31	13~17	14~16
			Est. Value	23.52	23.52	23.52
	34.3	18	Range	1~31	24~28	25~27
			Est. Value	35.28	34.3	34.3
	39.2*	8	Range	1~31	27~31	29~31
			Est. Value	38.22	38.22	38.22
B	17.64	15	Range	1~31	7~11	8~10
			Est. Value	16.66	16.66	17.64
	20.58	15	Range	1~31	10~14	10,12,13
			Est. Value	21.56	20.58	20.58
	23.52	15	Range	1~31	12~16	14~16
			Est. Value	22.54	24.5	23.52
	34.3*	15	Range	1~31	23,24,25,27,28	24, 25, 27
			Est. Value	35.28	35.28	35.28
	39.2	8	Range	1~31	25,27,29,30,31	29~31
			Est. Value	38.22	38.22	39.2

* Misclassification



(a) Company A



(b) Company B

Fig. 4 Estimation results of IPNN

3. Comparison of predicted and test results

The predicted strengths are compared with the results of the actual compression tests of two concrete companies for verification. The results of the compression tests of concrete may be affected by the type of test specimens, specimen size the type of moulds, curing conditions, the preparation of end surfaces, the rigidity of a testing machine, and the rate of application of stress. Besides, significant changes which have an influence on the compressive strength of concrete include those in the type of Portland cement, admixtures, source of aggregates, mix proportions, batching, mixing, and delivery. In these tests, the specified strengths of concrete are 17.64, 20.58, and 23.52 MPa and slump is 12cm. Cylindrical specimens with size ϕ 100×200mm, which are made according to the mix proportions shown in Tables 2 and 3, are used. The tests follow the requirements of KS F2405 (1997) and ASTM C39-93a at an age of 28 days[22, 23]. The results of the tests are shown in Table 7.

Comparing the specified strengths in the table, the maximum percentage of the differences between the specified strength by tests (f'_{c1}) and the specified strength in concrete mix proportions (f'_c) is 3.9 percent. In this paper, the specified strengths are the required average strength. This indicates that the results of tests show good agreement with the specified strengths.

Fig. 5 shows the estimated results obtained by PNN and IPNN comparing with the test results of two concrete companies A and B. Training patterns are the same as in the previous section (217 training patterns) and test patterns for specified compressive strengths of 17.64, 20.58, 23.52MPa with slump 12cm are the same as shown in Tables 2 and 3. The estimated results can be represented from the viewpoint of probability. The distribution function is normalized to have unity at the maximum point as a matter of convenience. To see more detailed results, for the case of the specified compressive strength 20.58MPa in Fig. 5(a), the number of specimens is 354 and the test result shows normal distribution, wherein the mean value of the specified strength is 20.38MPa and the standard deviation is 1.72MPa.

The distribution of concrete strength was estimated by the Parzen non-parametric estimator of the probability density functions used in the PNN algorithm. Density estimation was carried out for three constant smoothing parameters used in PNN (σ=1.0, 0.5, 0.1) and the smoothing parameters determined in IPNN as shown in Fig. 3. It is found that the estimated density function using the smoothing parameter in IPNN shows the best reasonable agreement with the distribution of the test results, while all the estimated density functions show a peak value at 20.58MPa for all the cases.

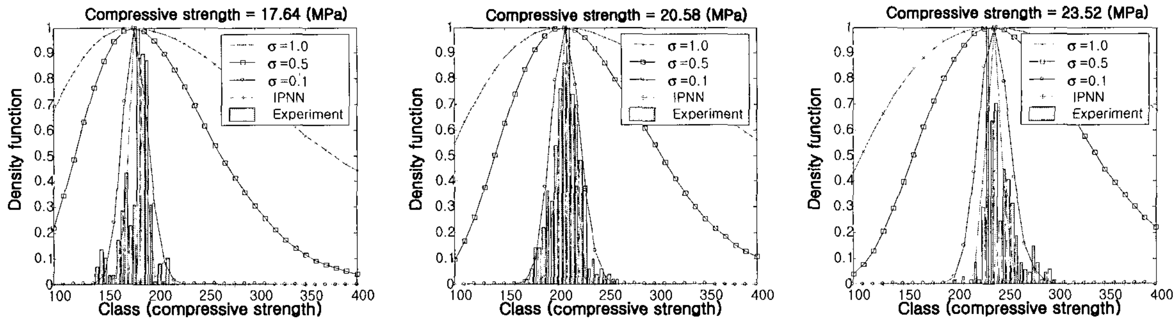
General trends for the cases of specified strengths of 17.64, 23.52MPa in company A and all the cases in company B are

