

Neurofuzzy system applications

Conclusion

The reasons for choosing integrative of two insufficient variants of fuzzy method for developing a successful recognition model, while the neural network and ANFD models cannot recognize the relationships with given data for their simplicity and speed of learning, not less.

The application of Cuckoo method as modeling of recognition systems for its closed form representation. Unfortunately, in one case of implementation of this recognition system did not include the training, obtained results by the neural network (ANFD) were poor.

Parameter	Value
Number of neurons	100
Number of hidden layers	1
Number of epochs	1000
Number of iterations	1000
Number of samples	1000
Number of clusters	10
Number of inputs	10
Number of outputs	1

Neurofuzzy system applications

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Introduction

- No-slump concrete (NSC) is defined as concrete having either very low or zero slump that traditionally used for prefabrication purposes.
- Some difficulties in the prediction of the compressive strength
- Neural networks (NNT) and ANFIS models are constructed
- Predict the 28-days compressive strength

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Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models

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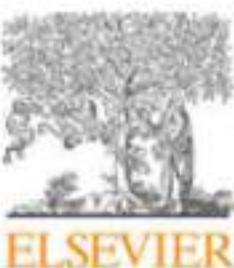
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ABSTRACT

No-slump concrete (NSC) is defined as concrete having either very low or zero slump that traditionally used for prefabrication purposes. The sensitivity of NSC to its constituents, mixture proportion, compaction, etc., enforce some difficulties in the prediction of the compressive strength. In this paper, by considering concrete constituents as input variables, several regression, neural networks (NNT) and ANFIS models are constructed, trained and tested to predict the 28-days compressive strength of no-slump concrete (28-CSNC). Comparing the results indicate that NNT and ANFIS models are more feasible in predicting the 28-CSNC than the proposed traditional regression models.

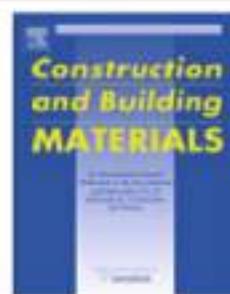
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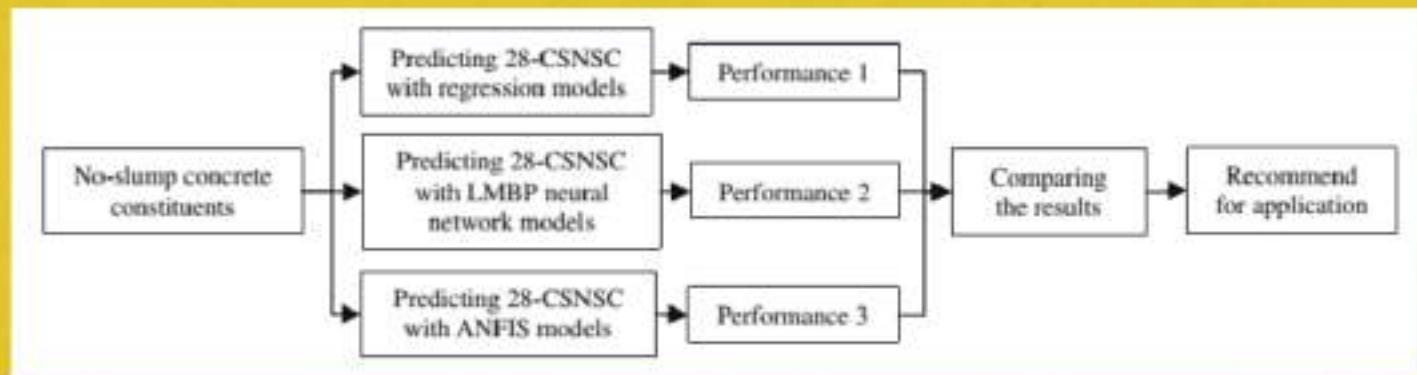
ABSTRACT

No-slump concrete (NSC) is defined as concrete having either very low or zero slump that traditionally used for prefabrication purposes. The sensitivity of NSC to its constituents, mixture proportion, compaction, etc., enforce some difficulties in the prediction of the compressive strength. In this paper, by considering concrete constituents as input variables, several regression, neural networks (NNT) and ANFIS models are constructed, trained and tested to predict the 28-days compressive strength of no-slump concrete (28-CSNSC). Comparing the results indicate that NNT and ANFIS models are more feasible in predicting the 28-CSNSC than the proposed traditional regression models.

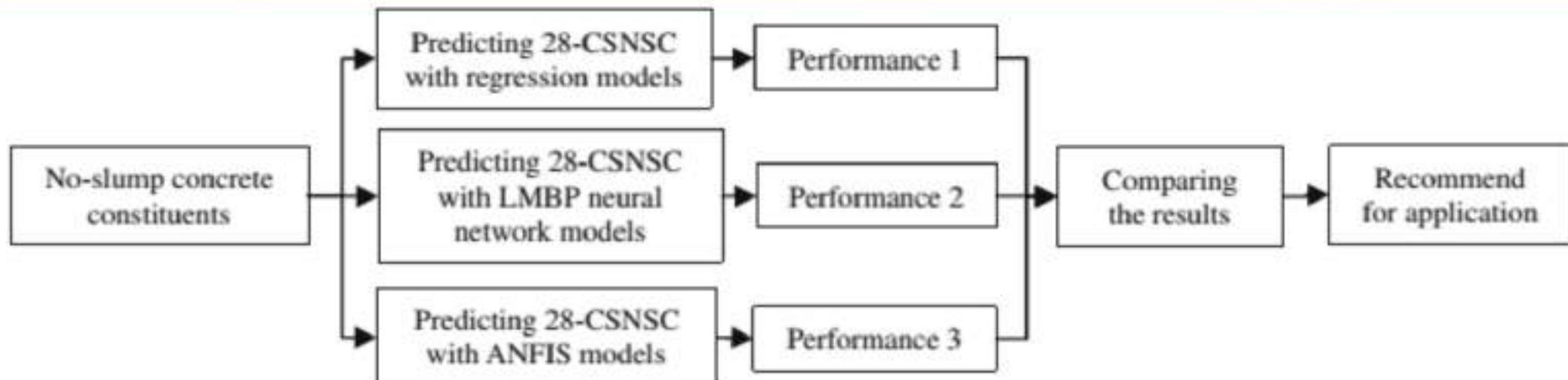
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Introduction

- Although the several methods has been proposed to predict the compressive strength of normal and high strength concrete, these methods has not been applied for no-slump concrete yet.
- The major purpose of this paper is to assess and compare the performance of:
 - Various regression
 - Artificial neural network (trained by LMBP)
 - ANFIS
- to predict the 28-days compressive strength of no-slump concrete



- Artificial neural network (trained by LMBP)
 - ANFIS
- to predict the 28-days compressive strength of no-slump concrete**



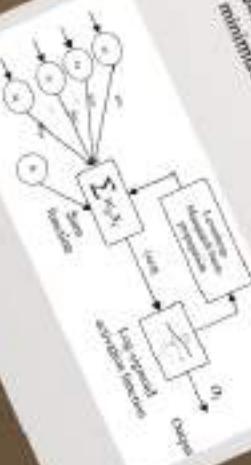
The notes:
 1. Regression
 2. Neural network and
 3. ANFIS models
 are trained and tested by using
 the gathered database.
 The prediction performances of
 the models are evaluated with
 root mean square and
 correlation factors.

1. Nonlinear/linear regression model

Linear regression:
 Relationship by a linear regression equation
 Nonlinear regression:
 Relationship by a nonlinear regression equation
 The general form of the nonlinear regression model (NLRM) can be state as follow:
 $y = f(a_i \times x_i)$
 where y , f , a_i and x_i are the dependent variable.
 The major issue:
 . Find an appropriate function f with
 . statistically well-adjusted coefficients a_i .
 This is accomplished through
 (iterative estimation algorithms)
 That usually performed by statistical methods:

2. ANN model

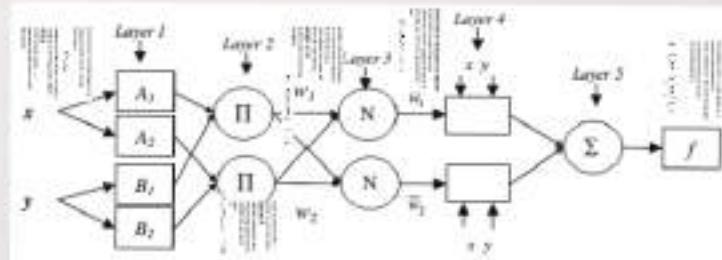
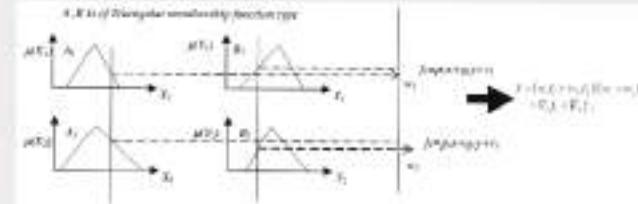
LMBP:
 After processing all of the output layer, the activated result of the target layer, the compared error will be propagated back toward the overall error to minimize the overall error.



ANFIS model

ANFIS is the famous hybrid neuro-fuzzy network for modeling the complex systems.

Rule 1: IF x is A_1 and y is B_1 , THEN $f_1 = p_1x + q_1y + r_1$.
 Rule 2: IF x is A_2 and y is B_2 , THEN $f_2 = p_2x + q_2y + r_2$.



Procedure

- 6 Regression
- 6 Neural network and
- 5 ANFIS models

**are trained and tested by using
the gathered database.**

**The prediction performances of
the models are evaluated with
root means square and
correlation factor**

1. Nonlinear/linear regression model

Linear regression :

Relationship by a linear regression equation

Nonlinear regression :

Relationship by a nonlinear regression equation

The general form of the nonlinear regression model (NLRM) can be state as follows:

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The major issue :

- Find an appropriate function f with statistically well-adjusted coefficients ai.**

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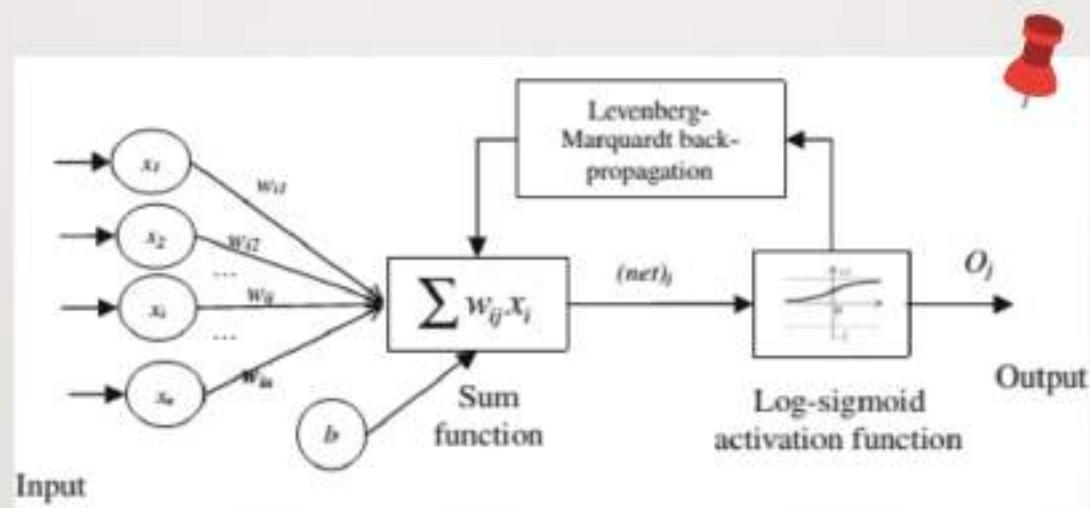
(iterative estimation algorithms)

