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ANALYSIS OF EXPERIMENTAL DATA USING A NEURAL NETWORK
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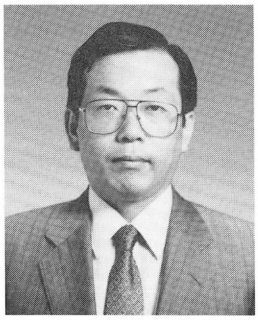

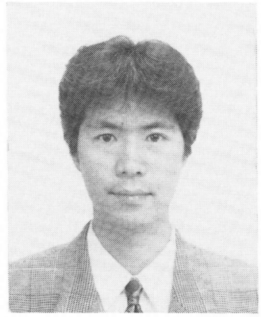

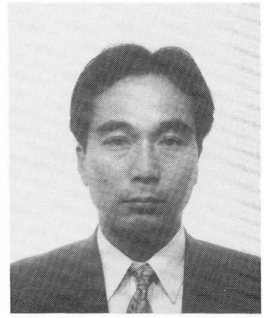

Tsukasa SEKIGUCHI　Taketo UOMOTO　Yoshiaki TAKADA　Tadashi WATANABE

SYNOPSIS

Models based on a neural network were used to analyze the data obtained from accelerated carbonation tests and concrete mixing. The models were compared with empirical equations proposed by other researchers, and a study was implemented to determine important factors not considered in the equations.
The results show that models based on a neural network are effective both in estimating the experimental results and in making important factors much easier to isolate than with conventional analysis. This indicates that a neural network is a valid way to analyze experimental data, not only for the estimating of values but also to help find important factors governing the phenomenon.

Keywords: neural network, analysis, experimental data, carbonation, mixing

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1. INTRODUCTION

It can be said that concrete technology is to a large extent based on experimental results and past site experience. This has led to the use of many empirical equations since the characteristics of concrete vary greatly. For this reason, evaluation of the characteristics of concrete should focus on variations.

It is common these days to see neural networks, which simulate the information processing functions of the human brain, being applied to handle fuzzy data. Fuzzy data can be handled by this type of method since the information is expressed not in definite logic but a scatter. Because of its advantages, neural networks have been tried in various fields, including letter and voice recognition and the control of robots. In this paper, a neural network model is proposed for the evaluation of experimental data obtained in accelerated carbonation tests and concrete mixing. We substitute empirical equations with a neural network model and determine the key factors governing the phenomena using the neural network's output.

2. NEURAL NETWORK

2.1 The principle of neural networks

Conventional computation methods follow logical processes with step by step serial processing. To simulate the normal human's activities in this way would require a very complex and detailed program.

In an attempt to solve this problem, the neural network has been developed. This means the simulation of information processing in the human brain. This method is completely different from conventional computation methods, since a large number of processing elements operate synchronously and carry out processing in parallel. These elements represent widely scattered information, and do not have strongly logical relationships. Consequently, this method is not always suitable for logically strict processing, but it is always suitable for the processing of information with fuzziness, such as analogy or association processing. Moreover, it is not necessary to design a complicated program, since techniques are different from the conventional computation method. The need is to prepare learning data and ensure feedback to the input as to whether the output from the network is correct or not; the network then learns to generate the correct answer by gradually changing the logical relationship. As a consequence, the network is flexible, and systems of information can change gradually by adding to, or supplementing the incomplete input information.

2.2 Model

An artificial brain cell is modeled using a multi-input one-output device as shown in Fig.1. This is called one unit. Units are connected by lines corresponding to nerve fibers. Signals are transmitted in one direction, and become inputs to connection units, which add a certain weight. The strength of a connection unit is represented by the value of this weighting. The summation of all weighted input values is reduced by a threshold value and the output is modified by a response function. In this research, a sigmoid function was used

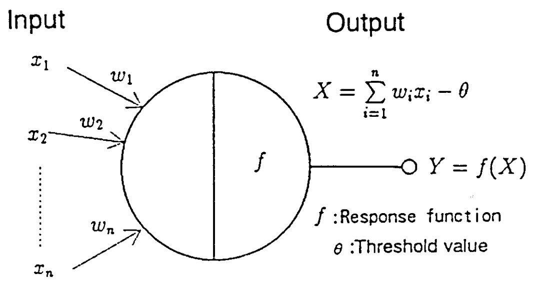

Fig.1 Unit

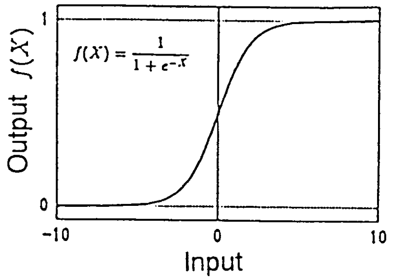

Fig.2 Sigmoid function

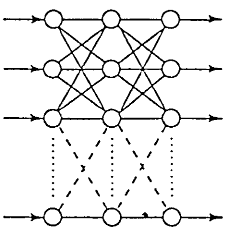
Fig.3 Layer type network

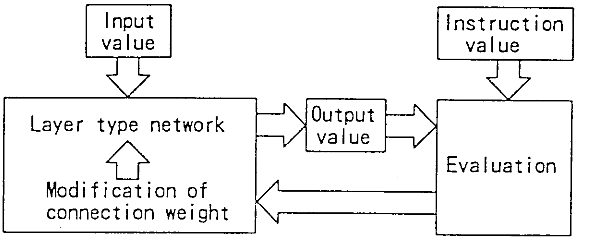

Fig. 4 Learning method

as shown in Fig. 2. The weights of connection units and the threshold values can be adjusted by learning. Processing elements of this type are connected in network form to carry out information processing. The model used in this study is called a layer type, and is shown in Fig. 3. In this model, signals travel from the input layer to the output layer.

