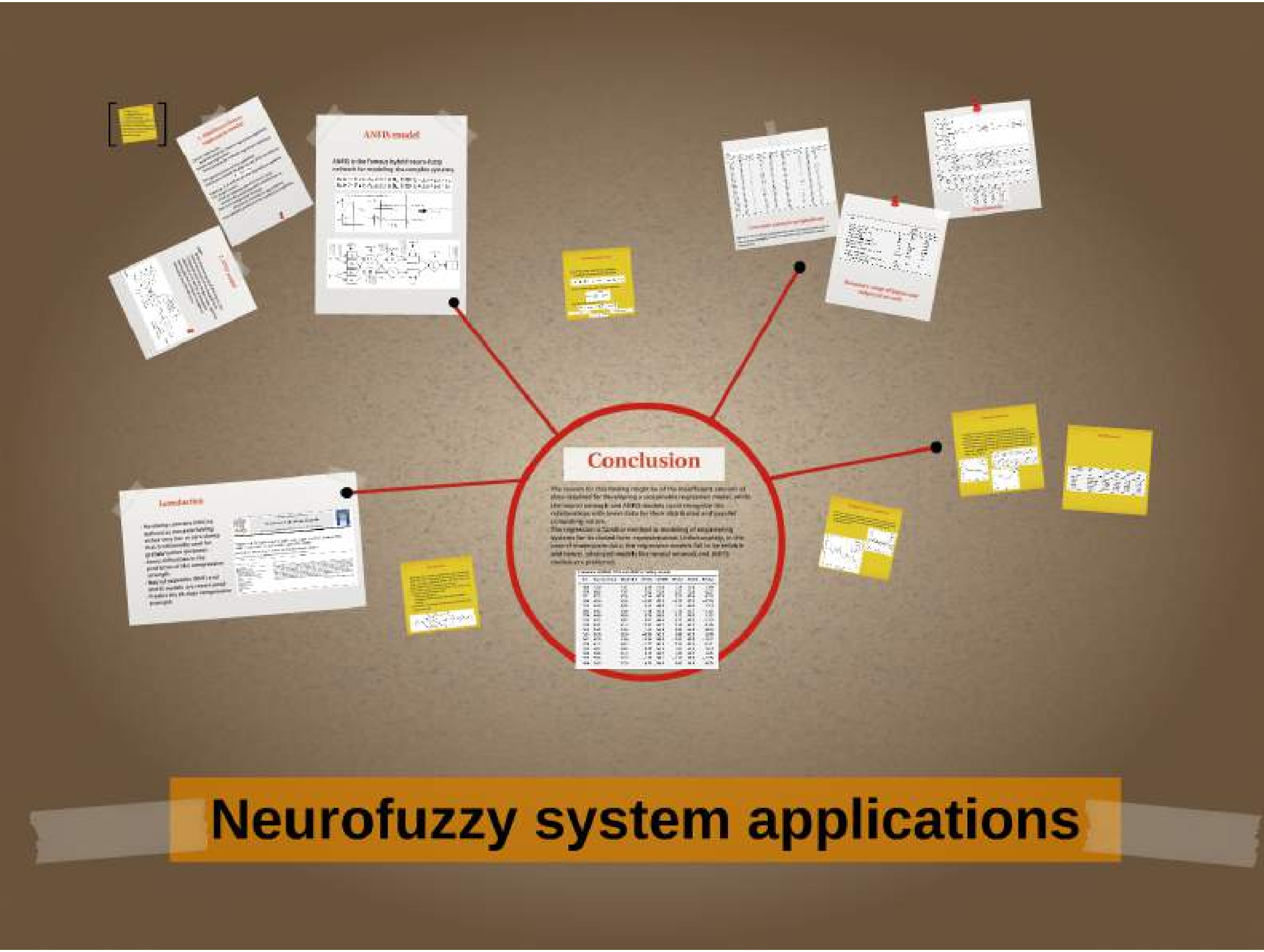
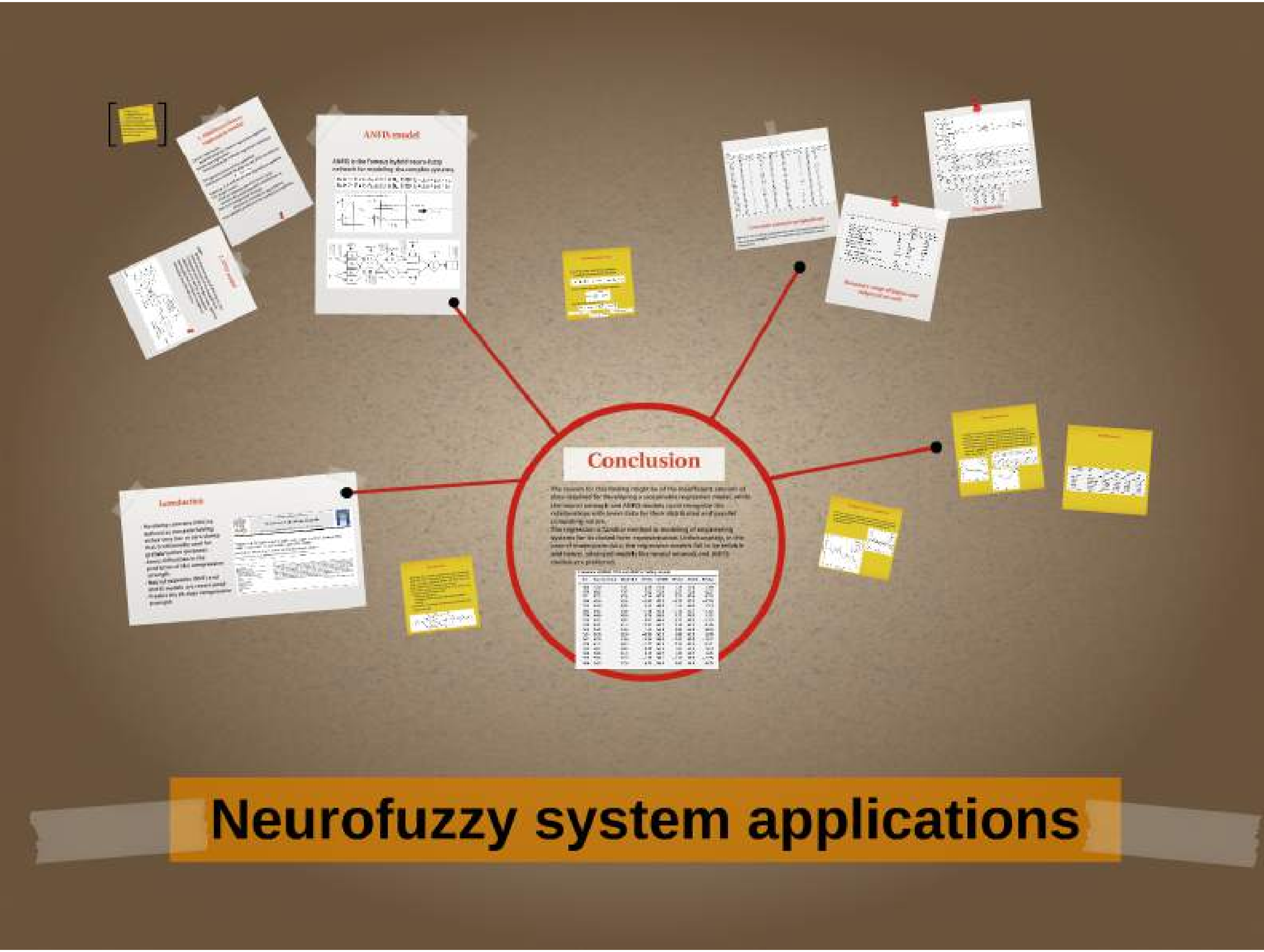

Conclusion
Neurofuzzy system applications


ANFIS model
Conclusion
Neurofuzzy system applications

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

Contents lists available at ScienceDirect

Construction and Building Materials

journal homepage: www.elsevier.com/locate/conbuildmat

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

Jafar Sobhani *, Meysam Najimi, Ali Reza Pourkhorshidi, Tayebeh Parhizkar

Building and Housing Research Centre, Pas Farhangian St, Sheikh Fazlollah Exp. Way, Tehran 13145-1696, Iran

ARTICLE INFO

Article history:
Received 27 June 2009
Received in revised form 23 October 2009
Accepted 23 October 2009
Available online 20 November 2009

Keywords:
No-slump concrete
Compressive strength
Regression
Neural networks
ANFIS

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.

Contents lists available at ScienceDirect

Construction and Building Materials

journal homepage: www.elsevier.com/locate/conbuildmat

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

Jafar Sobhani *, Meysam Najimi, Ali Reza Pourkhorshidi, Tayebeh Parhizkar

Building and Housing Research Center, Pas Farhangian St, Sheikh Fazlollah Exp. Way, Tehran 13145-1696, Iran

ARTICLE INFO

Article history:
Received 27 June 2009
Received in revised form 23 October 2009
Accepted 23 October 2009
Available online 20 November 2009

Keywords:
No-slump concrete
Compressive strength
Regression
Neural networks
ANFIS

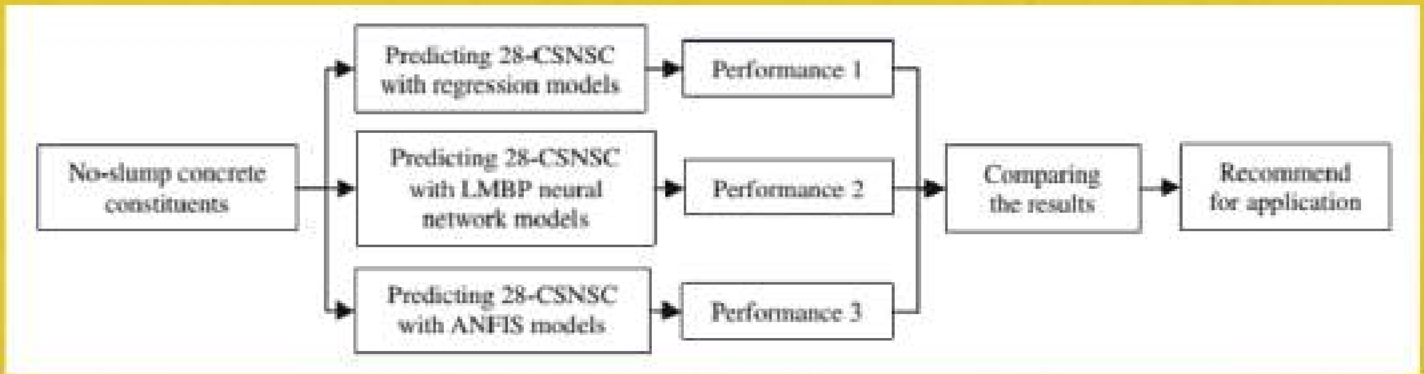
ABSTRACT

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.