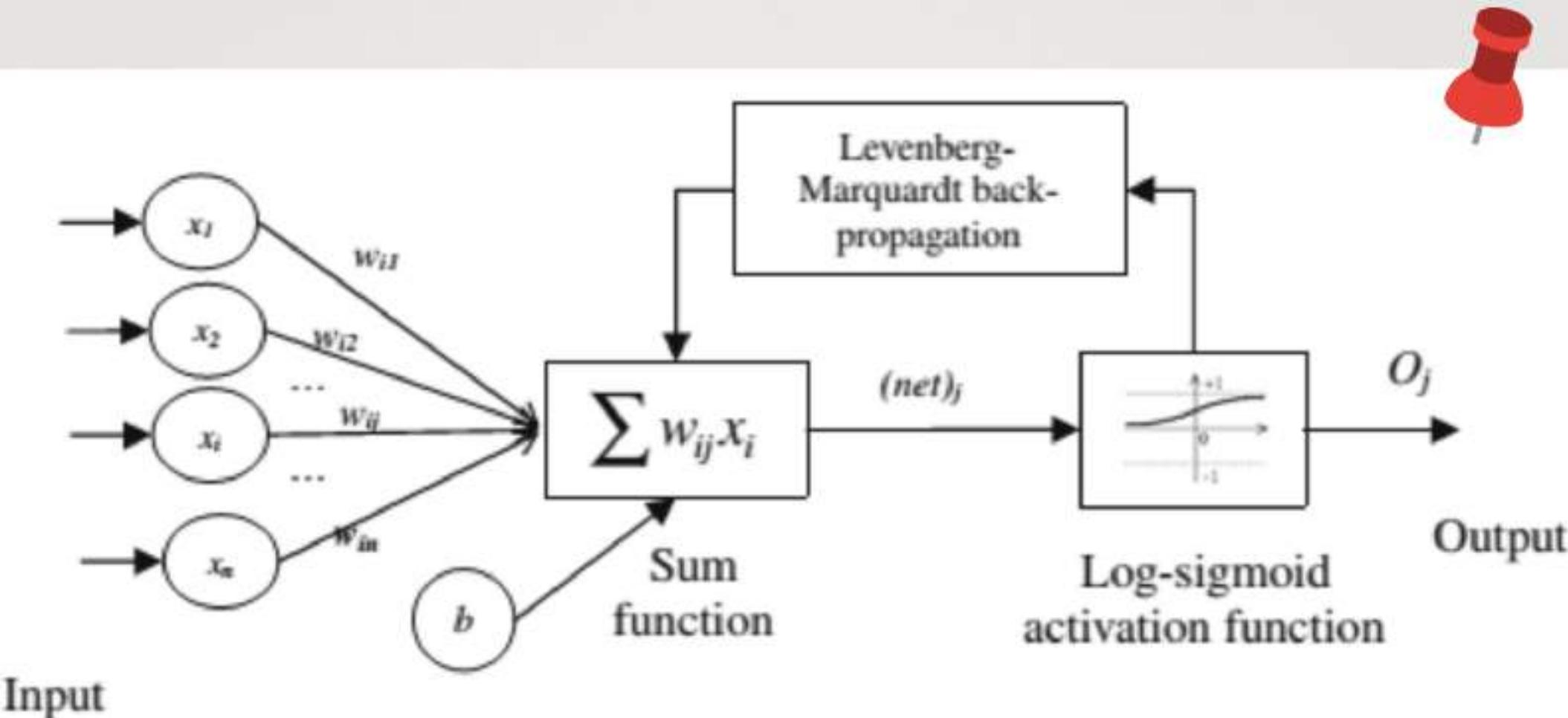
That usually performed by statistical methods.

2. ANN model

LMBP :

After processing all of the layers, the activated result of the output layer, compared with the target value, and the resulted error will be propagated backward the network's weight to minimize the overall error.



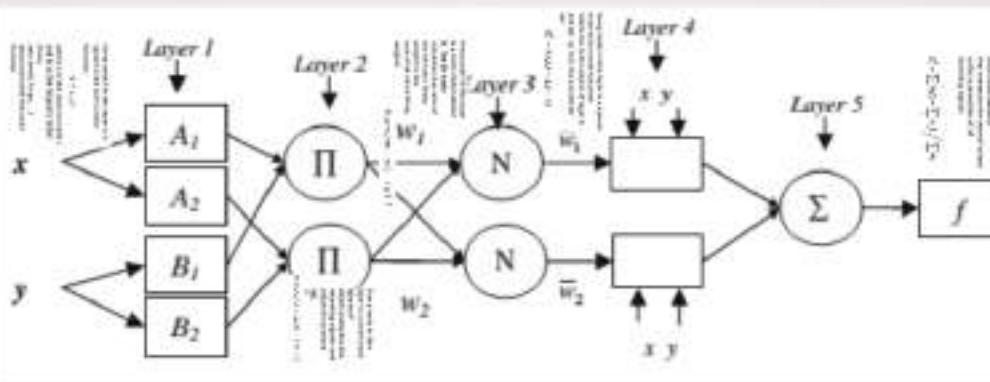
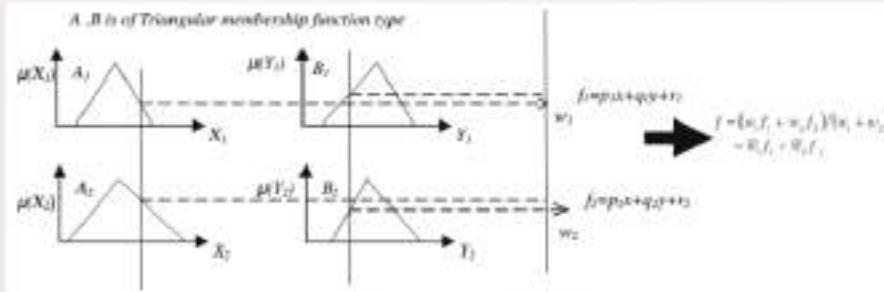


ANFIS model

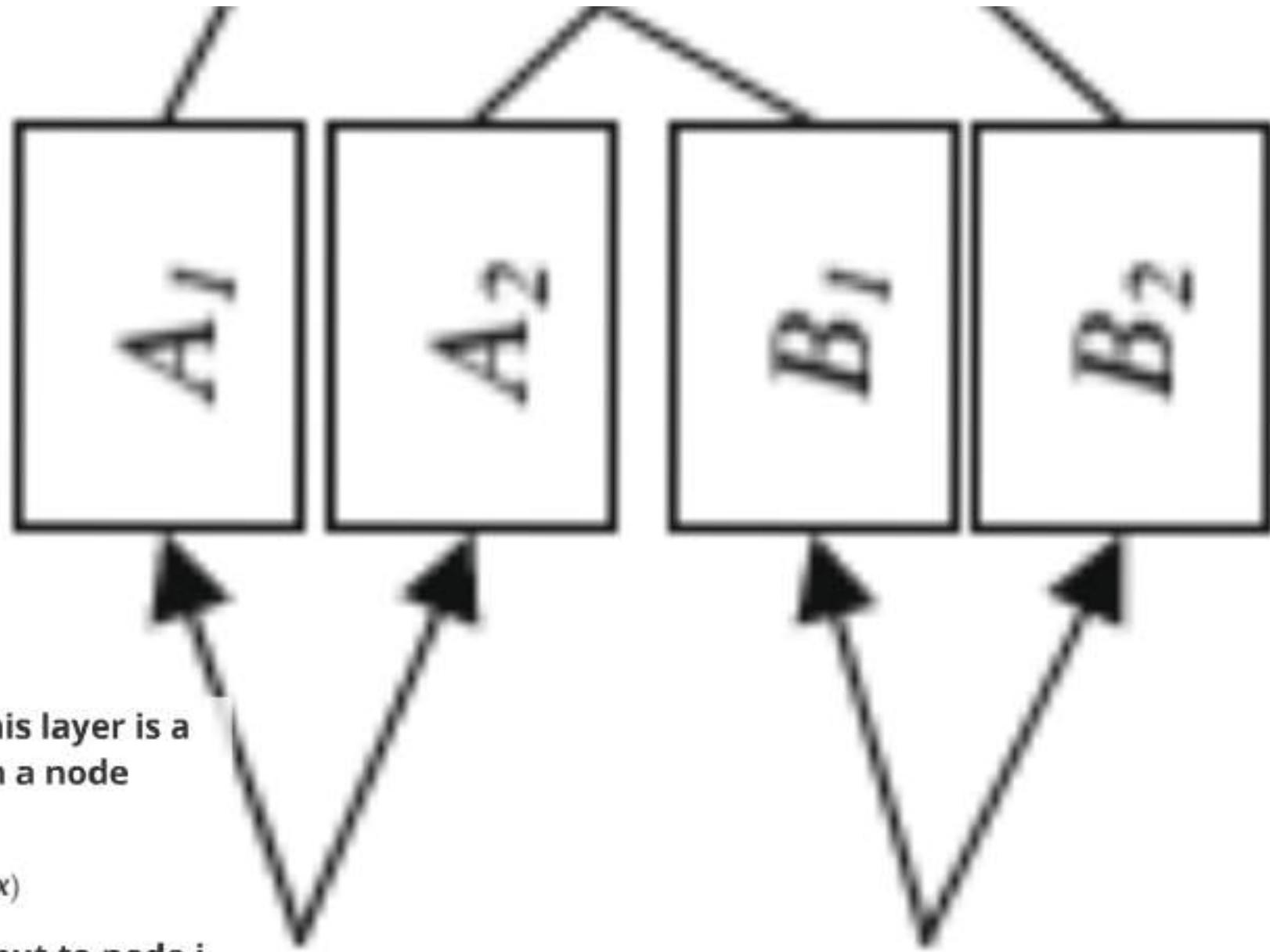
ANFIS is the famous hybrid neuro-fuzzy network for modeling the complex systems.

Rule 1: IF x is A_1 and y is B_1 , THEN $f_1 = p_1x + q_1y + r_1$.

Rule 2: IF x is A_2 and y is B_2 , THEN $f_2 = p_2x + q_2y + r_2$.



Layer 1



Every node i in this layer is a square node with a node function :

$$O_i^1 = \mu_{A_i}(x)$$

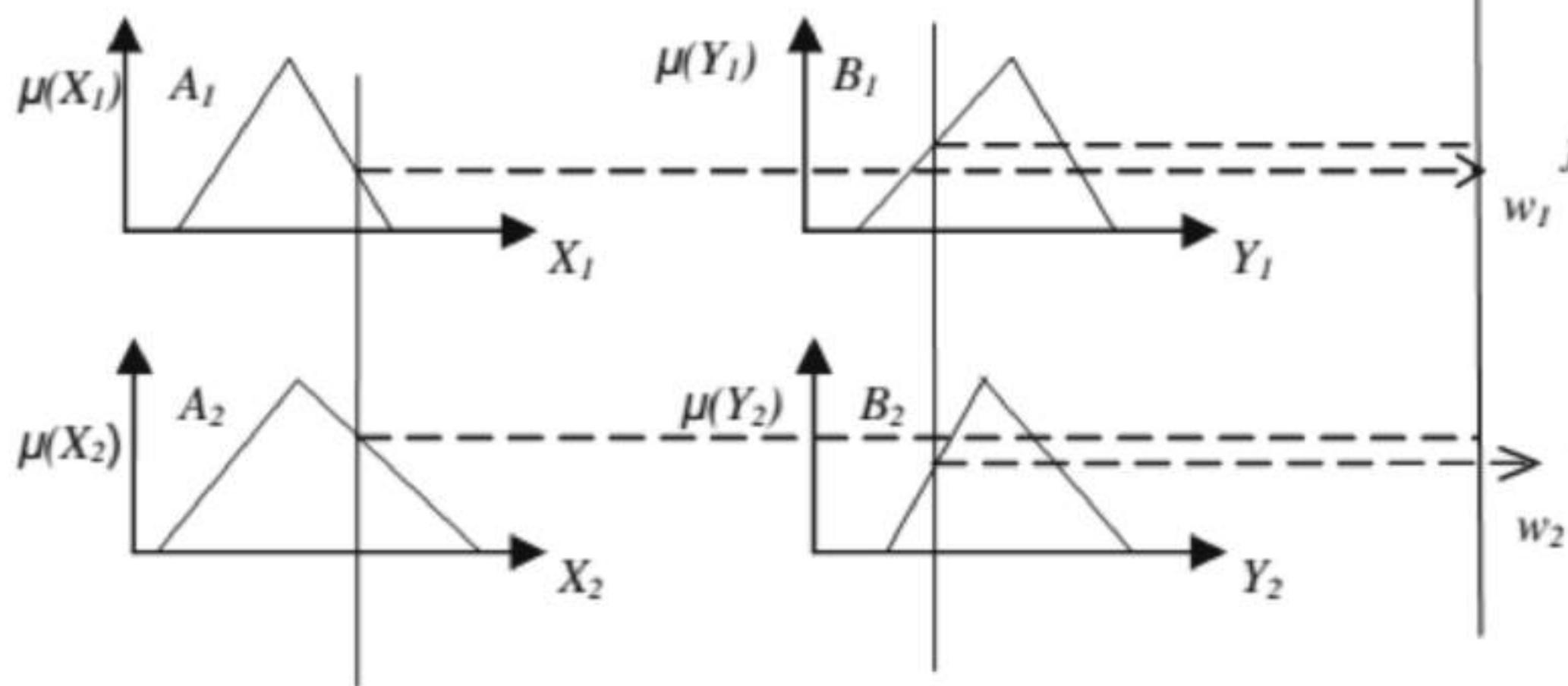
where x is the input to node i ,
and A_i is the linguistic label
(fuzzy
sets: small, large,...)
associated with this node
function.