2. 3 Learning method[1]~[5]

The most popular learning mechanism for layer-type networks, and the method adopted in this study, is described in next paragraph (see Fig. 4). If a certain pattern of input values is introduced into the input layer, a certain output value is obtained which depends on the value of the connection weights and which varies time-by-time. The squared error between this output and the instruction value acts as an evaluating function, and is used to adjust the connection weights and threshold values. In order to simplify the model, an input parameter of value -1 is always added so that the related threshold value can be dealt with as a weight.

Suppose following value and function are true for unit j

[input] $u_j = \sum_i w_{j,i} x_i - \theta_j$ (1)

[output] $y_j = f(u_j)$ (2)

$$f(u_j) = \frac{1}{1+e^{-u_j}} \quad (3)$$

where $w_{j,i}$:connection weight to unit i
x_i :input from unit i
θ_j :threshold value

Then the following error function is adopted:

$$E = \frac{1}{2}\sum_{j,c}(y_{j,c} - \hat{y}_{j,c})^2 \tag{4}$$

$\hat{y}_{j,c}$:value that unit j should output for a certain input vector c
$y_{j,c}$:actual output of unit j for a certain input vector c

A gradient descent method, entailing differentiation by parameter and adjusting the parameter in the gradient direction, may be used. In that case, each weight is changed using following equations:

$$\Delta w_{j,i} = -\varepsilon \frac{\partial E}{\partial w_{j,i}} \ (\varepsilon > 0) \tag{5}$$

Then we can find the local minimum of E. The algorithm is shown below.

$$\frac{\partial E}{\partial w_{j,i}} = \sum_c \frac{\partial E}{\partial y_{j,c}} \frac{dy_{j,c}}{du_{j,c}} \frac{\partial u_{j,c}}{\partial w_{ji,c}} \tag{6}$$

$$\begin{cases} \frac{dy_j}{du_j} = f\prime(u_j) & (7) \\ \frac{\partial u_j}{\partial w_{j,i}} = y_i & (8) \end{cases}$$

$$\Delta w_{j,i} = -\varepsilon \sum_c \frac{\partial E}{\partial y_{j,c}} f\prime(u_{j,c}) y_{i,c} \tag{9}$$

When all outputs are obtained using this algorithm, the connection weight can be changed. However if the value of ε is small enough, the connection weight can be changed every time an output is obtained, and the overall change is almost the same as in the gradient descent method.

$$\Delta w_{j,i} = -\varepsilon \frac{\partial E}{\partial y_{j,c}} f\prime(u_{j,c}) y_{i,c} \tag{10}$$

Thus, even in a case where the form of the evaluating function is unknown, the connection weight changes according to the gradient direction every time an output is obtained, and the output converges to an almost optimum value.

At the output layer

$$\frac{\partial E}{\partial y_{j,c}} = (y_{j,c} - \hat{y}_{j,c}) \tag{11}$$

$$\begin{aligned} f\prime(u_{j,c}) &= \frac{e^{-u_{j,c}}}{(1+e^{-u_{j,c}})^2} \\ &= y_{j,c}(1 - y_{j,c}) \end{aligned} \tag{12}$$

So

$$\Delta w_{j,i} = -\varepsilon \sum (y_j - \hat{y}_j) y_i (1 - y_j) y_i \tag{13}$$

$\frac{\partial E}{\partial y_j}$ is solved easily. On the other hand, $\frac{\partial E}{\partial y_j}$ isn't solved easily for units in hidden layers. Therefore we attempt to solve $\frac{\partial E}{\partial y_j^{(k)}}$ for k-layer units in the network.

$$\frac{\partial E}{\partial y_j^{(k)}} = \sum_i \frac{\partial E}{\partial y_i^{(k+1)}} \frac{dy_i^{(k+1)}}{du_i^{(k+1)}} \frac{\partial u_i^{(k+1)}}{\partial y_j^{(k)}}$$

$$= \sum_i \frac{\partial E}{\partial y_i^{(k+1)}} f\prime(u_i^{(k+1)}) w_{i,j}^{(k+1)} \quad (14)$$

$\frac{\partial E}{\partial y_j^{(k)}}$ has already been calculated (the error transfer from output to input). Thus $\frac{\partial E}{\partial y_j^{(k+1)}}$ can be solved. That is to say, we obtain the error transfer backward, from the output layer to the input layer. The learning algorithm of this minimize the squared error to the multi-layer network is called "back propagation" and is often used as a learning law for layer-type networks.

The problem in applying this algorithm is a suitable method of determining the practical learning constant, the weight increment per learning step, the number of hidden layer units, and the number of hidden layers, etc..

3. APPLICATION TO ACCELERATED CARBONATION TEST RESULTS

3.1 Carbonation of concrete

Concrete is high in alkalinity. However, the reaction between atmospheric carbon-dioxide, which diffuses into the concrete, and calcium hydroxide, which produced in the hydration process, reduces the alkalinity. This process is called carbonation, and it progresses from the surface inwards. Various equations have been proposed to predict the progress of concrete carbonation. The most popular of them is called the Square Root t Law,

$$X = k\sqrt{t} \quad (15)$$

where X : carbonation depth
t : time
k : coefficient of carbonation rate

Since carbonation under natural conditions takes a long period of time, we often use accelerated carbonation tests with high concentrations of carbon-dioxide and at high temperature. However, the results of accelerated tests do not always agree well among themselves. Therefore, the relationship between accelerated test results and carbonation under natural conditions is not clear. To solve this problem, it is important to obtain an equation for carbonation rate which takes account of the concentration of carbon-dioxide, temperature, and relative humidity etc..

