PREDICTION OF SILICA FUME CONCRETE STRENGTH BY ARTIFICIAL NEURAL NETWORKS

Sixth Jordanian International Civil Engineering Conference (JICEC06)

Amman, Jordan

10 – 12 March 2015

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Acknowledgments

- Arab Center for Engineering Studies (ACES)
- Manaseer Ready Mix Concrete
- Shehada Attoun & Mamoon Badri

Outline

- Overview
- Experimental Program
- ANN Modeling
- Results
- Conclusions

Overview

In the design of concrete mixes, three principal requirements for concrete are of importance:

- Quality
- Workability
- Economy

Economy

Utilization of silica fume (SF) in concrete production:

- reduction of environmental problems and hazards by proper SF disposal rather than dumping. This is critical with the huge amounts of SF production especially at industrialized countries.

- saving the limited landfill space with economical benefits.

Research objectives

- Silica fume utilization in concrete production instead of dumping it as a waste material
- Reduction of fine aggregate used in concrete production
- Predicting the strength using artificial neural networks

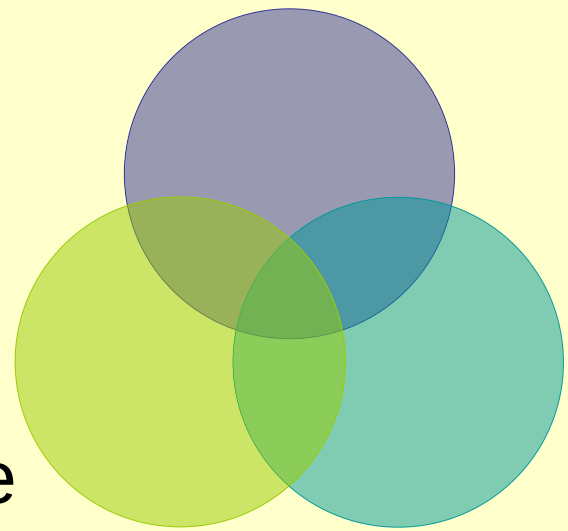
Methodology

Cementitious Materials =

cement + silica fume

W/C = 0.50, 0.55, 0.60

Cement



Age = 7, 28, 56 days

Aggregate
(coarse + fine)

Water

Compressive strength

Silica Fume Percentages 0, 5, 10, 15 (of fine aggregate)

Experimental program

ASTM standards

- Materials
- Mix design
- Preparation and casting of samples
- Testing of samples

Portland cement

Property	Results
Fineness (90-mm sieve)	8.3
Specific surface (m^2/kg)	281
Normal consistency (%)	28
Vicat setting time (min)	
Initial	145
Final	260
Specific gravity	3.15

Silica fume

Property	Results
SiO_2 Content (%)	90
Surface Area (m^2/kg)	20,000
Specific gravity	2.2
Unit weight (kg/m^3)	245
Fineness (45-mm sieve)	5.1