x

y

Rule 2: IF X is A_2 and y is B_2 , THEN

A, B is of Triangular membership function type



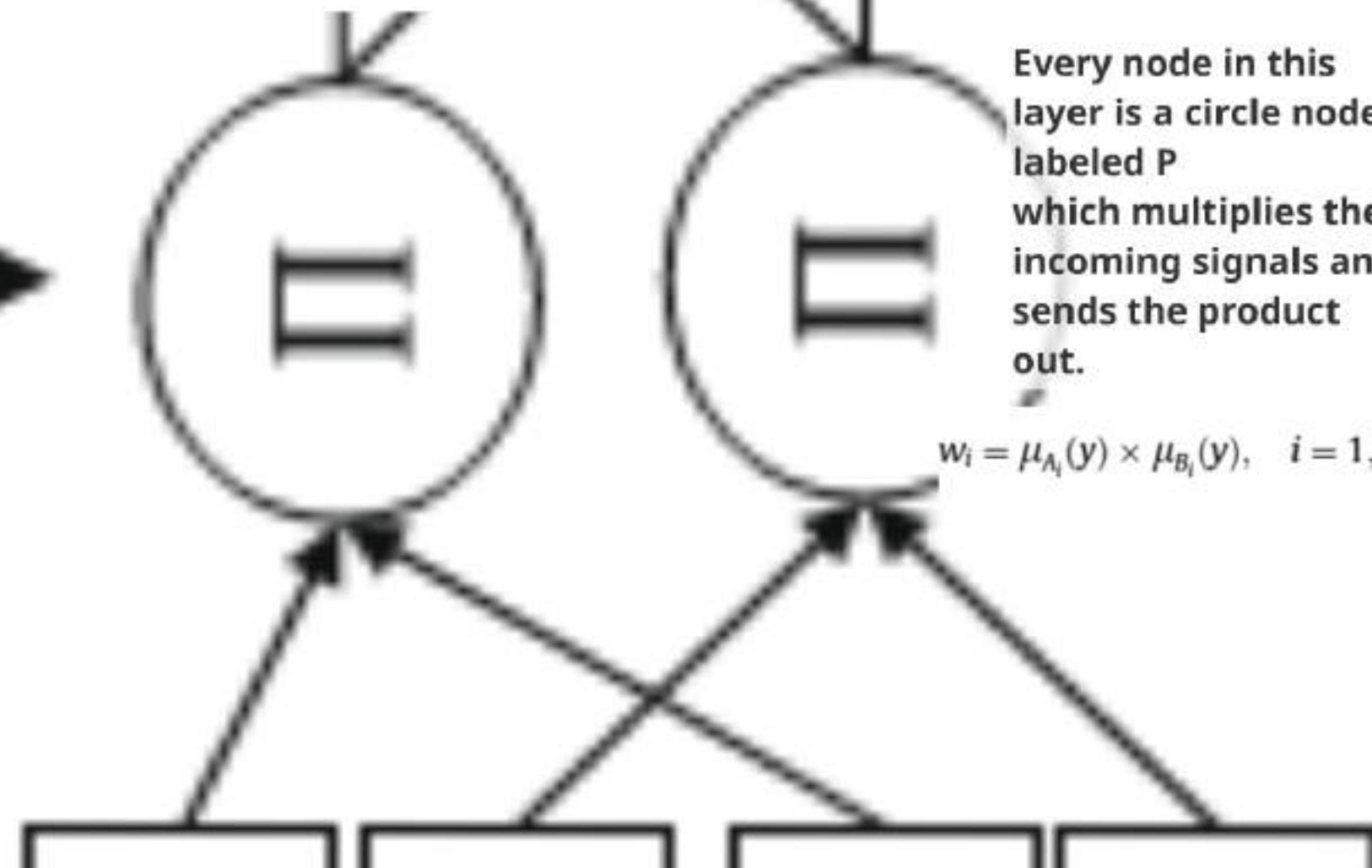
Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule's firing weight to the sum of all rule's firing weights



$$\bar{w}_i = w_i / (w_1 + w_2), \quad i = 1, 2$$

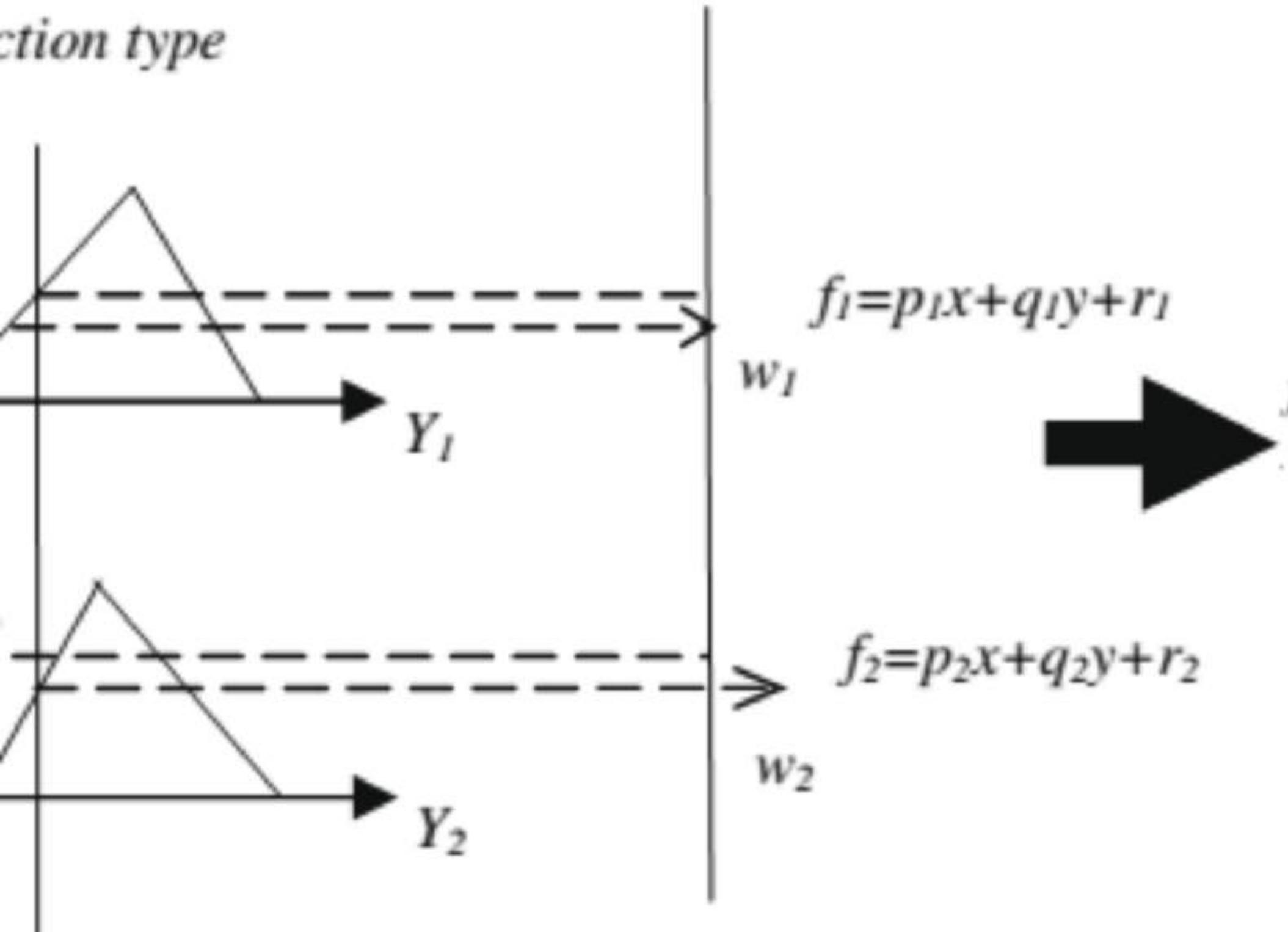
Layer 2 →

Every node in this layer is a circle node labeled P which multiplies the incoming signals and sends the product out.



$$w_i = \mu_{A_i}(y) \times \mu_{B_i}(y), \quad i = 1, 2$$

ction type

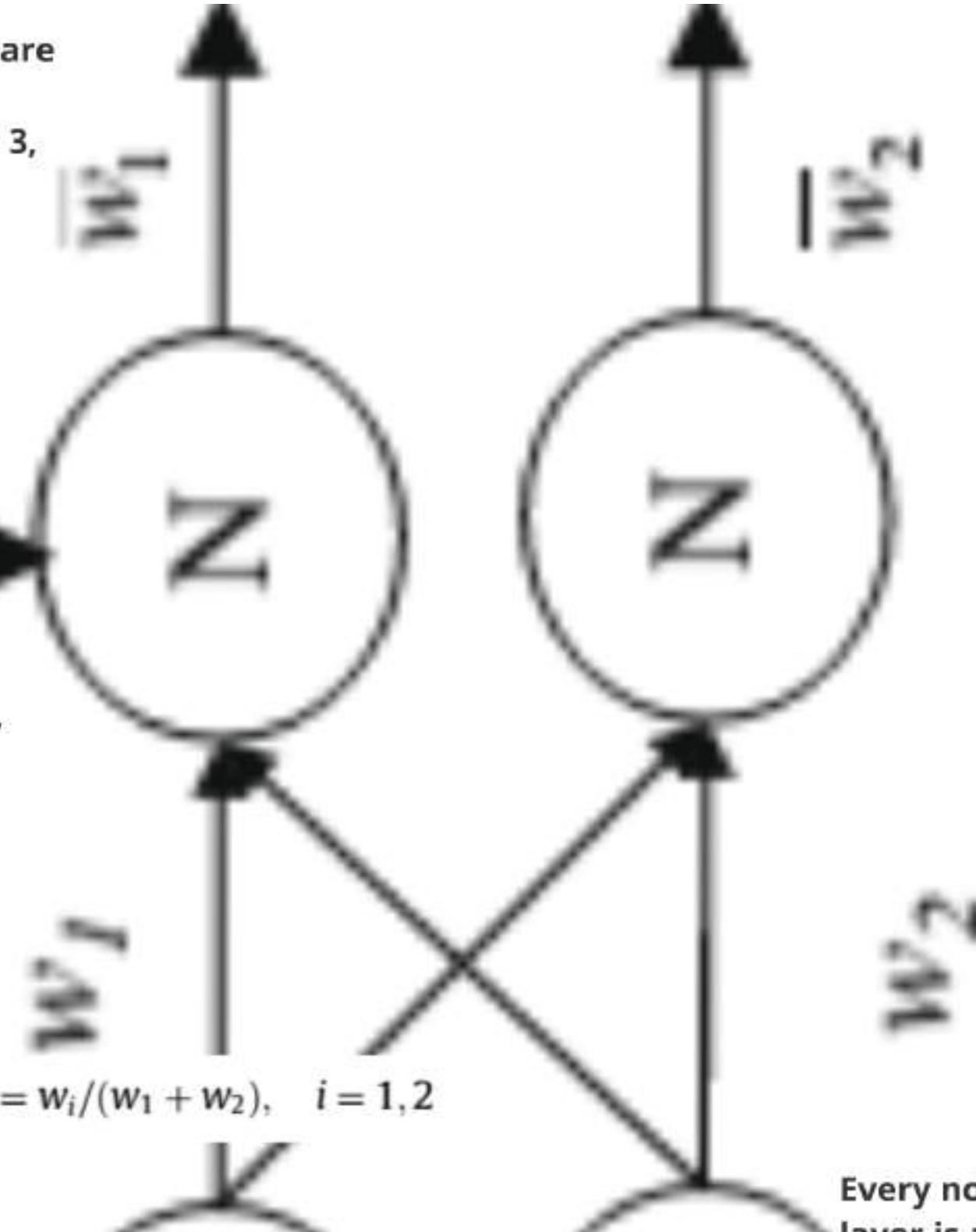


ode in this layer is a square
ith a node function:
 w_i is the output of layer 3,
 $\{p_i, q_i, r_i\}$ is the parameter

$$z^4 = \bar{w}_i(p_i x + q_i y + r_i)$$

Layer 3

Every node in this layer
is a circle node labeled
N. The i th node
calculates the ratio of
the i th rule's firing
weight to the
sum of all rule's firing
weights



