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A New Quality Control System For Concrete Production Using Neural Network

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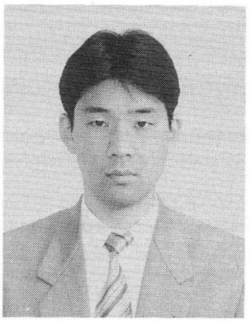

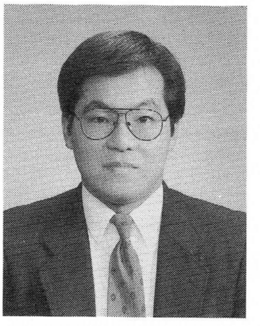

Takashi Ohya Taketo Uomoto Tomoaki Tsutsumi

A new method of determining the most suitable conditions of mix proportion and mixing energy for a particular quality of concrete is described. It is based on the use of a neural network to predict concrete quality for any mix proportion and mixing energy. By understanding the sensitivity of the relation between these conditions, optimized conditions can be obtained.
The method has been verified by comparing calculated results with the experimental data obtained on site. As a result, the new method is proposed as a quality control technique for concrete production.

Keywords: neural network, control system, sensitivity analysis, optimization, mixing

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1. INTRODUCTION

In concrete production, the mix proportion is conventionally designed for each batch mixed so as to obtain the required concrete quality. However, the quality of the concrete produced is not always consistent and, moreover, the concrete may sometimes be out of standard since quality is not checked for each batch. There might be a number of reasons for this problem; for instance, it is difficult to continuously monitor changes in water content, which are mainly caused by varying surface moisture ratio of the aggregate, and it is also difficult to predict how quality changes with variations in mix proportion and other conditions. There is a need to vary the mix proportion and mixing time so as to obtain concrete of consistent quality despite changes in the conditions of concrete production.

Neural networks can be used for problems that can not be approached in the normal way and for finding important governing factors by a simple process of learning. Once learning is complete, a neural network simulates the input-output relations of the given data, and changes in output against changes in input can be predicted.

In Sekiguchi's work[1], it was clarified that a neural network is applicable to the field of concrete mixing. In this new study, the authors attempt to construct a quality control system for concrete production using a neural network, applying an optimization method based on sensitivity.

2. NEURAL NETWORK[2]~[4]

2.1 The principles of neural networks

The neural network model, which is inspired by the neuronal architecture and operation of the human brain, consists of a large number of highly interconnected processing units. In contrast with conventional computation methods that follow a logical process with step-by-step serial processing, a neural network computation is processed in parallel. As a result, it has advantages in computation speed, ability to analyze fuzzy data, and ability to supplement incomplete or partially incorrect information. Further, there is no need to design a complicated program. The only requirement in applying the neural network concept is to prepare learning data and force the learning process using these data. That is, the interior relationship must be changed so as to generate the expected answer in an iterative process. As a consequence, neural networks are a promising path for solving the pattern recognition problems, problems which are hard to represent in equation form, and optimization problems in which there are complex combinations.

There are two types of neural network architecture, the mutual-connected type and the layer-type. The layer model is adopted in this study. (Fig. 1)

2.2 Neural network units

Each unit of the network is a multiple-input and one-output device as shown in Fig. 2. The operation of unit u_j is represented by Eq. 2. The response function is represented by a series function which takes the values from 0 to 1. Input signals are transported to the output layers by following Eqs. 1 to 3 in each unit.

$$u_j = \sum_i \omega_{ji} \cdot y_i - \theta_j \tag{1}$$

$$y_i = f(u_j) \tag{2}$$

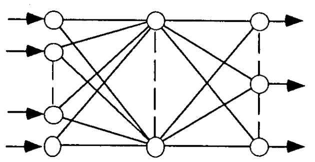


Fig.1 Layer-type neural network

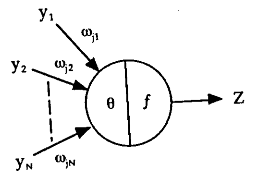


Fig.2 Neural network unit

$$f(u) = \frac{1}{1+e^{-u}} \tag{3}$$

where ω_{j_i} : connection weight between i and j

y_i : input from unit i

θ_j : threshold value

2.3 Learning algorithm

Learning in a neural network consists of modifying the connection weights and threshold values in an iterative process such that an error function is minimized. In a layer-type network, the connection weights and threshold values are gradually changed such that the error between the actual output of the network and the expected output for a certain pattern of input values is reduced.