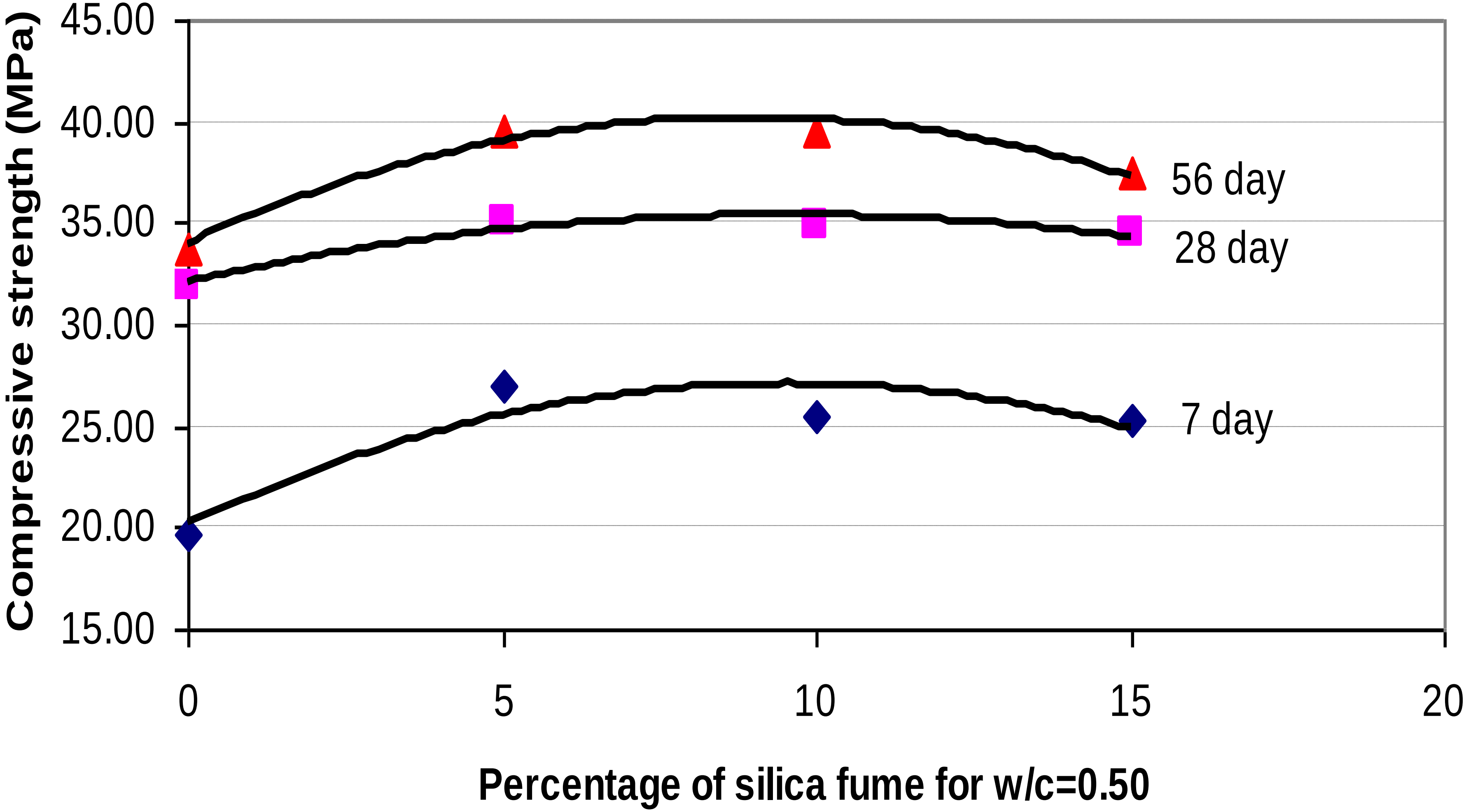
Grading aggregates

Fine aggregate			**Coarse aggregate**	
Size (mm)	Percent passing		Size (mm)	Percent passing
4.75	97.06		25.00	100
2.36	82.70		19.00	98.84
1.18	69.00		12.70	74.54
0.60	41.00		9.50	46.26
0.30	29.03		4.75	1.02
0.15	8.09			