Every node in this
layer is a circle node

$$f = (w_1 f_1 + w_2 f_2) / (w_1 + w_2)$$

= \overline{w}_1 f_1 + \overline{w}_2 f_2

Layer 4

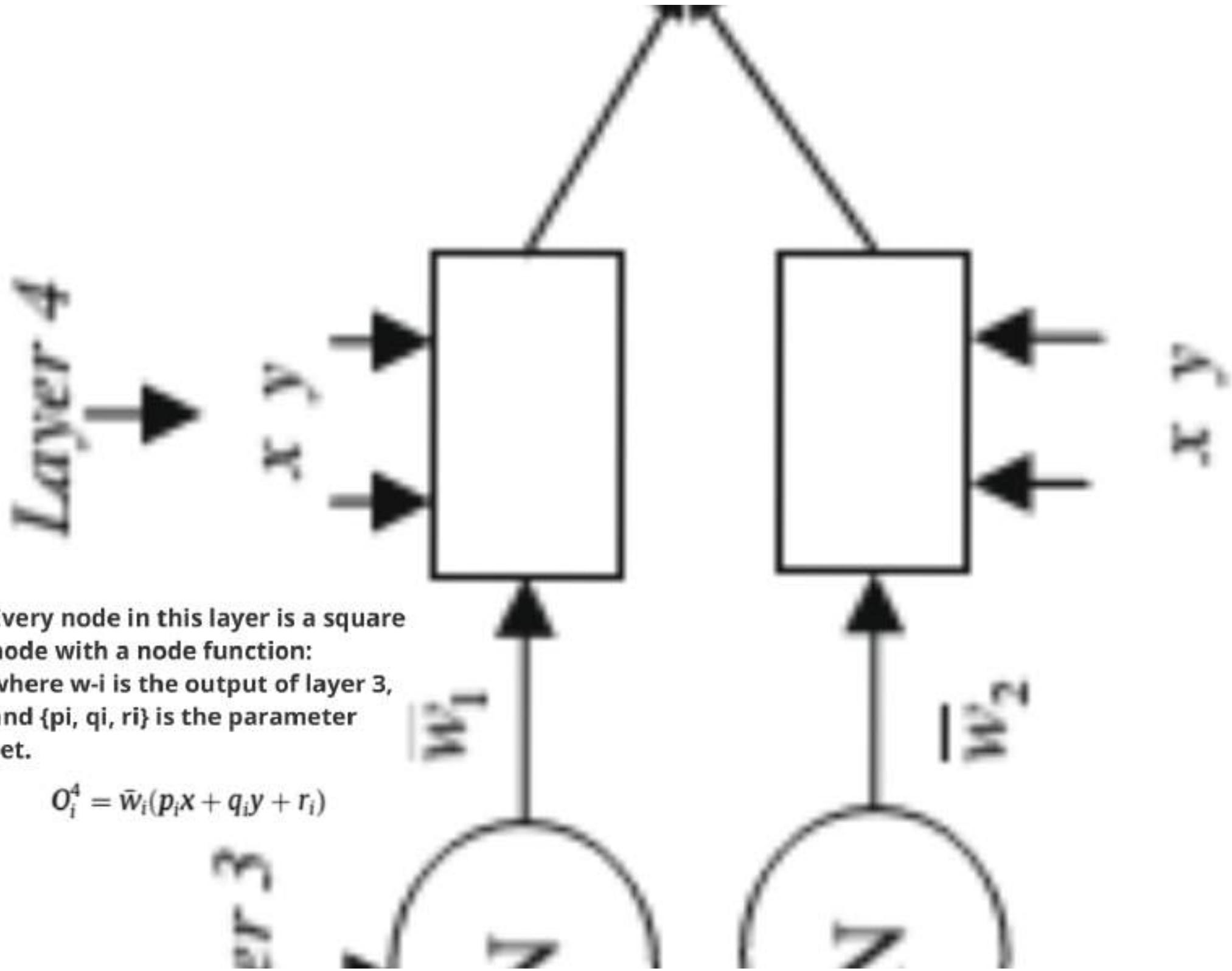
Layer 3

\bar{w}_1

\bar{w}_2

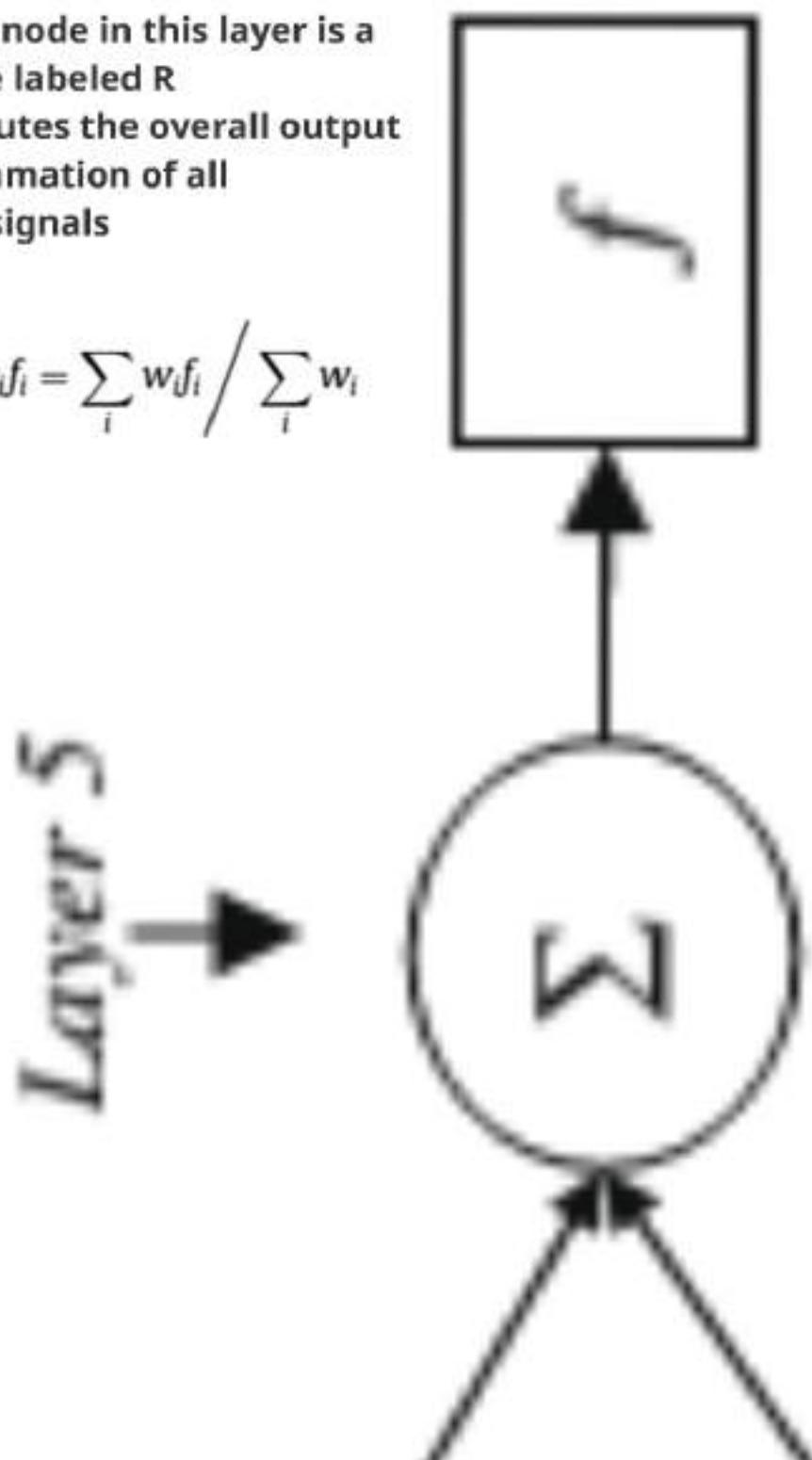
Every node in this layer is a square
node with a node function:
where w_i is the output of layer 3,
and $\{p_i, q_i, r_i\}$ is the parameter
set.

$$O_i^4 = \bar{w}_i(p_i x + q_i y + r_i)$$



The signal node in this layer is a circle node labeled R that computes the overall output as the summation of all incoming signals

$$o_i^5 = \sum_i w_i f_i = \sum_i w_i f_i / \sum_i w_i$$



Preprocessing of data

To prevent the saturation problem :
Log-sigmoid activation function

$$i_M = 0.1 + (0.9 - 0.1) \times (i_R - i_{min}) / (i_{max} - i_{min})$$

These norms are root means square :

$$\text{RMS} = \sqrt{\sum_{i=1}^p (f_{ci} - \hat{f}_{ci}) / P}$$

Correlation factor (CF) :

$$\text{CF}(f_c, \hat{f}_c) = \text{cov}(F_c, \hat{F}_c) / \sqrt{\text{cov}(\hat{F}_c, \hat{F}_c) \times \text{cov}(F_c, F_c)}$$

$$F_c = (f_{c1}, f_{c2}, \dots, f_{cp}), \quad \hat{F}_c = (\hat{f}_{c1}, \hat{f}_{c2}, \dots, \hat{f}_{cp})$$

$$\mu_c = E(F_c), \quad \hat{\mu}_c = E(\hat{F}_c)$$

$$\text{cov}(F_c, \hat{F}_c) = E[(F_c - \mu_c) \cdot (\hat{F}_c - \hat{\mu}_c)]$$

Table 1	Concrete Mixture Proportions
10001	Cement
10002	Silica fume
10003	Water
10004	Fine Aggregate
10005	Coarse Aggregate
10006	Filler
10007	Water to cementitious material
10008	Output / Target value
10009	28-day Compressive Strength of normal concrete (MPa)
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Table 3
Concrete mixture proportions.