3.2 Past investigations

In Uomoto's work[7], the water-cement ratio, temperature, and concentration of carbon-dioxide were chosen as important factors affecting carbonation, and an attempt was made to determine the relationship between these factors and carbonation rate. First of all, the reliability of the Square Root t Law was checked in the case of accelerated carbonation tests. The coefficient of carbonation rate was assumed to be a function of temperature, water-cement ratio, and concentration of carbon-dioxide. The following empirical equation based on the results of their own experiments and those of others' was proposed:

$$X = (2.804-0.847\log C)\times e^{(8.748-\frac{2563}{T})}\times(2.39W^2+44.6W-3980)\times10^{-4}\times\sqrt{Ct} \qquad (16)$$

where X : Carbonation depth (mm)
C : Concentration of carbon-dioxide (%)
T : Absolute temperature (K)
W : Water-cement ratio (%)
t : Time (week)

3.3 Application of a neural network (1)

a) Estimation model

The first need is to check whether the coefficient of carbonation rate as calculated by the equation above can be estimated from the temperature, water-cement ratio, and concentration of carbon-dioxide using a neural network. The data introduced into the network is the same as used to determine the equation. The number of learning data is 150, obtained from various experiments performed by more than 20 groups of researchers. These data are taken only from experiments with ordinary portland cement; other parameters selected are 10℃～40℃ in temperature, 30%～80% in water-cement ratio, and 0.07% (natural environment)～100% carbon-dioxide concentration. From these data, three factors (temperature, water-cement ratio, and concentration of carbon-dioxide) were selected as inputs for the network; the coefficient of carbonation rate was the output. Since there are the other contributory factors, such as curing conditions, relative humidity, and errors, etc., the input factors, which have the same value of each, do not always give the same coefficient of carbonation rate. Therefore, for such data, the average coefficient of carbonation rate has been adopted as the instruction value. After this treatment, the number of learning data becomes 71. The network has three layers and three units in the input layer, six units in the hidden layer, and one unit in the output layer, as shown in Fig.5.

b) Results and discussion

When learning has progressed until it converged, the output was checked. In the learning process, the weight modification per learning step was varied. One of the learning results (number of learning=80000) is shown in Table 1 and Fig.6. Next we estimate the result for the original 150 data by using the learned network and compare the result with an estimation by the empirical equation (Table 2). This comparison shows that the estimate made by the neural network is better than that by the equation for the data used in this case.

In order to further check the neural network against the equation, two of the three factors were fixed while the other was gradually changed or one factor was fixed while the others were gradually changed. The network's output for these conditions is shown in Figs.8, 9. In the graph, T represents temperature (℃), W is water-cement ratio (%), and C is concentration of carbon-dioxide (%). For example, T40.W60 means that concentration of carbon-dioxide was gradually changed under conditions of temperature 40℃ and water-cement ratio 60%. The same has been done for the empirical equation as a comparison. From these results, it can be seen that the output of the network is almost the same trend as the result given by the equation, which was derived from theoretical considerations. However, when the temperature is varied, the results are

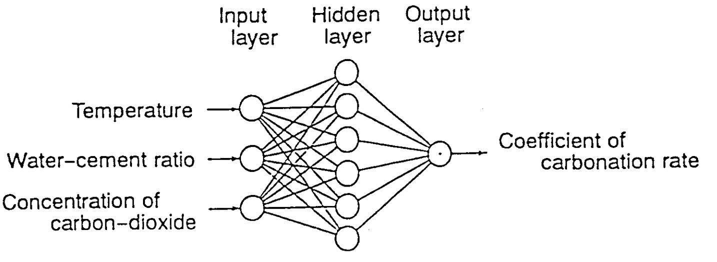

Fig. 5 Network model (1)

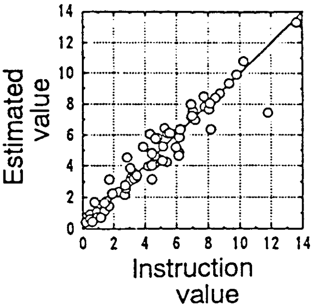

Fig.6 Estimation result (1)

Table 1 Eatimation results (Input 3)

Number of learning data	71
Learning times	80000
Average squard error	0.7364
Correlation coefficient	0.9570

Table 2 Comparison of the estimation results (1)

	Network (CASE1)	Proposed equation (eq. 16)
Number of data	150	150
Average squared error	1.3823	1.7244
Correlation coefficient	0.8878	0.8572

slightly different. As previously mentioned, the equation was obtained from experimental data at 20℃～40℃. After this work, test results for 50℃ were obtained, and they matched the curve drawn by this network.

3.4 Application of a neural network (2)

a)The estimation model

As a next step, the curing conditions were added as an input parameter, since they may influence the coefficient of carbonation rate. Since curing conditions cannot be described by a simple numerical value as can the other three factors, three units are chosen to represent curing. Each one, when given a value of 1 represents a certain curing condition — water curing, steam curing, or spray curing. Air curing is represented by a value of 0 for all three units. Therefore, using this method, four different curing conditions can be distinguished. Because many of the data used in the previous section were obtained from experiments with water curing, 46 further data points are added, many of which are obtained from experiments with other curing conditions. As in the previous section, the input parameters of learning data, which are now six, do not always give the same coefficient of carbonation rate, so we regarded the average of it as the instruction value. After this treatment, the number of learning data becomes 96. The network is the same as that used in section 3.3, except that there are six units in the input layer and eight in the hidden layer (Fig. 9).