Concrete mix design

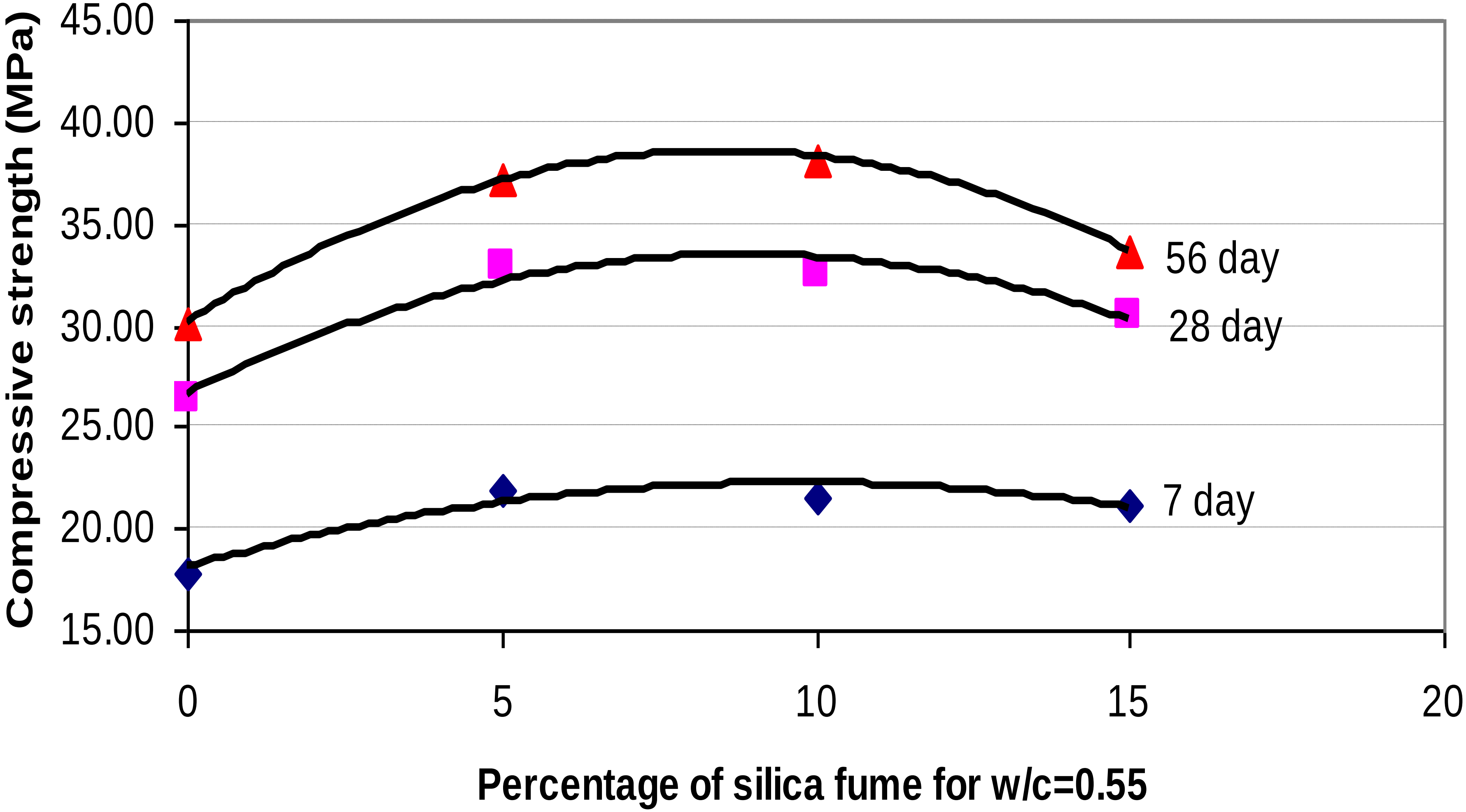
w/c	w/cm	SF (%)	SF (kg/m³)	C (kg/m³)	CM (kg/m³)	W (kg/m³)	FA (kg/m³)	CA (kg/m³)
0.50	0.50	0	0	400	400	200	340	1360
	0.48	5	17		417		323	
	0.46	10	34		434		306	
	0.44	15	51		451		289	
0.55	0.55	0	0	400	400	220	340	1360
	0.53	5	17		417		323	
	0.51	10	34		434		306	
	0.49	15	51		451		289	
0.60	0.60	0	0	400	400	240	340	1360
	0.58	5	17		417		323	
	0.55	10	34		434		306	
	0.53	15	51		451		289	

w/c=0.50



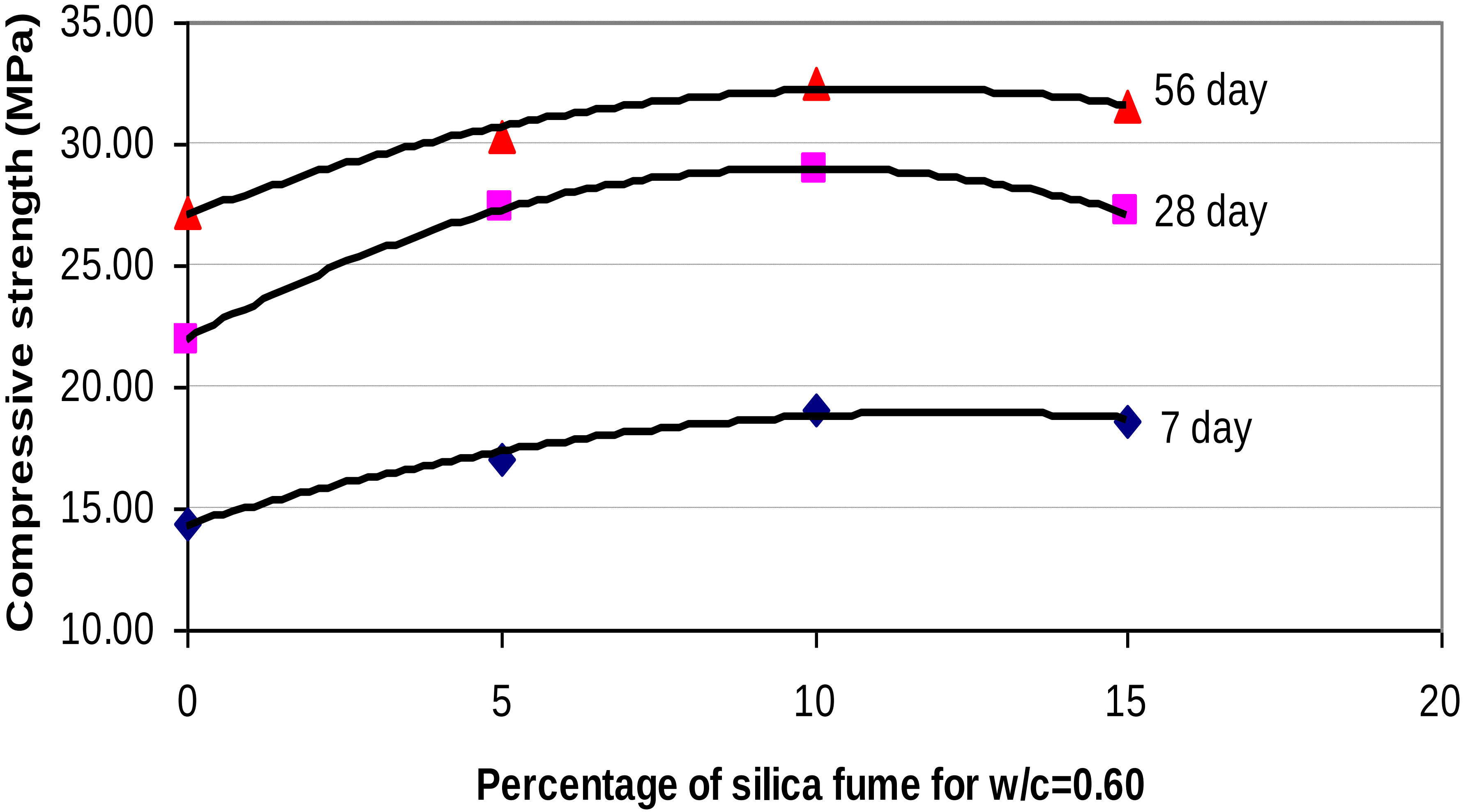
Compressive strength (MPa)
45.00
40.00
35.00
30.00
25.00
20.00
15.00
0
5
10
15
20
56 day
28 day
7 day
Percentage of silica fume for w/c=0.50