Introduction

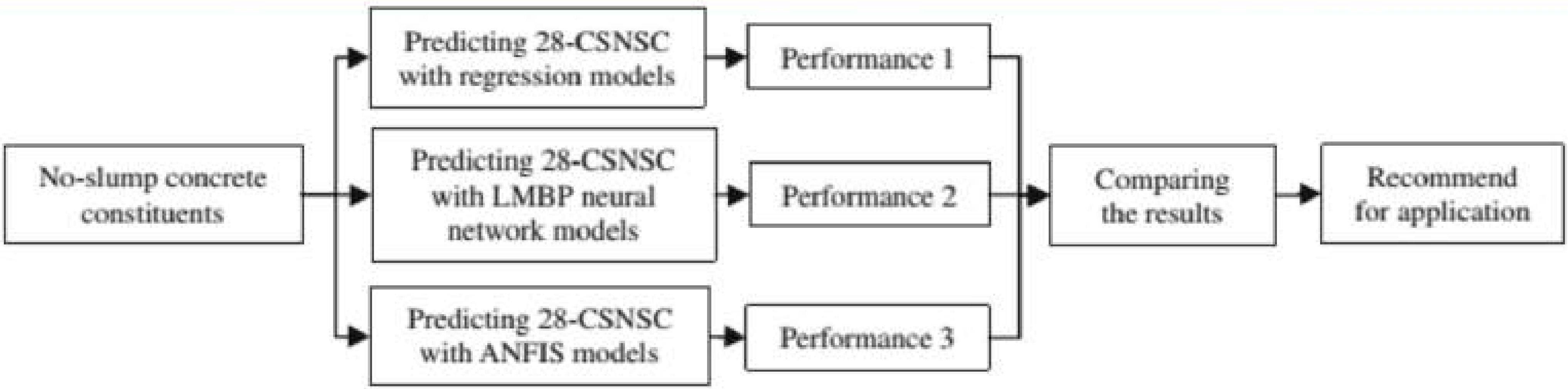
- Although the several methods has been proposed to predict the compressive strength of normal and high strength concrete, these methods has not been applied for no-slump concrete yet.
- The major purpose of this paper is to assess and compare the performance of:
  - Various regression
  - Artificial 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



- 6 Regression
- 6 Neural network and
- 6 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 factor

1. Nonlinear/linear regression model

Linear regression :
Relationship by a linear regression equation
Nonlinear regression :
Relationship by a linear regression equation

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

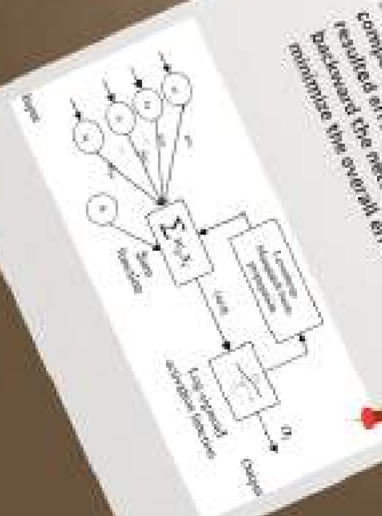
$$y = f(a_i \times x_i)$$

where y, f, ai and xi are the dependent variable.
The major issue :
- Find an appropriate function f with statistically well-adjusted coefficients ai.

This is accomplished through (iterative estimation algorithms)
That usually performed by statistical methods.

2. ANN model

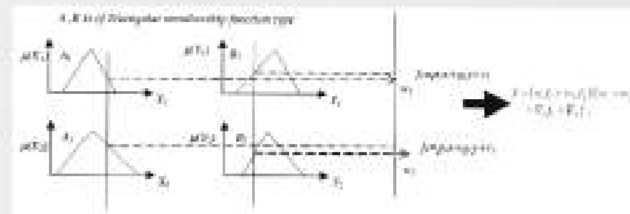
LMBP :
After processing all of the layers, the activated result of the output layer, compared with the target value, and the resulted error will be propagated backward the network's weight to minimize the overall error.

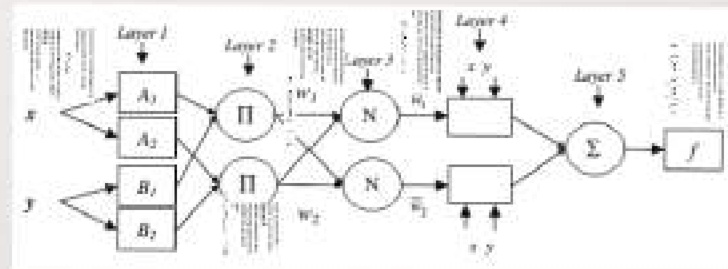


ANFIS model

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 $f_2 = p_2x + q_2y + r_2$.





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 linear regression equation

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

$$y = f(a_i \times x_i)$$

where y, f, ai and xi are the dependent variable.

The major issue :

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

This is accomplished through

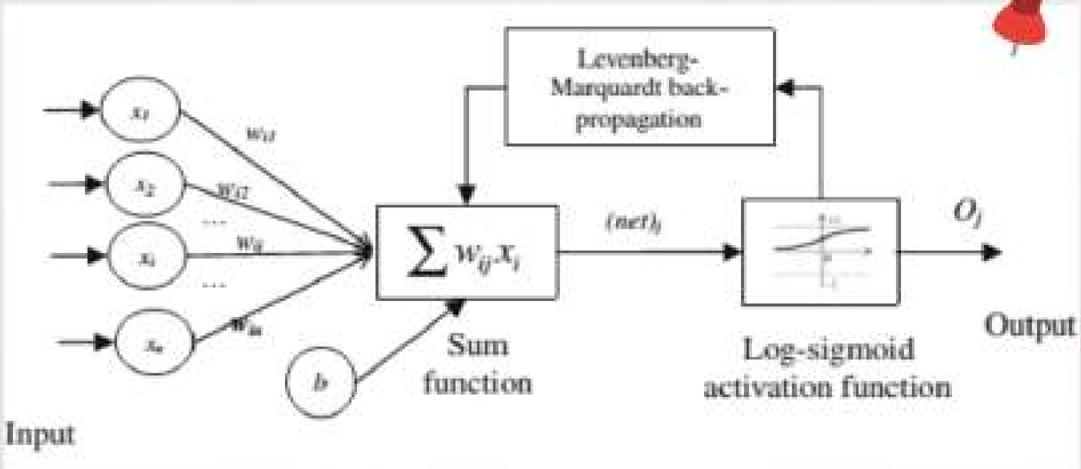
(iterative estimation algorithms)

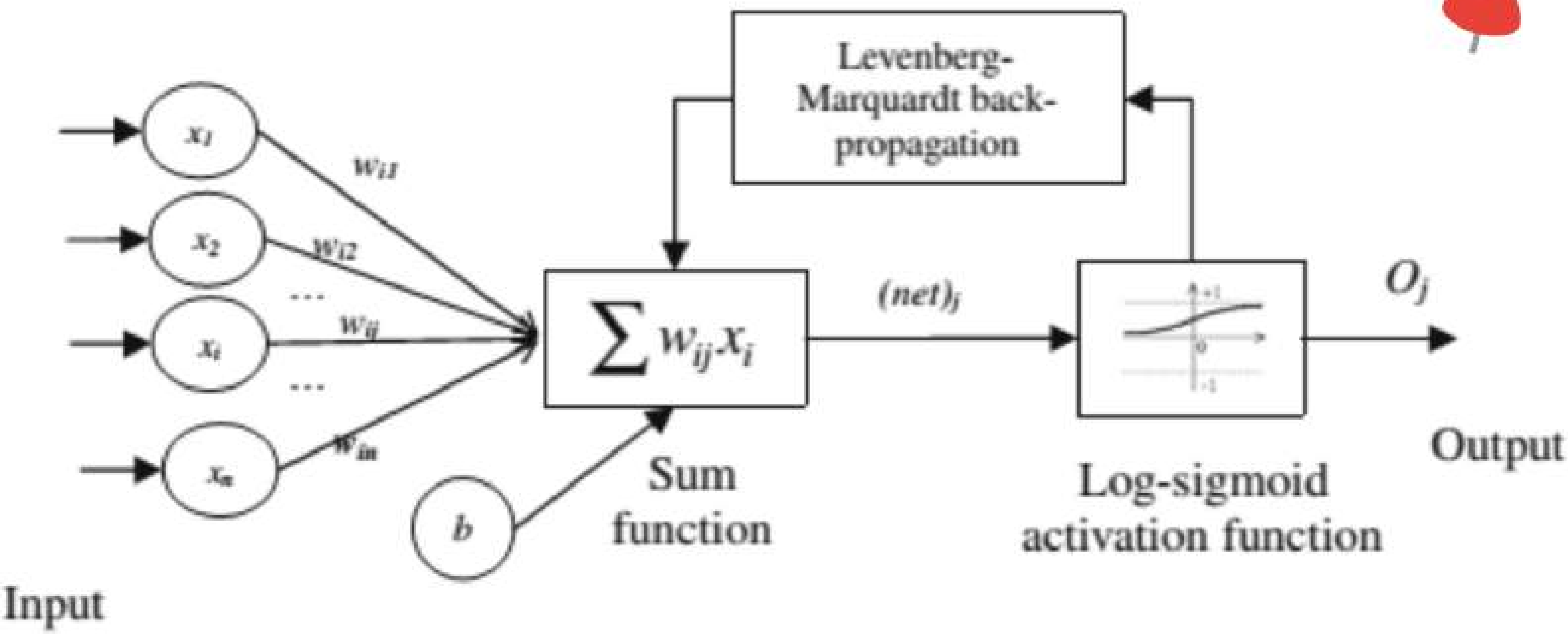
That usually performed by statistical methods.

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.

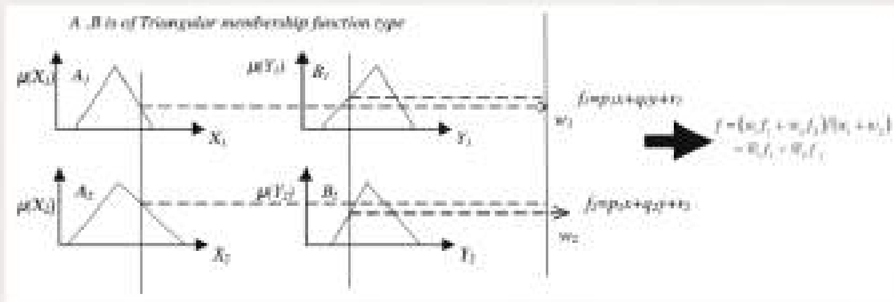


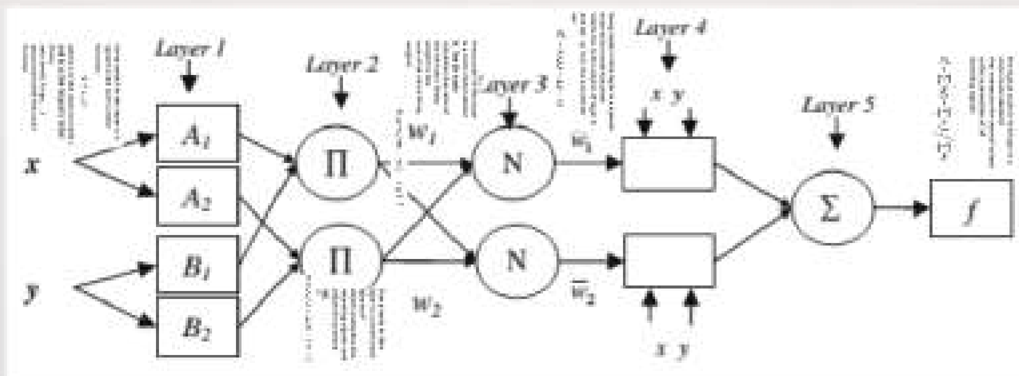

Levenberg-
Marquardt back-
propagation
x_1
x_2
x_i
x_n
w_{i1}
w_{i2}
w_{ij}
w_{in}
...
...
$\sum w_{ij} x_i$
$(net)_j$
O_j
b
Sum
function
Log-sigmoid
activation function
Output
Input