Table 7 Results of compression tests

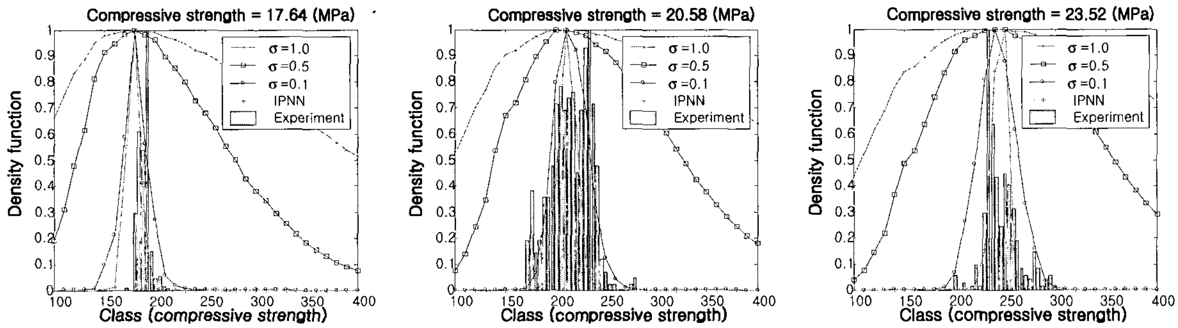
Company	Mix proportion		Test		
	Specified strength (f_c',MPa)	Slump(cm)	Number of tests	Standard deviation (σ,MPa)	Specified strength (f_{cl}', MPa)
A	17.64	12	447	1.26	18.33(3.9)
	20.58	12	354	1.72	20.38(1.0)
	23.52	12	372	1.77	23.91(1.7)
B	17.64	12	345	1.11	17.64(0.0)
	20.58	12	435	1.59	20.58(0.0)
	23.52	12	363	1.62	23.91(1.7)

* The numerical values in parentheses present the percentages of the differences between the specified strength by test results and the specified strength on mix proportion.

** The range of error percentages is 0.0 to 3.9 percent.



(a) Company A



(b) Company B

Fig. 5 Comparison of estimated result with test results

almost the same as the aforementioned results. These results, which bring a probabilistic point of view in addition to classification/prediction capability, are practically attractive, while the conventional methods such as statistical analyses, neural network, etc. can give a deterministic value, since the tests of concrete strength for specimens under the same conditions show distributed characteristics in nature. Moreover, IPNN provides an automatic way to predict the concrete strength based on the concrete mix proportion data.

4. Conclusions

This paper presents probabilistic neural network technique to predict the compressive strength of concrete. The use of probabilistic neural network to predict and manufacture concrete with expected strength at construction sites is a very promising method.

The concrete mix proportions and the slump values of two ready-mixed concrete companies are used as inputs to the networks, and the compressive strength of concrete is defined as classes to be predicted by the networks. The estimation performance of PNN was improved by considering the correlation between input data and targeted output values. Improved probabilistic neural network (IPNN) was proposed to automatically calculate the smoothing parameter in the conventional PNN by using the scheme of dynamic decay adjustment algorithm. The validity of the proposed method was proven by comparing the predicted strength with the test results of the concrete. It has been found that the estimation results using the smoothing parameter in IPNN show the best agreement with the distribution of the test results. The distribution of concrete strength was successfully estimated using the Parzen's density estimator which gives a probabilistic point of view, not a deterministic value.

This study demonstrates the efficacy of the probabilistic neural network-based technique for predicting compressive strength of concrete based on concrete mix proportions. This method can contribute to the maintenance of concrete quality for optimal concrete mixes. As the database containing mix proportions and specified and tested strengths is expanded over the time, the probabilistic neural network using the training data obtained from this database will become more effective and the resulting predictions will become more reliable. As future study, other important data that also affect concrete strength such as the uncertainty of concrete(i.e., the quality variation of aggregate and cement, measuring error, mixing conditions, etc.) and the type of cement(i.e., Portland cement, High Early Strength Portland Cement, Moderate - Heat Portland Cement, Alumina Cement, Slag Cement, etc.) and in-field conditions(i.e., delivery distance, curing conditions, etc.) and their co-relationships need to be collected and considered in the probabilistic neural network.