w/c=0.55



Compressive strength (MPa)
45.00
40.00
35.00
30.00
25.00
20.00
15.00
0
5
10
15
20
56 day
28 day
7 day
Percentage of silica fume for w/c=0.55

w/c=0.60

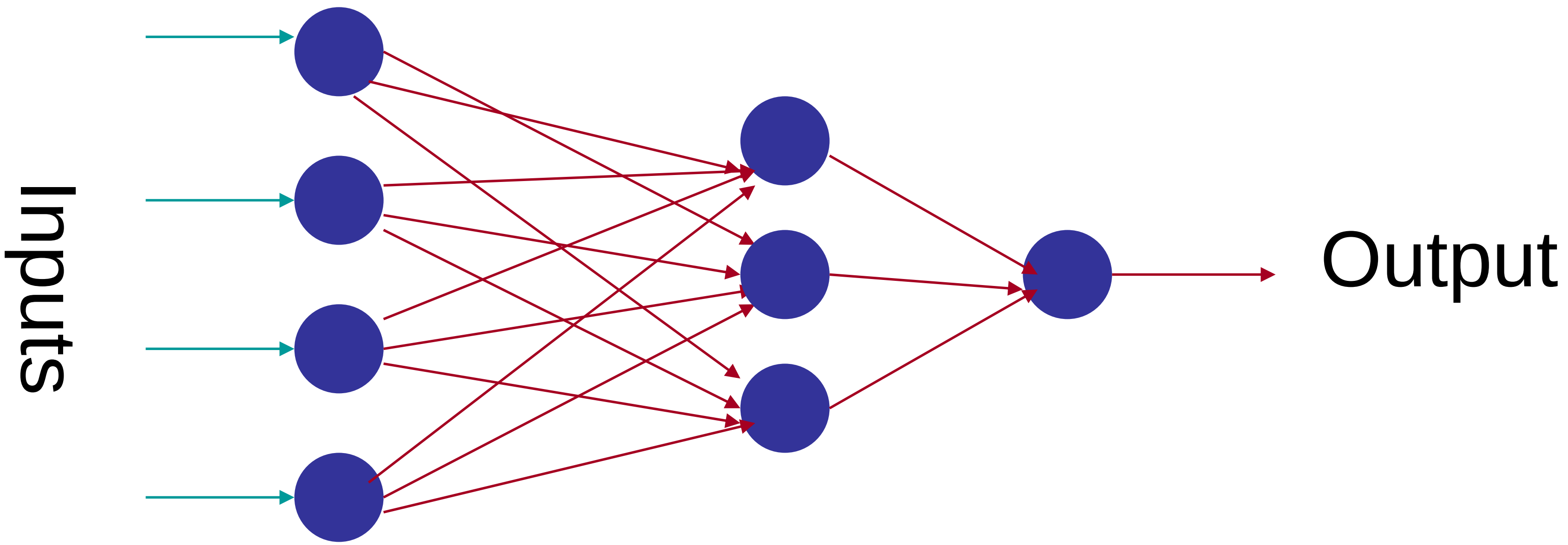


Compressive strength (MPa)
35.00
30.00
25.00
20.00
15.00
10.00
0
5
10
15
20
56 day
28 day
7 day
Percentage of silica fume for w/c=0.60