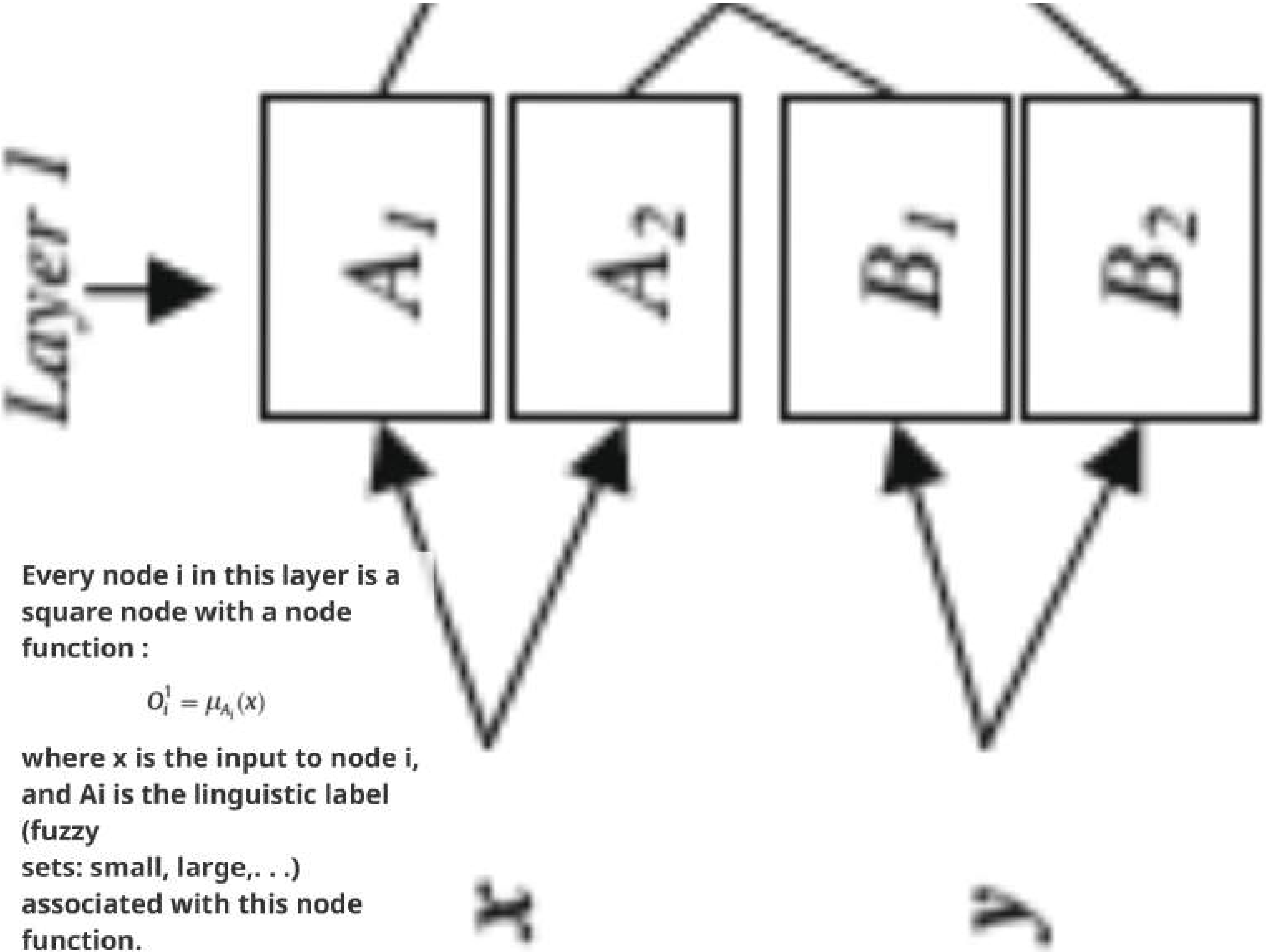
ANFIS model

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 $f_2 = p_2x + q_2y + r_2$.





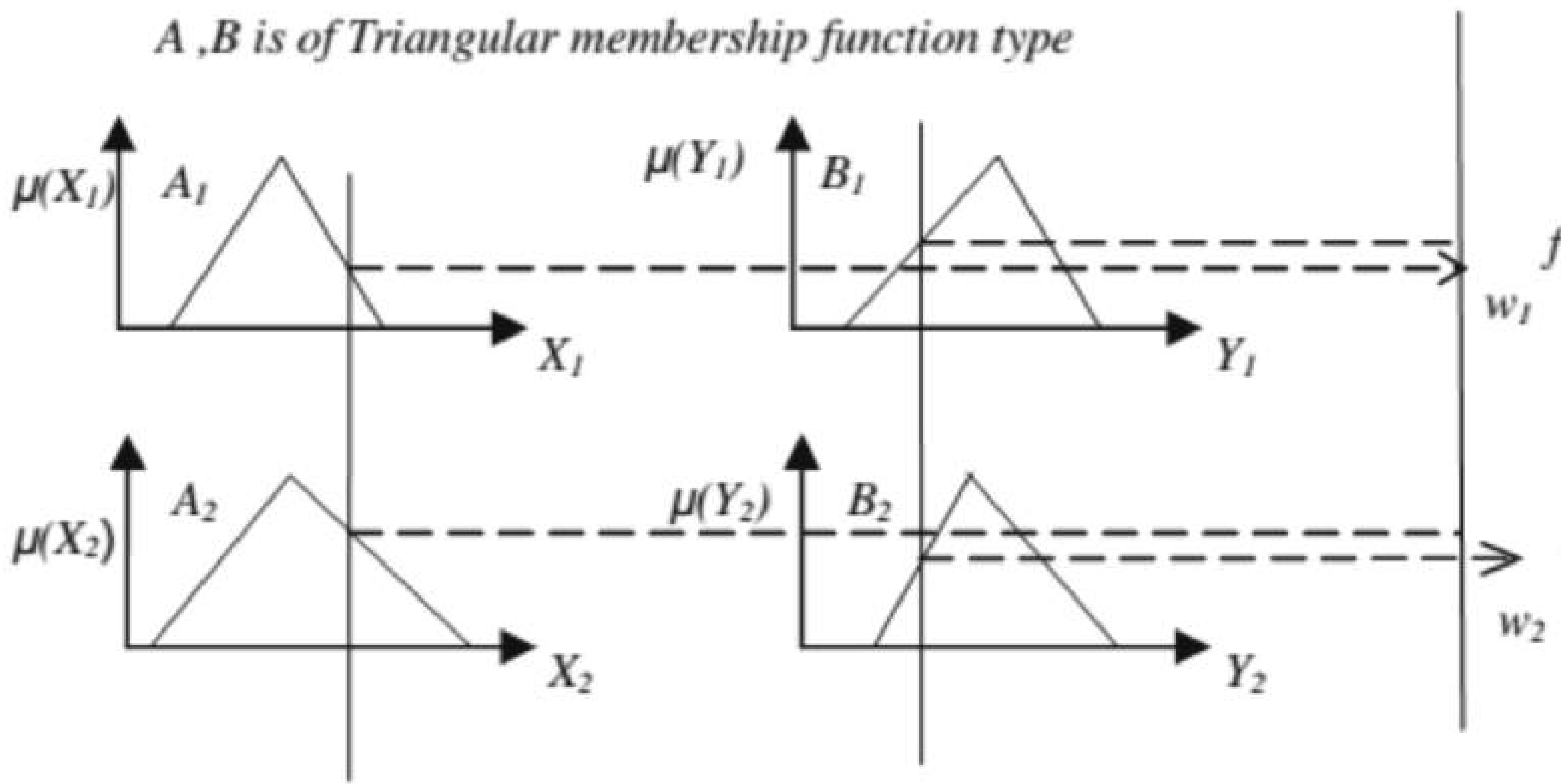


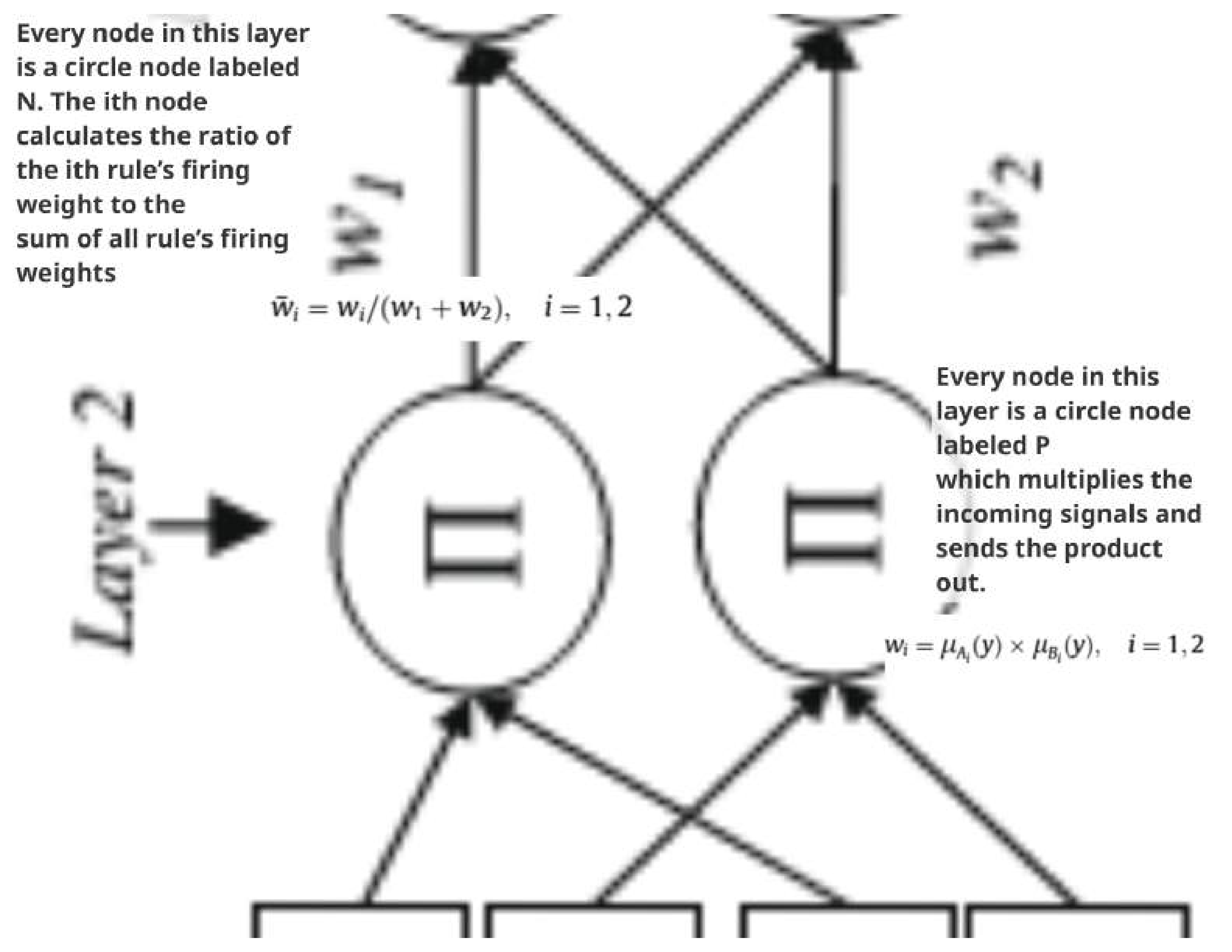
Every node i in this layer is a square node with a node function :