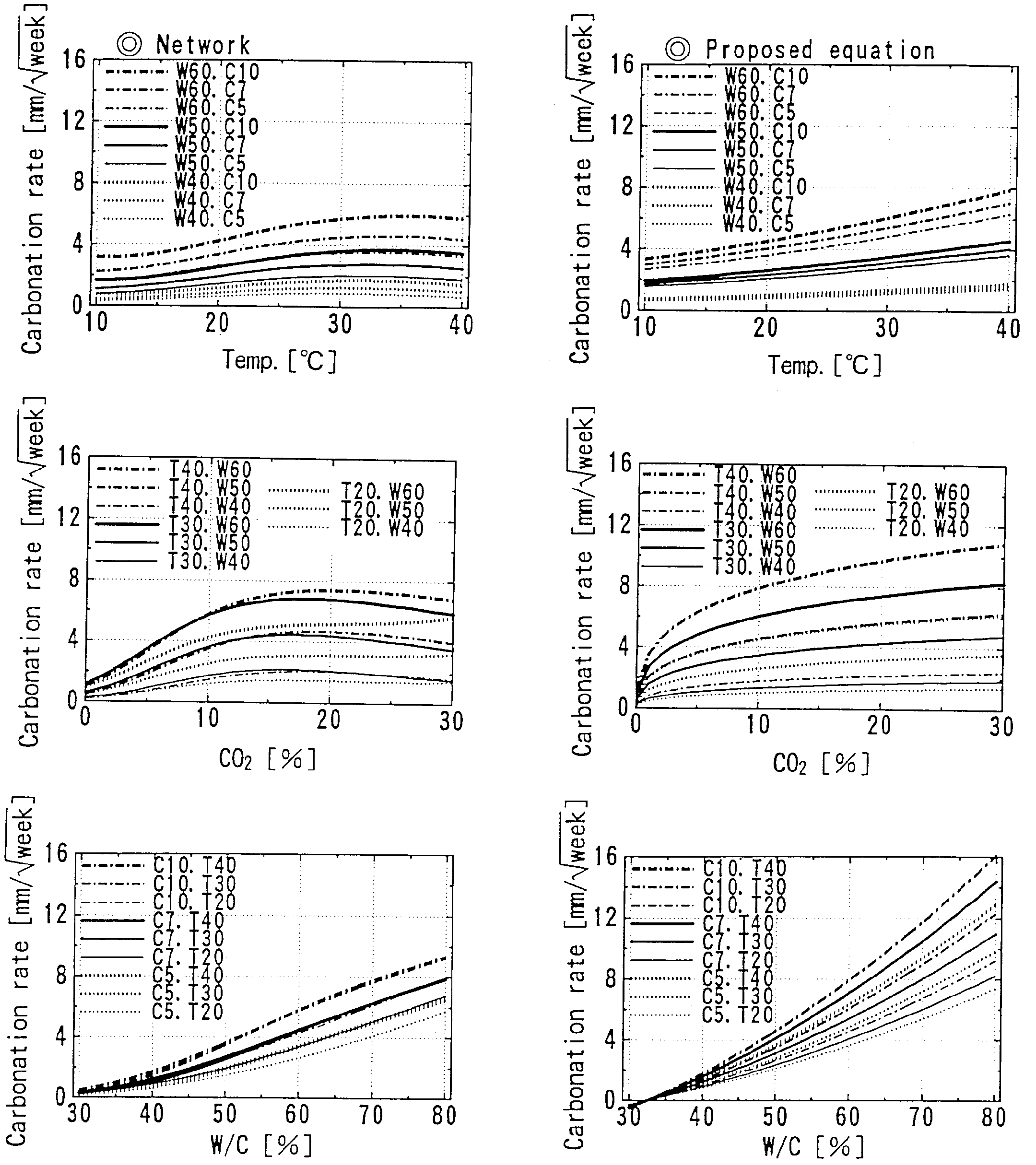

Fig.7 Network's output (1)

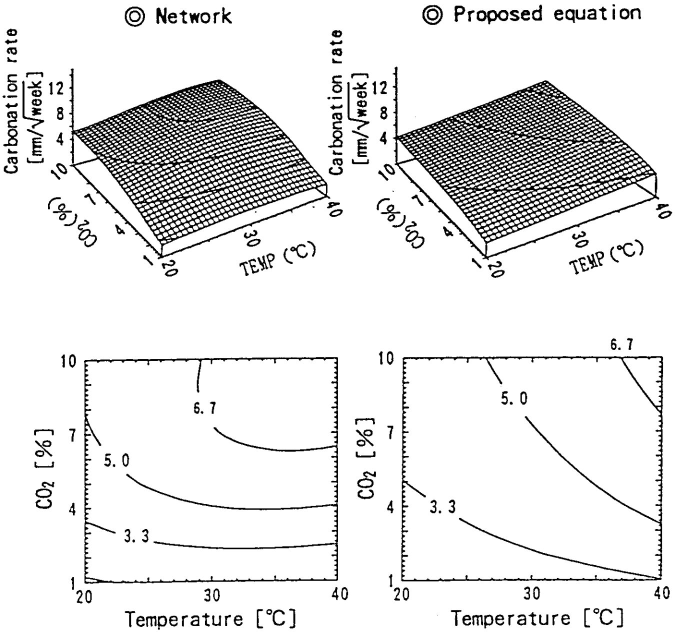

Fig. 8 Network's output at water-cement ratio 60%

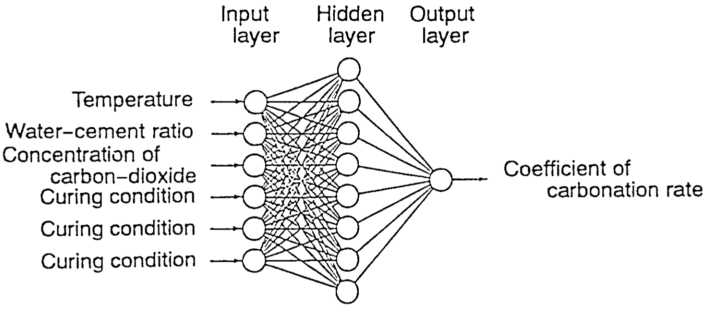

Fig. 9 Network model (2)

Table 3 Learning results (Input6)

Number of learning data	96
Learning times	150000
Average squared error	0.5274
Correlation coefficient	0.9705

Table 4 Comparison of the estimation results (2)

	Network		Proposed equation
	Input 6	Input 3	(eq. 16)
Nuber of data	141	141	141
Average squard error	0.9124	1.3616	1.5912
Correlation coefficient	0.9285	0.8914	0.8218