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

where $y_{j,c}$: output value of neural network

$\hat{y}_{j,c}$: expected output value

To find the minimum of E derived for any input pattern, it is necessary to change each weight using the following equation:

$$\Delta\omega_{ji} = -\varepsilon\frac{\partial E}{\partial\omega_{ji}} \tag{5}$$

This is the gradient descent method, and entails differentiation with respect to a design parameter and adjusts the design parameter down to the gradient direction. According to the input-output relationship defined in Eqs. (1) to (3), Eq. (5) can be expanded as follows.

$$\frac{\partial E}{\partial\omega_{ji}} = \sum_c \frac{\partial E}{\partial y_{j,c}}\cdot\frac{\partial y_{j,c}}{\partial u_{j,c}}\cdot\frac{\partial u_{j,c}}{\partial\omega_{j,c}} \tag{6}$$

In addition, the following equations are derived from Eqs. (1) to (3):

$$\frac{\partial y_{j,c}}{\partial u_{j,c}} = f'(u_{j,c}) \tag{7}$$

So,

$$\frac{\partial u_{j,c}}{\partial \omega_{j,c}} = y_{ji,c} \tag{8}$$

$$\Delta\omega_{ji} = -\varepsilon \sum_{c} \frac{\partial E}{\partial y_{j,c}} \cdot f'(u_{j,c}) \cdot y_{ji,c} \tag{9}$$

As for learning in hidden layers, it is decided to take the value of $\frac{\partial E}{\partial y_{j,c}}$ from the $\frac{\partial E}{\partial y_{j,c}}$ value in the following layer.

Then, $\frac{\partial E}{\partial y_j^{(l)}}$ of unit j in layer l is derived from $\frac{\partial E}{\partial y_j^{(l+1)}}$ of unit i in layer $(l+1)$.

$$\frac{\partial E}{\partial y_j^{(l)}} = \sum_{i} \frac{\partial E}{\partial y_i^{(l+1)}} \cdot \frac{\partial y_i^{(l+1)}}{\partial u_i^{(l+1)}} \cdot \frac{\partial u_i^{(l+1)}}{\partial y_j^{(l)}} \tag{10}$$

From Eq. (1),

$$\frac{\partial u_i^{(l+1)}}{\partial y_j^{(l)}} = \omega_{ij}^{(l)} \tag{11}$$

Therefore,

$$\frac{\partial E}{\partial y_j^{(l)}} = \sum_{i} \frac{\partial E}{\partial y_i^{(l+1)}} \cdot f'(u_i^{(l+1)}) \cdot \omega_{ij}^{(l)} \tag{12}$$

Consequently, $\frac{\partial E}{\partial y_j^{(l)}}$ can be derived from the already calculated $\frac{\partial E}{\partial y_i^{(l+1)}}$. This means that the error is transfered backward from the following layer to the preceding layer, in a process called "back propagation."

3. PREPARATION OF LEARNING DATA

In the application of a neural network, it is essential to prepare much accurate data distributed over a wide range. For this purpose, site experiments were conducted using a $3m^3$ forced mixer.

After mixing, the concrete was transported to a nearby yard in a concrete mixer truck. The characteristics of the concrete, such as slump, air content, and unit volume of concrete, were then measured. Specimens for compressive strength tests were also taken. Some aggregate was also collected to measure the amount of surface moisture for each batch. The time taken to charge all the materials was measured by observing monitors that display the mixer interior. Slump values were measured in units of 0.1 cm, although the usual standard is 0.5 cm.

Thirty one batches for each of three mix proportions were mixed as shown in Table 1, and one each of 13 further mix proportions as shown in Table 2. The latter set were performed so as to determine the universality of the network. The measurement items and number of measurements are shown in Table 3. The characteristics of the concrete were determined from the average of multiple measurements on each batch, and stuff and equipment limitations meant we had to repeat the sampling and measurement cycle. As a result, the experiment was devised such that sampling and measurement be limited to 3 cycles thus preventing variations in time-dependent characteristics such as slump loss.

Table 1 Mix proportions

No.	W/(C+F)	s/a	Unit content (kg/m³)							
			Water	Cement	Fly ash	Fine aggr.		Coarse aggr.		Admixt.
						River sand	Land sand	River gravel	Crushed stone	
1	50.1	32.1	167	268	66	—	558	1235	—	0.835
2	46.2	37.7	162	281	70	465	199	1149	—	0.878
3	47.6	41.5	169	284	71	506	217	745	317	0.888

Table 2 Mix proportions and mixing times

No.	W/C (%)			G_{max} (mm)		Unit content of water (kg/m³)			Mixng time (sec)		
	40	55	60	25	40	150	165	180	60	120	300
1	O			O			O		O		
2		O		O			O		O		
3			O	O			O		O		
4	O				O		O		O		
5		O			O		O		O		
6	O			O				O			O
7	O			O		O			O		
8		O		O		O			O		
9	O			O		O					O
10		O		O				O	O		
11		O		O			O			O	
12		O		O			O				O
13			O	O			O				O

Table 3 Measurement items and number of measurements

Mix proportion	Number of batches	The number of measurement for each batch						
		Surface moist. ratio	Mixing energy	Charged materials	Slump	Air content	Comp. strength	Unit weight
Table 1	3	1	1	1	30	30	90	30
Table 2	90	1	1	1	5 or 6	6	3	6
Table 3	13	1	1	1	15	15	5 or 15	15

The range of obtained data was 8.4~19.4 cm in slump, 4.3~6.0% in air content, and 21.2~33.2 MPa in compressive strength. The final number of data points available was 106 batches.

4. PREDICTION OF CONCRETE QUALITY

4.1 Model

First we try to predict concrete qualities such as slump, air content, and compressive strength from the charged content of materials and mixing energy by using the layer-type neural network. The model comprises the two steps shown in Fig. 3. In the first step, the "true"mix proportion, in which water content and aggregate content are corrected by estimating the surface moisture content of the aggregate, is determined. In the second step, concrete characteristics are predicted from the "true" mix proportion and mixing energy. These two networks are trained independently. In the prediction process with trained networks, the output of the first network is adopted as the input of the second. As a consequence, the quality of concrete can be predicted from the weight of charged materials and the mixing energy (which is assumed to be the cumulative power consumption of the mixer).