Mixture	Cement (kg/m ³)	Silica fume (kg/m ³)	Water (kg/m ³)	Fine aggregates (kg/m ³)	Coarse aggregates (kg/m ³)	Filler (kg/m ³)	w/cm	Average 28-days CSC (MPa)
NSC-1	350	0	95.2	575.9	1273	0	0.27	61.1
NSC-2	350	0	98.5	558.2	1325.4	0	0.28	54.0
NSC-3	339.5	0	97.7	605.3	1273	10.5	0.28	65.7
NSC-4	339.5	0	97.6	535	1247	10.5	0.28	62.2
NSC-5	336	0	97.6	535	1247	14	0.28	54.5
NSC-6	332.5	0	97.7	655.3	1273	17.5	0.28	63.1
NSC-7	329	0	97.6	535	1247	21	0.28	52.2
NSC-8	325.5	0	97.7	655.3	1273	24.5	0.28	64.1
NSC-9	410	0	117.8	491.2	1273	0	0.29	59.9
NSC-10	350	0	100.9	460.3	1419.8	0	0.29	61.9
NSC-11	350	0	102.6	535	1247	0	0.29	64.2
NSC-12	332.5	17.5	105.6	535	1247	0	0.30	62.2
NSC-13	380	0	118.1	354.2	1440.6	0	0.31	60.5
NSC-14	350	0	107.6	535	1247	0	0.31	61.5
NSC-15	325.5	24.5	107.8	535	1247	0	0.31	65.0
NSC-16	343	0	107.6	535	1247	7	0.31	61.2
NSC-17	320	0	97.7	671.8	1247	38.5	0.31	63.2
NSC-18	346	27.3	115.6	484	1289	156.3	0.31	76.7
NSC-19	380	0	121.1	502.5	1325.4	0	0.32	67.4
NSC-20	320	0	102.2	679.1	1259.7	19	0.32	62.8
NSC-21	320	0	103.2	665.6	1234.2	57	0.32	60.3
NSC-22	350	0	120.4	526.2	1325.4	0	0.34	63.5
NSC-23	350	0	119	710.6	1121.5	0	0.34	59.6
NSC-24	350	0	120	623.3	1208.7	94	0.34	61.1
NSC-25	252.6	19.6	95	828	1206	0	0.35	66.7
NSC-26	345.2	27.1	129.9	482	1282	155.5	0.35	71.2
NSC-27	375	0	134	1300	600	0	0.36	64.0
NSC-28	332.5	17.5	129.9	509.8	1325.4	0	0.37	61.4
NSC-29	343	27	136.9	480	1278	154.9	0.37	71.2
NSC-30	252.6	19.6	103.4	836	1063	135	0.38	62.7
NSC-31	258.9	0	98.4	835	1083	135	0.38	55.0
NSC-32	350	0	139.7	591.3	1145.5	188	0.40	58.3

Concrete mixture proportions

96 Total : For training (interpolation) and testing (extrapolation) of the proposed models, 79 and 17 samples were randomly chosen respectively

Inputs

Cement (kg/
Silica fume (k
Water (kg/

Table 3

Concrete mixture proportions.

Mixture	Cement (kg/m ³)	Silica fume (kg/m ³)	Water (kg/m ³)	Fine aggregates (kg/m ³)	Coarse aggregates (kg/m ³)	Filler (kg/m ³)	w/cm	Average 28-days CSC (MPa)
NSC-1	350	0	95.2	575.9	1273	0	0.27	61.1
NSC-2	350	0	98.5	558.2	1325.4	0	0.28	54.0
NSC-3	339.5	0	97.7	655.3	1273	10.5	0.28	65.7
NSC-4	339.5	0	97.6	535	1247	10.5	0.28	62.2
NSC-5	336	0	97.6	535	1247	14	0.28	54.5
NSC-6	332.5	0	97.7	655.3	1273	17.5	0.28	63.1
NSC-7	329	0	97.6	535	1247	21	0.28	52.2
NSC-8	325.5	0	97.7	655.3	1273	24.5	0.28	64.1
NSC-9	410	0	117.8	491.2	1273	0	0.29	59.9
NSC-10	350	0	100.9	460.3	1419.8	0	0.29	61.9
NSC-11	350	0	102.6	535	1247	0	0.29	64.2
NSC-12	332.5	17.5	105.6	535	1247	0	0.30	62.2
NSC-13	380	0	118.1	354.2	1440.6	0	0.31	60.5
NSC-14	350	0	107.6	535	1247	0	0.31	61.5
NSC-15	325.5	24.5	107.8	535	1247	0	0.31	65.0
NSC-16	343	0	107.6	535	1247	7	0.31	61.2
NSC-17	320	0	97.7	671.8	1247	38.5	0.31	63.2
NSC-18	346	27.3	115.6	484	1289	156.3	0.31	76.7
NSC-19	380	0	121.1	502.5	1325.4	0	0.32	67.4
NSC-20	320	0	102.2	679.1	1259.7	19	0.32	62.8
NSC-21	320	0	103.2	665.6	1234.2	57	0.32	60.3
NSC-22	350	0	120.4	526.2	1325.4	0	0.34	63.5
NSC-23	350	0	119	710.6	1121.5	0	0.34	59.6
NSC-24	350	0	120	623.3	1208.7	94	0.34	61.1
NSC-25	252.6	19.6	95	828	1206	0	0.35	66.7
NSC-26	345.2	27.1	129.9	482	1282	155.5	0.35	71.2
NSC-27	375	0	134	1300	600	0	0.36	64.0
NSC-28	332.5	17.5	129.9	509.8	1325.4	0	0.37	61.4
NSC-29	343	27	136.9	480	1278	154.9	0.37	71.2
NSC-30	252.6	19.6	103.4	836	1063	135	0.38	62.7
NSC-31	258.9	0	98.4	835	1083	135	0.38	55.0
NSC-32	350	0	139.7	591.3	1145.5	188	0.40	58.3

Inputs	Range		
		Minimum	Maximum
Cement (kg/m^3)	C	252.6	410
Silica fume (kg/m^3)	SF	0	27.3
Water (kg/m^3)	W	95	139.7
Fine aggregate (kg/m^3)	FA	354.2	1300
Coarse aggregate (kg/m^3)	CA	600	1440.6
Filler (kg/m^3)	FI	0	188
Water to cementitious material	W/CM	0.27	0.4
<i>Output (Target value)</i>			
28 days-Compressive Strength of no-slump concrete (MPa)	28-CSNSC	50	78

Boundary range of inputs and output of records

Inputs	Range		
		Minimum	Maximum
Cement (kg/m^3)	C	252.6	410
Silica fume (kg/m^3)	SF	0	27.3
Water (kg/m^3)	W	95	139.7
Fine aggregate (kg/m^3)	FA	354.2	1300
Coarse aggregate (kg/m^3)	CA	600	1440.6
Filler (kg/m^3)	FI	0	188
Water to cementitious material	W/CM	0.27	0.4
<i>Output (Target value)</i>			
28 days-Compressive Strength of no-slump concrete (MPa)	28-CSNSC	50	78

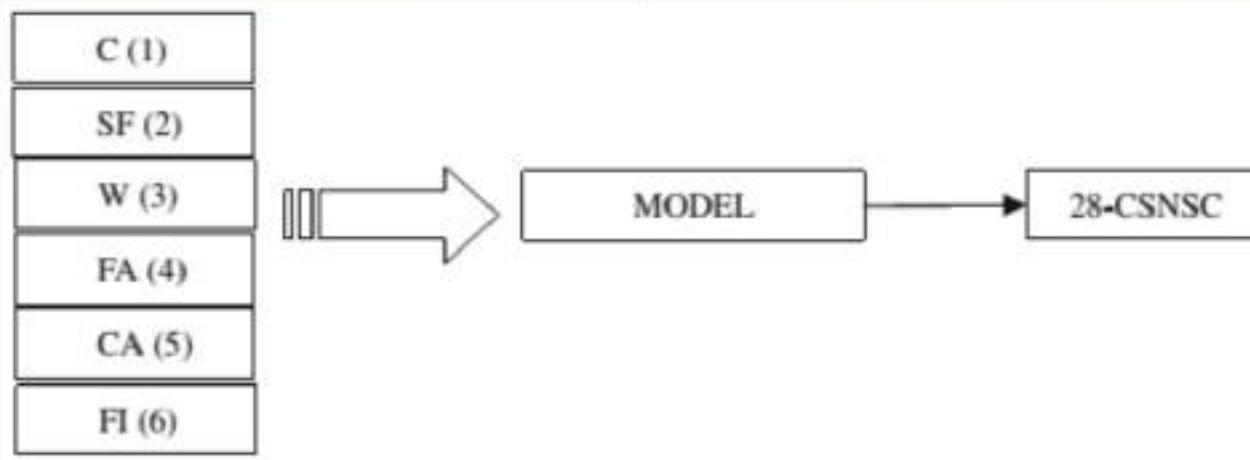


TABLE 5
Proposed models to predict the 28-CSNSC.

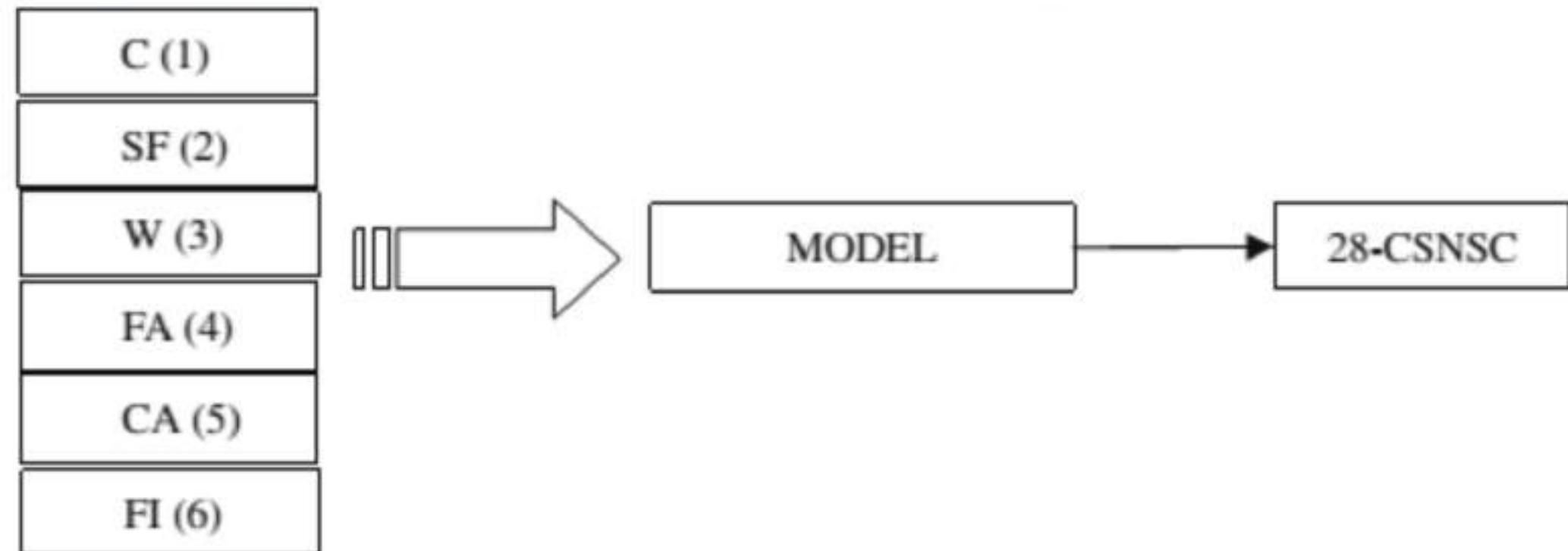
Model	Group	Reg. type	Linear/nonlinear regression model
I-1	(1)	1th Polynomial	$a_0 + a_1 C + a_2 SF + a_3 W + a_4 FA + a_5 CA + a_6 Fl$
I-2		2th Polynomial	$a_0 + a_1 C + a_2 SF + a_3 W + a_4 FA + a_5 CA + a_6 Fl + a_7 C^2 + a_8 SF^2 + a_9 W^2 + a_{10} FA^2 + a_{11} CA^2 + a_{12} Fl^2$
I-3	(2)	Fractional	$a_0 + a_1 W/(C + SF) + a_2 W/(FA + CA + Fl)$
I-4		Power-fractional	$a_1 (W/(C + SF))^{a_0} + a_2 (W/(FA + CA + Fl))^{a_3}$
I-5		Partial polynomial-fractional Type 1	$a_1 (W/(C + SF))^{\frac{1}{2}} + a_2 (W/(FA + CA + Fl))^{\frac{1}{2}}$
I-6		Partial polynomial-fractional Type 2	$a_0 + a_1 W/(C + SF) + a_2 (W/(C + SF))^2 + a_3 ((FA + CA + Fl)/(C + SF)) + a_4 ((FA + CA + Fl)/(C + SF))^2$

Table 6
Evaluated coefficients of regression models.

Model	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}
I-1	-1.262	0.094	0.45	-0.118	1.303	1.152	0.192	-	-	-	-	-	-
I-2	-3.665	1.563	-0.292	0.662	-1.72	8.627	-0.446	-1.013	0.736	-0.787	5.337	-5.198	0.703
I-3	0.453	-0.3	0.471	-	-	-	-	-	-	-	-	-	-
I-4	-	-0.574	0.363	1.162	0.166	-	-	-	-	-	-	-	-
I-5	0.41	0.293	-0.254	-0.005	-	-	-	-	-	-	-	-	-
I-6	0.015	0.097	-0.099	-0.12	0.009	-	-	-	-	-	-	-	-

Model code	Interpolation (training) performance		Extrapolation (testing) performance	
	CF	RMS	CF	RMS
I-1	0.7821	3.2366	0.7943	2.7087
I-2	0.8449	2.7784	0.8350	2.6080
I-3	0.3811	4.8019	0.5872	3.3049
I-4	0.4088	4.7402	0.5561	3.3180
I-5	0.3499	4.8865	0.5166	3.5361
I-6	0.4086	4.7406	0.5606	3.3285

Parameters



used models to predict the 28-CSNSC.