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References

1. Snell, L.M., Van Roekel, J.V., and Wallace, N.D., "Predicting Early Concrete Strength", *Concrete International*, Vol.11, No.12, 1989, pp.43~47.
2. Popovics S., "History of a mathematical model for strength development of Portland cement concrete", *ACI Materials Journal*, Vol.95, No.5, 1998, pp.593~600.
3. Oh, J. W., Lee, I.W., Kim, J. T., and Lee, G. W., "Application of Neural Networks for Proportioning of Concrete Mixes", *ACI Material Journal*, Vol.96, No.1, 1999, pp.61~67.
4. Lee, S.C., *Prediction of Concrete Strength Using Artificial Neural Networks, Engineering Structures*, Vol. 25, 2003, pp. 849~857.
5. Kim, J. I., Kim, D. K., Feng, M. Q., and Yazdani, F., "Application of Neural Networks for Estimation of Concrete Strength", *Journal of materials in Civil Engineering*, ASCE, Vol.16, No.3, 2004, pp.257~264.
6. Touretzky, D.S., Thibadeau, R.H. and Romero, R.D., "Optical Chinese character recognition using probabilistic neural networks", *Pattern recognition*, Vol.30, No.8, 1997, pp.1279~1292.
7. Raghu, P.P. and Yegnanarayana, B., "Supervised texture classification using a probabilistic neural network and constraint satisfaction model", *IEEE transactions on neural networks*, Vol.9, No.3, 1998, pp.516~522.
8. Lin, S. H., Kung, S. Y., and Lin, L. J., "Face recognition/detection by probabilistic decision-based neural network", *IEEE transactions on neural networks*, Vol.8, No.1, 1997, pp.114~132.
9. Chtioui, Y., Bertrand, D., Devaux, M.F. and Barba, D., "Comparison of multilayer perceptron and probabilistic neural networks in artificial vision. Application to the discrimination of seeds", *Journal of chemometrics*, Vol. 11, No.2, 1997, pp.111~129.
10. Wang, Y., Adali, T., Kung, S. Y., and Szabo, Z., "Quantification and segmentation of brain tissues from MR images: a probabilistic neural network approach", *IEEE transactions on image processing*, Vol. 7, No.8, 1998, pp.1165~1181.
11. Holmes, E., Nicholson, J. K., and Tranter, G.., "Metabonomic Characterization of Genetic Variations in Toxicological and Metabolic Responses Using Probabilistic Neural Networks", *Chemical research in toxicology*, Vol.14, No.2, 2001, pp.182~191.
12. Zaknich, A., "Introduction to the modified probabilistic neural network for general signal processing applications", *IEEE transactions on signal processing : a publication of the IEEE Signal Processing Society*, Vol. 46, No.7, 1990, pp.1980~1990.
13. Yang, Z. R., Platt, M. B., and Platt, H. D., "Probabilistic Neural Networks in Bankruptcy Prediction", *Journal of business research*, Vol. 44, No.2, 1999, pp.67~74.
14. Goh, A. T. C., "Probabilistic neural network for evaluating seismic liquefaction potential", *Canadian geotechnical journal: Revue canadienne de géotechnique*, Vol.39, No.1, 2002, pp.219~232.
15. Aoki, T., Ceravolo, R., De Stefano, A., Genovese, C., and Sabia, D., "Seismic vulnerability assessment of chemical plants through probabilistic neural networks", *Reliability engineering & system safety*, Vol.77, No.3, 2002, pp.263~268.
16. Sinha, S. K. and Pandey, M. D., "Probabilistic Neural Network for Reliability Assessment of Oil and Gas Pipelines", *Computer-aided civil and infrastructure engineering*, Vol. 17, No.5, 2002, pp.320~329.
17. M.R. Berthold and J.Diamond, "Boosting the performance of RBF networks with dynamic decay adjustment", *Advances in Neural Information Processing Systems*, No.7, 1995, pp.521~528.
18. M.R. Berthold, "A probabilistic extension for the DDA algorithm, in: Int. Conf. on Neural Network", *IEEE*, New York, Vol.1, 1996, pp. 341~346.
19. Specht, D. F., *Probabilistic Neural Networks*, Neural Networks 3, 1990, pp.109~118.
20. Parzen, E., "On estimation of a probability density function and mode", *Annals of Mathematical Statistics*, Vol.33, 1962, pp.1065~1076.
21. Cacoullos, T. "Estimation of a multivariate density", *Annals of the Institute of Statistical Mathematics*, Tokyo, Vol.18, No.2, 1966, pp.179~189.
22. M.R. Berthold and J.Diamond, *Constructive training of probabilistic neural networks*, Neurocomputing, 1998, pp. 167~183.
23. Jin, X., Cheu, R.L., and Srinivasan, D, "Development and adaptation of constructive probabilistic neural network in freeway incident detection", *Transportation Research Part C*, Vol.10, 2002, pp.121~147.
24. ASTM. "Standard Test Method for Compressive Strength of Cylindrical Concrete Specimens", *Annual Book of ASTM Standards: ASTM39-93a*, Vol.4, No.2, 1992, pp.22~24.
25. Korean Standard Association, *Stand Test Method for Compressive Strength of Cylindrical Concrete Specimens*, KS F2405, 1997, 199pp.
26. Rumelhart, D. E., McClelland, J. L., & the PDP Research Group, *Parallel distributed processing*, Vol.1: Foudations. Cambridge, MA: The MIT Press., 1986.