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PREDICTION METHOD FOR VC-VALUE OF ROLLER-COMPACTED DAM CONCRETE USING NEURAL NETWORK

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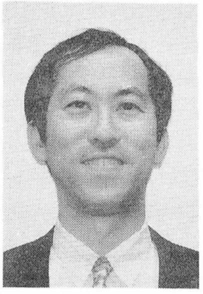
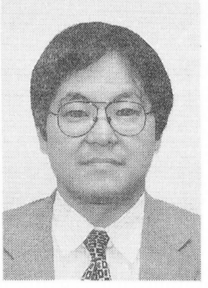
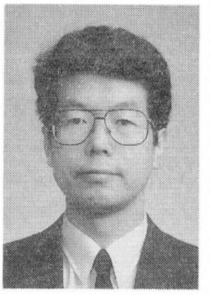

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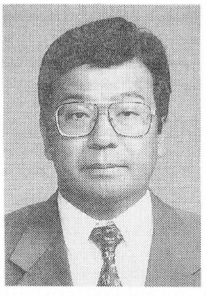


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In this paper, an advanced method of quality control for the mixing of roller-compacted dam (RCD) concrete is presented. The method to predicting the workability function VC value from the input parameters of mix proportion and mixing energy using a neural network. A successful neural network system for prediction of VC value was developed using experimental data. According to sensitivity analysis, the parameters surface moisture of fine aggregate, volume of fine aggregate, water volume and power consumption are shown to be important parameters which have a significant effect on VC value.

Keywords: neural network, RCD concrete, VC value, mixing quality control, power consumption

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1. Introduction

Roller-compacted dam (RCD) concrete is widely used for dams due to its advantages of economy and suitability. RCD concrete contains little water per unit volume and it is very important to control water volume, since variations in water volume may sensitively affect the quality of concrete (consistency). Water content is usually controlled by measuring the moisture ratio of aggregates and by VC testing after mixing. The former, the measurement of the surface moisture ratio of aggregate, is carried out of every batch. VC testing is carried out as a sampling test about once an hour. Concrete is a complex none-homogeneous material that consists of aggregate, cement, and water. It is difficult to predict consistency by developing a physical model, so a model based on fluid mechanics with cohesion is not suitable. When such a physical model can not be developed, predictions based on inverse analysis are usually carried out experimental. Such prediction rely on stochastic methods such as regression analysis and quantitative theory.

However, in order to deal basically as the linear equation using a stochastic method, the regression analysis entails replacing the nonlinear parameters with linear regression analysis approximately and eliminating the parameters with high correlation among the many explanation parameters. Recently, great attention has focused an neural network systems[1),2)] as a way to solve problems that are difficult to estimate using existing stochastic method. There are same cases of neural network systems being applied to civil engineering evaluations. Examples are the solution and evaluation of complicated and experimental problems, scenery evaluations[3)], slope stability evaluation[4)] and damage level evaluations[5)~8)]. Uomoto's[9),10)] use of a neural network in the quality control of ordinary concrete mixing as one of them. This study shows that a system based on choosing a concrete mix proportion, and the maximum and integrated mixer power consumption can predict the final compressive strength of the concrete, its air ratio, and slump. Based on the findings, an optimum system for controlling variations in quality at batching plants is proposed. In comparison with ordinary concrete with slump, it is difficult for RCD concrete to apply such a quality control method to be used in ordinary concrete so that the mixing torque by mixer could become to be constant after increasing at the beginning.

It has been proposed the idea that quality control can be base on the relationship between mix proportion characteristics and VC value obtained by linear regression analysis such that the paste fine aggregate pore ratio that assumes to divide the paste volume in concrete 1m^3 by the fine aggregate pore volume can relate closely with the consistency[11),12)]. Although this idea helps in mix proportion design, some problems remain predicting VC value in real time because of limitations an available input items.

In this paper, the neural network system is developed by choosing as input items the volumes of aggregate, cement, and fly ash, water and the surface moisture ratio of fine aggregate, specific gravity of aggregate, water absorption ratio, and power consumption in mixing. Real time VC value are predicted for batching plants. Moreover, the parameters affecting VC value are obtained by the sensitivity analysis using the developed neural network system.

2. Estimation of VC value using neural network

(1) Mixer torque

Quality control is carried out at experimentally concrete batching plants using mixer torque as an important parameter, since mixer torque value easily available on the control panel. An experienced operators know that a tiny variation in surface moisture ratio of the fine aggregate can be affected the mixer torque, and consistency may be varied by controlling the surface moisture. It is well known that there is an optimum mixing time, since the power consumption of the mixer relates to concrete slump[13),14)]. According to Uomoto[9)], measuring the mixer power consumption are method of measuring the force directly acting on the wings of the mixer, while the energy transferred to the concrete can be predicted from mixer torque value. In this paper, mixer power consumption in used instead of mixer torque since mixer power consumption can be considered equivalent to mixer torque.