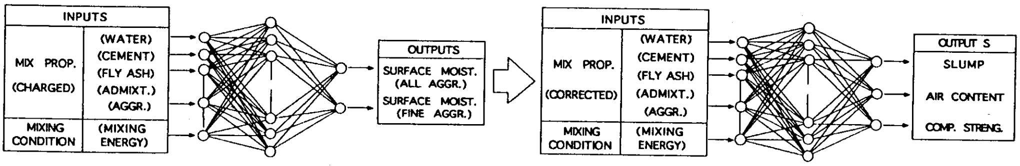


Fig.3 Model for prediction of concrete quality

Table 4 Inputs and outputs

	Inputs (13 Units)	Outputs (2 Units)
Mixing energy	Cumulative value Converged value Maximum value	
Charged materials	Water Cement Fly ash Fine aggr. (2 types) Total aggr. (3 types) Water red. agent Superplast.	Surface moist. wt of fine aggr. Surface moist. wt of total aggr.

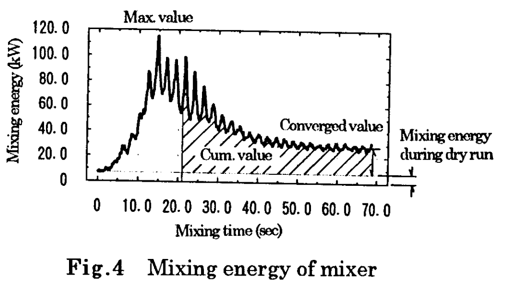


Fig.4 Mixing energy of mixer

In predicting concrete quality, the prediction could be made more accurate by adding input items, such as maximum mixing energy and converged level of mixing energy . However, we are attempting to optimize the mix proportion and mixing energy for a particular quality of concrete. Since factors that can be controlled independently should be selected as input items, aforementioned factors are not suitable for they cannot be controlled.

On the other hand, we are attempting to predict concrete quality in one step from the weight of charged materials (uncorrected by the surface moisture ratio of the aggregates) and the mixing energy only. Hence, the prediction accuracy of this one step model is considerably low compared with the two step network used in this study. For this reason, the model shown in Fig. 3 is adopted.

It is true that there are many factors which affect the quality of concrete, such as the temperature of the mixed concrete and the aggregate and cement quality. However, we did not treat these factors as inputs since they would have been almost constant over the short term of the experiment (July to August 1993).

4.2 Prediction of surface moisture weight of aggregates

a) Model

The network used to predict the surface moisture content of the aggregates has three layers and 18 units in the hidden layer. The input and output items are shown in Table 4. Although we used several types of fine aggregate and coarse aggregate, we attempted to predict the sum of the surface moisture content on the fine aggregates and that on all aggregates because of the impossibility of predicting each aggregate individually.

We failed to measure mixing energy or the surface moisture ratio for some samples, so the remaining 97 data were adopted for learning. As shown in Fig. 4, it was possible to define the three specific values of mixing energy as the difference in mixing energy between an actual run and a dry run. The weight of materials charged into the mixer was automatically measured for each batch. The surface moisture content of the aggregates were calculated from the surface moisture ratio measured for samples in each batch. All data were normalized before the learning process.

As learning progresses, the error between the network's output and the instruction value gradually diminishes. However, the prediction error for untrained data reaches a local minimum while that for learning data is still falling. This is called "overtraining," and should be avoided to achieve universality. Therefore, we randomly chose six of the learning data, and carried out the learning process by sequentially checking the error between the output and the instruction value for the six data. Learning was terminated when the error reached the local minimum.

Table 5 Estimation results

Items	Mean square error (kg/m^3)		Correlation coefficient	
	Learning data	Untrained data	Learning data	Untrained data
Surface moist. wt of fine aggr.	2.41	4.16	0.990	0.974
Surface moist. wt of total aggr.	6.10	3.41	0.983	0.981

(Note) Mean square error : Average of squared error between predicted value and instruction value

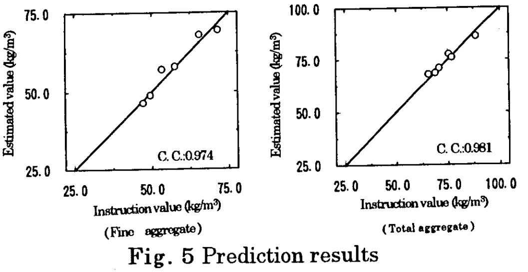


Fig. 5 Prediction results (surface moist. of aggr.)

b)Results and Discussion

Since the initial values could not be determined theoretically, learning was tried several times with different initial values for the connection weights and threshold values, and the convergence level of the error was checked. The connection weights and threshold value giving the most reliable result were chosen. The result for untrained data after 100,000 learning events is shown in Fig 5. This indicates that the trained network can make predictions with good accuracy. The surface moisture content of the aggregates is expressed in the unit weight per 1 m^3 of concrete.