Model	Group	Reg. type	Linear/nonlinear regression model
(1)		1th Polynomial	$a_0 + a_1 C + a_2 SF + a_3 W + a_4 FA + a_5 CA + a_6 FI$
		2th Polynomial	$a_0 + a_1 C + a_2 SF + a_3 W + a_4 FA + a_5 CA + a_6 FI + a_7 C^2 + a_8 SF^2 + a_9 W^2 + a_{10} FA^2 + a_{11} CA^2 + a_{12} FI^2$
(2)		Fractional	$a_0 + a_1 W/(C + SF) + a_2 W/(FA + CA + FI)$
		Power-fractional	$a_1 (W/(C + SF)) a_2 + a_3 (W/(FA + CA + FI)) a_4$
		Partial polynomial-fractional Type 1	$a_1 (W/(C + SF))^2 + a_3 (W/(FA + CA + FI))^2$

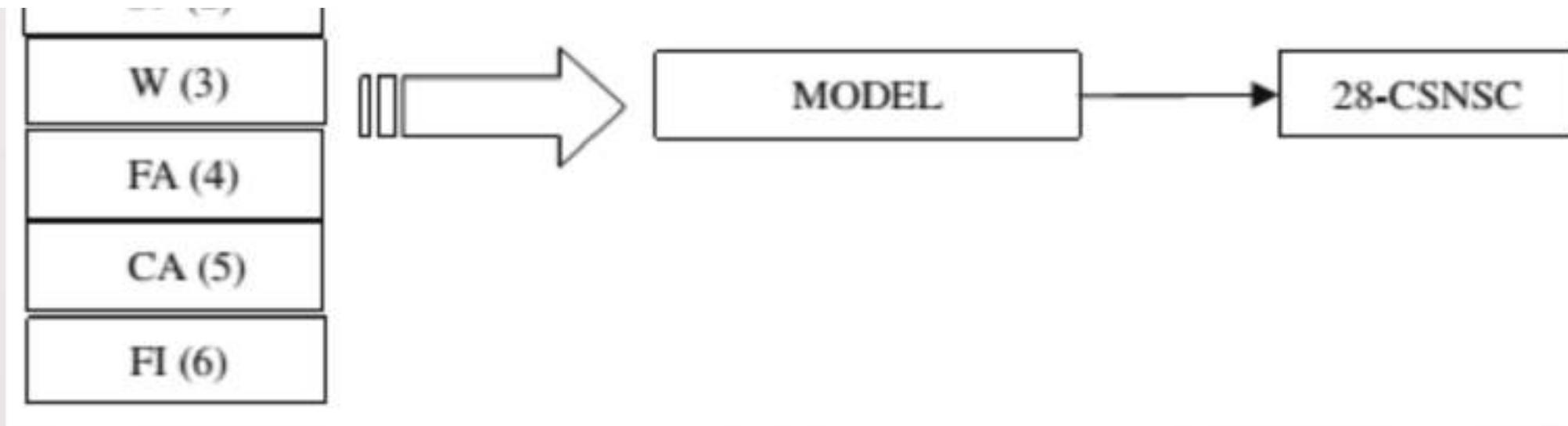


Table 5

Proposed models to predict the 28-CSNSC.

Model	Group	Reg. type	Linear/nonlinear regression model
I-1	(1)	1th Polynomial	$a_0 + a_1C + a_2SF + a_3W + a_4FA + a_5CA + a_6FI$
I-2		2th Polynomial	$a_0 + a_1C + a_2SF + a_3W + a_4FA + a_5CA + a_6FI + a_7C^2 + a_8SF^2 + a_9W^2 + a_{10}FA^2 + a_{11}CA^2 + a_{12}FI^2$
I-3	(2)	Fractional	$a_0 + a_1W/(C+SF) + a_2W/(FA+CA+FI)$
I-4		Power-fractional	$a_1(W/(C+SF))a_2 + a_3(W/(FA+CA+FI))a_4$
I-5		Partial polynomial-fractional Type 1	$a_1(W/(C+SF))^2 + a_3(W/(FA+CA+FI))^2$
I-6		Partial polynomial-fractional Type 2	$a_0 + a_1W/(C+SF) + a_2(W/(C+SF))^2 + a_3((FA+CA+FI)/(C+SF)) + a_4((FA+CA+FI)/(C+SF))^2$

Table 6

Evaluated coefficients of regression models.

Model	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}
I-1	-1.262	0.694	0.45	-0.118	1.303	1.152	0.192	-	-	-	-	-	-
I-2	-3.665	1.563	-0.292	0.662	-1.72	8.627	-0.446	-1.013	0.736	-0.787	5.337	-5.198	0.703
I-3	0.453	-0.3	0.471	-	-	-	-	-	-	-	-	-	-
I-4	-	-0.574	0.362	1.102	0.166	-	-	-	-	-	-	-	-
I-5	0.41	0.293	-0.254	-0.005	-	-	-	-	-	-	-	-	-
I-6	0.615	0.097	-0.099	-0.12	0.009	-	-	-	-	-	-	-	-

Model code	Interpolation (training) performance		Extrapolation (testing) performance	
	CF	RMS	CF	RMS

Table 5

Proposed models to predict the 28-CSNSC.

Model	Group	Reg. type	Linear/nonlinear regression model
I-1	(1)	1th Polynomial	$a_0 + a_1C + a_2SF + a_3W + a_4FA + a_5CA + a_6FI$
I-2		2th Polynomial	$a_0 + a_1C + a_2SF + a_3W + a_4FA + a_5CA + a_6FI + a_7C^2 + a_8SF^2 + a_9W^2 + a_{10}FA^2 + a_{11}CA^2 + a_{12}FI^2$
I-3	(2)	Fractional	$a_0 + a_1W/(C+SF) + a_2W/(FA+CA+FI)$
I-4		Power-fractional	$a_1(W/(C+SF))a_2 + a_3(W/(FA+CA+FI))a_4$
I-5		Partial polynomial-fractional Type 1	$a_1(W/(C+SF))^2 + a_3(W/(FA+CA+FI))^2$
I-6		Partial polynomial-fractional Type 2	$a_0 + a_1W/(C+SF) + a_2(W/(C+SF))^2 + a_3((FA+CA+FI)/(C+SF)) + a_4((FA+CA+FI)/(C+SF))^2$

Table 6

Evaluated coefficients of regression models.

Model	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}
I-1	-1.262	0.694	0.45	-0.118	1.303	1.152	0.192	-	-	-	-	-	-
I-2	-3.665	1.563	-0.292	0.662	-1.72	8.627	-0.446	-1.013	0.736	-0.787	5.337	-5.198	0.703
I-3	0.453	-0.3	0.471	-	-	-	-	-	-	-	-	-	-
I-4	-	-0.574	0.362	1.102	0.166	-	-	-	-	-	-	-	-
I-5	0.41	0.293	-0.254	-0.005	-	-	-	-	-	-	-	-	-
I-6	0.615	0.097	-0.099	-0.12	0.009	-	-	-	-	-	-	-	-

Model code	Interpolation (training) performance		Extrapolation (testing) performance	
	CF	RMS	CF	RMS
I-1	0.7821	3.2366	0.7943	2.7087
I-2	0.8449	2.7784	0.8350	2.6080
I-3	0.3811	4.8019	0.5872	3.3049
I-4	0.4088	4.7402	0.5561	3.3180
I-5	0.3499	4.8665	0.5166	3.5361
I-6	0.4086	4.7406	0.5606	3.3285

Parameters

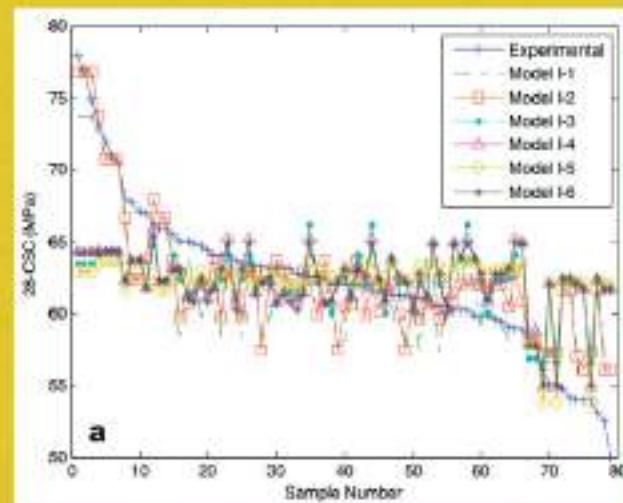
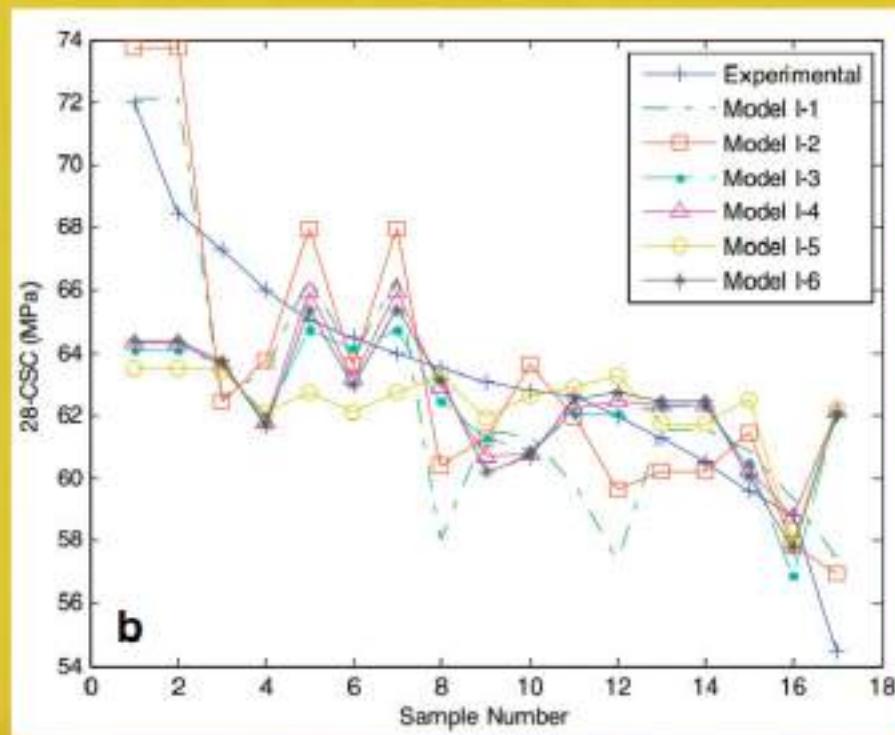
471	-	-	-	-	-	-
362	1.102	0.166	-	-	-	-
254	-0.005	-	-	-	-	-
099	-0.12	0.009	-	-	-	-