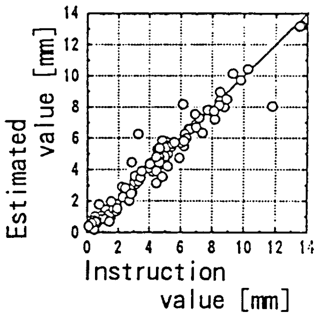

Fig. 10 Estimation result (2)

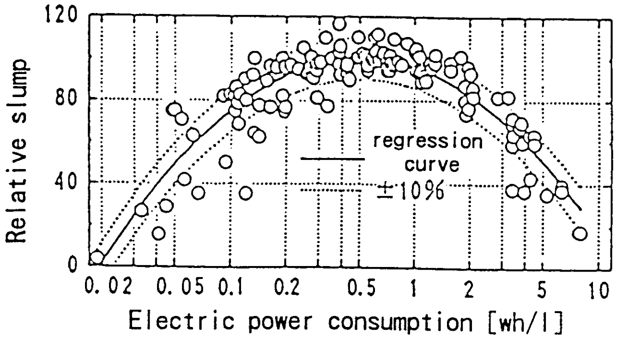

Fig. 11 Generalization of slump variation curve

b) Results and discussion

Learning is stopped when the network's output converges and has a value little different from the instruction value. The relationship between instruction values and estimated values as obtained by the learned network is shown (Table 3, Fig. 10). These results demonstrate that the correlation of the instruction values and estimated values is better than that obtained from a network with a three unit input layer. To compare the results of the network with a three units input layer and the equation, 141 of the 150 data used in section 3.3 — for which the curing conditions are known — are used (Table 4). It is clear that including curing conditions as input parameters improves the estimation, and results indicate that it can give a better estimation than both the network with a three-unit input layer and the empirical equation.

4. APPLICATION TO MIXING TEST RESULTS

4.1 The mixing of concrete

The mixing of concrete must be carefully managed to get the best quality. However, as things stand now, the mixing method is specified only such that the standard deviation of fractional volumes of mortar and aggregate in the concrete must be lower than a certain value as given in JIS A 1119. The characteristics of the concrete are not considered at all. Further, the results of various past experiments related to concrete mixing cannot be compared because there are no quantitative parameters which are independent of mixer type or mixer volume.

4.2 Past investigations

In the research carried out by Kishi, et al. [8], the effects of mixer type and mixing time on the characteristics of concrete were examined by using identical materials and mix proportions. Results showed that characteristics such as slump and compressive strength altered with increasing mixing time, even after the constituents in the mixer had become uniform. The trend of such changes depended on the mixer type. Thus, the characteristics of concrete depend not only on the mixing time but also on the mixer type. Finally, it was demonstrated that identical characteristics could be obtained if the same total amount of electric power per unit volume of concrete were used regardless of differences in mixer type and mixing time. The electric power consumption of a mixer is the power (the rotational torque) acting on the mixer wings directly during mixing time. This means that the work, the sum of the product of external force on the concrete and its displacement, can be used as an evaluation parameter.

In research by Uomoto, et al. [9], the same things were examined in terms of different mix proportions. And then, even in the different mix proportion; with different water-cement ratios, water per volume, maximum size of aggregate, or addition of chemical admixture, it was shown that the characteristics of concrete are affected by an increase in mixing time. Where different mixers or mix proportions are used, the quantitative evaluation method based on electric power consumption was proposed. Slump, air content, and compressive strength were chosen as parameters representing the characteristics of the concrete, and these were normalized to relative slump, relative air content, and relative compressive strength. The regression curve for each was plotted (Eq. 17-19). Of these parameters, the change in slump value with mixing time was great and showed a characteristic tendency to increase with mixing time and then decrease after reaching maximum value in a certain time (Fig. 11).

[Slump]

$$SIr = 95.74 - 29.07 \log P - 49.63 (\log P)^2 \tag{17}$$

where SIr :relative slump
(ratio of a slump at each mixing time SI to maximum slump $SImax$ $= SI/SImax \times 100$)
P :electric power comsumption of mixer (wh/l)

except in the case of using superplasticizer

[Air content]

(a)In the case of plain concrete

$$Airr = 100.0 - 15.7 \log P + 15.7 (\log P)^2 \tag{18.a}$$

(b)In the case of AE concrete

$$Airr = 100.0 - 102.9 \log P - 3.6 (\log P)^2 + 93.3 (\log P)^3 \tag{18.b}$$

where $Airr$: relative air content when an electric power consumption of 1 wh/l is regarded as 100
P :electric power comsumption of mixer (wh/l)

[Compressive strength]

$$CSr = 100.0 + 407 \log P \tag{19}$$

where Csr :relative compressive strength when an electric power consumption of 1 wh/l is regarded as 100
P :electric power comsumption of mixer (wh/l) ($P > 0.05$ wh/l)

4.3 Estimation of influential factors using a neural network

a)Method of estimation

The network's learning ability is used to check the validity of using the mixer's electric power consumption as a parameter to estimate the changing characteristics of concrete with mixing time. It can be expected that a suitable relationship between input factors and outputs will improve the degree of convergence of learning and the correlation between instruction values and

Table 5 Mix proportion of learning data

Name of mix proportion	Gmax (mm)	W/C(%)	Water per volume (kg/m³)	Chemical admixture	Mixer type
F 1	10	55	213		Pan type F
F 2	20	55	196		
F 3	40	55	182		
F 1'	10	55	198	A E agent	
F 2'	20	55	182		
F 3'	40	55	169		
M 1	20	40	165		Pan type M
M 2	20	40	165	Water reducing agent	
M 3	20	40	165	Superplasticizer①	
M 4	20	40	165	Superplasticizer②	
M 1'	20	40	165		2-axis type
M 2'	20	40	165	Water reducing agent	
M 3'	20	40	165	Superplasticizer①	
M 4'	20	40	165	Superplasticizer②	
M 5	20	40	175		Pan type M
M 6	20	55	175		
M 7	20	70	178		
M 8	20	40	185		

