



Using Artificial Neural Networks to Connect Concrete Composition and Rheology to Printability Requirements in 3D Concrete Printing 3DCP Applications

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Problem under exam – 3D Concrete Printing

3D Concrete Printing is achieving great potential in the last years, as concrete and cement industries need a great **development** to reach the same level of more advanced industries.

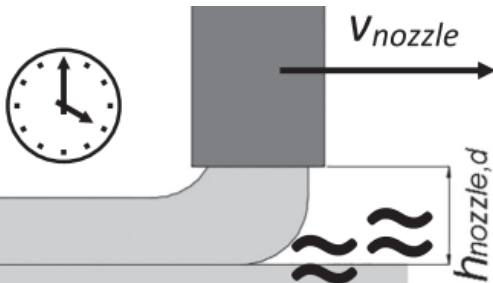
Pros	Challenges
1. Safety	1. Reinforcements
2. Costs	2. Design
3. Productivity	3. Durability

Pumpability: ability of the material to be pumped through a hose. The material should behave as a fluid, with low yield strength.

Extrudability: concrete has to be extruded through a nozzle. The mix should develop tensile strength able to guarantee its extrusion.

Buildability: the layers should be stiff enough to avoid lateral deformations, which can be responsible for the collapse of the layered element.

T. Wangler et al. (2019)



Introduction – Database generation for the case of study

Potentialities and challenges of **3D Concrete printing** are well-known nowadays. Literature on this topic is huge, and it can be interesting to develop a Database from it, in order to implement an **AI** tool as the **ANN**.

1 Selection of the paper database

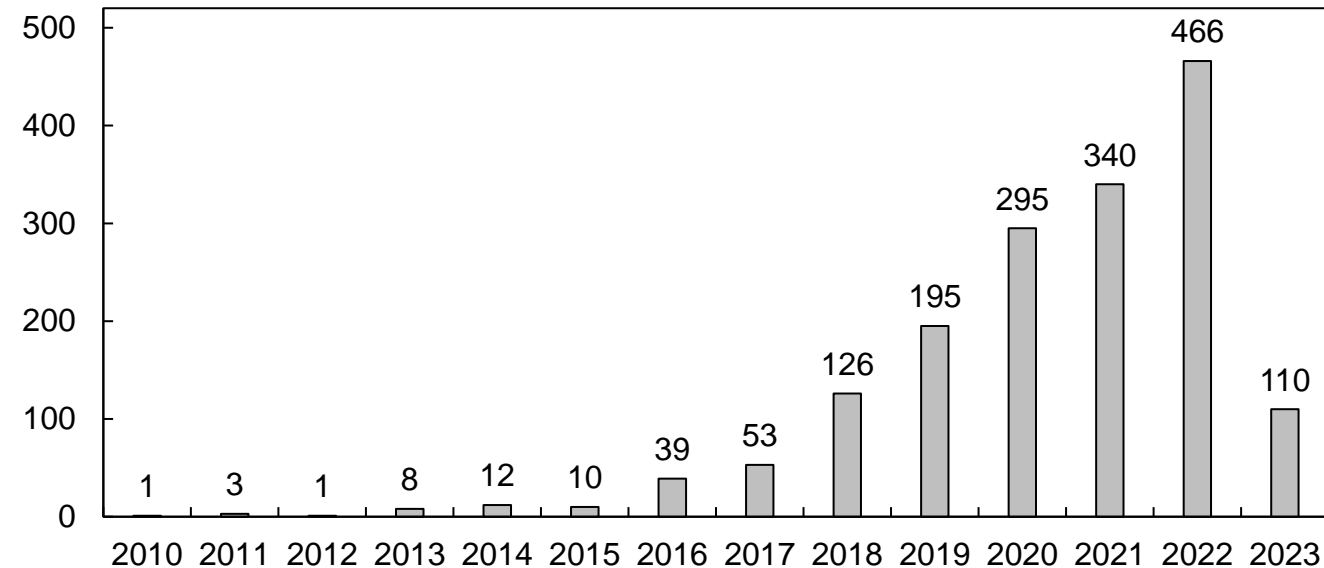
2 Definition of the strings to adopt

3 Collection of papers

4 Acceptance or Rejection

5 Storing of data

Number of Publications over years



Criterion for the Acceptance or Rejection of a paper

It is fundamental for the generation of a **Database**, to differentiate between the most useful papers and the ones that can be discarded, thus not relevant for the main objective of the database.

