Prediction of Engineering Properties of Alkali-Activated Slag Mortar (AASM) Using Artificial Neural Network (ANN)

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ABSTRACT

In recent years, alkali-activated material is one of new construction material concerning carbon reduction and waste recycling. Alkali-activated slag mortar (AASM) has high mechanic properties and low thermal conductivity in previous studies. It also has high potential for in-situ applications. Therefore, the modeling for evaluating the engineering properties of AASM is important. On the other hands, Artificial Neural Network (ANN) is a normally common artificial intelligence modeling. It was successfully used to predict the engineering properties of concrete. In this study, the AASM specimens cast with the different Liquid-solid ratio (L/S=0.50, 0.55, 0.60), alkali equivalent (N=0.5, 0.75, 1%) and waste LCD glass sand replace the slag (R=0, 10,20%).

The testing results shows that the final setting time, 7-days compressive strength and thermal conductivity of AASM is influenced mainly by the variable of L/S, N and R. The final setting time and thermal conductivity of AASM decrease with the increasing of L/S, N and R, respectively. The 7-days compressive strength of AASM increasing due to the increase of N and the decrease of N and R, respectively. On the other hands, the root of mean square of Error (RMSE) of ANN prediction results is less than 20%. ANN can be used to predict the engineering properties of AASM.

Keywords: Alkali-Activated Slag Mortar, Artificial Neural Network

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1. INTRODUCTION

In recent years, many industry wastes are usually reused in construction engineering for environment sustainable consideration. The ground granulated blast furnace slag (GGBFS) is a by-product from the iron and steel industry and the major components are SiO₂, CaO, Al₂O₃ and the other oxides. The large quantity of GGBFS is produced every year in Taiwan and caused the environmental problems. On the other hands, Taiwan is one of major LCD panel producers in the world, next to South Korea. The LCD waste glass has increased rapidly. Therefore, the processing of GGBFS and LCD waste glass should develop towards recycling, including construction material. The alkali-activated material is one of new construction material concerning carbon reduction and waste recycling.

In previous study (Yang 2012, Wang 2014, 2016, 2017), the Alkali-activated slag mortar (AASM) contain waste glass has high mechanic properties and low thermal conductivity. The GGBFS and LCD waste glass particle is dissolved in the alkaline solution and the Si and Al gel is formed on the surface of particle. Then, the polysialate is occurred and form the networked structure as following (Davidovits 2008):

$$Mn[-(SiO_2)Z - AIO_2]n \cdot wH_2O$$

(1)

where, M indicates the positive ion of metal, n indicates the degree of polymerization, z indicates the ratio of silica to aluminum and normally equal the range of 1 to 3. The sketch of different structures of polycondensation were shown as Figure 1.



Figure 1: structures of polysialates (Davidovits 2008)

Previous studies (Wang 2014, 2016, 2017) investigated the Liquid-solid ratio (L/S), alkali equivalent (N) and LCD waste glass replacement (R) are the significantly factors and affect its engineering properties. It also has high potential for in-situ applications.

2. ARTIFICAL NEURAL NETWORK (ANN)

A biological neuron is composed of dendrites, synapses, axon and the cell body. The typical artificial neuron, shown as Figure 1, is a mathematical model based on the biological neuron and it is the basic element of artificial neural network (ANN). ANNs are massively parallel systems composed of many processing elements connected by links of variable weights (Gupta 2013, Soares 2018).



Figure 1: Simplified model of an artificial neuron (Gupta 2013)

The backpropagation neural networks (BPN) is one of commonly used ANN. The backpropagation neural networks, shown as Figure 2, generally have a layered structure with an input, an output, and one or more hidden layers. The modification process is continued in the output layer, where the error between the network outputs and desired targets is calculated, and then propagated back to the network through a learning mechanism. The BPN is successfully used to predict the engineering properties of concrete (Bilgehan, 2010, Gupta 2013). Therefore, ANN with backpropagation training algorithm is used in this study.



Figure 2: A typical ANN topology (Gupta 2013)

3. EXPERIMENTAL PLAN

3.1 EXPERIMENTAL MATERIALS

The characteristics of the raw materials of alkali-activated GGBFS used in this study are described as follows:

(1) GGBFS: in this study, it is produced by China Steel Corp. and pulverized by CHC Resources Corp in Taiwan. Its properties conform to CNS12549. The physic properties and chemical composition was shown as Table 1 and Table 2, respectively.