Table 6 Variation of network

Case	Parameter relating to the mixing			Number of hidden layer
	Electric power consumption	Mixing time	Mixer type	
A − 1	○			10
A − 2	○			12
A − 3	○			14
B − 1		○		10
B − 2		○		12
B − 3		○		14
C − 1	○		○	12
C − 2	○		○	14
C − 3	○		○	16
D − 1		○	○	12
D − 2		○	○	14
D − 3		○	○	16
E − 1	○	○	○	12
E − 2	○	○	○	14
E − 3	○	○	○	16

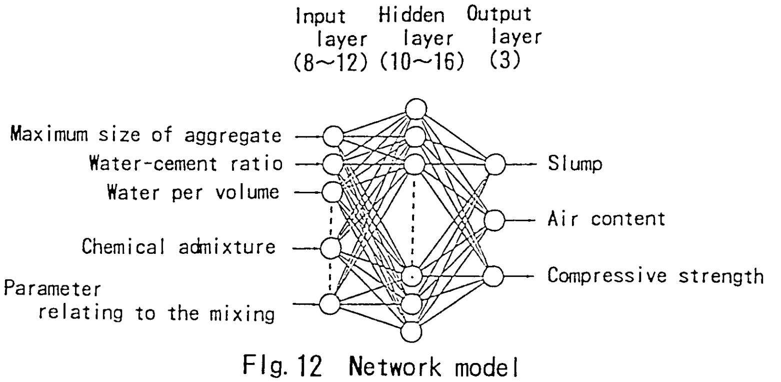

Fig. 12 Network model

outputs. A layer type network was forced to learn using the data obtained by Uomoto, et al. [9] Five combinations of input data were set up from three input factors: mixing time, mixer type, and power consumption. These were applied to the network and the results compared. The combinations are shown in Table 6. Factors relating to the mix proportion, such as water-cement ratio or chemical admixture, were adopted as inputs to all combinations. The characteristics which we wish to estimate are slump, air content, and compressive strength.

b)Model

The number of learning data was 108 and these were distributed in the range of 40 % ~ 70 % in water-cement ratio, 10mm ~ 40mm in maximum size of aggregate, 165kg/m^3 ~ 185kg/m^3 in water per unit volume, and included added chemical admixtures such as air-entraining agents, water reducing agents, and superplasticizers (two cases). Three types of mixer were used in the experiments: two different speeds of 100 l pan-type mixers, and a 90 l "horizontal 2-axis" mixer. The mix proportions of the concrete are shown in Table 5, and for each mix proportion, the slump, air content, and compressive strength were measured at six points between 10sec and 1000sec. As Table 5 shows, to clarify the effect of each factor, experiments were carried out with the others held constant in each mix proportion. The resulting distribution of learning data is clustered. The factors relating to the mixing time are added to the five factors shown in Table 5, the number of input factors become six. It is not denied that there are few learning data compared with them. As for how to represent the learning data, numerical values were given to factors such as water-cement ratio and electric power consumption, etc.. For factors that cannot be represented by quantitative values, such as chemical admixture or mixer type, etc., units were prepared for each factor and set up 1 or 0 as in Section 3.4. The network has three layers, and the number of units in the hidden layer was three cases (see Table 6) for five sets considered in 4.3 a). Because not to progress the learning were wanted to avoid, for the reason that the number of hidden layer was not suitable. The numbers of units in the input layer was eight in set A and set B, eleven in set C and set D, and twelve in set E (Fig. 12).

c)Comparison of results

The results of 10,000 learning events in each case are shown in Table 7. To ensure the same learning conditions in all five sets, the weight modification per learning step was the same in each case. In all cases, the output values of air content and compressive strength were better than that of slump in accuracy, and have already converged by the 10,000th step. Thus, there is no difference in convergence level of all the combinations of parameters relating to mixing. Differences in convergence level due to the number of units in the hidden layer were small in all sets. When compared with the set E, to which all parameters relating to mixing are applied, sets C and D have lower convergence levels and sets A and B are much lower. And comparing set A with set B or set C with set D, whether the electric power consumption or the mixing time was adopted as a parameter, almost the same results were obtained and no difference could be pointed out. Based on the differences between sets which include mixer type as an input parameter (set C and set D) and sets which do not (set A and set B), it can be said that mixer type is also an important parameter beside mixing time and electric power consumption. To verify this, the networks in set A and set B were left for 30,000 learning steps, and the convergence

Table 7 Learning results (Learning times 10000)

Case	Slump		Air content		Compressive strength	
	Average error	Correlation coefficient	Average error	Correlation coefficient	Average error	Correlation coefficient
A－1	4.3072	0.9117	0.0273	0.9801	474.88	0.9874
A－2	5.8087	0.9087	0.0331	0.9757	443.87	0.9867
A－3	5.5401	0.9043	0.0332	0.9758	360.76	0.9867
B－1	4.3911	0.9126	0.0307	0.9775	577.96	0.9850
B－2	5.7660	0.9065	0.0329	0.9760	414.81	0.9890
B－3	8.0331	0.8910	0.0366	0.9733	321.18	0.9904
C－1	0.9319	0.9712	0.0146	0.9893	247.97	0.9926
C－2	0.9871	0.9695	0.0172	0.9875	247.94	0.9927
C－3	1.0656	0.9671	0.0205	0.9850	264.49	0.9921
D－1	0.8806	0.9728	0.0154	0.9888	254.58	0.9924
D－2	1.0564	0.9674	0.0164	0.9880	271.37	0.9920
D－3	0.8738	0.9731	0.0139	0.9899	247.15	0.9927
E－1	0.8839	0.9728	0.0137	0.9900	253.72	0.9925
E－2	0.8122	0.9750	0.0122	0.9911	249.52	0.9926
E－3	0.7442	0.9771	0.0116	0.9916	234.11	0.9931