A Criterion based on **frequency** has been adopted for the **Acceptance or Rejection** step of the database generation procedure. This consists of considering the paper as useful if it gives information on parameters that have been seen as frequently cited also in other papers. In this way, the most meaningful parameters are visualized along with the papers.

Paper under exam

Listing of the parameters considered

Study of the frequency of such parameters

Application of the criterion

Parameters cited in the database

Mix design parameters

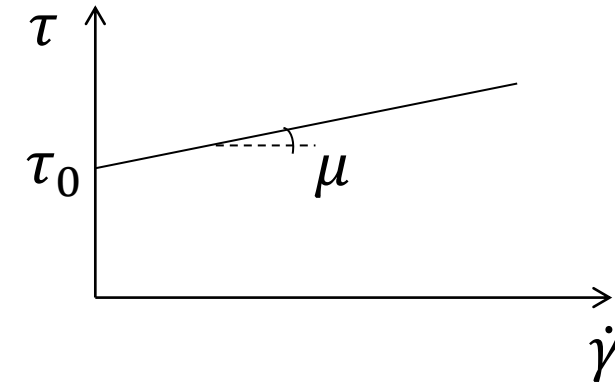


- Binder
- Water to binder ratio
- Aggregate to binder ratio
- Superplasticizer
- Retarder
- Accelerator
- Viscosity modifiers
- Fibres
- Various admixtures
- ...

Printing process parameters



- Printing speed
- Pumping speed
- Nozzle shape
- Nozzle height
- time
- ...



INPUT PARAMETERS

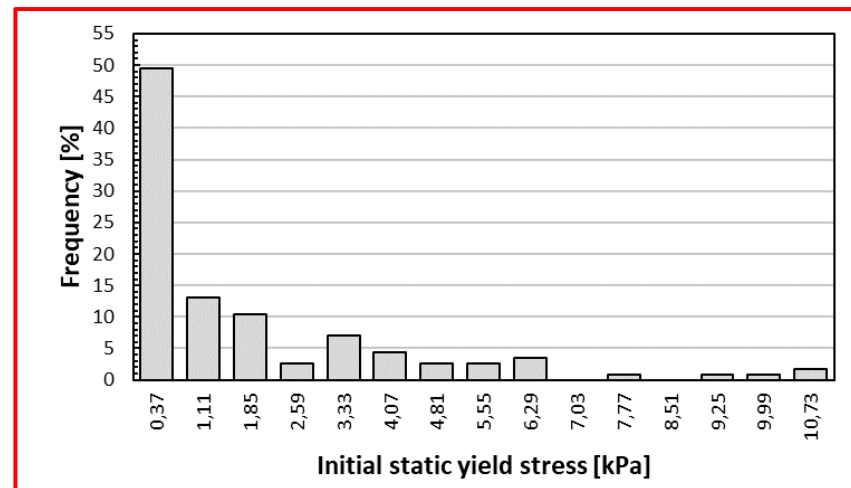
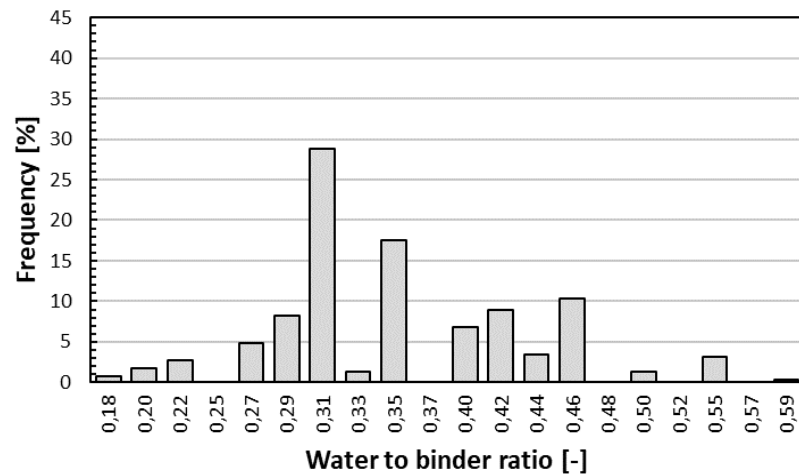
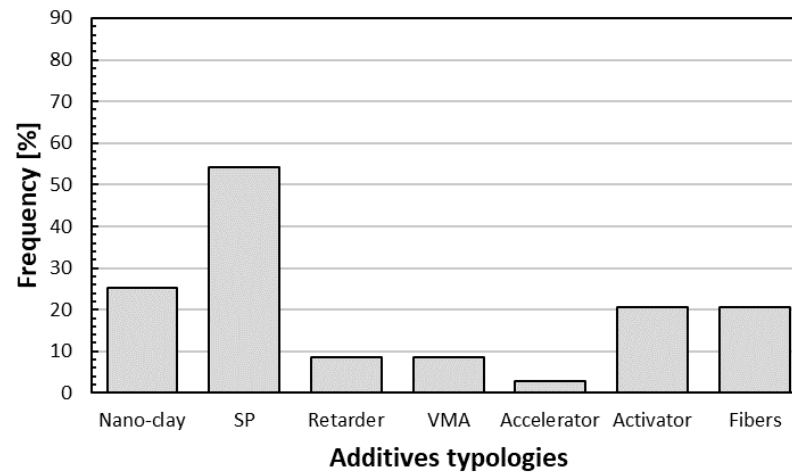
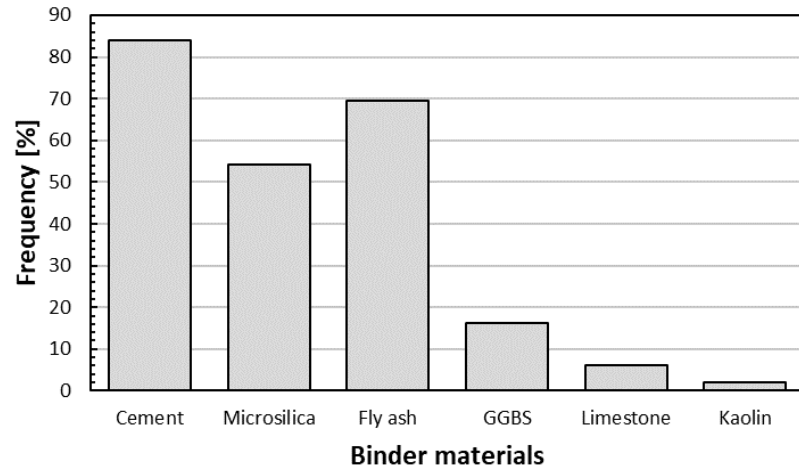
OUTPUT PARAMETERS