Need for modeling

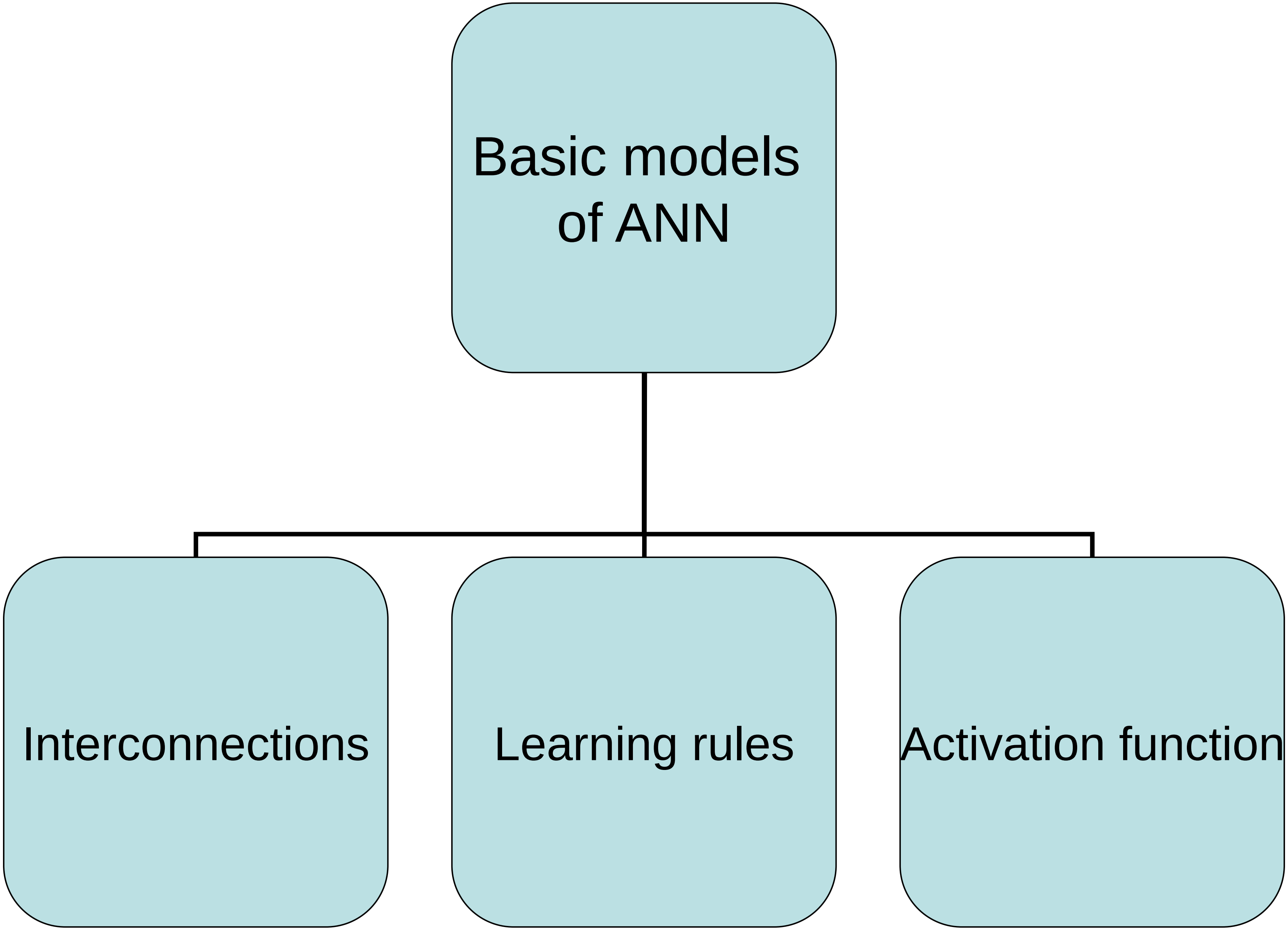
- What if………..?
- Too many variables (strength, curing time, SF(%), FA, CA, w/c, etc……).
- Linear/nonlinear models failed to predict the behavior accurately (Ashteyat et al. 2012).
- Additional tests are costly, time and labor intensive.