Bulk density	Fineness	Activi	ty Index
(g/cm ³)	(cm²/g)	7 days	28 days
2.89	4000	89.5	119.6

Table 1 Physic properties of GGBFS

Table 2 Chemical composition of GGBFS

SiO ₂	AI_2O_3	Fe ₂ O ₃	CaO	All other oxides	L.O.I.
33.47	14.79	0.40	41.61	9.15	0.58

- (2) LCD waste glass: The LCD waste glass sand is from Chi Mei Optoelectronics Corp. It is ground by dry grinding with a crusher and ball mill into fine liquid crystal glass sand with large particle size. The fineness of LCD waste glass is 2009 cm2/g
- (3) Alkaline solutions: In this study, the commercially available alkali at a purity of 98% is used as the alkali activator and it was mixed with deionized water to make a 5 N NaOH solution.
- (4) The alkali metal silicate solution: The No. 3 sodium silicate solution produced by Rong Xiang Industrial Co., Ltd., and the chemical properties are shown in Table 1.

Table 3 Chemical composition of alkali agent composition analysis

Pilot project	(Unit:%)			
	NaOH	NaCO₃	NaCl	Fe
alkali agent composition analysis	98.2	0.165	0.0135	0.0004

Table 4 Chemical composition of LCD waste glass and alkali metal silicate solution

items	(Unit:%)								
liems	SiO ₂	AI_2O_3	Fe ₂ O ₃	CaO	K ₂ O	Na ₂ O	TiO ₂	Fe	SiO ₂ /Na ₂ O
LCD waste glass	62-48	16.67	9.41	2.70	0.20	0.64	0.01	-	-
Alkali metel silicate solution	28-30	-	-	-	-	9-10	-	0.02	2.8-3.3

3.2 Test mix proportions and variables

This study used different liquid-solid ratios (L/S=0.50, 0.55 and 0.60), alkaline solutions (N=0.5%, 0.75% and 1%), and waste LCD glass replacement (R=0, 10 and 20%), respectively. The mix proportion of AASM is shown in Table 5. In total, 81 AASM cube specimens (50x50x50 mm) were cast and cured at 25°C. The engineers are primarily interested to the workability, safety and thermal properties of construction material. Therefore, the final setting time (T_f), 7-days compressive strength (f_c) and thermal conductivity (λ) were investigated, respectively, in this study.

3.3 EXPERIMENTAL METHOD

. The setting time test followed ASTM C403 specifications. The 7-days compressive strength was tested in according to ASTM C109. The thermal conductivity was measured with a portable heat transfer meter.

		Ta	able 5 The r	nix proportion o	of AASM	
1/9	N	R	GGBFS	LCD waste	Sodium silicate	Sodium
		(%)		glass	solution	hydroxide
		0	1377	0	640	49
	0.50	10	1239	137.7	640	49
		20	1102	275.4	640	49
		0	1371	0	613	73
0.50	0.75	10	1234	137.1	613	73
		20	1097	274.2	613	73
		0	1365	0	586	97
	1.00	10	1229	136.5	586	97
		20	1092	273	586	97
		0	1312	0	675	46
	0.50	10	1181	131.2	675	46
		20	1050	262.4	675	46
		0	1306	0	649	69
0.55	0.75	10	1175	130.6	649	69
		20	1045	261.2	649	69
		0	1301	0	623	92
	1.00	10	1171	130.1	623	92
		20	1041	260.2	623	92
		0	1252	0	707	44
	0.50	10	1127	125.2	707	44
		20	1002	205.4	707	44
		0	1247	0	682	66
0.60	0.75	10	1122	124.7	682	66
		20	998	249.4	682	66
		0	1242	0	657	88
	1.00	10	1118	124.2	657	88
		20	994	248.4	657	88

3.4 DISCUSSION ON EXPERIMENTAL RESULTS

. The experimental result is shown as Table 6 and each value indicates the average of 3 specimens. The discussion on the experimental results is described as follows:

(1) Final setting time

. As N is 0.5% and the L/S is increased from 0.50 to 0.55, the final setting time is prolonged by 131 mins. As the L/S is increased to 0.60, the final setting time is prolonged by 227 min. the setting time is prolonged due to increasing of the water content of the alkali metal silicate solution.