Table 5 summarizes these results. The mean error of prediction for fine aggregate was 2 kg/m^3, and that for all aggregates was 1.9 kg/m^3. With an actual water content of 160~170 kg/m^3, assuming that material measurements are perfect, the results mean that the network can predict the overall water content of a batch to an accuracy of $\pm$1.2%. Further, this error corresponds to $\pm$0.2~0.3% in the fine aggregate surface moisture ratio when the fine aggregate content is 558~723 kg/m^3. According to these results, this network model has better accuracy than a moisture meter, which gives a $\pm$0.5% error. In particular, this network model is relatively precise even when the aggregates have a surface moisture ratio of over 10%.

4.3 Prediction of Concrete Quality

a) Model

As the next step, we attempt to predict concrete quality from the mix proportion corrected by surface moisture ratio of aggregates. The inputs to the network are eight as shown in Table 6. The effect of a change in fine aggregate content, under the condition that the total aggregate content is constant, can be simulated when inputs are selected as shown in the table; that is, the effect of a change in s/a can be determined on condition that the total aggregate content does not change. The output items consist of slump, air content, and compressive strength. The number of units in the hidden layer is 18.

Before learning, six samples were selected from the learning data to check for overtraining as before. Though the concrete characteristics were determined through multiple measurements during the experiment shown in Table 3, averages were adopted as learning data.

Table 6 Inputs and outputs

Inputs (8 Units)		Out puts (3 Units)
Mixing energy (cumulative)		Slump Air content Comp. strength
Mix prop. (corrected)	Water Cement Fly ash Fine aggr. Total aggr. Water red. agent Superplast.	

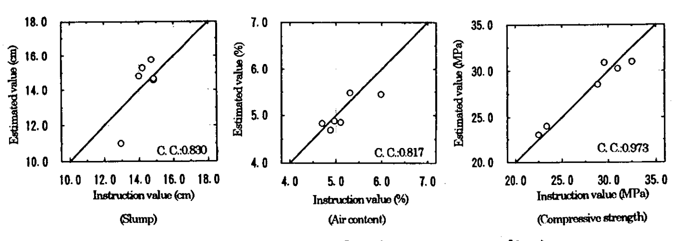


Fig. 6 Prediction results (concrete quality)

b) Results and Discussion

Learning was terminated when convergence was verified and the error for the chosen data began to increase (at around 20,000 learning events). The result for untrained data is shown in Fig 6, and Table 7 shows a summary of

Table 7 Estimation results

Items	Mean square error		Correlation coefficient	
	Learning data	Untrained data	Learning data	Untrained data
Slump	1.20 cm	1.14	0.927	0.830
Air content	0.042 %	0.072	0.933	0.817
Comp. streng.	17.0 MPa	9.36	0.939	0.973

the results.

The mean error is about 1 cm in slump, 0.25% in air content, and 0.92 MPa in compressive strength. This implies that if we cast concrete in the mix proportion determined by the network, the quality of the mixed concrete will be distributed in this range. This accuracy would be acceptable in practice for it is better than the JIS standard, which is ±2.5 cm in slump and ±1% in air content. On the other hand, it is anomalous in that the accuracy of prediction for untrained data is greater than that for learned data. This results from the insufficiency of data. Thus, it is necessary to prepare more data for learning and to check for overtraining in practical use.

5. SENSITIVITY ANALYSIS

5.1 Sensitivity Analysis Using Neural Network

Sensitivity analysis is used to estimate the response to a change in one parameter. A great deal of research has been conducted for applications such as optimization and reanalysis. Sensitivity can be effectively used to estimate perturbing factors, optimization methods, and reanalysis.

In this section, we proposed a method of calculating the input-output sensitivity of the neural network from the connection weights and threshold values of the trained network, with the purpose of optimization of mix proportion and mixing energy.

Suppose the following values and functions are true for unit j:

Input

$$u_j = \sum_i \omega_{ji} \cdot y_i - \theta_j \tag{13}$$

Output

$$y_i = f(u_j) \tag{14}$$

$$f(u) = \frac{1}{1+e^{-u}} \tag{15}$$

And the sensitivity $\frac{\partial y_i^{(N)}}{\partial y_j^{(0)}}$ of the input-output of an N-layer neural network, the output of unit i against the input of unit j, is calculated as the following equation:

$$\frac{\partial y_i^{(N)}}{\partial y_j^{(0)}} = \sum_{k1}\sum_{k2}\cdots\sum_{k(N-1)} \frac{\partial y_i^{(N)}}{\partial y_{k1}^{(N-1)}} \cdot \frac{\partial y_{k-1}^{(N-1)}}{\partial y_{k-2}^{(N-2)}} \cdots \frac{\partial y_{k(N-1)}^{(1)}}{\partial y_j^{(0)}} \tag{16}$$