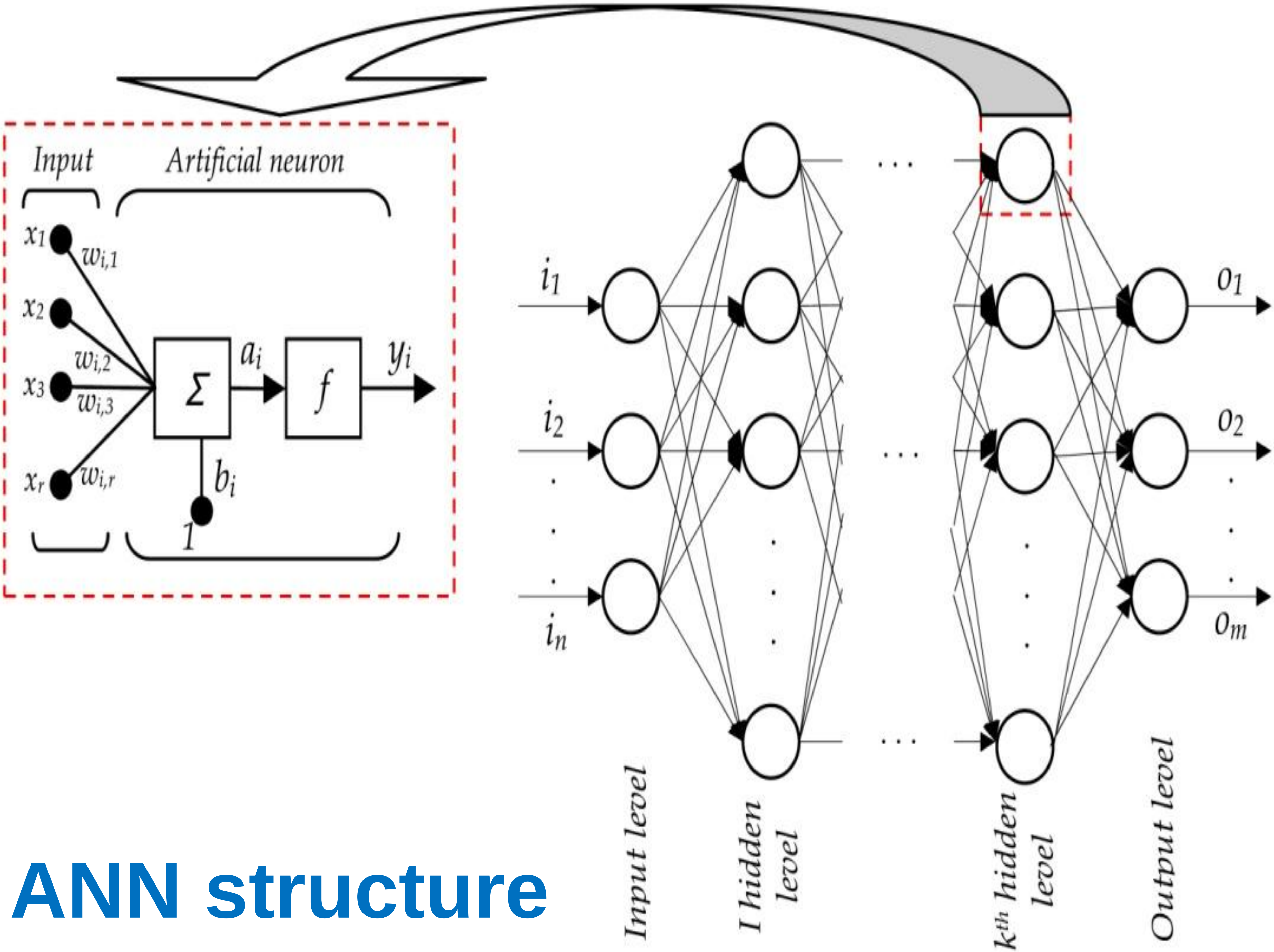
Artificial neural networks



ANN: Many artificial neurons that are linked together according to a specific network structure.