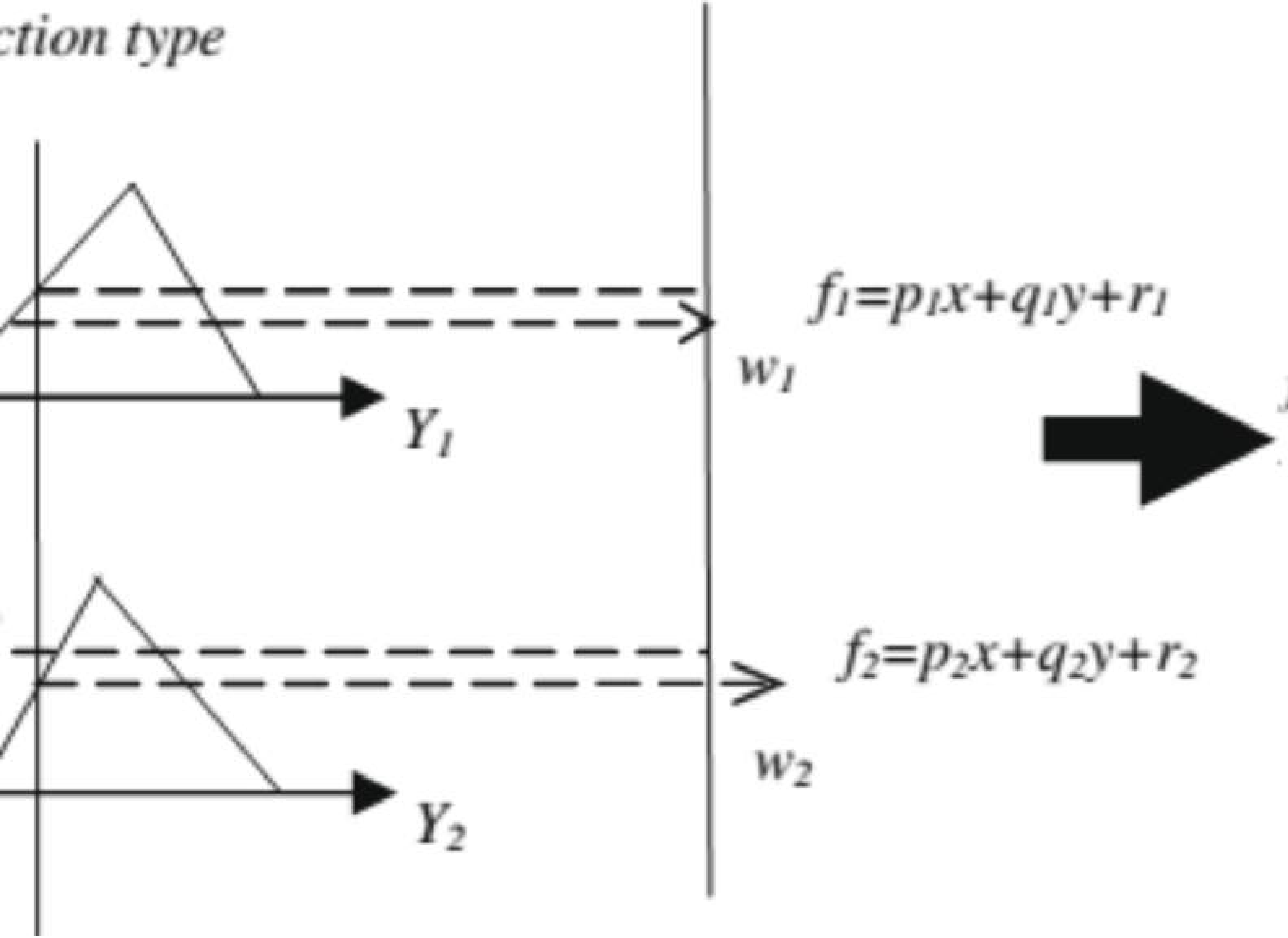
$$O_i^1 = \mu_{A_i}(x)$$

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

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



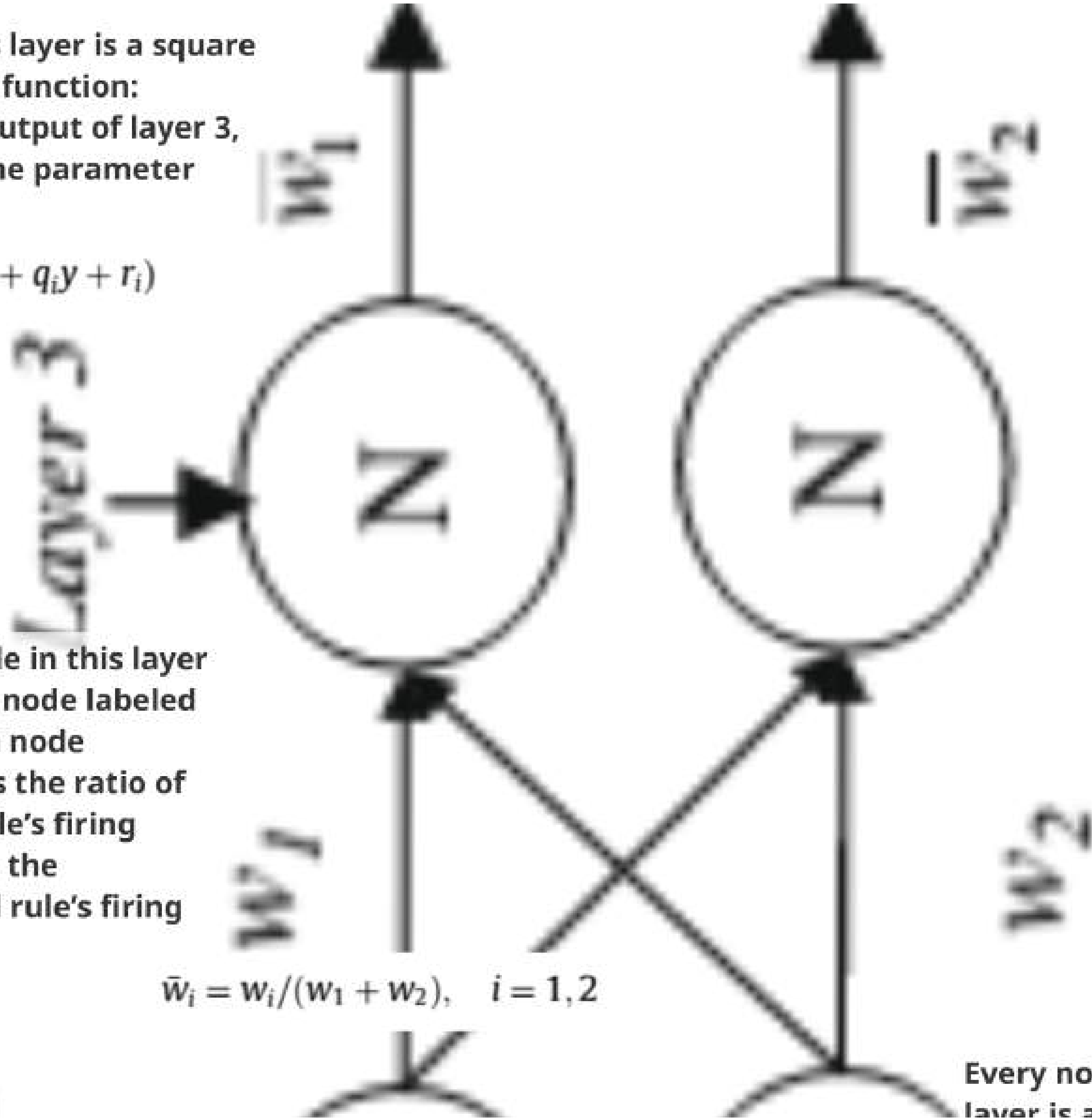

Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule's firing weight to the sum of all rule's firing weights
$\bar{w}_i = w_i/(w_1 + w_2), \quad i = 1, 2$
w_1
w_2
Layer 2
Π
Π
Every node in this layer is a circle node labeled P which multiplies the incoming signals and sends the product out.
$w_i = \mu_{A_i}(y) \times \mu_{B_i}(y), \quad i = 1, 2$



ction type
f1=p1x+q1y+r1
w1
Y1
f2=p2x+q2y+r2
w2
Y2

ode in this layer is a square
ith a node function:
w-i is the output of layer 3,
, qi, ri} is the parameter

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

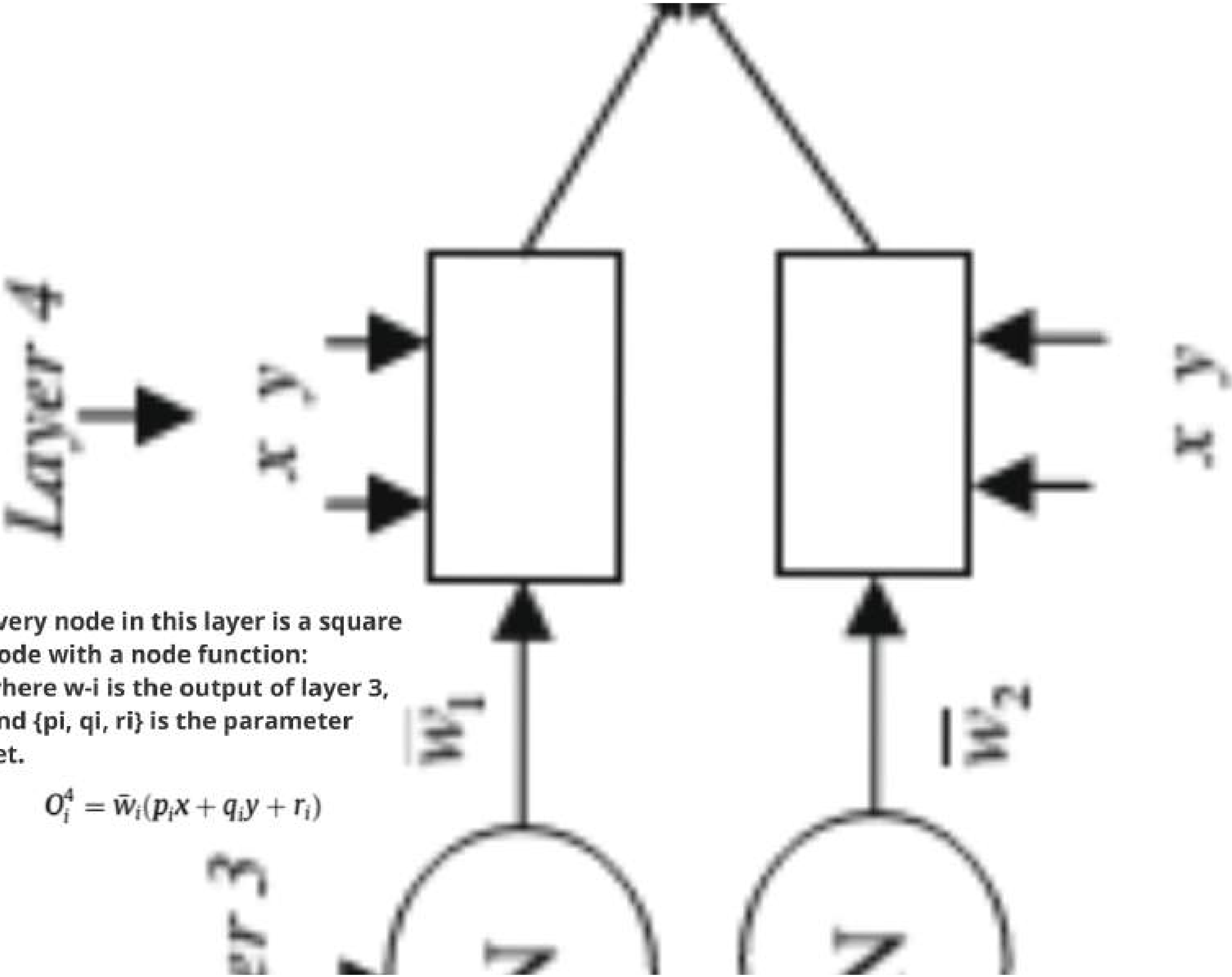


Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule's firing weight to the sum of all rule's firing weights

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

Every node in this layer is a circle node

$$f = (w_1 f_1 + w_2 f_2)/(w_1 + w_2)$$
$$= \overline{w}_1 f_1 + \overline{w}_2 f_2$$