From Eqs. (13)~(15),

$$\frac{\partial y_i^{(l+1)}}{\partial y_j^{(l)}} = \frac{\partial y_i^{(l+1)}}{\partial u_i^{(l+1)}} \cdot \frac{\partial u_i^{(l+1)}}{\partial y_j^{(l)}}$$

$$= f'(u_i^{(l+1)}) \cdot \omega_{ij}^{(l)} \tag{17}$$

In the three-layered neural network model,

$$\begin{aligned}\frac{\partial y_i^{(2)}}{\partial y_j^{(0)}} &= \sum_k \frac{\partial y_i^{(2)}}{\partial y_k^{(1)}} \cdot \frac{\partial y_k^{(1)}}{\partial y_j^{(0)}} \\ &= \sum_k f'(u_i^{(2)}) \cdot \omega_{ik}^{(1)} \cdot f'(u_k^{(1)}) \cdot \omega_{kj}^{(0)} \\ &= y_i^{(2)}(1-y_i^{(2)}) \sum_k \omega_{ik}^{(1)} \cdot y_k^{(1)}(1-y_k^{(1)}) \cdot \omega_{kj}^{(0)} \end{aligned} \tag{18}$$

Ultimately, the sensitivity at any input value can be calculated from the connection weights, threshold values, and output at each unit in the network.

5.2 Neural Network Model for Sensitivity Analysis

Although sensitivity analysis is not the main purpose of this study (it was only used to calculate the optimization process in this study), one numerical result is illustrated below. The network used for sensitivity analysis had three layers and 18 units in the hidden layer. Input and output items are shown in Table 8. The prediction accuracy achieved by this network is nearly the same as that of the one described in the previous section. One input is different from the former model: the mixing time is treated as an input in this network model, since all inputs should be independent in an evaluation of sensitivity. With the aim of evaluating the effect on concrete quality of changes in s/a, given that the fine aggregate content is constant and the total aggregate content is constant, the fine aggregate content and total aggregate content are adopted as inputs.

Sensitivity is calculated at the point shown in Table 9. At which mix proportion and mixing time, many data are used for learning. The results are expressed as the variation in output against a 1% increase in input by Eq. (18).

5.3 Results and Discussion[5]

Figure 7 shows the sensitivity for each input item, and Table 10 shows the three factors which have the most effect. The '+' mark in the table represents an output that increases with a rise in input, while '-' means the opposite. The result shown is for the degree of change in quality resulting from a change in one factor while keeping the other factors constant. The present model does not consider a relative adjustment in mix proportion with respect to a change in one factor. (So, it brings a change in total volume of concrete) That is, the result shows the effect of a batching error.

a) Effect on Slump

The result shows that water content has the most effect on slump as it is known. However, the degree of it is a little smaller, though it is usually considered that a 1.2% increase in water content results 1% slump increase. An increase in cement or fly ash content causes a decrease in water-binder ratio, or the equivalent of a relative decrease in water content in this calculation; that is , a decrease in slump. The same fact was indicated by the result. The reliability of the result for superplasticizer could not be verified because the range of learning data was quite narrow.

b) Effect on Air Content

A decrease in cement content and an increase in fine aggregate ratio (equivalent to an increase in fine aggregate and a decrease in total aggregate) results an higher

Table 8 Inputs and outputs (for sensitivity analysis)

Inputs (8 Units)		Outputs (3 Units)
Mixing time		
Mix prop. (corrected)	Water	Slump
	Cement	
	Fly ash	Air content
	Fine aggr.	
	Total aggr.	Comp. streng.
	Water red. agent	
	Superplast.	

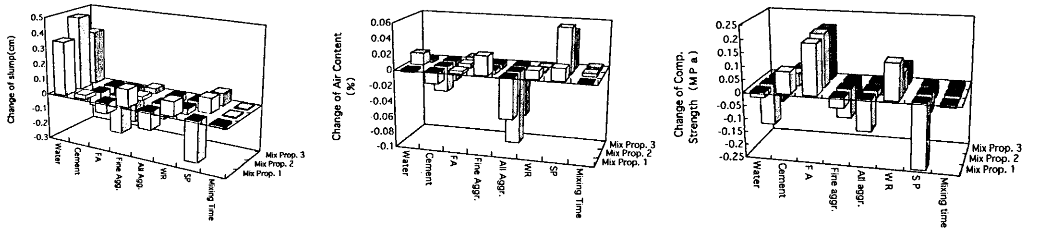
Table 9 Default values for sensitivity analysis

No.	Mix proportion (kg/m³)							Mixing time (sec)
	W	C	FA	S	a	WR	SP	
1	175.7	251.7	62.1	597.5	1869.6	3.38	2.01	39.4
2	164.4	266.7	65.7	675.6	1842.6	3.63	1.50	39.2
3	175.6	280.3	68.9	725.1	1792.1	3.76	1.50	39.2

Table 10 Affecting factors for each quality measure

order	Slump			Air content			Comp. strength		
	Prop. 1	Prop. 2	Prop.3	Prop. 1	Prop. 2	Prop.3	Prop. 1	Prop. 2	Prop.3
1	+W	+W	+W	-a	-a	-a	-SP	+FA	+FA
2	-SP	-FA	-FA	+s	+SP	+SP	+FA	-W	-s
3	+s	-C	-C	+SP	-C	-C	+WR	-s	-W

(NOTE) W : Water content ; C : Cement content ; FA : Fly ash content ; s : sand content
WR : Water reducing agent content ; a : Total aggregate content ;
SP : Superplasticizer content
\+ means positive correlation, - means negative correlation



a) Slump

b) Air content

c) Compressive strength

Fig. 7 Results of sensitivity analysis

air content. The calculation gives the same result. A 1% change in fine aggregate or total aggregate content caused 0.3~0.4% change in fine aggregate ratio in this mix proportion. Since it is thought that a 0.5~1.0% increase in fine aggregate ratio brought a 1% increase in air content, the calculation result shows 1/10 of this knowledge. This is because the fine aggregate content was increased without increasing the water content in the calculation.