. As L/S is 0.55 and the N is 0.5%, the final setting time is 595 min. As N increases to 1%, final setting time is shortened by 100 min, indicating that an increase in the N can shorten the setting time.

. The result also shows that the setting time increases as the glass sand replacement increases. It indicates that the glass sand cannot rapidly undergo a polyreaction with slag and OH- ions due to the glass sand is water repellent. So, the (2) 7-days compressive strength

. Table 6 shows that as the L/S is 0.50 and R=0, the 7-days compressive strength of AASM is 0.51, 44.37 and 49.55 MPa, respectively. The strength of AASM is increasing with increasing of N. The slag is dissolved faster because of higher N of alkaline solution. The microstructure of AASM will be more density and increase the strength.

. it also shows that 7-days compressive strength of AASM is decreasing with increasing of L/S. Due to increasing of the water content of the alkali metal silicate solution, thus, the 7-days compressive strength reduced.

. As N is 0.5% and 0.55%, the 7-days compressive strength of AASM decreases with the LCD waste glass replacement, respectively. However, as N is 1.0%, the opposite trend occurred. Compared to GGBFS, the dissolved velocity of LCD waste glass is slower. As N is 1.0%, the alkaline solution can damage the slag structure and the slag is dissolved faster. The extra product of LCD waste dissolved can increase the strength.

(3) thermal conductivity

In Table 6, the thermal conductivity of AASM is range of 0.9510 to 1.2755 WM/K. It shows that the AASM has excellent performance in heat insulation. It also shows that thermal conductivity of AASM is increasing with L/S and decreasing with N and R.

L/S	N	R (%)	T _f	S _{Tf}	f _c	S _{fc}	λ	S _λ
		(70)	(111115)	(111115)	(IVIFa)	(IVIF a)	(VVIVI/K)	(VVIVI/K)
0.50		0	464	13.53	10.51	0.65	1.1153	0.0010
	0.50	10	552	17.35	6.81	0.34	1.0673	0.0006
		20	690	13.45	5.17	0.77	1.0457	0.0007
0.50		0	413	9.17	44.37	2.67	1.0413	0.0011
	0.75	10	491	17.06	37.67	1.70	1.0272	0.0010
		20	616	20.52	28.11	1.96	1.0074	0.0005

Table 6 Experimental results

		0	356	12.29	49.55	1.76	1.0253	0.0003
	1.00	10	425	6.08	55.77	2.26	0.9771	0.0006
		20	557	2.65	56.37	3.93	0.9510	0.0011
		0	595	9.02	9.34	0.62	1.2075	0.0006
	0.50	10	620	7.81	6.31	0.55	1.0884	0.0003
		20	839	12.53	4.90	0.16	1.0550	0.0008
		0	540	5.29	44.18	2.22	1.0713	0.0004
0.55	0.75	10	566	8.54	29.69	0.66	1.0497	0.0003
		20	740	8.54	17.31	1.17	1.0515	0.0004
		0	495	19.47	45.35	1.24	1.0411	0.0011
	1.00	10	500	4.58	51.18	2.20	1.0411	0.0011
		20	733	4.58	51.73	1.68	1.0144	0.0004
		0	691	12.77	5.27	0.45	1.2755	0.0007
	0.50	10	953	7.00	4.42	0.52	1.0615	0.0006
		20	1184	32.19	3.71	0.27	1.0771	0.0012
		0	616	15.39	16.84	1.58	1.1206	0.0006
0.60	0.75	10	761	11.53	10.80	0.93	1.0916	0.0004
-		20	983	15.72	8.34	0.68	1.0553	0.0008
		0	546	8.72	36.26	1.26	1.1031	0.0008
	1.00	10	716	24.27	37.61	1.69	1.0593	0.0019
		20	852	11.79	40.61	1.43	1.0762	0.0008

4. PREDICTION METHOD

4.1 GENERATION OF TRAINING AND TESTING DATA

The experimental results discussed in the Section 3.4 clearly show that there exists a strong dependence of the final setting time, 7-days compressive strength and thermal conductivity on L/S, N and R of AASM. To estimate the influence of L/S, N and R of AASM on the extent of these three properties of AASM, the ANN model is used in this study.

Total 81 sets experimental data are divided training set and testing set. 10 testing set is random selected by the computer program with Microsoft EXCEL. The remaining data were used for the training set of ANN model.