A comparison of power consumption between ordinary concrete and RCD concrete is shown in Figure.1 and Figure 2, respectively. High-frequency components in the time history of mixer power consumption are observed in both. However, although a flat curve is observed with RCD concrete, it is peaked in ordinary concrete. The reason derives from the mortar ratio, since mortar acts as a lubricant between coarse aggregates particles. In the case of ordinary concrete, the gear friction between aggregates governs the torque value since the mortar can not be formed at first. The concrete becomes a viscous fluid as the mortar component forms with elapsed time. On the other hand, in the case of RCD concrete, the concrete does not become a viscous fluid even at the end of mixing because of low mortar ratio, so torque remains gear friction. Since the power consumption with RCD concrete is flat, the mean value can be used as a characteristic parameter. Integration power consumption per unit dividing integrated value of time history of power consumption during mixing is chosen as an input parameter in this paper. Therefor, the simple parameter of integrated power consumption is assumed in the developed system.

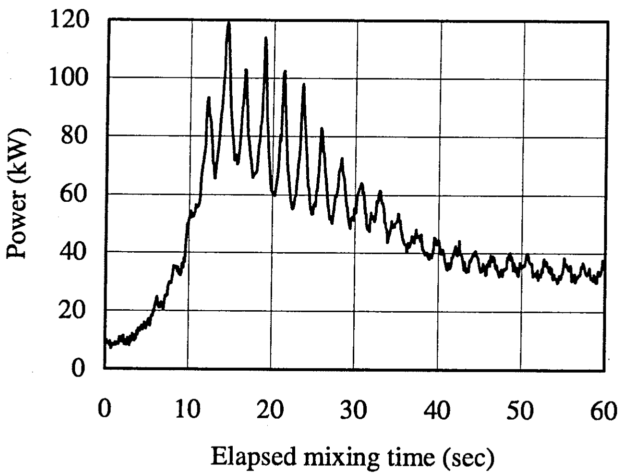

Figure 1 Power consumption in mixing (ordinary concrete)

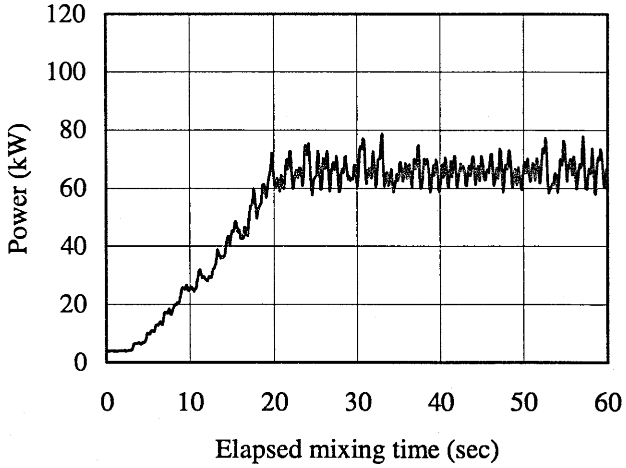

Figure 2 Power consumption in mixing (RCD concrete)

(2) Input parameters of proposed system

The data obtained before and during mixing are chosen as input parameters and the VC value obtained after mixing is the output parameter. There are 19 input parameters, as shown in Table 1. Criteria for choosing input parameters are limited to obtain automatically and to obtain as daily care for the sake of real time prediction. Therefore, although graduation of fine aggregate size, solid content ratio, fine aggregate under 15 mm, and surface moisture ratio of the coarse aggregate (G4) are related to consistency, we do not choose these as input parameters in the proposed system. Since the surface moisture ratio of the coarse aggregate can be measured only once a day, the mix proportion is adjusted by the weight of coarse aggregate with a particular surface moisture content. However, since the surface moisture ratio of fine aggregate affecting greatly VC value is measured in each batch, the surface moisture ratio of fine aggregate is chosen as an input parameter. The specific gravity of aggregate and water absorption ratio are also chosen as input parameters. This is because the VC value may be affected by varying a kind of stone in each pit of dam site. It is well known that ready-mixed concrete temperature can greatly affect the consistency. The data used in this paper are obtained for a short period from spring to summer. Although the temperature varies between 18 and 30 ℃, the concrete temperature varies only by 20 $\pm$1.0℃. Therefore, The concrete temperature is not chosen as an input parameter because its variation is small.