SYS

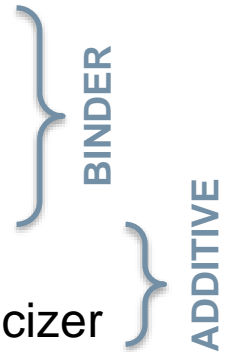


Development of the ANN – Parameters selection



Input parameters:

- Cement
- Micro silica
- Fly ash
- GGBS
- Nano clay
- Superplasticizer
- Time from last shearing
- Water to binder ratio
- Aggregate to binder ratio
- Maximum aggregate diameter



Output:

- SYS



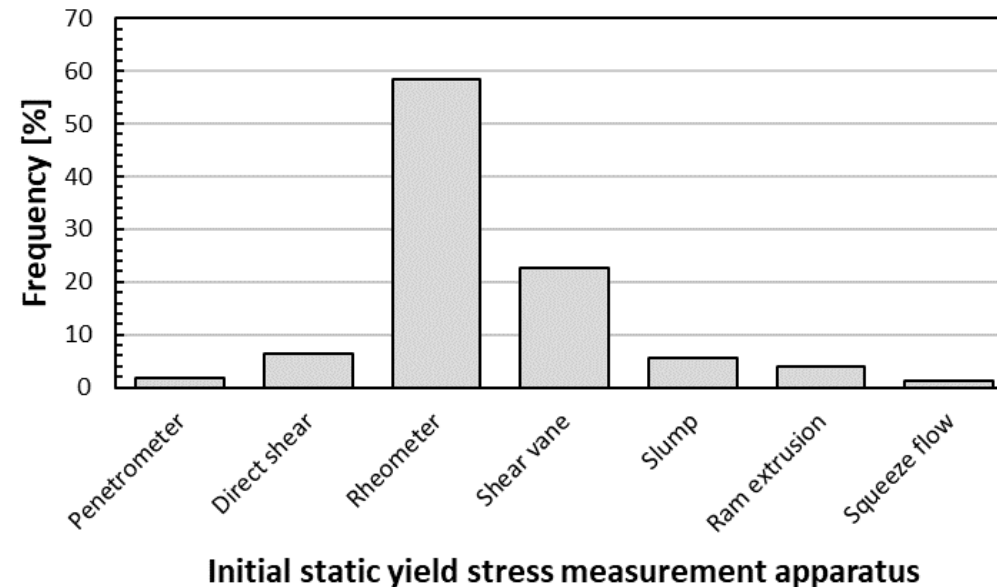
Development of the ANN – Testing typology for SYS

Values of the SYS can be found experimentally through different **testing typologies**, and (according to Jayathilakage (2022)) even testing the same mix, the **SYS** value change with the testing type.