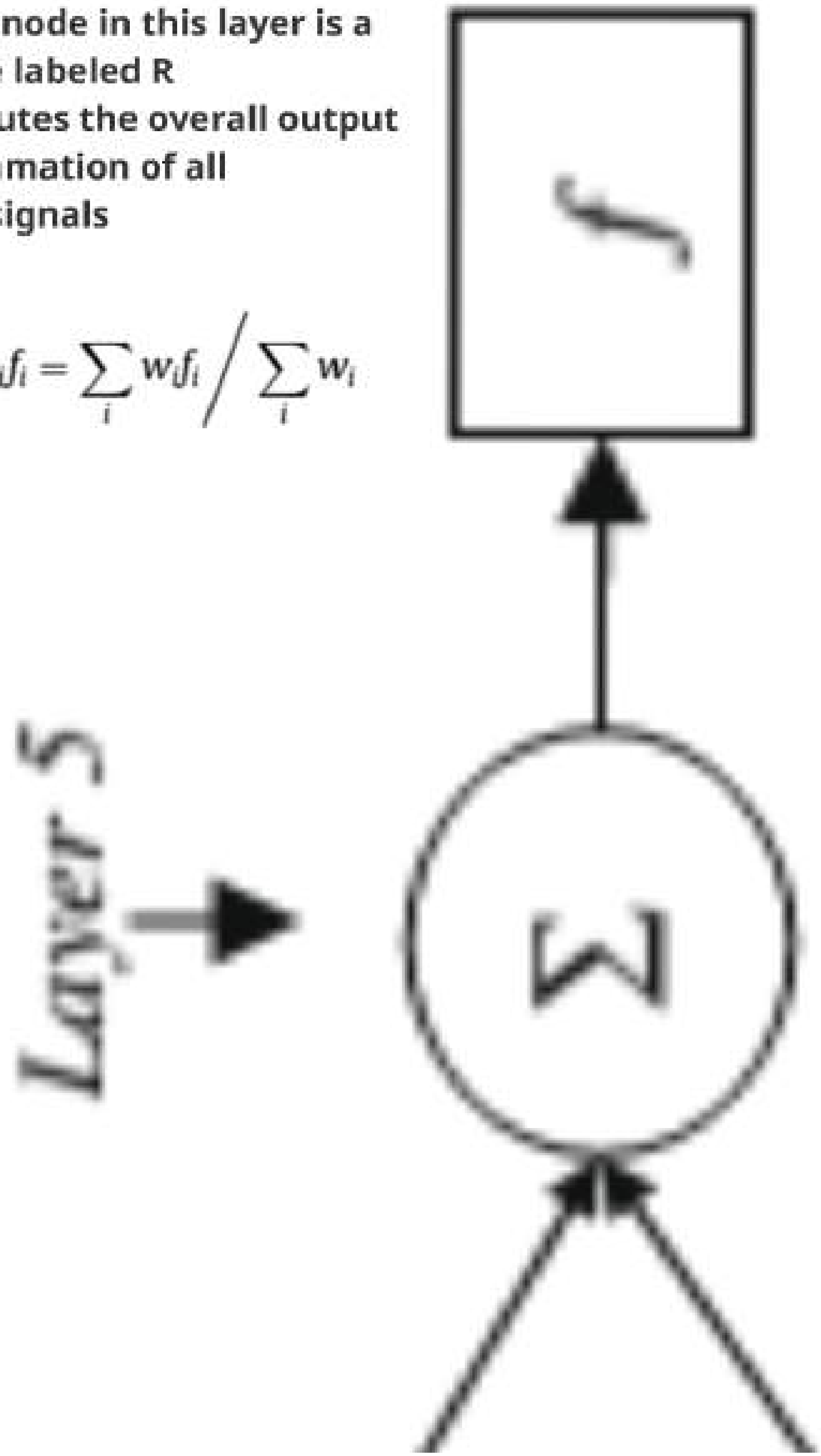


Every node in this layer is a square node with a node function:
where w-i is the output of layer 3, and {pi, qi, ri} is the parameter set.

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

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

$$O_i^5 = \sum_i \bar{w}_i f_i = \sum_i w_i f_i \Big/ \sum_i w_i$$



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 :

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

Correlation factor (CF) :

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

$$\mathrm{Fc} = (f_{c1}, f_{c2}, \ldots, f_{cp}), \quad \hat{F}_c = (\hat{f}_{c1}, \hat{f}_{c2}, \ldots, \hat{f}_{cp})$$

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

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

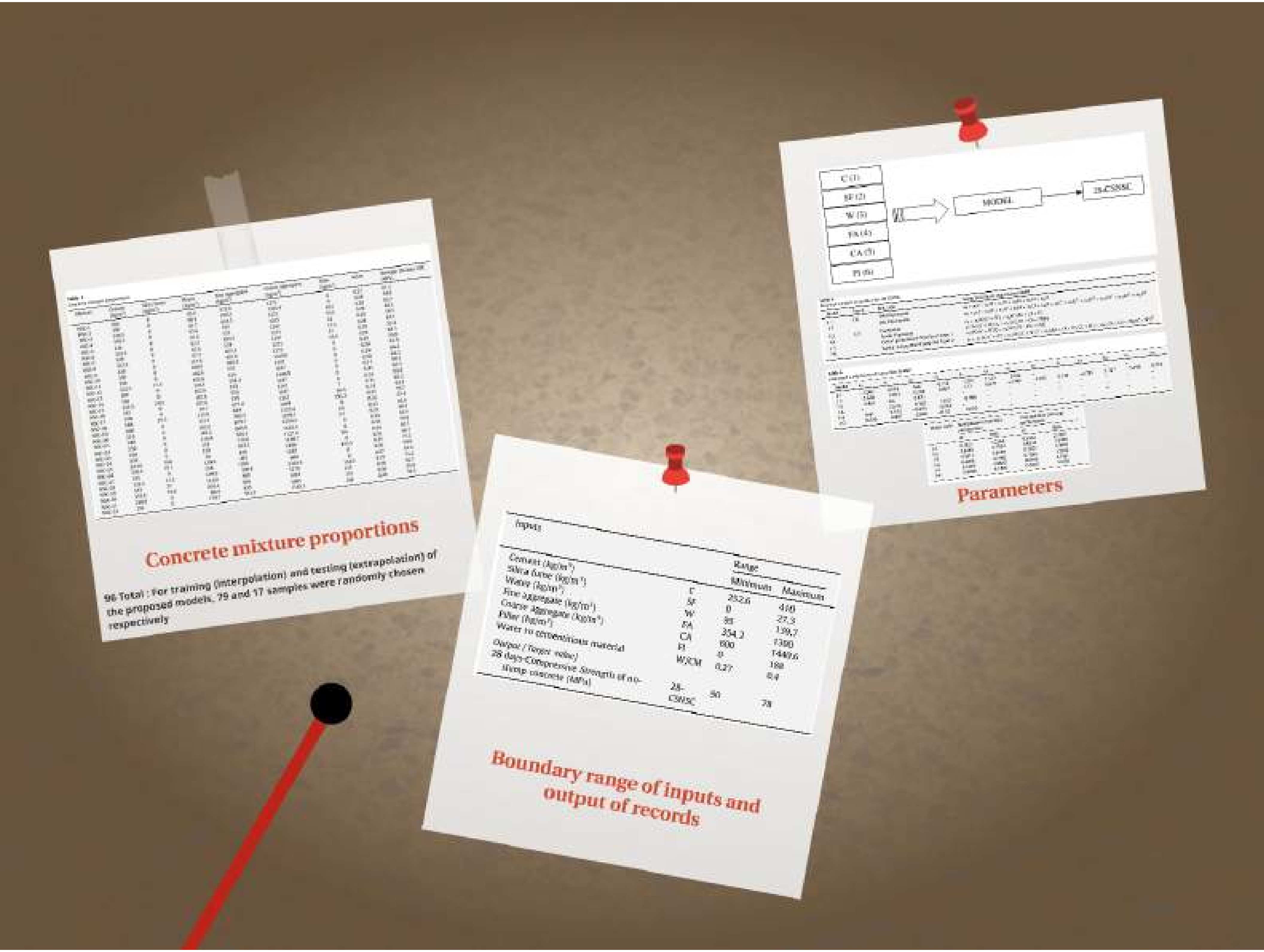

Concrete mixture proportions
96 Total : For training (interpolation) and testing (extrapolation) of the proposed models, 79 and 17 samples were randomly chosen respectively
Inputs
Range
Minimum
Maximum
Cement (kg/m3) C 252.6 410
Silica fume (kg/m3) SF 0 27.3
Water (kg/m3) W 95 139.7
Fine aggregate (kg/m3) FA 354.2 1300
Coarse aggregate (kg/m3) CA 600 1440.6
Filler (kg/m3) Fl 0 188
Water to cementitious material W/CM 0.27 0.4
Output / Target value
28 days-Compressive Strength of no-slump concrete (MPa) 28-CSNSC 30 78
Boundary range of inputs and output of records
C (1)
SF (2)
W (3)
FA (4)
CA (5)
Fl (6)
MODEL
28-CSNSC
Parameters

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

Concrete mixture proportions

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

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
Output (Target value)			
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
Output (Target value)			
28 days-Compressive Strength of no-slump concrete (MPa)	28-CSNSC	50	78

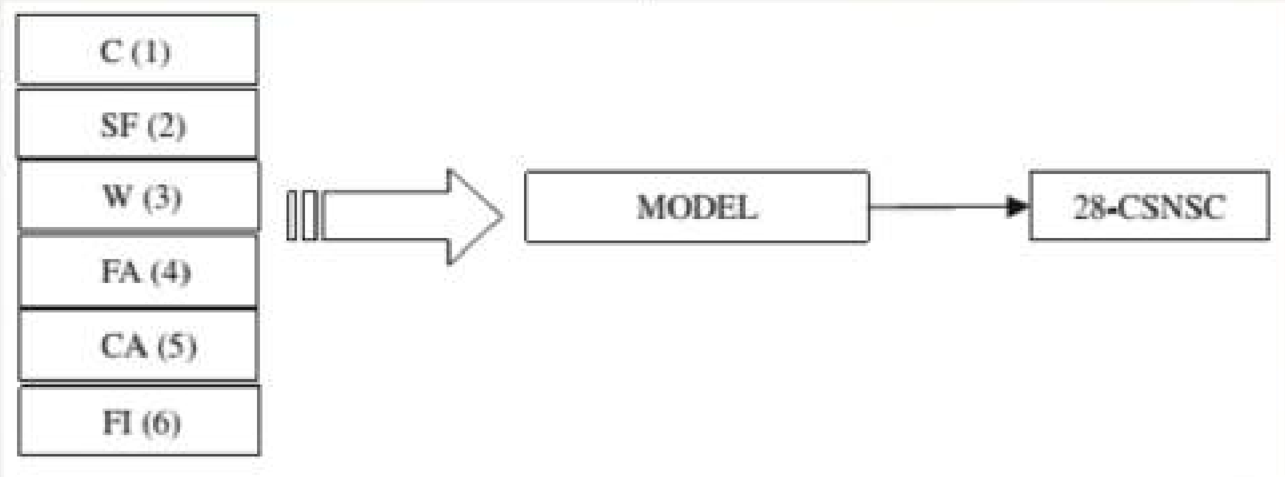


Table 5
Proposed models to predict the 28-CSNSC.