Since VC testing is carried out for the quality control of RCD concrete consistency, it is chosen as the output parameter. The VC value is obtained from a small test machine in this paper. Concrete with aggregate under 14mm is obtained as a specimen for VC testing by wet-screening. Thus, the results obtained are slightly different from the consistency of concrete obtained from batching plants. However, it is well known that a VC value obtained from a small testing machine can be correlated to a VC value obtained from a full-size machine with full-size aggregate. The proposed system is developed using a small testing machine. The cement used in mixing is a moderate-heat Portland cement. Mixing duration in the tests is 90 sec. Mixer power consumption is obtained by integrating the power from the time of material input until 30 sec of mixing.

Table 1 Input items

Input items	Range of data
1. Volume of coarse aggregate G1 (80 to 120mm)	916～1096kg
2. Volume of coarse aggregate G2 (40 to 80mm)	748～812kg
3. Volume of coarse aggregate G3 (20 to 40mm)	630～790kg
4. Volume of coarse aggregate G4 (5 to 20mm)	818～978kg
5. Volume of fine aggregate (S)	1278～1464kg
6. Volume of cement and fly ash (C+S)	207.4～264.9kg
7. Water volume(W)	53.46～127.40kg
8. Surface moisture ratio of fine aggregate (Sr)	3.1～8.3%
9. Specific gravity of coarse aggregate (G1)	2.7～2.74
10. Water absorption ratio of coarse aggregate (G1)	0.19～0.39%
11. Specific gravity of coarse aggregate (G2)	2.7～2.75
12. Water absorption ratio of coarse aggregate (G2)	0.18～0.50%
13. Specific gravity of coarse aggregate (G3)	2.70～2.74
14. Water absorption ratio of coarse aggregate (G3)	0.33～0.87%
15. Specific gravity of coarse aggregate (G4)	2.68～2.73
16. Water absorption ratio of coarse aggregate (G4)	0.79～1.53%
17. Specific gravity of fine aggregate (S1)	2.65～2.67
18. Water absorption ratio of fine aggregate (S1)	1.34～1.82%
19. Integrated power consumption (30sec)	606～680kWh/m^3

(3) Structure of neural network system

A neural network system is a system in which the neurons and synapses of cerebral nerves are modeled mathematically by cells and networks[15]. Learning using a combination of well-selected data can lead to the development of a complicated nonlinear model. A hierarchical neural network developed by the learning method with teaching data is adopted, as shown in Figure 3. One layer used widely in general is adopted as the medium layer. Nodes between 1.0 to 2.0 times the nodes of the input layer are experientially appropriate, although no rule to determine the number of nodes of the medium layer can not generally established. 30 nodes that is 1.5 times the nodes of input layer are chosen as the nodes of the medium layer from the results of case studies in this paper. Since values between 0.2 to 2.0 as the temperature T of sigmoid function are appropriate from existing studies[16], T is chosen as T=1.0.

3. Input data used in learning

Data are gathered using a batching plant equipped with a forced concrete mixer with a double axis and 3000ℓ capacity. The parameters affecting variations in VC value are (1) error of VC test, (2) variation in surface moisture ratio of aggregate, and (3) measurement errors of materials. Measurement equipment errors are such that the coarse aggregate (G1) is within 3%, the fine aggregate and the coarse aggregate (G2 to G4) within 2%, and the volume of fly ash, cement, and water within 2%. 97 mixing data are chosen by varying the combination of mix proportion with volume of cement and fly ash 110, 120 and 130 kg/m^3 in test construction as