※ Average error means average square error between the estimated value and instruction value

Table 8 Learning results (Learning times 30000)

Case	Slump		Air content		Compresive strength	
	Average error	Correlation coefficient	Average error	correlation coefficient	Average error	Correlation coefficient
A－1	2.6750	0.9339	0.0221	0.9838	709.89	0.9845
A－2	2.2918	0.9504	0.0176	0.9872	371.42	0.9893
A－3	2.3083	0.9502	0.0219	0.9841	353.04	0.9902
B－1	3.4495	0.9315	0.0226	0.9835	759.98	0.9840
B－2	2.2529	0.9517	0.0262	0.9810	363.14	0.9903
B－3	7.4777	0.9018	0.0344	0.9753	350.44	0.9899

※ Average error means average square error between the estimated value and instruction value

Table 9 Estimation by the regresion equation

	Slump	Air content	Compresive strength
Number of data	84	72	105
Average squard error	0.6428	0.0320	358.24
Correlation coefficient	0.9708	0.9908	0.9902

Table 10 Estimation by the network(C-1)

	Slump	Air content	Compresive strength
Number of data	84	72	105
Average squared error	0.4254	0.0172	169.29
Correlation coefficient	0.9801	0.9950	0.9952

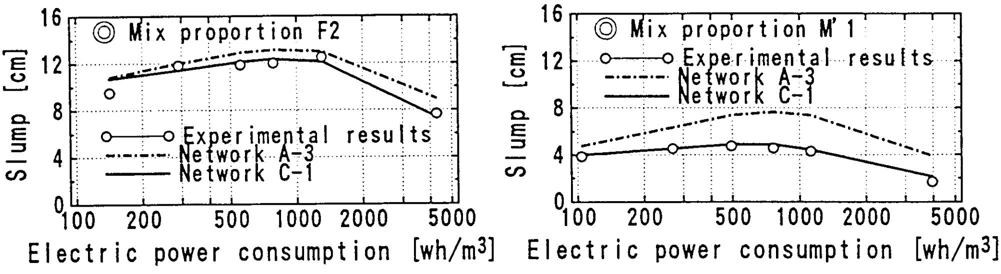

Fig. 13 Instruction value and network's output(1)

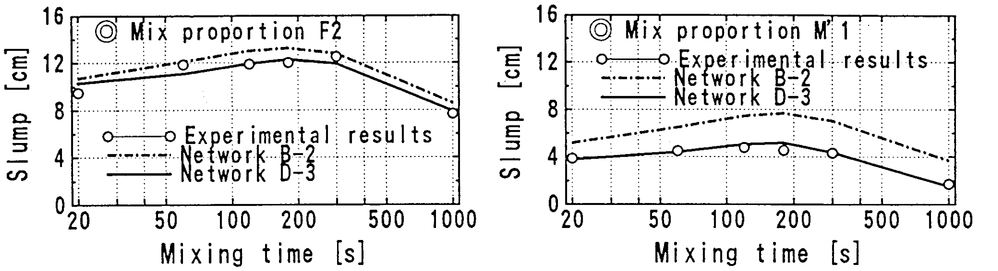

Fig. 14 Instruction value and network's output(2)

levels were also checked (Table 8). The results showed that their convergence levels are quite similar, with set B a little higher. Their convergence levels are lower than those of sets C, D, and E. Based on these results, it is advisable to select the mixer type as a parameter representing the characteristics of the mixing process. However, a better estimation is obtained when many units are used in the network, since the degrees of freedom of the connection weights increases if the number of learning data is same. In this analysis, whether the mixing time or the electric power consumption is selected, there is no great difference in the accuracy of each estimated value.

d) Discussion

The network's output is compared with the regression equation in section 4.2. The generalized values can be obtained from the regression equation and the standard values, such as maximum slump or air content and compressive strength, when the electric power consumption of mixer is 1 wh/l. After these calculations, the original values were estimated and compared with the outputs of the network. This comparison is not essential because different input data are given to the regression equation and the network, and because the regression estimation has limited application. However, it does act as a reference for evaluating the accuracy of the network estimation (Table 9). The results of the network(C-1) estimation for the same data are also shown in Table 10. These comparisons show that the estimations by the network are better than those by the regression equation for all factors.

Next, consider the performance of the network. To investigate the relationship between the network estimate and instruction value in each mix proportion, the

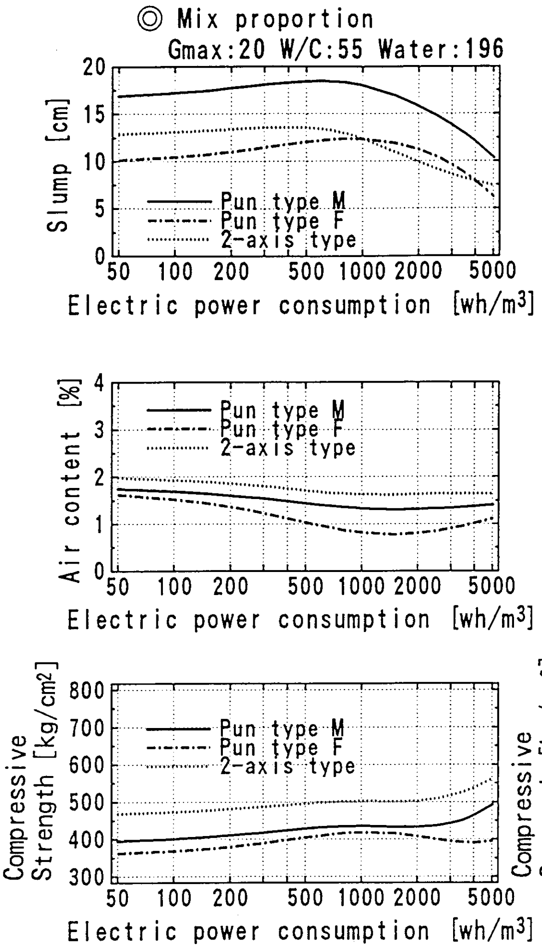

Fig. 15 Estimated values in deffernt mixer type (1)