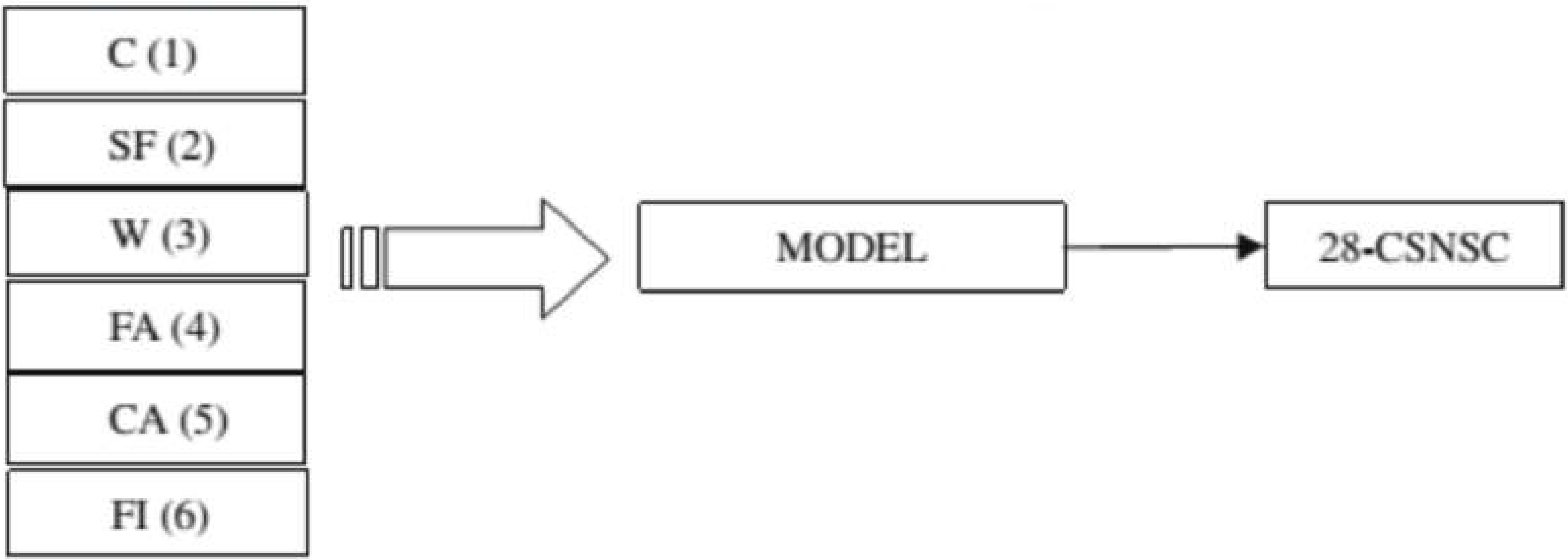
Model	Group	Reg. type	Linear/nonlinear regression model
I-1	(1)	1th Polynomial	$\alpha_0 + \alpha_1 C + \alpha_2 SF + \alpha_3 W + \alpha_4 FA + \alpha_5 CA + \alpha_6 FI$
I-2		2th Polynomial	$\alpha_0 + \alpha_1 C + \alpha_2 SF + \alpha_3 W + \alpha_4 FA + \alpha_5 CA + \alpha_6 FI + \alpha_7 C^2 + \alpha_8 SF^2 + \alpha_9 W^2 + \alpha_{10} FA^2 + \alpha_{11} CA^2 + \alpha_{12} FI^2$
I-3	(2)	Fractional	$\alpha_0 + \alpha_1 W/(C+SF) + \alpha_2 W/(FA+CA+FI)$
I-4		Power-fractional	$\alpha_1(W/(C+SF))\alpha_2 + \alpha_3(W/(FA+CA+FI))\alpha_4$
I-5		Partial polynomial-fractional Type 1	$\alpha_1(W/(C+SF))^{\alpha_2} + \alpha_3(W/(FA+CA+FI))^{\alpha_4}$
I-6		Partial polynomial-fractional Type 2	$\alpha_0 + \alpha_1 W/(C+SF) + \alpha_2(W/(C+SF))^2 + \alpha_3((FA+CA+FI)/(C+SF)) + \alpha_4((FA+CA+FI)/(C+SF))^2$

Table 6
Evaluated coefficients of regression models.

Model	α_0	α_1	α_2	α_3	α_4	α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{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	3.1285

Parameters



5

sed models to predict the 28-CSNSC.

del	Group	Reg. type	Linear/nonlinear regression model
	(1)	1th Polynomial	$a_0 + a_1C + a_2SF + a_3W + a_4FA + a_5CA + a_6FI$
		2th Polynomial	$a_0 + a_1C + a_2SF + a_3W + a_4FA + a_5CA + a_6FI + a_7C^2 + a_8SF^2 + a_9W^2 + a_{10}FA^2 + a_{11}CA^2 + a_{12}FI^2$
	(2)	Fractional	$a_0 + a_1W/(C+SF) + a_2W/(FA+CA+FI)$
		Power-fractional	$a_1(W/(C+SF))a_2 + a_3(W/(FA+CA+FI))a_4$
		Partial polynomial–fractional Type 1	$a_1(W/(C+SF))_2^a + a_3(W/(FA+CA+FI))_4^a$

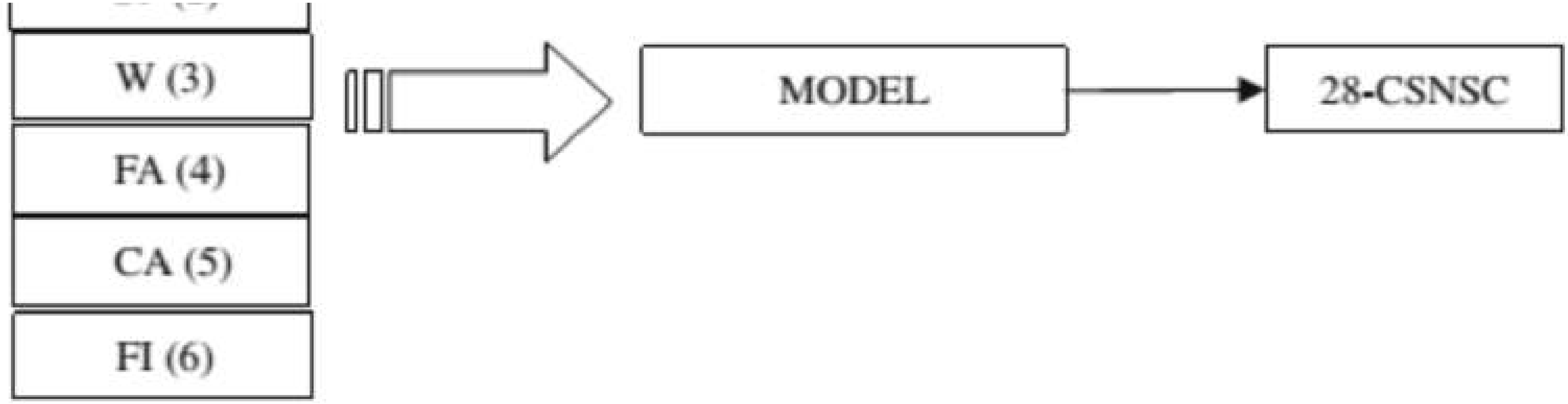


Table 5
Proposed models to predict the 28-CSNSC.

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	$a_1(W/(C+SF))_2^a + a_3(W/(FA+CA+FI))_4^a$
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

FI (6)

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	$a_1(W/(C + SF))_2^a + a_3(W/(FA + CA + FI))_4^a$
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

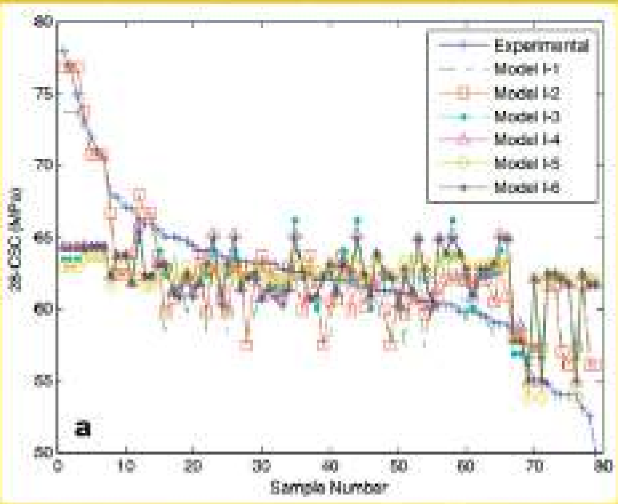
471	–	–	–	–	–	–
362	1.102	0.166	–	–	–	–
254	−0.005	–	–	–	–	–
099	−0.12	0.009	–	–	–	–

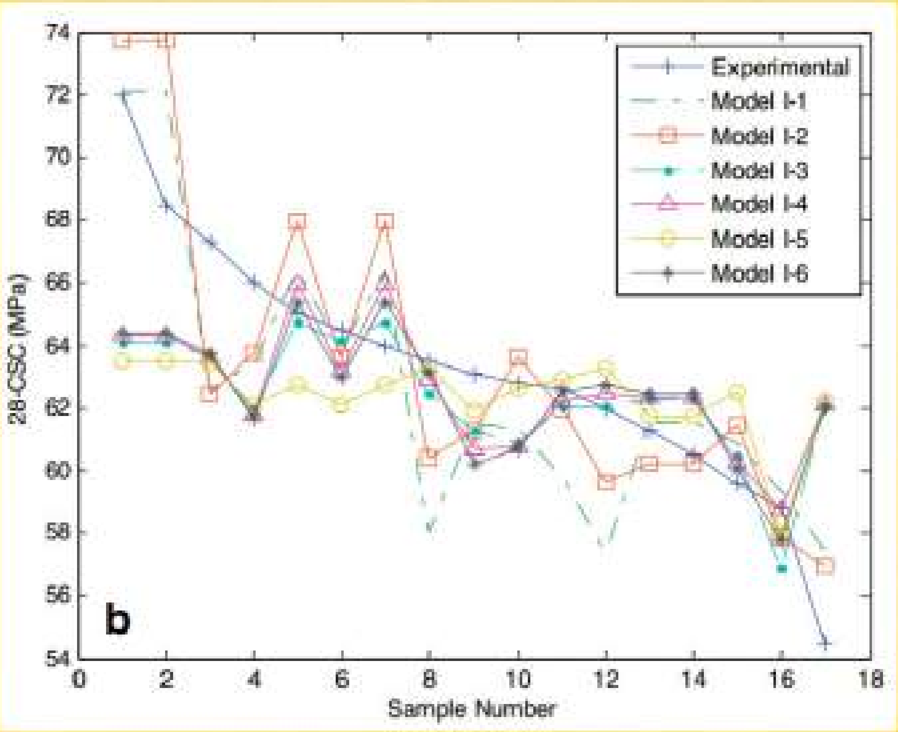
Model code	Interpolation (training) performance		Extrapolation (testing) performance	
	CF	RMS	CF	RMS
I-1	0.7821	3.2366	0.7943	2.7087
I-2	0.8449	2.7784	0.8350	2.6080
I-3	0.3811	4.8019	0.5872	3.3049
I-4	0.4088	4.7402	0.5561	3.3180
I-5	0.3499	4.8665	0.5166	3.5361
I-6	0.4086	4.7406	0.5606	3.3285