In order to train an ANN which gives as output the SYS the **rheometric** measurements are selected, because they should be coherent with each other.

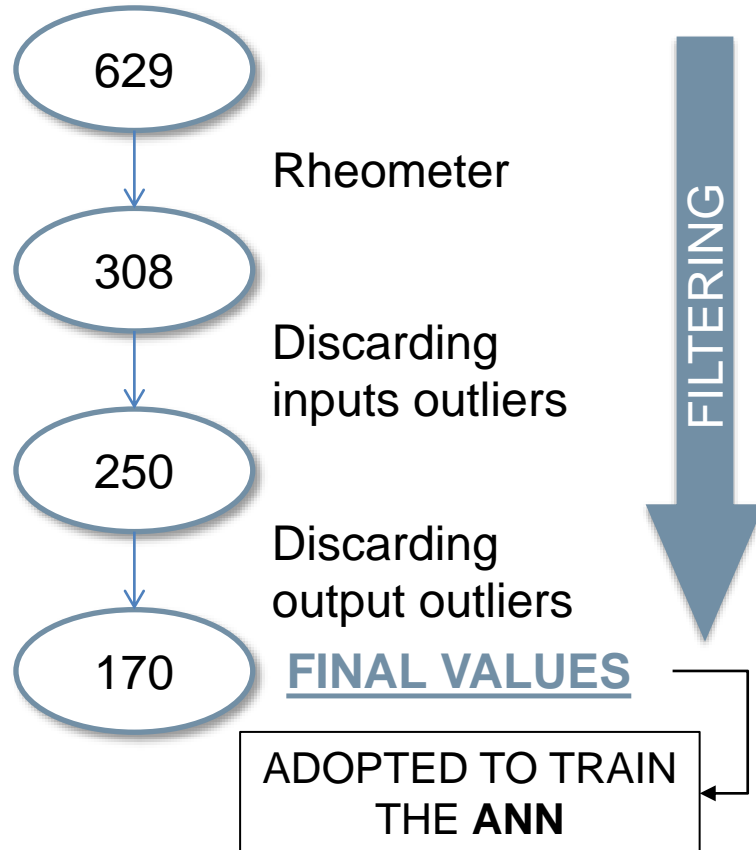
Testing typologies:

- Penetrometer
- Direct shear
- Rheometer
- Shear vane
- Slump
- Ram extrusion
- Squeeze flow