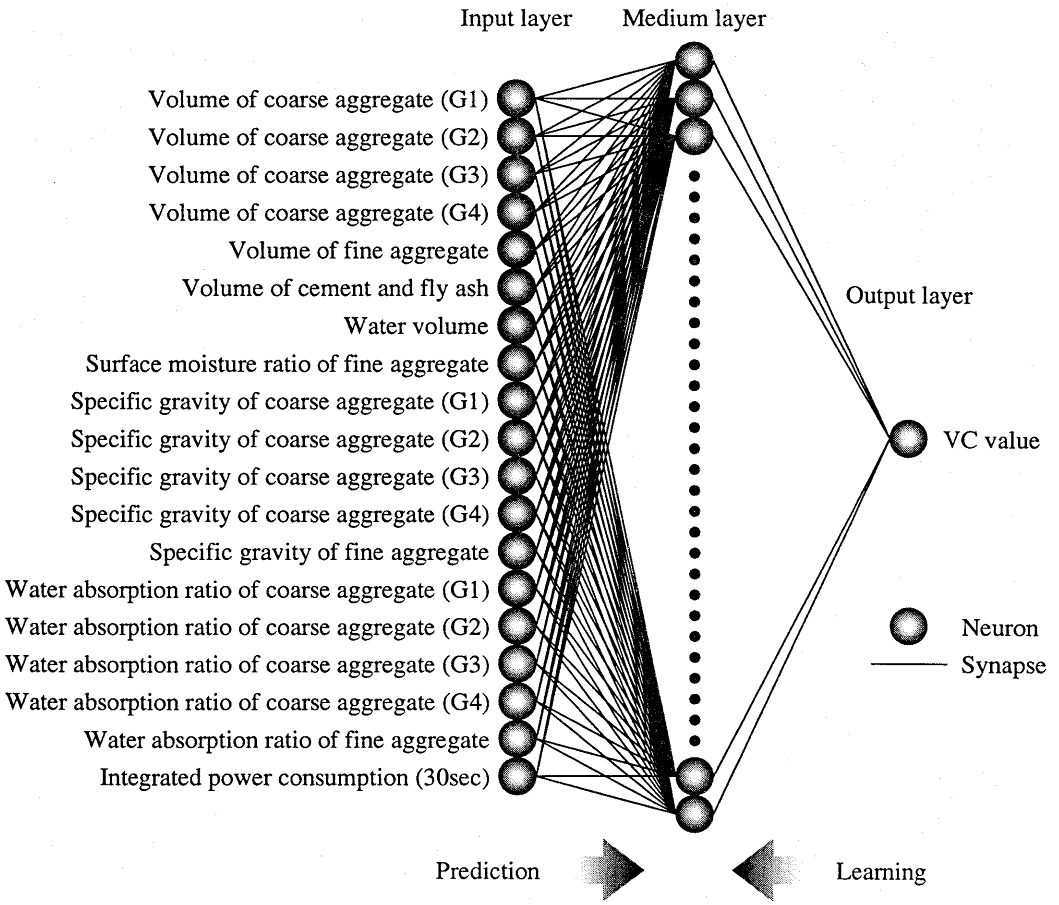

Figure.3 Developed neural network system

shown in Table 2. The range of test data as shown in Table 1 widely cover the range of actual data with actual mix proportion with 2000 ℓ /batch. Therefore, the proposed system obtained in this paper is reliable if the uncertainty of the actual data is considered.

21 mixing data for verification are chosen from 97 mixing data in order to eliminate bias errors. Therefore, 76 data are obtained as learning data. It is well known that neural networks improve as the number of data points increases for the same reason that linear regression analysis with the evaluation equation of least mean squares method. Since actual data contain errors, it is important for data used to appropriately represent the population. From existing studies[17)], it is judged that the number of data obtained in the above manner are suitable for the prediction of the population.

4. Learning and verification

Generally, in solving complicated problems with neural networks, the errors fall with increasing learning. However, excessive learning leads to the increasing of prediction errors. In order to avoid excessive learning, the relationship between the number of learning steps and

Table 2 Mix proportions in test mixing

No.	W/ C+F	C+F kg/m^3	Per unit (kg/m^3)*1									N. of mixes *2
			W	C	F	S	Coarse aggregate kg/m^3				Ad	
			kg/m^3				G1	G2	G3	G4	%	
1	78.2	110	86	77	33	637	417	417	417	417	0.275	3(1)
2	82.7	110	91	77	33	634	415	415	415	415	0.275	5(2)
3	87.3	110	96	77	33	630	412	412	412	412	0.275	1(0)
4	70.8	120	85	84	36	635	416	416	416	416	0.300	4(2)
5	75.0	120	90	84	36	632	413	413	413	413	0.300	20(6)
6	79.2	120	95	84	36	628	411	411	411	411	0.300	4(1)
7	69.2	130	90	91	39	629	412	412	412	412	0.325	10(3)
8	75.0	120	90	84	36	699	396	396	396	396	0.300	2(0)
9	79.2	120	95	84	36	695	394	394	394	394	0.300	5(0)
10	75.0	120	90	84	36	636	416	416	416	396	0.300	15(4)
11	73.3	120	88	72	48	636	416	416	416	416	0.300	7(2)
Total number of mixes												76(21)

*1:Maximum size of coarse aggregate Gmax=120mm, air=1.5±1%

*2: Number of mixes and number in () indicates number of verification mixes.