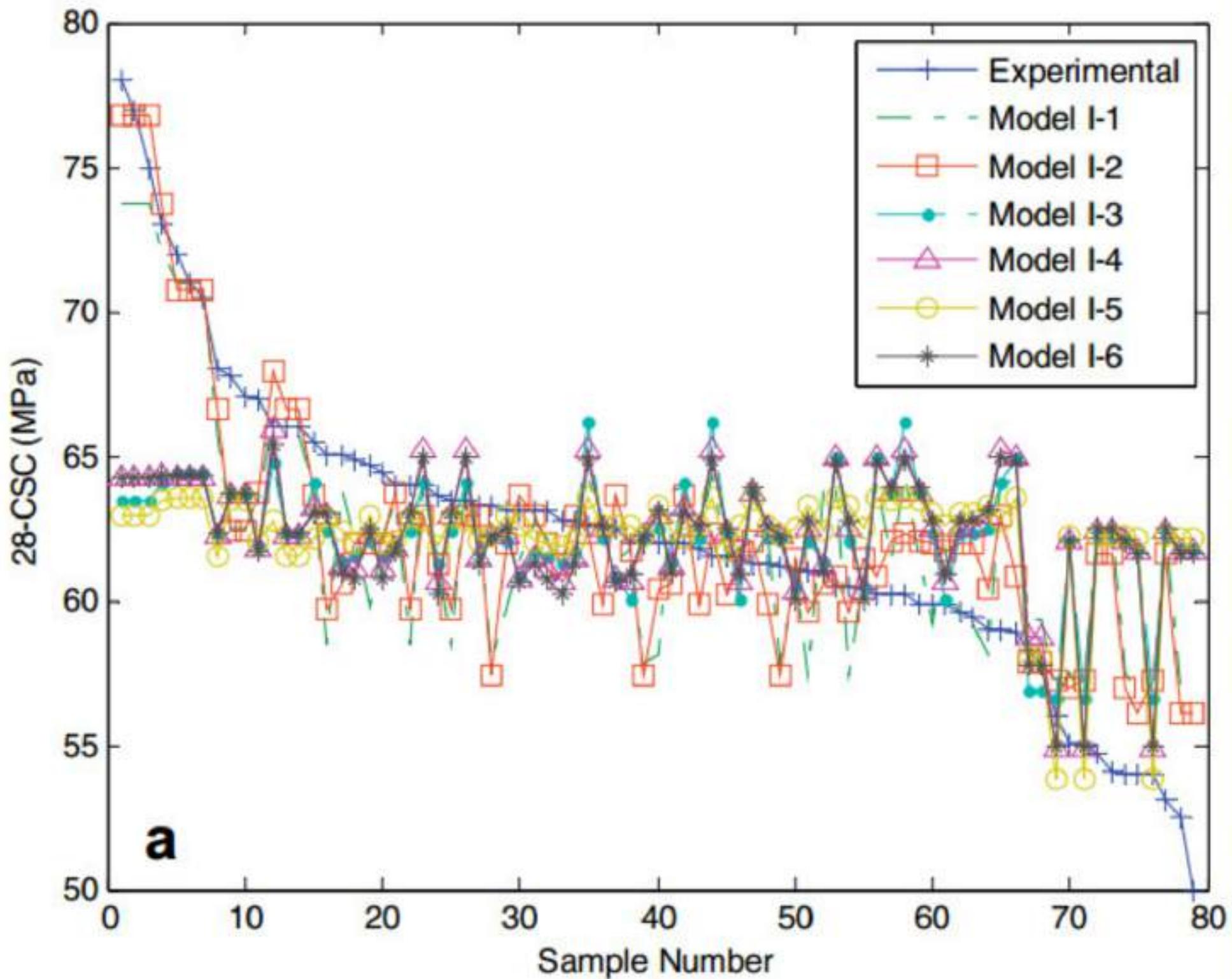
Model code	Interpolation (training) performance		Extrapolation (testing) performance	
	CF	RMS	CF	RMS
I-1	0.7821	3.2366	0.7943	2.7087
I-2	0.8449	2.7784	0.8350	2.6080
I-3	0.3811	4.8019	0.5872	3.3049
I-4	0.4088	4.7402	0.5561	3.3180
I-5	0.3499	4.8665	0.5166	3.5361
I-6	0.4086	4.7406	0.5606	3.3285

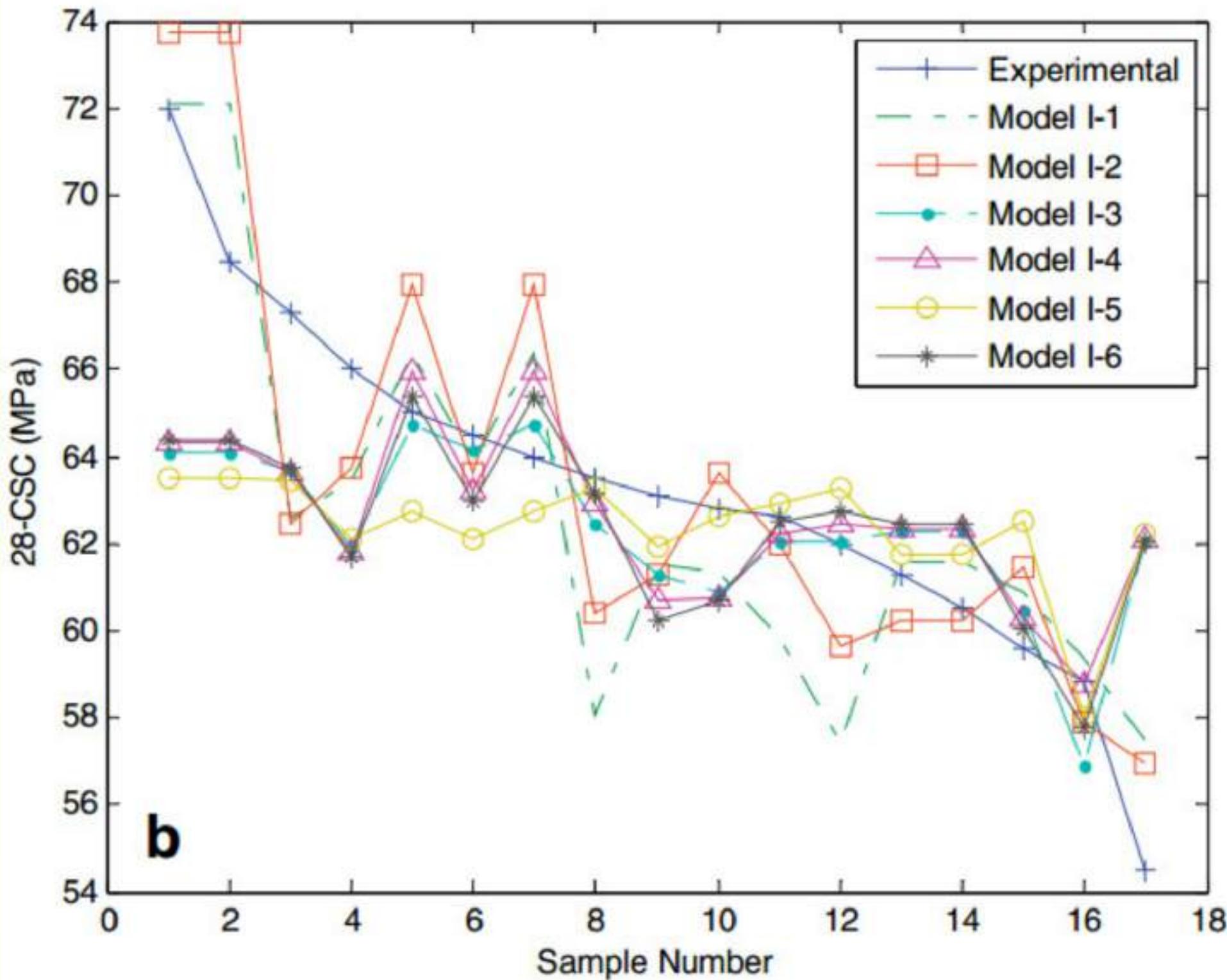
Parameters

Nonlinear/linear regression

As it can be seen in this figure, the model is to some extent poor in predicting the 28-CSNC. The reason for this finding is related to the lower data available for developing a reasonable NLRM.







Neural network

To make a decision on the completion of the training processes, two termination states are declared: state 1 means that the training of neural network was ended when the maximum epoch of process reached (1000) while state 2 means the training ended when minimum error norm of network gained. It is clear that the preferred termination state the state 2.



ANFIS model

ANFIS model	MF	Training set		Testing set	
		CF	RMS	CF	RMS
ANM1	Triangular	0.9820	0.9814	0.9461	1.5790
ANM2	Trapezoidal	0.9225	2.0053	0.9281	1.6697
ANM3	Bell-shape	0.9820	0.9806	0.9472	1.5743
ANM4	Gaussian	0.9820	0.9806	0.9472	1.5750
ANM5	II-shape	0.9355	1.8356	0.9362	1.6219

Neural network

To make a decision on the completion of the training processes, two termination states are declared: state 1 means that the training of neural network was ended when the maximum epoch of process reached (1000) while state 2 means the training ended when minimum error norm of network gained. It is clear that the preferred termination state the state 2.

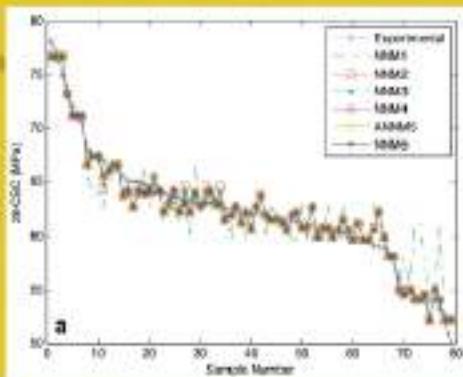
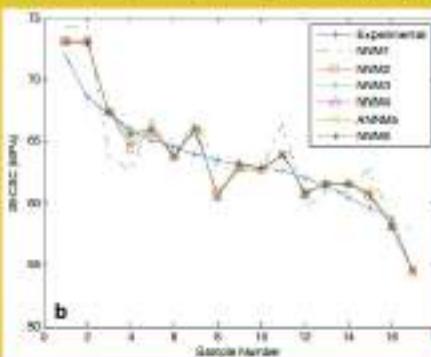


Table 8 General properties of NMN6							
Name	Training method/algorithm	Activation function in Hid. layer	Activation function in output layer	No. of PE in hidden	Output neurons	MLP number	Epochs
Web-based tool-recognizer	Supervised/semi-supervised- Backward BP	Un-named	Sigmoid function	Variable	4	2	

Table 9 Summary of results for 2D-CG2 predictions						
Name	No. of PE in	Training set	Testing set	Termination rule	Termination rule	
NMN1	2	2	0.0000	0.0111	24.000	1
NMN2	2	2	0.0007	0.0009	23.000	1
NMN3	1	3	0.0004	0.0001	23.000	1
NMN4	4	3	0.0010	0.0002	23.000	1
NMN5	4	4	0.0019	0.0001	23.000	240
NMN6	1	6	0.0005	0.0001	23.000	231



ended when minimum error norm of clear that the preferred termination

Table 8

General properties of NNMs.