Development of the ANN – Reduction of data due to filtering

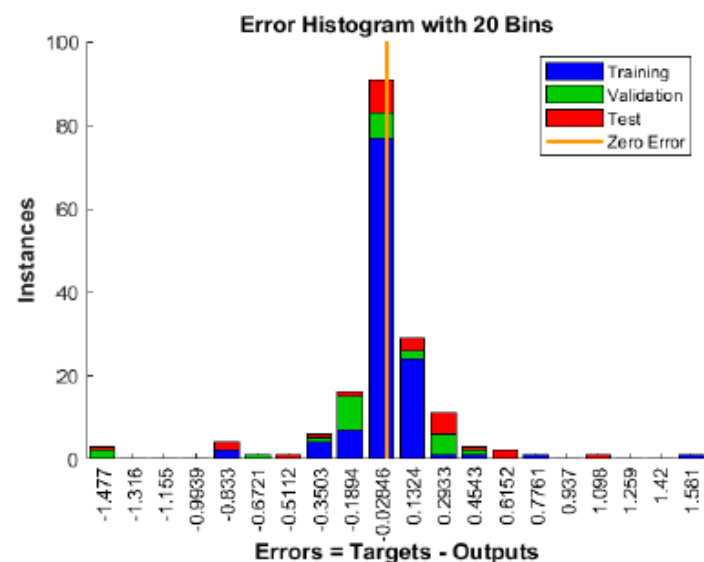
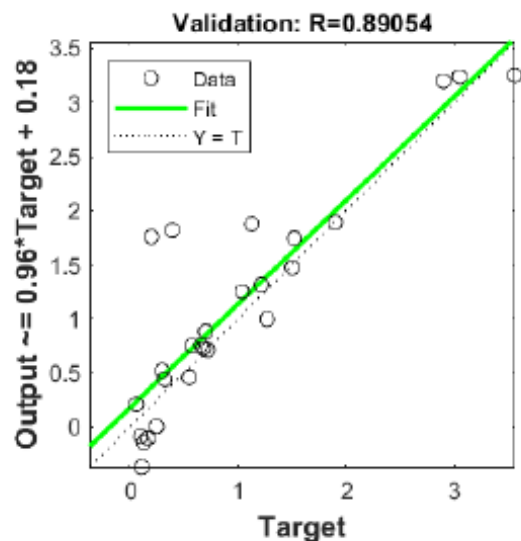
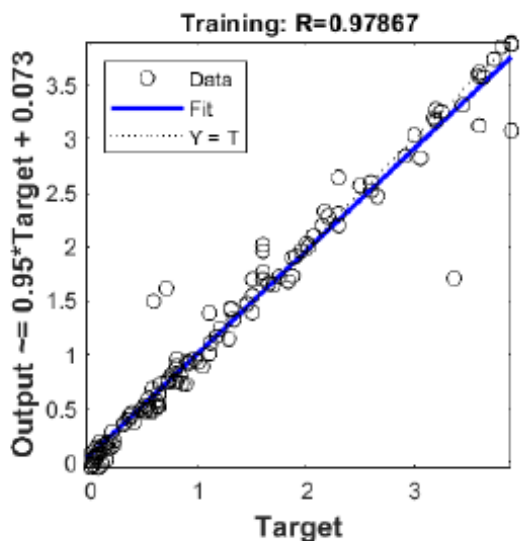
Starting from the **output** , the number of values of the SYS can be **filtered** in order to reduce the error when developing the ANN algorithm, along with all the corresponding values of the **input parameters**.



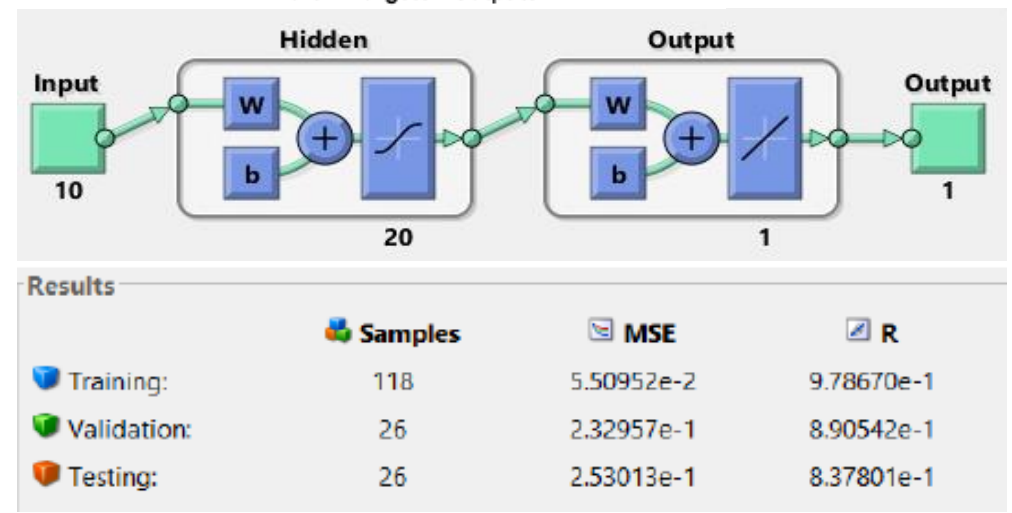
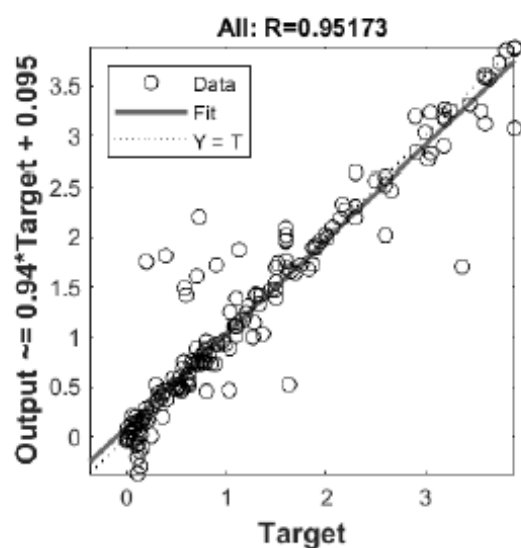
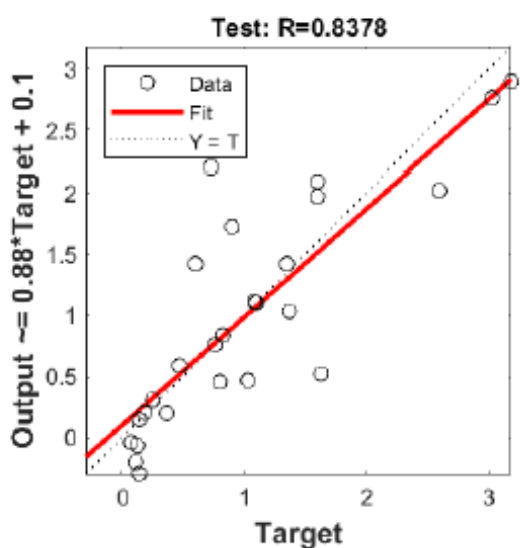
Parameter	Minimum	Maximum	Mode	St. Dev.
Aggr. max size (mm)	0	2.00	2.00	0.78
Water/binder ratio	0.17	0.45	0.35	0.05
Aggr./binder ratio	0	2.26	1.50	0.60
Cement (%)	0	100	70	37.97
Microsilica (%)	0	26	0	4.56
Fly ash (%)	0	85	0	27.77
GGBS (%)	0	100	0	19.77
Nano filler (%)	0	4.00	0	0.50
SP (%)	0	2.00	0	0.53
Time from shearing (min)	0	20	0	7.40
Static yield stress (kPa)	0.003	3.900	1.600	1.090