W: water volume, C: cement, F: fly ash, S: fine aggregate, Ad: admixture

errors is investigated. The relationship between the number of learning data and the resulting error is shown in Figure 4. Recognized errors become smaller with increasing learning. However, prediction errors become smaller with increasing learning at the first and larger later. Unknown obliviously the reason to arise the excessive learning, it is supposed that the origin of the excessive learning may be on the system structures such as node number, number of medium layers, the characteristics of input items and learning data. Parametric studies are carried out by varying the node number of the medium layer N=25, 30, 35, and 40 and the temperature of the sigmoid function T=0.5, 1.0 and 2.0. The developed system is adopted as an optimum system when recognized errors is minimized. The system obtained using 7000 learning steps with N=30 and T=1.0 is chosen as the optimum. The workstation to develop the system was HP-Apollo Model 715/50. The time taken to develop the system was about 5 minutes. Predictions are instantaneous. The results of learning data and the results predicted the verification data using the developed system show Figure 5 and Figure 6, respectively. These figures indicate the relationship between actual data and output data that predicted by the developed system using inputs corresponding to actual data. It can be said that verification and learning are satisfactory with the developed system. The target VC value is 20sec. Although many data concentrate around the target VC value, VC values over 30 sec. are also predicted as well. It is found that the coefficient of variance (C.O.V.) of prediction error is a constant, since the error increases with the VC value increasing. Histograms of recognized error on learning and prediction error on verification are shown in Figure 7 and Figure 8, respectively. The standard deviation (S.D.) of recognized error and predicted error are σr =5.71sec and σp=7.45sec respectively. Both S.D. values are smaller than the target control criteria for the error in VC value, 20±10sec, and are not biased. According to existing studies[18),19)], the C.O.V. of VC values obtained by VC tests in laboratory is about 0.2. Clearly the developed system using a neural network is accurate enough to predict VC values because the S.D. at the target VC value of 20sec. is 4sec. This example demonstrates that a neural network is a useful way to solve complex problems with multiple nonlinear input parameters.

On the other hand, in developing the hierarchy structure of the neural network system, as shortcoming is that decisions about medium layer and the number of learning steps must be made through trial and error, since no formal method of development has been established. However, it can be solved the problem using the sensitivity analysis described in the following chapter.

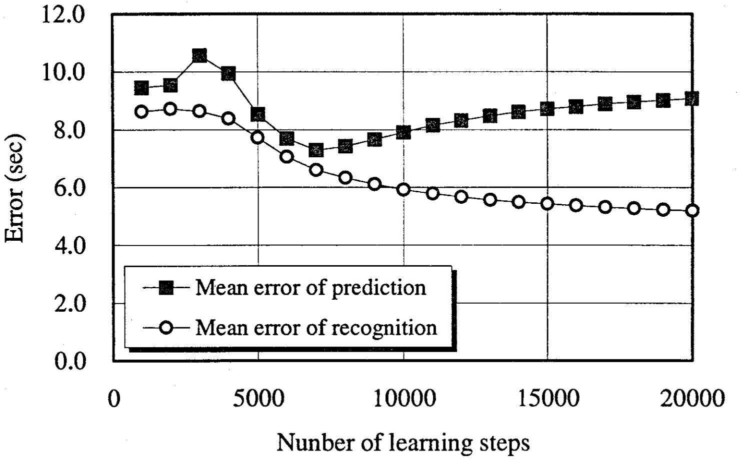

Figure 4 Errors in learning steps and elapsed time

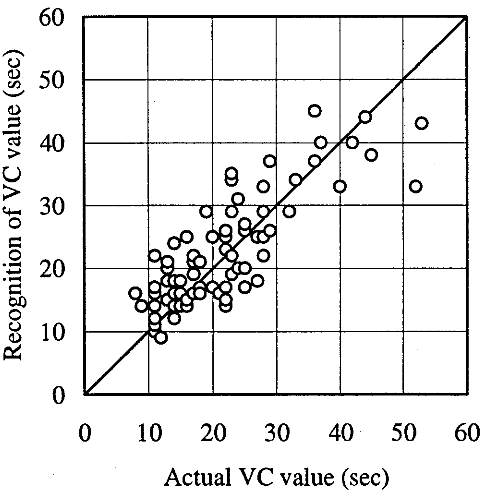

Figure 5 Results of leaning (N=7000)

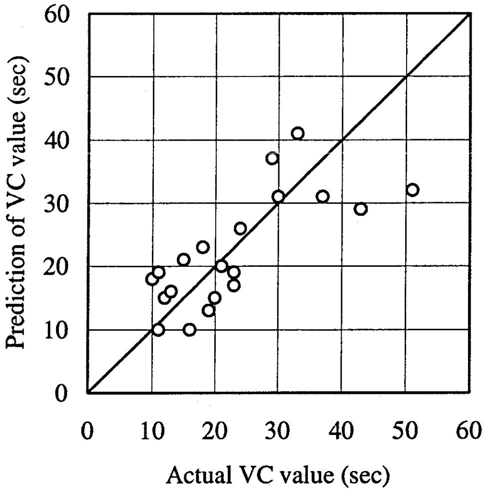

Figure 6 Results of verification (N=7000)