It is natural that the air content increases with increasing superplasticizer content. However, the degree of this effect could not be determined for the reason given in the section a).

c) Effect on Compressive Strength

An increase in cement and fly ash content brings a decrease in water-binder ratio; that is, higher compressive strength. This can be observed in these results. Compressive strength is affected more by fly ash content than cement content. Compressive strength is considerably promoted by adding fly ash. It is generally believed that an increase in fly ash content will cause a decrease in compressive strength, which seems contrary to these results. However, the conditions considered here are different: fly ash did not replace cement but was added in this calculation.

d) Summary

The trained neural network stores information about the input-output relationship of learning data in the form of connection weights and threshold values. Sensitivity analysis by neural network is able to indicate the learning data trends since outputs are linked smoothly within the range of the learning data. Moreover, the sensitivity can be calculated quantitatively. This method makes it possible not only to clarify concrete mixing but also to help establish permissible batching errors.

6. OPTIMIZATION OF CONCRETE MIX PROPORTION

6.1 Optimization theory[6]

Once any problems with a design or plan are solved, certain preconditions and constraints must be adhered to. In general, the best solution needs to be selected from among a number of solutions that meet the conditions. This is an optimization problem which can be represented mathematically as follows.
The aim is to minimize an objective function subject to the equality and inequality constraints,

$$g_j(X) \geq 0 \tag{19}$$

$$h_j(X) = 0 \tag{20}$$

That is, find vector X or variables X1....Xn such that

$$f(X) \rightarrow 0 \tag{21}$$

There are numerous methods of solving this type of optimization problem. In this study, the constrained problem is converted into an unconstrained one by using the interior penalty function method. The gradient descent method using a neural network is then used to find the optimal solution.

a) Gradient descent method
The gradient descent method is an iteration process in which an objective function is minimized (or maximized) by changing design variables to achieve the steepest-possible descent. The function can be effectively taken to the minimum (extreme) by gradually changing the design variables according to the direction of the gradient at each iteration step.

Suppose an objective function with n variables is given as in Eq. (22), and its sensitivity vector (gradient vector) is represented as Eq. (23).

$$f(X) = f(x_1, x_2, \cdots, x_n) \tag{22}$$

$$\nabla f(X) = \left\{ \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \cdots, \frac{\partial f}{\partial x_n} \right\}^T \tag{23}$$

Where, T: transpose form of the matrix

Optimization is then performed by gradually changing the variables according to the following equation:

$$x_{k+1} = x_k - \tau \nabla f(x_k) \tag{24}$$

τ :search step

Since only the direction of the vector is needed, the gradient vector is normalized as follows.

$$\overline{\nabla f} = \nabla f / |\nabla f| \tag{25}$$

b) Interior penalty function method
The constrained optimization problem with inequality constraints is converted into an unconstrained one by adopting a penalty function $\varphi[\ ]$.

$$f^*(x) = f(x) + r\sum_{j=1}^{m} \varphi\left[g_j(x)\right] \tag{26}$$

Where $f^{*}(x)$: extended objective function

r : penalty coefficient

$\varphi[g_j(x)]$: penalty function.

This interior penalty function is assumed to monotonously decrease within $[0,\infty)$ and which become infinitely large at the constraint boundary ($g_j(x)=0$).

$$f^{*}(x,r)=f(x)+r\sum_{j=1}^{m}\frac{1}{g_j(x)} \tag{27}$$

(where, $r^{(1)}>r^{(2)}>r^{(3)}>\cdots$)

After this conversion, the optimization problem can be solved as an unconstrained problem.

A problem with both equality and inequality constraints can also be solved by adopting the following extended objective function (though we do not solve for equality constraints in this study):

$$f_m(x,r)=f(x)+r\sum_{j=1}^{k}\frac{1}{g_j(x)}+r^{-0.5}\sum_{j=k+1}^{m}\{h_j(x)\}^2 \tag{28}$$

6.2 Calculation model

We now attempt to estimate the mix proportion and mixing energy for the required concrete quality by using the neural network with this interior penalty function method and the gradient descent method.

A flow chart of the prediction process is shown in Fig. 8. This is an iteration process in which the quality predicted by the neural network closes on the required value.