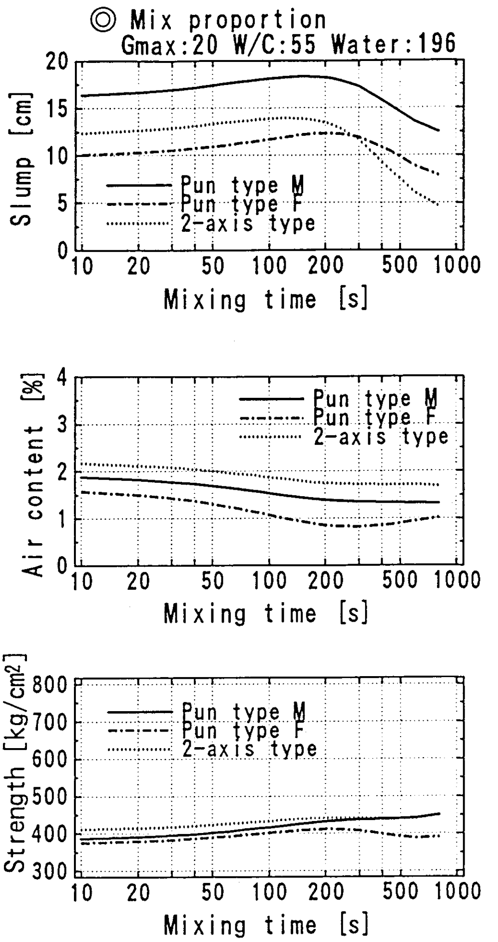

Fig. 16 Estimated values in deffernt mixer type (2)

relationships of slump versus electric power consumption and slump versus mixing time are shown in Figs. 13 and 14. The estimation is not affected by the chosen value of parameters, and the estimation results are acceptable. It can also be said that networks including mixer type as an input parameter (set C and set D) give better results than those not including mixer type. Additionally, networks that do not include mixer type as an input parameter (in mix proportion M1') give larger results although the behavior is similar. Therefore, the mixer type affects the estimates. Based on this fact, suppose that with a certain mix proportion and three types of mixer are used, then the relationship between the output parameters (slump, air content, and compressive strength) and input parameters (mixing time and electric power consumption) are shown in Figs. 15 and 16. In all cases, the mixer type affects the behavior of the estimated value. However, there are problems in the distribution of learning data as mentioned before, so the reliability of this result is not certain.

Finally, consider the suitability of learning data. The network modifies the connection weights and self-organizes to give a correct value according to the instruction value. Therefore, the distribution of learning data is important as well as its accuracy. If only to adjust the estimation value to the instruction value of learning data, it is probable that the coincidence of them becomes rather good when there are bad distribution of learning data and the degree of freedom of network's connection weights are large. In this case, though, the reliability of the estimate for the extent of not learning is not so high. To use the network obtained by learning for the sake of mentioned above, the reliability is not so high unless the data are independent of all input items and distributed over as wide a range as possible. Ideally, the number of learning data should be increased as in an exponential function as the number of input items rises. In this analysis (see Table 5), if the data are classified according to mixer type, then for mix proportion F1～F3', in which a pan-type F was used, the water-cement ratio is constant, for M1～M8, in which pan-type M was used, the maximum size of aggregate is constant, and for M1'～M4', in which the two-axis mixer type was used, all the data except the chemical admixture were the same. Therefore, to use such data that two or more items are constant is not perfect. The experimental mixing data used in this analysis are obtained from the identical experiment, different from the results of accelerated carbonation test. Thus the errors caused by differences in experimental method can be neglected, but the number of learning data is relatively few compared with the number of input items, and the distribution of learning data is poor. For this reason, the reliability of the estimate to the extent where there is no learning data is low.

5. CONCLUSION

In this research, a number of neural network models are applied to data obtained through experiment on concrete, and their applicability is examined. The following results were obtained.

(1) Application to accelerated carbonation tests

Carbonation depths as mesured in experiments are estimated using the conventional empirical equation (considering carbon-dioxide, temperature, and water-cement ratio as influential factors) and by a neural network models. The results are compared. It is clear that estimation by the network is better than that by the empirical equation. The accuracy of estimation is also shown to increase when curing conditions, which are not considered in the equation, are included as an input parameter.

(2)Application to the mixing of concrete

The learning function of a neural network is used to find suitable factors for evaluating how the characteristics of concrete are affected by mixing time. A comparison of mixing time and electrical power consumption shows that there is no certain difference between them. In each case, the accuracy of the estimation is improved by including the mixer type as an input parameter.

(3)Data analysis by neural network

When an empirical equation is proposed to fit some experimental data, or if multi-regression analysis is done, the basic equation is derived according to a theoretical background. The result depends on whether the theoretical assumption is correct or not. A neural network method can be said to have the following characteristics.

1. The ability to determine the relationship between each factor through learning. In this relationship, there are no subjective assumptions by the researcher, so it can be used to find theoretical background.

2. By comparing the convergent level of each case, in which the input combination of learning data is different, the affecting factor can be easily obtained.

3. Learning and estimation accuracy can be improved by increasing the reliability of the data, or by obtaining new data, or by incorporating a new factor, and so on.

4. The network's learning data accuracy is important, since in the learning process, the error between the instruction value and network output value forms the basis of evaluation. Thus it is necessary to prepare many accurate data that are distributed over a wide range.

Finally, it can be said that a neural network is applicable to the field of concrete technology. If a method of finding clear information about the relationship between inputs and outputs can be obtained by an analysis of the connections within the network, a wider range of applications can be expected.

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