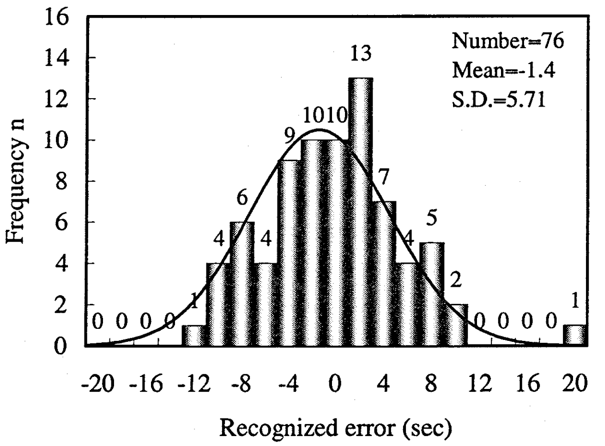

Figure 7 Recognized error distribution of learning

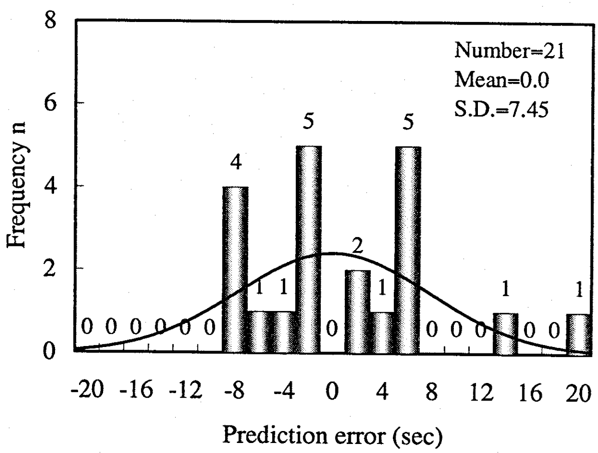

Figure 8 Error distribution of verification

5. Sensitivity analysis

(1) Method of sensitivity analysis

Sensitivity analysis of outputs against inputs is carried out with the developed neural network system. The process of predicting VC values is verified by comparing the sensitivity of output against input. Although a theoretical description of sensitivity analysis is given in Reference (8), the computational method used is explained bellow.

Variation in VC value can be computed by discretely varying the value of target items in the range $\pm\sigma$ (σ is the S.D.) from the mean value while holding other inputs fixed their mean values. The sensitivity δ_i of input item i around the mean value can be calculated as Equation (1).

$$\delta_i = \frac{|VC_{+\sigma} - VC_m| + |VC_m - VC_{-\sigma}|}{2VC_m} \tag{1}$$

Where, δ_i : the sensitivity of input item around the mean value against VC value, $VC_{+\sigma}$: VC value corresponding to mean value +1.0 σ of input data, $VC_{-\sigma}$: VC value corresponding to mean value -1.0 σ of input data, VC_m: VC value corresponding to mean value of input data.

Combined sensitivity on the adjustment of mix proportion induced from the variation of surface moisture ratio using the sensitivity around mean value of each input items is obtained to combine as $\Sigma\,\delta_i^2$ using Equation.(1).

However, when parameters indicate a correlation among input items, it is assumed as the probability with a condition as shown in Figure (2).

$$P_r = P(E|a)\cdot P(a) \tag{2}$$

The probability with a condition can be described as the occurrence probability Pr of E with the condition of parameter a. A similar approach can be also used in sensitivity analysis. A correlation exists between the surface moisture ratio and the fine aggregate. The fine aggregate is adjusted the in mix proportion according to measurements of the surface moisture ratio. Thus the measured volume of fine aggregate tends to increase with rising surface moisture ratio. Assuming the parameters with a correlation as independent parameter, a contradiction occurs among the combination values obtained using each parameter. Computing the sensitivity, the parameters with correlation are treated as the probability with a condition in this study. The sensitivity analysis is proceeded by input items with a correlation varying the value corresponding to the correlation and other parameters fixing the mean value. Concretely, the parameters with the correlation over 0.7 are chosen and the parameters having not a contradiction with characteristics of fresh concrete among the chosen parameters assume as the parameters with a correlation.