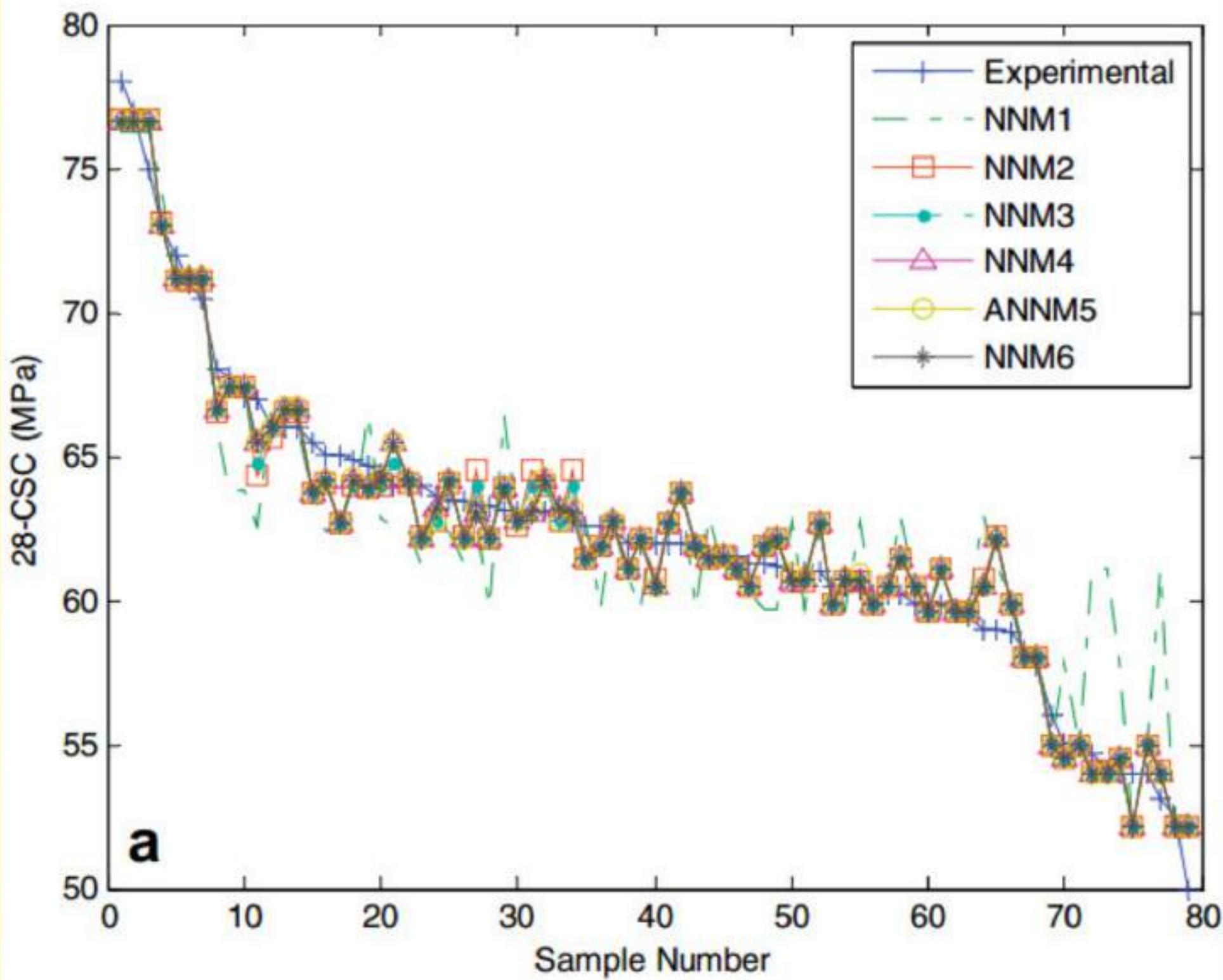
Type	Training method/algorithm	Activation function in HLs	Activation function in output layer	No. of PE in HL	Layers number	HLs number
Feed-forward back-propagation network	Supervised/Levenberg-Marquardt BP	Log-sigmoid	Linear transfer function	Variable	4	2

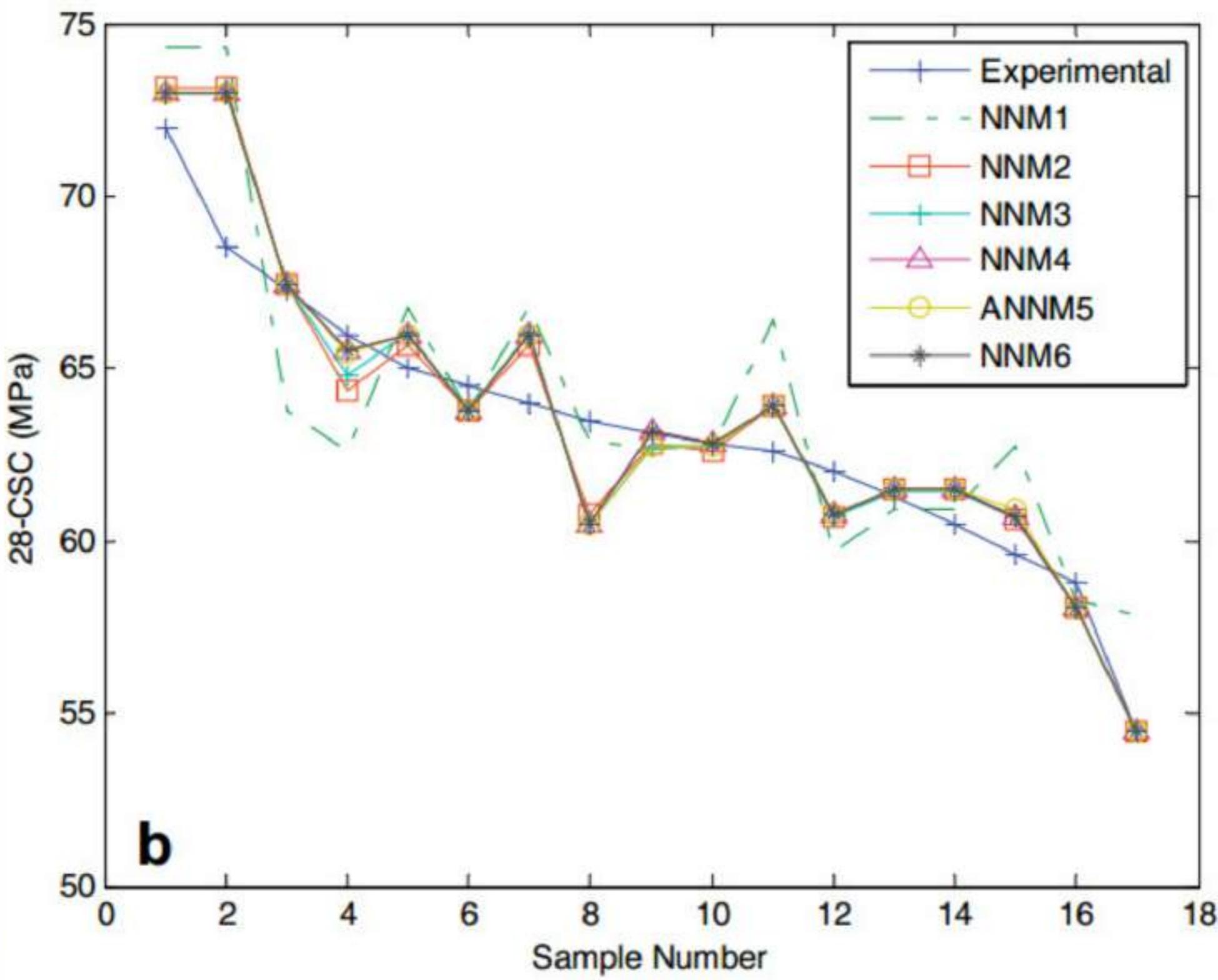
Table 9

Summary of NNMs for 28-CSNC prediction.

Name	No. of PE in		Training set		Testing set		Termination epoch	Termination state
	HL1	HL2	CF	RMS	CF	RMS		
NNM1	2	2	0.8898	2.3705	0.8515	2.3376	1000	1
NNM2	3	2	0.8907	2.3606	0.8669	2.2430	1000	1
NNM3	3	3	0.9606	1.4440	0.9185	1.7607	1000	1
NNM4	4	3	0.9820	0.9806	0.9473	1.5748	852	2
NNM5	4	4	0.9820	0.9806	0.9473	1.5748	348	2
NNM6	5	4	0.9820	0.9806	0.9473	1.5748	267	2







ANFIS model

ANFIS model	MF	Training set		Testing set	
		CF	RMS	CF	RMS
ANM1	Triangular	0.9820	0.9814	0.9461	1.5790
ANM2	Trapezoidal	0.9225	2.0053	0.9281	1.6697
ANM3	Bell-shape	0.9820	0.9806	0.9472	1.5743
ANM4	Gaussian	0.9820	0.9806	0.9472	1.5750
ANM5	Π -shape	0.9355	1.8356	0.9362	1.6219

Conclusion

- The reason for this finding might be of the insufficient amount of data required for developing a sustainable regression model, while the neural network and ANFIS models could recognize the relationships with lower data for their distributed and parallel computing nature.
- The regression is familiar method in modeling of engineering systems for its closed-form representation. Unfortunately, in the case of inadequate data, the regression models fail to be reliable and hence, advanced models like neural network and ANFIS models are preferred.

Evaluation of NLRM, NNM and ANM for testing records.

ID	Experimental	Model1-2	RE (%)	NNM6	RE (%)	ANM4	RE (%)
S80	72.0	73.7	2.39	73.0	1.39	73.0	1.39
S79	68.5	73.7	7.62	73.0	6.57	73.0	6.57
S7	67.3	62.4	-7.24	67.5	0.22	67.4	0.22
S44	66.0	63.8	-3.40	65.5	-0.76	65.5	-0.76
S75	65.0	68.0	4.55	66.0	1.54	66.0	1.54
S96	64.5	63.6	-1.38	63.8	-1.16	63.7	-1.16
S74	64.0	68.0	6.18	66.0	3.13	66.0	3.12
S59	63.5	60.4	-4.87	60.5	-4.72	60.5	-4.73
S38	63.1	61.3	-2.92	63.2	0.16	63.2	0.16
S42	62.8	63.6	1.33	62.8	0.00	62.8	0.00
S11	62.5	62.0	-0.96	63.9	2.08	63.9	2.08
S61	62.0	59.6	-3.84	60.8	-2.02	60.8	-2.02
S24	61.3	60.2	-1.77	61.5	0.33	61.5	0.31
S23	60.5	60.2	-0.48	61.5	1.65	61.5	1.63
S34	59.6	61.5	3.15	60.7	1.85	60.7	1.85
S29	58.8	57.9	-1.58	58.1	-1.28	58.0	-1.28
S64	54.5	57.0	4.53	54.5	0.00	54.5	0.05

Evaluation of NLRM, NNM and ANM for testing records.

ID	Experimental	Model I-2	RE (%)	NNM6	RE (%)	ANM4	RE (%)
S80	72.0	73.7	2.39	73.0	1.39	73.0	1.39
S79	68.5	73.7	7.62	73.0	6.57	73.0	6.57
S7	67.3	62.4	-7.24	67.5	0.22	67.4	0.22
S44	66.0	63.8	-3.40	65.5	-0.76	65.5	-0.76
S75	65.0	68.0	4.55	66.0	1.54	66.0	1.54
S96	64.5	63.6	-1.38	63.8	-1.16	63.7	-1.16
S74	64.0	68.0	6.18	66.0	3.13	66.0	3.12
S59	63.5	60.4	-4.87	60.5	-4.72	60.5	-4.73
S38	63.1	61.3	-2.92	63.2	0.16	63.2	0.16
S42	62.8	63.6	1.33	62.8	0.00	62.8	0.00
S11	62.6	62.0	-0.96	63.9	2.08	63.9	2.08
S61	62.0	59.6	-3.84	60.8	-2.02	60.8	-2.02
S24	61.3	60.2	-1.77	61.5	0.33	61.5	0.31
S23	60.5	60.2	-0.48	61.5	1.65	61.5	1.63
S34	59.6	61.5	3.15	60.7	1.85	60.7	1.85
S29	58.8	57.9	-1.58	58.1	-1.28	58.0	-1.28
S64	54.5	57.0	4.53	54.5	0.00	54.5	0.05

Conclusion

- The reason for this finding might be of the insufficient amount of data required for developing a sustainable regression model, while the neural network and ANFIS models could recognize the relationships with lower data for their distributed and parallel computing nature.
- The regression is familiar method in modeling of engineering systems for its closed-form representation. Unfortunately, in the case of inadequate data, the regression models fail to be reliable and hence, advanced models like neural network and ANFIS models are preferred.

Evaluation of NLRM, NNM and ANM for testing records.

ID	Experimental	Model I-2	RE (%)	NNM6	RE (%)	ANM4	RE (%)
S80	72.0	73.7	2.39	73.0	1.39	73.0	1.39
S79	68.5	73.7	7.62	73.0	6.57	73.0	6.57
S7	67.3	62.4	-7.24	67.5	0.22	67.4	0.22
S44	66.0	63.8	-3.40	65.5	-0.76	65.5	-0.76
S75	65.0	68.0	4.55	66.0	1.54	66.0	1.54
S96	64.5	63.6	-1.38	63.8	-1.16	63.7	-1.16
S74	64.0	68.0	6.18	66.0	3.13	66.0	3.12

Neurofuzzy system applications

Conclusion

The reasons for choosing integrative of two insufficient variants of fuzzy method for developing a successful recognition model, while the neural network and ANFD models cannot recognize the relationships with given data for their simplicity and speed of learning, not less.

The application of Cuckoo method as modeling of recognition systems for its closed form representation. Unfortunately, in one case of implementation of this recognition system did not include the training, obtained results by the neural network (ANFD) were poor.

Parameter	Value
Number of neurons	100
Number of hidden layers	1
Number of epochs	1000
Number of iterations	1000
Number of samples	1000
Number of clusters	10
Number of inputs	10
Number of outputs	1