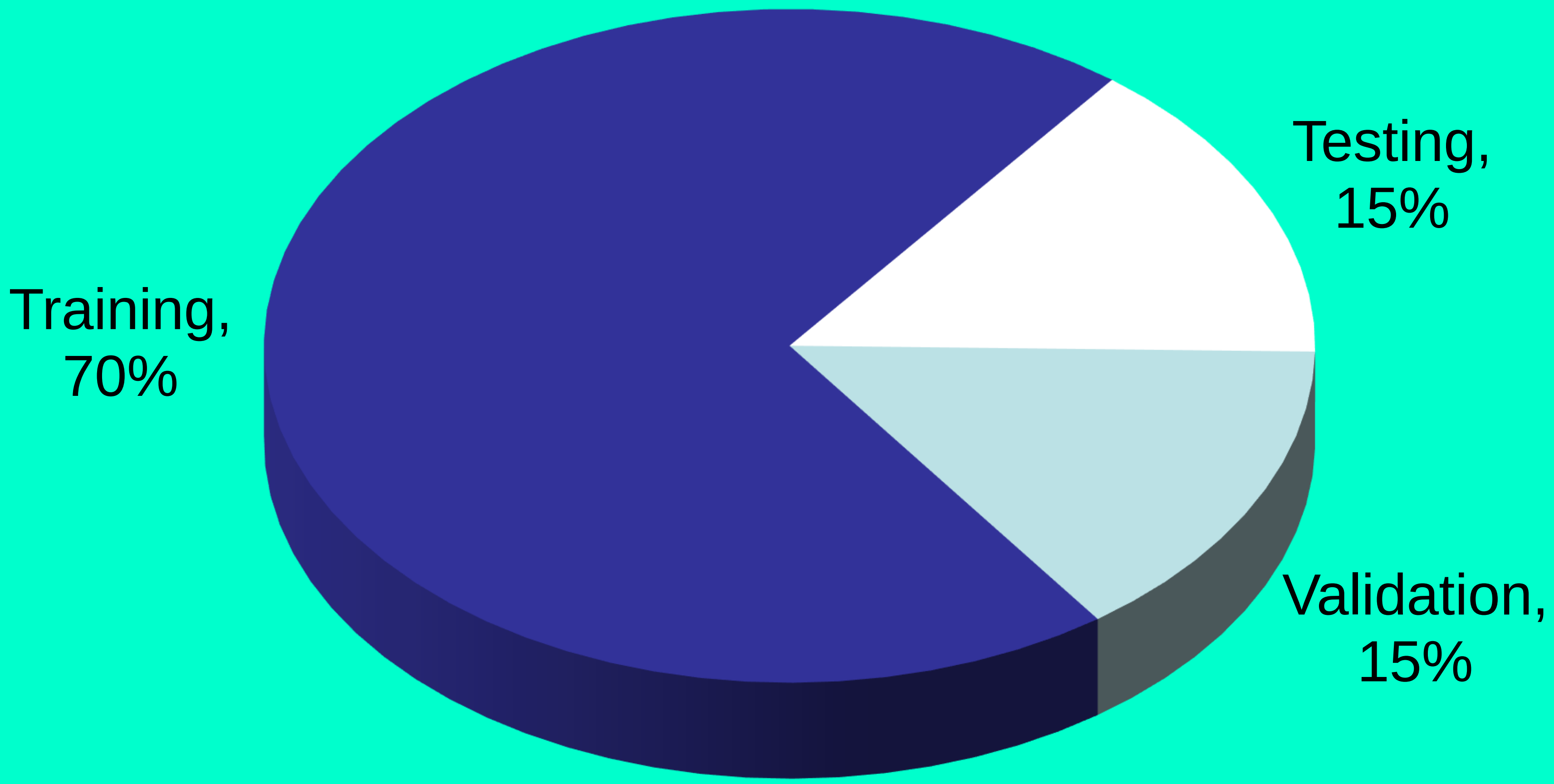
Transform the inputs into meaningful outputs.


Basic models of ANN
Interconnections
Learning rules
Activation function



ANN structure

Distribution of the data sets



Structure / performance of model

Model properties

Output	Input	Structure	Function
F	W/C, R, P, W/CM, SF, C, CM, W, FA, CA, T	11-3-1	Tanh-Tanh