The parameters with a correlation obtained by above manner are one of concerning with variation of water. As an example, Figure 9 shows the relationship between the surface moisture ratio of fine aggregate and the water volume, Figure 10 shows the relationship between the surface moisture ratio of fine aggregate and the fine aggregate value and Figure 11 shows the relationship between the mixer power consumption and the water volume. According to the relationship mentioned above, combined sensitivity is obtained by assuming that four parameter, the surface moisture ratio of fine aggregate, the water volume, the fine aggregate value, and mixer power consumption, are completely correlated. Five parameters without a correlation, such as cement and fly ash value and coarse aggregate (G1 to G4) value are assumed as independent parameters. Since the sensitivity analysis is carried out using the same mix proportion and aggregate obtained from the same pit, the specific gravity and water absorption ratio associated with the aggregate are assumed constant.

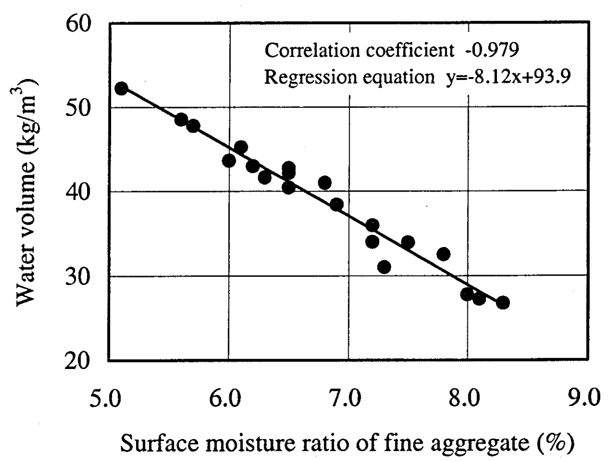

Figure 9 Relationship between surface moisture ratio of fine aggregate and water volume

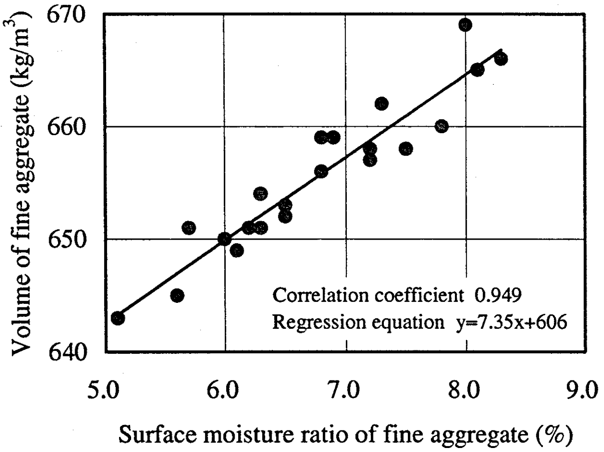

Figure 10 Relationship between surface moisture ratio of fine aggregate and volume of fine aggregate

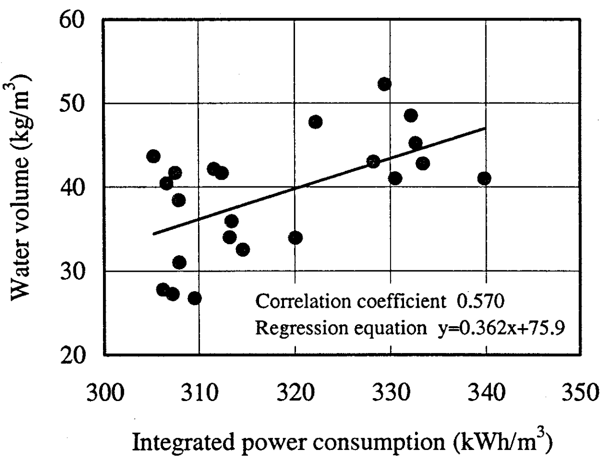

Figure 11 Relationship between integrated power consumption and water volume

(2) Results of sensitivity analysis

The sensitivity analysis is carried out using 22 mixing data with the same mix proportion and the same aggregate from among 97 mixing data tested. Figure 12 shows the histogram of VC value for sensitivity analysis. The mean VC value is 21.8sec., the standard deviation 10.6sec. and the coefficient of variance 48.5%. The VC value varies widely as shown in the figure, even with the same mix proportion. Figure 13 shows the results of sensitivity analysis of each input items against VC.

The most sensitive input item is the water moisture ratio of fine aggregate. Sensitivity of surface moisture ratio of fine aggregate because the variation of water volume and fine aggregate may have an extreme effect on VC value. Although the surface moisture ratio of fine aggregate is measured every batch, adjustments are not carried out until the next batch. Expert engineers know as well that reflecting abrupt changes in surface moisture ratio of fine aggregate on the mix proportion can lead to consequent instability in concrete consistency. Thus, the adjustment of mix proportion is a complex process of complicated decision-making that takes into account trends in time history of variation in surface moisture ratio. In comparison with most parameters explained by equipment measurement error, large variations in VC value result from parameters related to water that are difficult to control.