The objective function is defined as follows, where $S_i(x)$ denotes the output of the network and C_i denotes the required quality, as shown in Table 11.

$$f(x)=\frac{1}{2}\sum_i\{S_i(x)-C_i\}^2 \tag{29}$$

The extended objective function with the six constraints given by Eq. (30) is derived from Eq. (27).

$$\begin{gathered}145\leqq W\leqq 185\\ 195\leqq C\leqq 370\\ 45\leqq FA\leqq 85\\ 580\leqq s\leqq 780\\ 35.0\leqq W/(C+FA)\leqq 60.0\\ 31.0\leqq s/a\leqq 42.0\end{gathered} \tag{30}$$

Where, W: unit water content
C: unit cement content
FA: unit fly ash content
s: unit fine aggregate content ......(kg/m^3)
W/(C+FA): water-binder ratio
s/a: fine aggregate ratio ......(%)

Table 11 Default values of quality

Mix prop.	Slump (cm)	Air content (%)	Comp. strength (MPa)
1	13.5	5.5	24.9
2	15.0	5.0	27.0
3	15.5	5.0	29.9

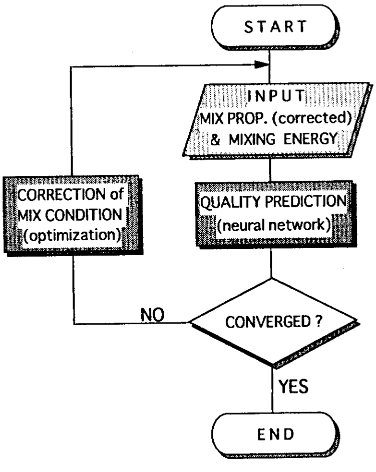


Fig. 8 Flow chart of optimization

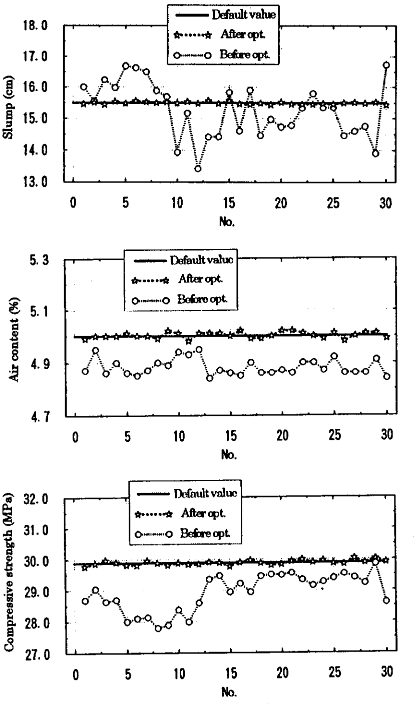


Fig. 9 Optimization results

Then,

$$\frac{\partial f^*}{\partial x_i} = \frac{\partial f^*}{\partial f}\frac{\partial f}{\partial x_i} + \sum_j \frac{\partial f^*}{\partial g_j}\frac{\partial g_j}{\partial x_i}$$

$$= \sum_j \{S_j(x) - C_i\}\frac{\partial S_j}{\partial x_i} + \sum_j \left(-r_k \frac{1}{\{g_j(x)\}^2}\right)\frac{\partial g_j}{\partial x_i} \quad (31)$$

Since the sensitivity $\partial S / \partial x$ can be calculated, the objective function (the error between the predicted quality and the required quality) is minimized in an iterative process as the input factor x is gradually changed according to Eqs. (32)and (33).

$$x_{k+1} = x_k - \tau \nabla f^*(x_k, r_k) \quad (32)$$

$$\nabla f^*(x,r) = \left\{\frac{\partial f^*}{\partial x_1}, \frac{\partial f^*}{\partial x_2}, \cdots, \frac{\partial f^*}{\partial x_n}\right\}^T \quad (33)$$

Convergence is achieved if any of the following criteria will meet:

$$f^* \leq \varepsilon$$

$$\frac{|f^*(r_{i-1}) - f^*(r_i)|}{|f^*(r_i)|} \leq \delta \quad (34)$$

ε , δ : small constants

Table 12 Mix proportions and mixing energy before and after optimization

Mix prop.		W/(C+F) (%)	Mix proportion (kg)							Mixing energy (kwh/m³)
			Water	Cement	FA	Sand	Aggr.	WR	SP	
1	Before	55.0	172.6	251.9	62.1	593.5	1872.7	3.38	2.01	0.0957
	After	45.5	157.7	279.5	67.2	564.0	1872.7	3.15	2.01	0.0871
2	Before	52.3	173.7	266.7	65.7	673.8	1833.3	3.63	1.50	0.0972
	After	45.9	155.0	271.5	66.4	654.1	1833.3	2.59	1.50	0.0721
3	Before	50.6	176.8	280.3	68.9	722.7	1790.9	3.76	1.50	0.0782
	After	49.8	172.2	273.3	72.5	641.5	1790.9	2.53	1.50	0.0762

(Note) FA : Fly ash ; WR : Water reducing agent ; SP : Superplasticizer

Table 13 Quality before and after optimization

Mix prop.		Slump (cm)	Air content (%)	Comp. strength (MPa)
1	Before	15.7	5.4	23.3
	After	13.51	5.47	24.9
2	Before	16.1	4.9	29.0
	After	15.04	4.98	27.0
3	Before	16.5	4.7	29.2
	After	15.48	4.98	29.8

The factors which are changed in this process comprise [Mixing energy of mixer] , [Water content] , [Cement content] , [Fly ash content] , [Fine aggregate content] , and [Water-reducing agent content] .

Experimental data (for mix proportion and mixer power consumption) are introduced as the initial values in this optimization process.