4.2 ANN Model

The ANN Model with BPN is created by MATLAB software toolbox. 2 hidden layers are used in ANN model and each hidden layer contains 10 neurons. The Gradient descent algorithm back-propagation learning rule is logarithmic sigmoid (logsig). Learning rate is 0.4 with training performance goal 10⁻¹⁰, momentum constant 0.1 and maximum number of epochs 1000.

4.3 DISCUSSION ON PREDICTION RESULTS

The ANN model is then tested and the results are compared by means of root mean squared error, RMSE

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{1}^{n} (y_p - y_e)^2} \tag{1}$$

Where, y_p and y_e indicate the ANN predict value and experimental result, respectively. *n* indicates the total amount of ANN predict. In this study, *n* is equal 10.

The ANN prediction result is shown as Table 7. The RMSE values range of final setting time, 7-days compressive strength and thermal conductivity is 18.98 mins, 2.78 MPa and 0.0033 WM/K, respectively. The ANN prediction results are less than 20% experimental results and indicate the accuracy of ANN model. The ANN model is successful to be used to predict the engineering properties of AASM.

		R	T _f			f _c			λ			
L/S	Ν	(%)	(n	nins)		(N	(MPa)			(WM/K)		
_			Experiment	ANN	RMSE	Experiment	ANN	RMSE	Experiment	ANN	RMSE	
0.50	0.75	0	450	469		10.05	10.35		1.1164	1.1011		
0.50	0.75	10	415	402		42.21	43.89		1.0412	1.0411		
0.50	1.00	20	496	516		35.87	38.43		1.0275	1.0218		
0.55	0.50	10	560	534		54.25	60.90		0.9513	0.9740		
0.55	0.50	20	625	674	18.98	5.98	3.46	2.78	1.0882	1.0803	0.0033	
0.55	0.75	10	851	693		4.97	3.63		1.0559	1.0593		
0.55	1.00	0	574	612		30.06	3.46		1.0495	1.0531		
0.60	0.50	20	473	505		44.1	42.91		1.0423	1.0522		
0.60	1.00	10	1194	1129		3.68	3.46		1.0757	1.0648		

	Table 7	ANN	prediction	result
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5. CONCLUSIONS

The results of the experiment in this study verify the commonly known phenomena that the final setting time, 7-days compressive strength and thermal conductivity have a strong inverse dependency on the L/S, N and R of AASM. This study also indicates the ability of the multilayer feedforward backpropagation neural network as a good technique for the mix proportion, final setting time, final setting time relationship, respectively.

REFERENCES

Bilgehan, M. and Turgut, P. (2010), "The use of neural networks in concrete compressive strength estimation", Comput. Concrete, 7(3), 721-283.

Davidovits, J. (2008), Geopolymer Chemistry and Applications, Géopolymer Institute, Saint-Quentin, France, pp. 19-36.

Gupta, S., (2013), "Using Artificial Neural Network to Predict the Compressive Strength of Concrete containing Nano-silica," *Civil. Eng. Arch.*, 1(3), 96-102.
Soares F. M. and Nunes R. (2018), Neural Network Programming with Python, Packt

Soares F. M. and Nunes R. (2018), Neural Network Programming with Python, Packt Publishing.

- Wang, W.C., Wang, H.Y. and Lo, M.H. (2014), "The engineering properties of alkaliactivated slag pastes exposed to high temperatures," *Constr. Build. Mater.*, **112**(1), 962-969.
- Wang, W.C., Wang, H.Y. and Chou, H.C. (2016), "A study of the engineering properties of alkali-activated waste glass material (AAWGM)," Constr. Build. Mater., 112(1), 962-969.
- Wang, C.C., Wang, H.Y., Chen, B.T. and Peng, Y. C. (2017), "Study on the engineering properties and prediction models of an alkali-activated mortar material containing recycled waste glass," Constr. Build. Mater., 132(1), 130-141.
- recycled waste glass," Constr. Build. Mater., 132(1), 130-141. Yang, T.R., Chang, T.P., Chen, B.T., Shih, J. Y. and Lin, W.L. (2012), "Effect of alkaline solutions on engineering properties alkali-actived GGBFS paste," J. Marine SCI. *Tech.*, **20**(3), 311-318.