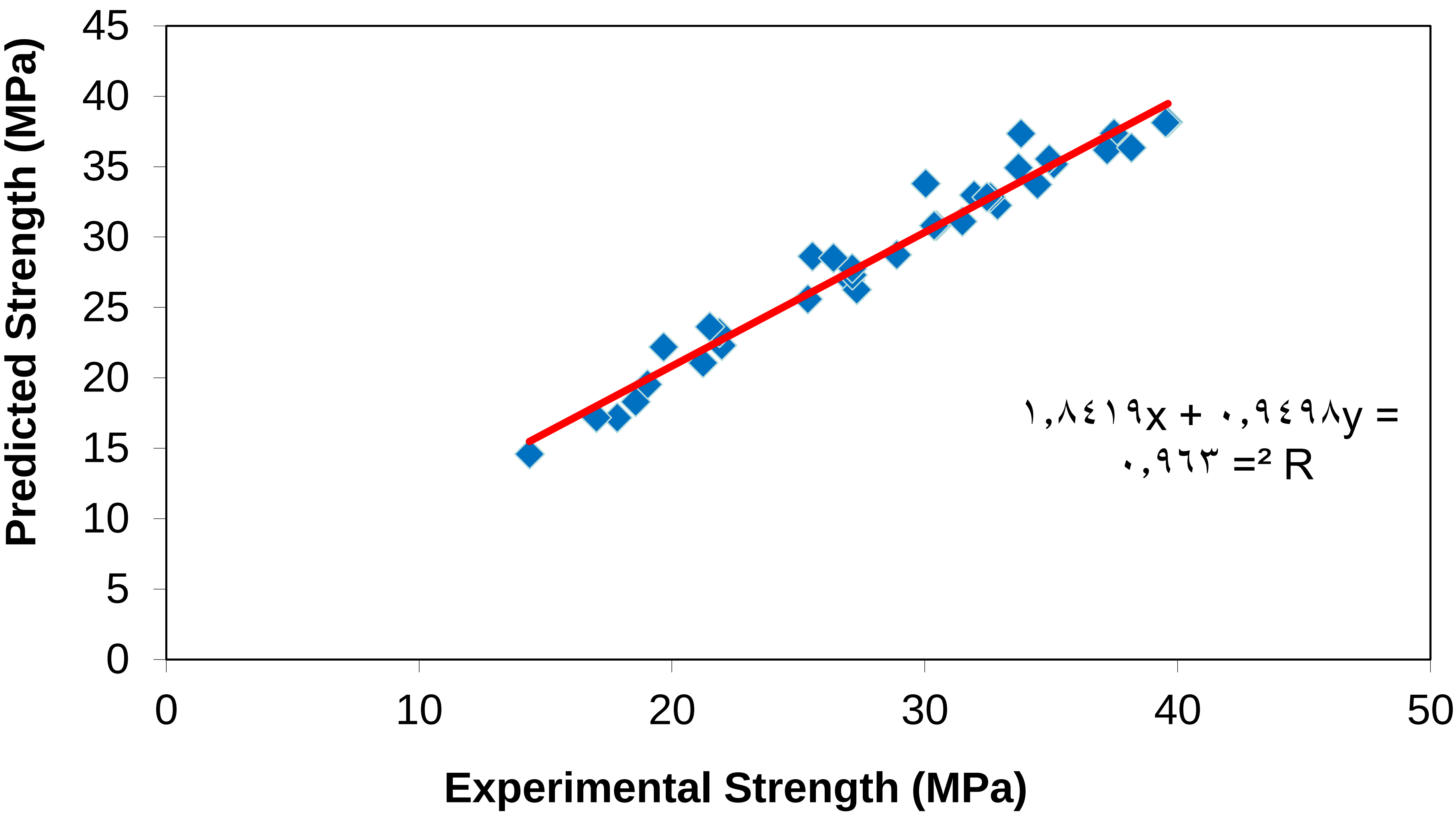
Model parameters

R^2	MSE
0.9630	0.0003

Biases and connection weights (11-3-1)

	N_1	N_2	N_3	F
W/C	0.5169	0.6599	-0.4807	
R	0.9067	-0.5552	0.5400	
P	0.0790	-0.4035	-0.1915	
W/CM	-0.5330	-0.2054	-0.6107	
SF	0.5718	0.4802	-0.2124	
C	0.4128	-0.5978	0.3507	
CM	-0.5552	-0.7530	0.0458	
W	0.3913	-0.1413	0.1097	
FA	0.4591	-0.3856	-0.4945	
CA	-0.0117	0.0801	-0.1829	
T	0.1732	0.1140	-1.5488	
F	-2.0374	-0.6912	-0.7412	
Bias	0.2527	-1.0939	0.1474	0.6727

Predicted & experimental values



Summary and conclusions (1/2)

- Strength benefits were up to 21.6% over control concrete (5% replacement level).
- Concrete strength was acceptable for most structural applications and reinforced concrete construction.
- ANNs were employed feasibly for estimating concrete strength.
- One hidden layer with three neurons was used in constructing the model (11-3-1).

Summary and conclusions (2/2)

- Strength determination of silica fume concrete can be predicted accurately and reliably using the proposed ANN model (R^2 = 96.3%, MSE = 0.0003).

- Model can always be calibrated to include a wider range of input variables.

- Considering experimental laboratory tests to be cumbersome, expensive, and time intensive, the use of the proposed model can be a viable and powerful alternative for estimating the compressive strength of silica fume concrete easily and efficiently.

Thank you for your attention.