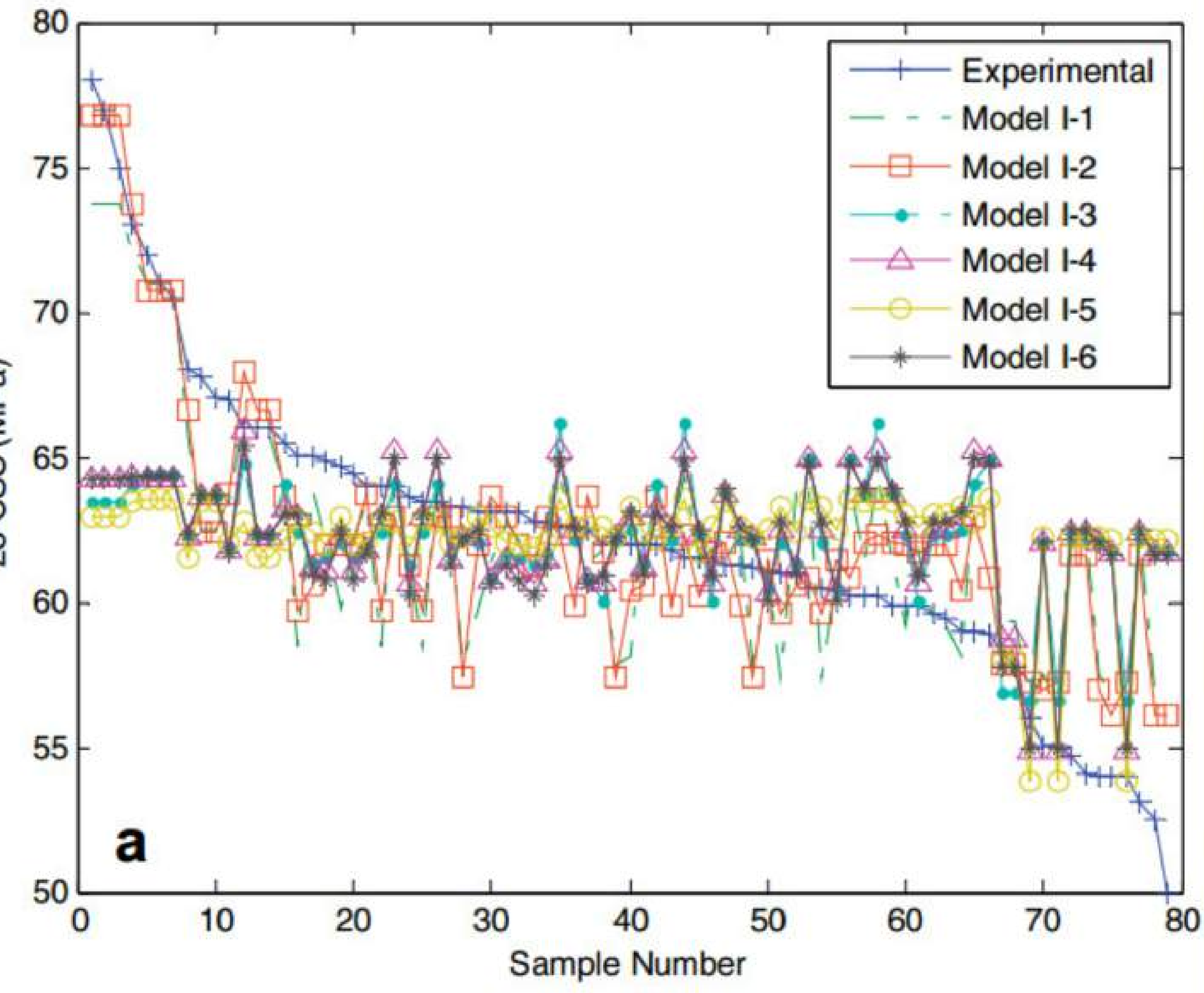
Parameters

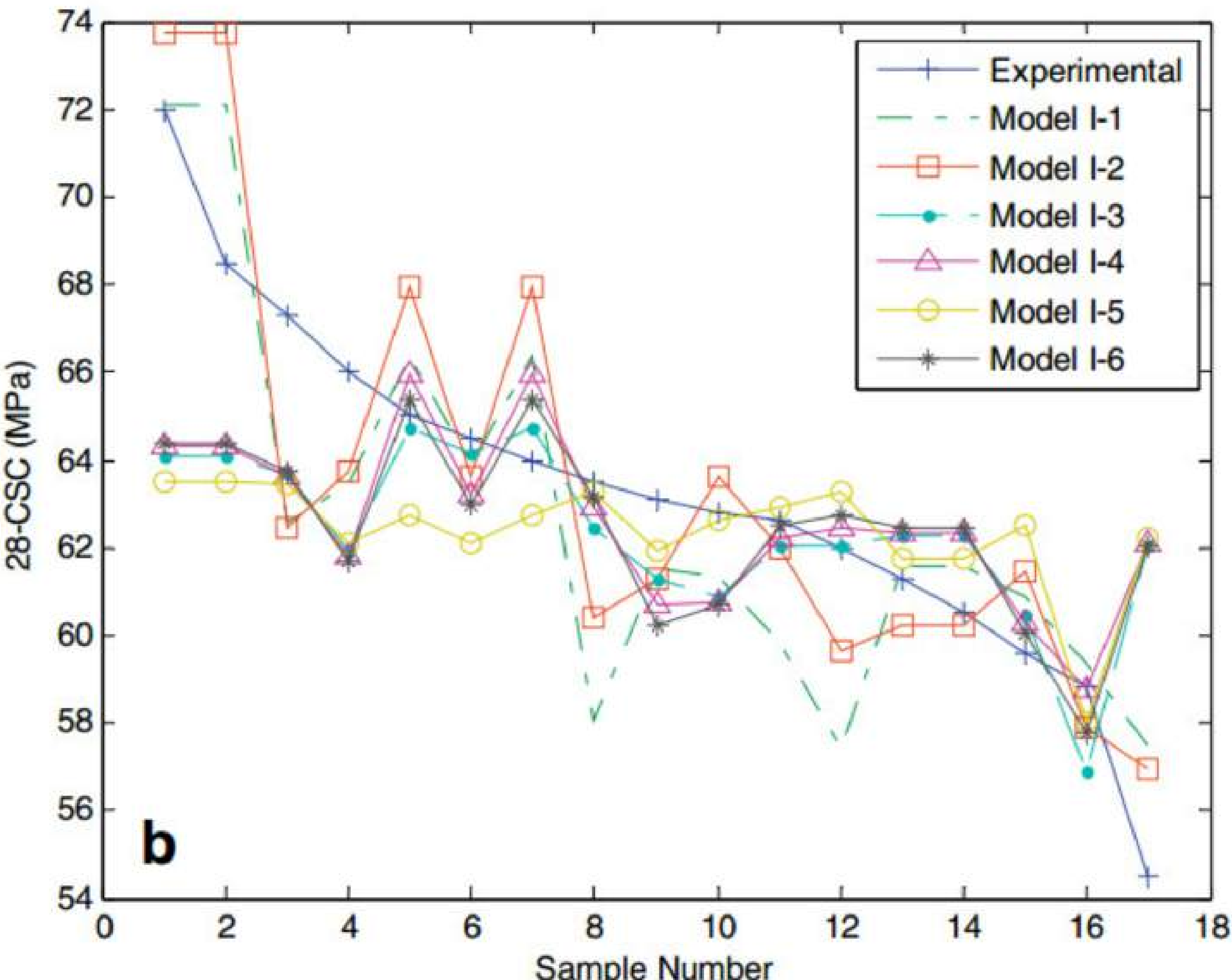
Nonlinear/linear regression

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





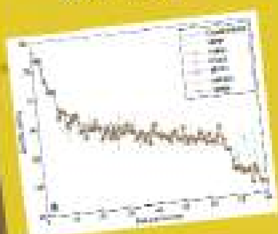

Experimental
Model I-1
Model I-2
Model I-3
Model I-4
Model I-5
Model I-6
28-CSC (MPa)
Sample Number
a
80
75
70
65
60
55
50
0
10
20
30
40
50
60
70
80

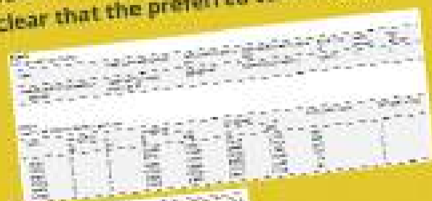


28-CSC (MPa)
Sample Number
Experimental
Model I-1
Model I-2
Model I-3
Model I-4
Model I-5
Model I-6
b
74
72
70
68
66
64
62
60
58
56
54
0
2
4
6
8
10
12
14
16
18

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.



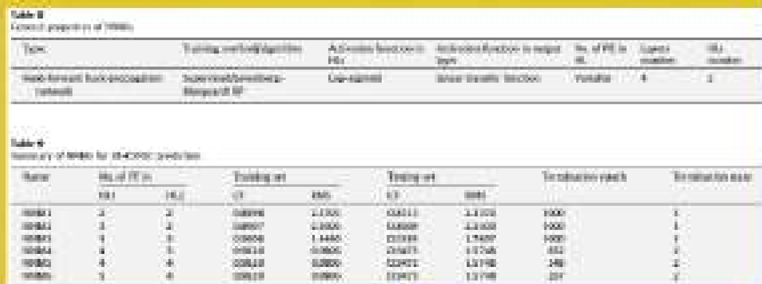


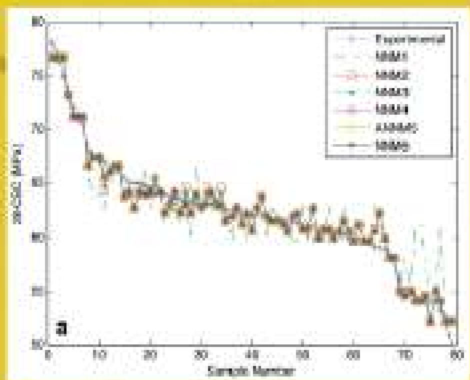
ANFIS model

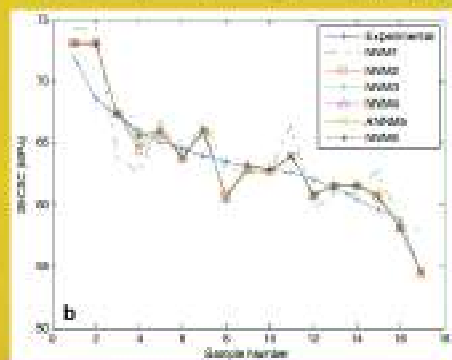
ANFIS model	MF	Training set		Testing set	
		CF	RMS	CF	RMS
ANM1	Triangular	0.9820	0.9814	0.9461	1.5790
ANM2	Trapezoidal	0.9225	2.0053	0.9281	1.6697
ANM3	Bell-shape	0.9820	0.9806	0.9472	1.5743
ANM4	Gaussian	0.9820	0.9806	0.9472	1.5750
ANM5	Π-shape	0.9355	1.8356	0.9362	1.6219

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.







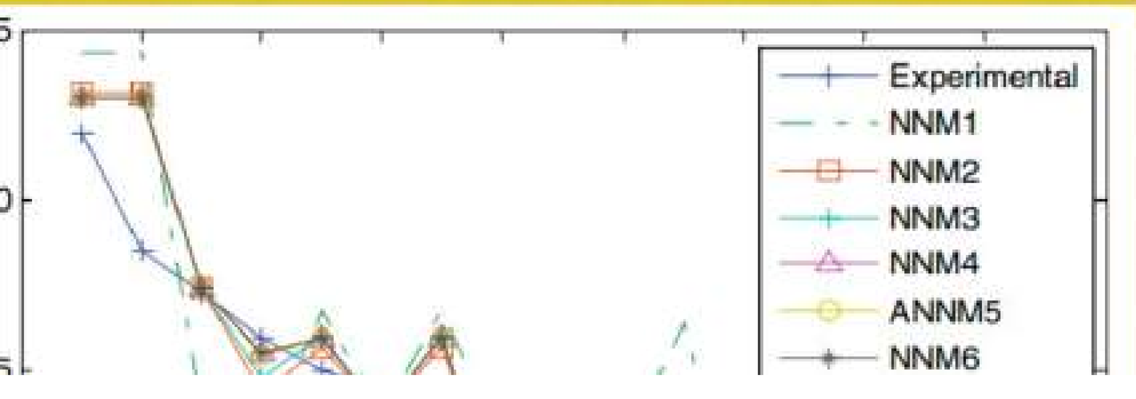
ded when minimum error norm of
clear that the preferred termination