Development of the ANN – MATLAB tool



It is possible to train an ANN with one output and 10 inputs. The hidden neurons are set as 20 (from iterative trails, in order to minimize the error).



Predictions through ANN – Limits of the case of study

Binder composition		Additives	
Cement content (%)	<input type="text" value="80"/>	Nano filler content (%)	<input type="text" value="0.1"/>
Microsilica content (%)	<input type="text" value="0"/>	Superplasticizer content (%)	<input type="text" value="0.1"/>
Fly ash content (%)	<input type="text" value="20"/>	Time	
GGBS content (%)	<input type="text" value="0"/>		
Water/binder ratio	<input type="text" value="0.32"/>	Time from last shearing (min)	<input type="text" value="3"/>
Aggregates		Calculate SYS	
		Static Yield Stress (kPa)	
		<input type="text" value="2.522"/>	
Aggregates/binder ratio	<input type="text" value="1.5"/>		
Aggregates maximum size (mm)	<input type="text" value="2"/>		

Parameter	Test 1	Test 2	Test 3	Test 4	Test 5
Aggr. max size (mm)	2.00	0.65	2.00	0	1.00
Water/binder ratio	0.32	0.35	0.42	0.35	0.35
Aggr./binder ratio	1.50	0.75	1.02	0	1.00
Cement (%)	80	70	0	70	0
Microsilica (%)	0	5	8	5	0
Fly ash (%)	20	25	78	25	50
GGBS (%)	0	0	14	0	50
Nano filler (%)	0.10	0.50	0	0.25	0
SP (%)	0.10	0.30	0	0	0
Time from shearing (min)	3	15	0	20	20
Static y. s. measured (kPa)	2.600	0.660	0.380	0.200	1.570
Static y. s. predicted (kPa)	2.522	0.760	0.459	0.196	1.899
Error (%)	3.0	15.2	20.9	1.7	21.0

Prediction capability is very limited, as also the number of data is. In order to build a more efficient **predicting ANN**, data must be more or number of inputs must be lower.

Conclusions and Outlook

- Although literature is rich of publications, the number of data in the database is very limited, especially for ANN applications.
- The ANN has shown to have a low error, but still far from practical applications because of the reduced predicting abilities.
- Database can be improved every day, by adding more data.
- ANN can be more generic, considering the overall printing process and giving information to the printability of concrete mixes.



Thank you for the attention!

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