The variation of VC value in Figure 12 is compared using each sensitivity obtained above. It is supposed that the sensitivity of each input items mentioned above may be induced by the variation of VC value. The adaptation of developed neural network system is estimated to compared the variation of actual VC value with the variation obtained to sum up the variation of VC value computed by the sensitivity of input items.

The sensitivity of VC value to each input item is summed up using Equation (3).

$$\delta_{T0}^{\ 2} = \sum_{i=1}^{n} \delta^2{}_i \tag{3}$$

Equation(3) is obtained by assuming that every input item is independent. Although strictly a computation that considers the correlation between parameters is necessary, the gross sensitivity is obtained by the sum of squares as a simplified model in this paper. From computations, δ_{T0}=0.49 is obtained. Moreover, VC values obtained in the VC test contains measurement errors. Since measurement errors are δ_m=0.2 according to an existing study, the variation in VC value is obtained as Equation (4).

$$\delta_{T0}^{\ 2} = \delta_{T0}^{\ 2} + \delta_m^{\ 2} = 0.49^2 + 0.2^2 = 0.53^2 \tag{4}$$

In comparison with the actual VC value of 58.5%, these results demonstrate the accuracy of the developed system, although there are some scatter. Thus, these results back up the concept of

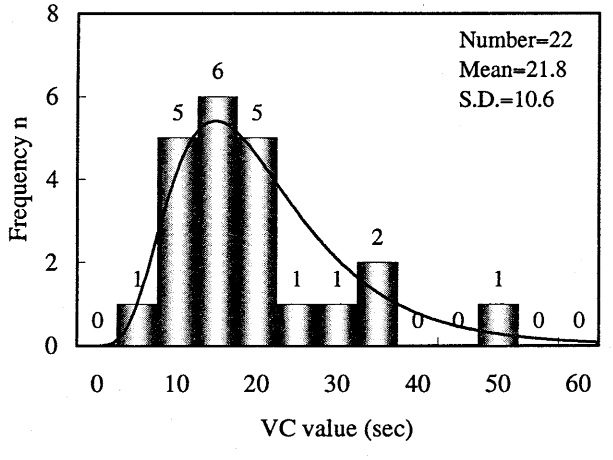

Figure 12 Variation of VC value

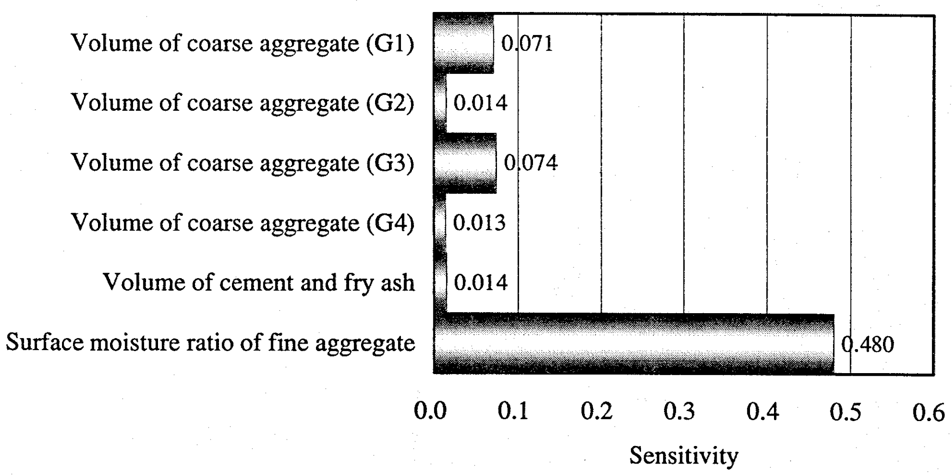

Figure 13 Sensitivity of each input items

the developed neural network, and it is thought that this system can be applied to batching plants in situ.

5. Conclusion

It is clear that this advanced system of quality control for roller-compacted dam concrete based on a neural network can successfully predict VC values. The findings of this paper are as follows.

(1) VC value in actual batching plants are well-predicted using neural network by taking the mix proportion, mixer power consumption, and measurements equipment of surface moisture ratio as inputs.
(2) The accuracy of predictions of VC values of RCD concrete is about 5 sec. Thus, the developed system is accurate enough to predict VC value given that criterion for VC values in VC tests is 20 ± 10sec.
(3) The parameters affecting VC value have been verified by carrying out the sensitivity analysis with the developed neural network. The parameters found to have high sensitivity are ① surface moisture ratio of fine aggregate, ② volume of fine aggregate, ③ water volume, and ④ integrated power consumption.

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