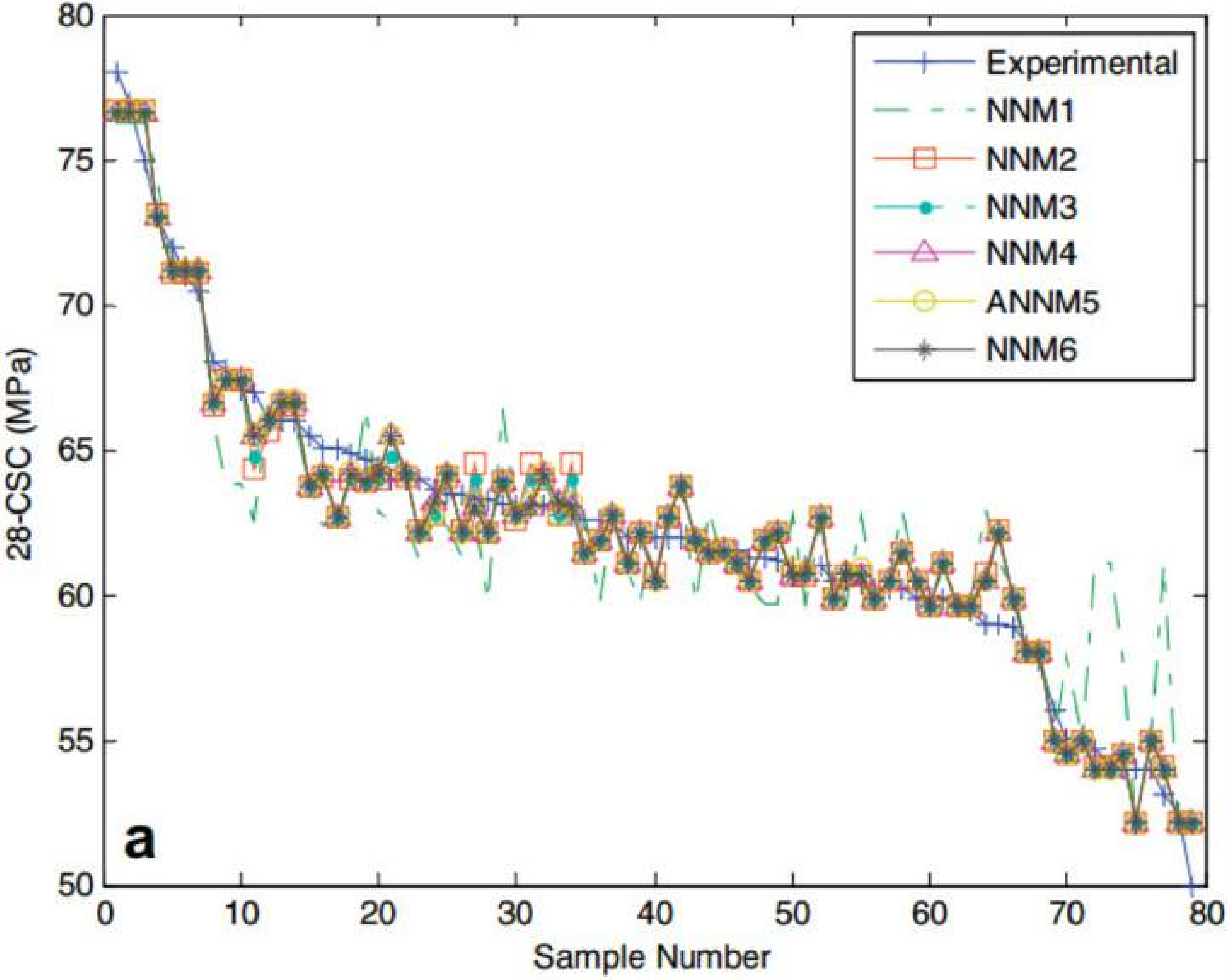
Table 8
General properties of NNMs.

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

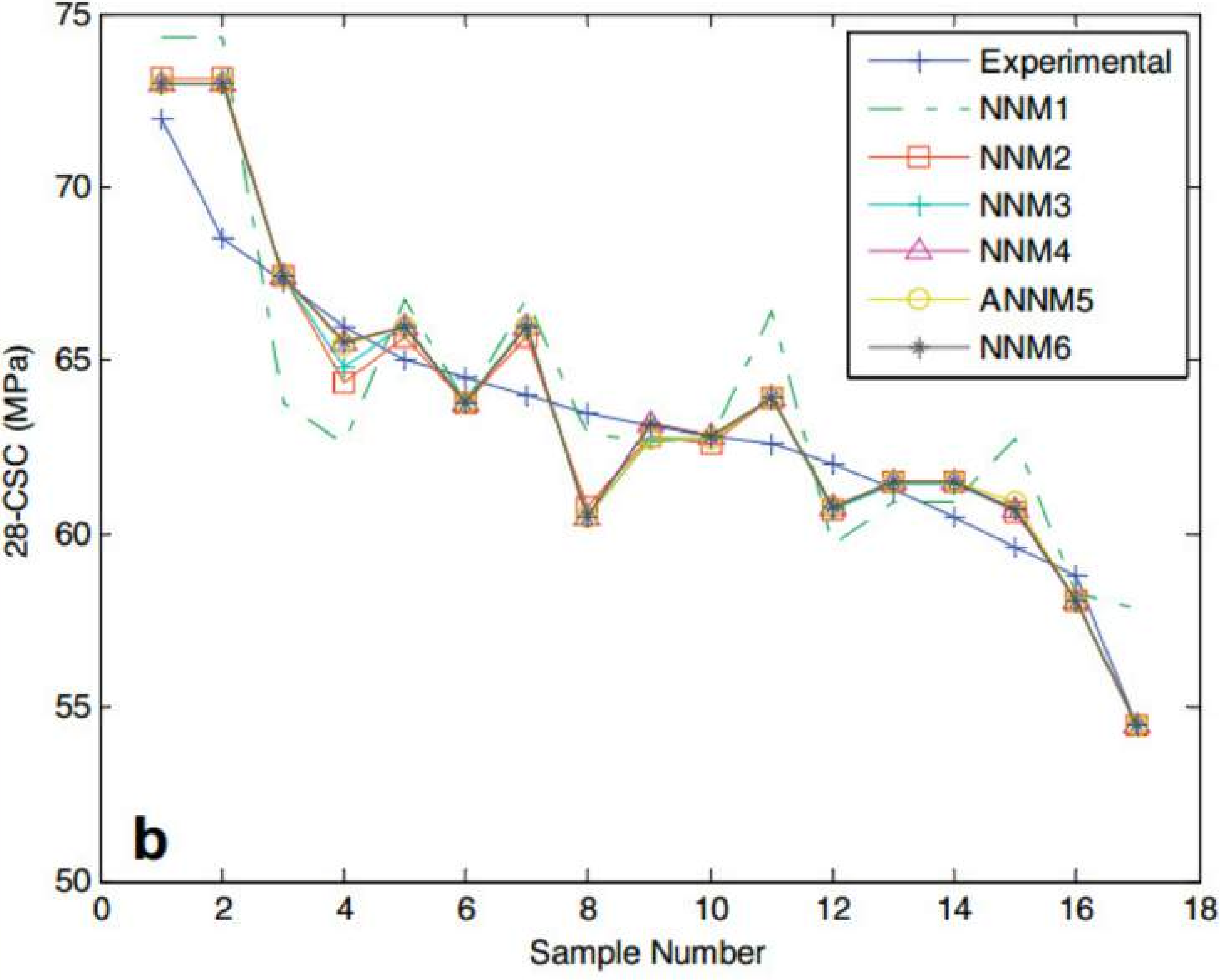
Table 9
Summary of NNMs for 28-CSNSC prediction.

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





Experimental
NNM1
NNM2
NNM3
NNM4
ANNM5
NNM6
28-CSC (MPa)
Sample Number
a
80
75
70
65
60
55
50
0
10
20
30
40
50
60
70
80



Experimental
NNM1
NNM2
NNM3
NNM4
ANNM5
NNM6
28-CSC (MPa)
Sample Number
b
75
70
65
60
55
50
0
2
4
6
8
10
12
14
16
18

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	62.6	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

Evaluation of NLRM, NNM and ANM for testing records.

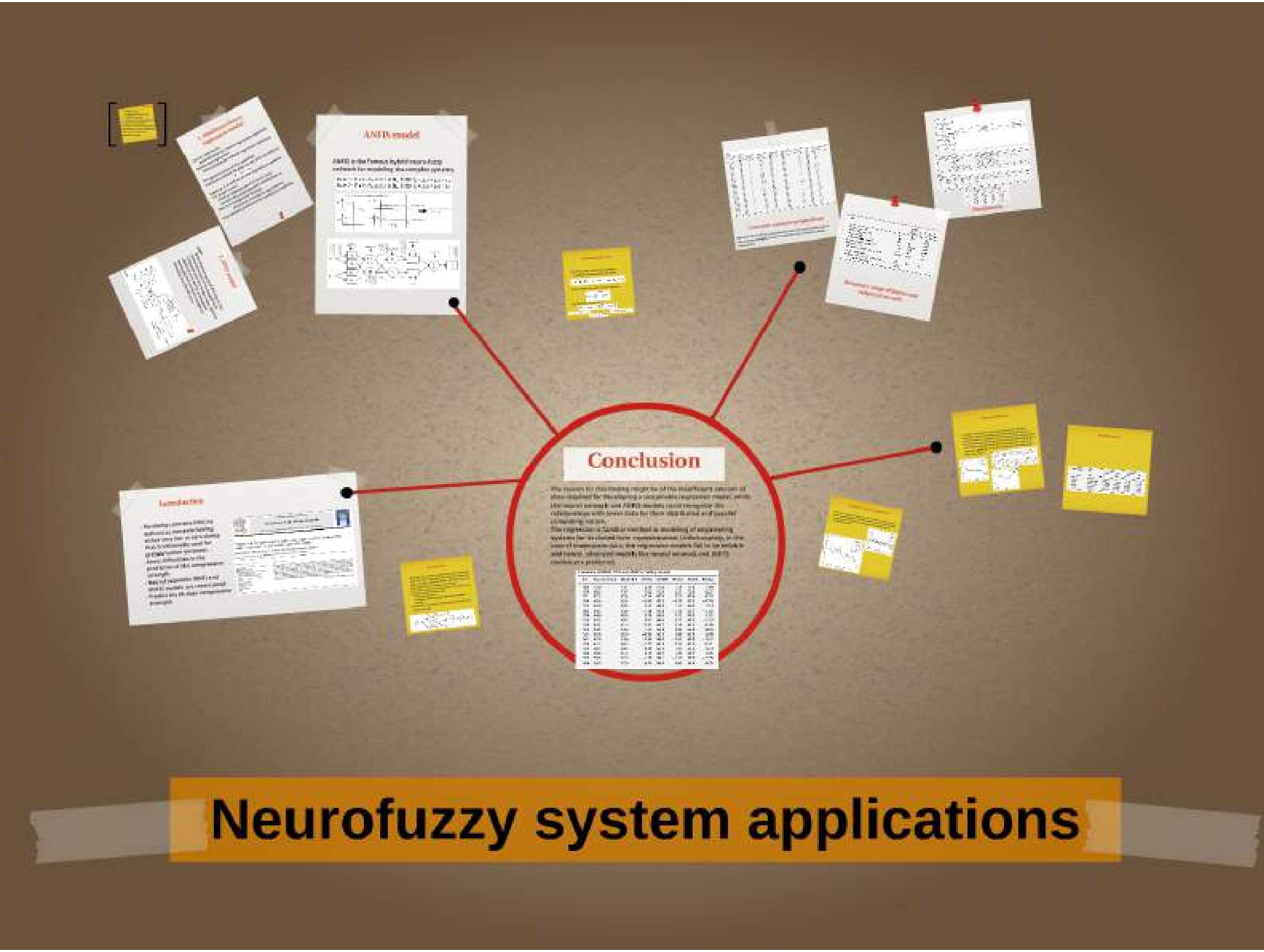
ID	Experimental	Model I-2	RE (%)	NNM6	RE (%)	ANM4	RE (%)
S80	72.0	73.7	2.39	73.0	1.39	73.0	1.39
S79	68.5	73.7	7.62	73.0	6.57	73.0	6.57
S7	67.3	62.4	−7.24	67.5	0.22	67.4	0.22
S44	66.0	63.8	−3.40	65.5	−0.76	65.5	−0.76
S75	65.0	68.0	4.55	66.0	1.54	66.0	1.54
S96	64.5	63.6	−1.38	63.8	−1.16	63.7	−1.16
S74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


ANFIS model
Conclusion
Neurofuzzy system applications