6.3 Results and discussion

The results of optimization are shown in Fig. 9. A comparison of the mixing energy, mix proportion, and concrete quality before and after optimization is shown in Tables 12 and 13. The aggregate was in the saturated surface-dry state and the water content includes the surface moisture of the aggregate. The total volume of concrete before and after optimization was not always equivalent, since we did not adopt total volume as a constraint.

The outputs of the network for optimized mix proportion and mixing energy correspond well with the required quality level, while the deviation in quality in non-optimized concrete was fairly large(Fig. 9). The deviation is effectively reduced by use of the neural network, though some deviation remains as a result of prediction errors in the network.

The optimization process needs only some dozens of iterations in each case. Furthermore, this calculation cost can be reduced further by improving the objective function and the convergence calculation method, and also by using more suitable data as the initial input values.

7. SYSTEM PROPOSAL

We have demonstrated that the surface moisture content of aggregates and concrete quality can be predicted to good accuracy, and further that optimized mix proportions and mixing energies for a required quality can be calculated. On this basis, we propose a new quality control system for concrete production by combining these methods.

A flow chart of the proposed method is shown in Fig. 10. There are two main processes: prediction of the surface moisture content of the aggregate and optimization of the mix proportion and mixing energy.

The first step is to predict the surface moisture content of the aggregate (both fine aggregate and total aggregate) from the charge of each ingredient and three specific values of mixing energy (cumulative, maximum, and converged value) by using Neural Network 1 (N.N1).

Next, the mix proportion and mixing energy are optimized so as to bring the concrete quality predicted from the true mix proportion (corrected by the surface moisture content of the aggregate) to the required quality using Network 2 (N.N2). The sensitivity used in the optimization process is calculated by the connection weights and threshold values of Network 2. The quality is estimated at each step of the optimization, and iterative calculations are continued until the error between predicted quality and required quality converges.

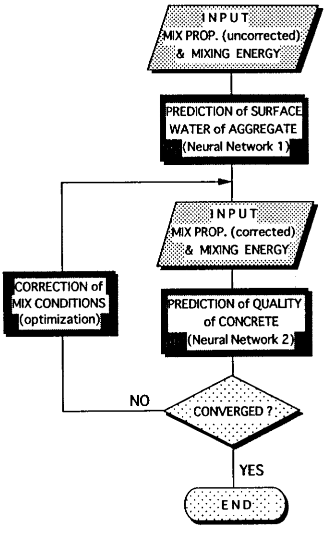


Fig. 10 Flow chart of quality control system for concrete production

From this calculation, we obtain suitable conditions for the required concrete quality. Prediction using the trained neural network terminates in a very short period and the number of iterations required for optimization is only some dozens. The calculation terminates within a few seconds even when running on a personal computer, and the result is of good use when mixing the next batch. It is true that the optimized conditions cannot be obtained before mixing, since the cumulative mixing energy is needed to predict the surface moisture content of the aggregates, but if we mix in two steps combining two mixer, an estimate can be made before mixing. That is, the surface moisture of the aggregate is predicted using information obtained from the upper mixer (used for dry mixing) and then the concrete is mixed in the lower mixer with the proper mixing energy and corrected mix proportion. Accordingly, a higher quality of concrete can be obtained.

8. Conclusions

In this study, a new method of quality control in concrete production based on a neural network is proposed. The on-site availability of the method using experimental data obtained at the site is also examined. Issues related to the discussion presented here can be summed up as follows.

(1) Prediction of surface water content

It is shown that factors which cause estimation difficulties, such as surface moisture content of the aggregate, can be predicted to high accuracy. The mean error in predicting the total water content for each batch is only 1.2%, even in tests with low-grade fine aggregates with a surface moisture ratio of over 10%. Consequently, changes in the dominant factor causing quality changes, i.e. the water content in each batch, can be checked.

(2) Prediction of concrete quality

A neural network is suitable for field data, since the prediction accuracy obtained with field data is the same as that for data obtained from indoor tests.

(3) Sensitivity analysis using neural network

It is possible to isolate affecting factors and estimate the degree of their effect by carrying out a sensitivity analysis on the connection weights and threshold values of the trained neural network.

By using this method, changes in concrete quality resulting from variations in mix proportion caused by batching errors can be estimated. The method is easily applied by preparing learning data and teaching a network. The method involves no subjective assumptions by the authors, and all estimates are quantitative. It is a very promising method for quantitatively clarifing the input-output relationships with respect to different phenomena.

(4) Optimization of concrete quality
Suitable conditions for a required quality of concrete can be obtained by the proposed system, which is based on the above methods. The optimized conditions cannot be obtained before mixing, since the cumulative mixing energy is required. However, a two-step mixing offers one possible solution to this dilemma. The system can be easily reworked to apply such a mixing method.

(5) Summarize
At present, there is a degree of concern as regards the quality of concrete during the mixing process. A great deal of reliance is placed on the intuition of engineers, yet the quality of the concrete produced is still not always constant. A neural network makes it possible to predict the quality of concrete easily and immediately upon mixing.

The network can be updated with training sessions as new data becomes available. The prediction accuracy depends greatly on the reliability of the data, so there is a need to establish a management system for obtaining a large amounts of accurate data distributed over a wide range. It is also necessary to increase prediction accuracy by incorporating other factors (such as the temperature of the mixed concrete or mixing water) into the system.

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