Società Italiana Infrastrutture Viarie

SIIV ACADEMY , Torino 15th April 2024

ADVANCEMENTS IN ROAD ENGINEERING TOWARDS GREEN AND DIGITAL TRANSITION

SIIV
Società Italiana Infrastrutture Viarie

Mechanical behaviour of asphalt concretes for road pavements: predictive modelling by Machine Learning

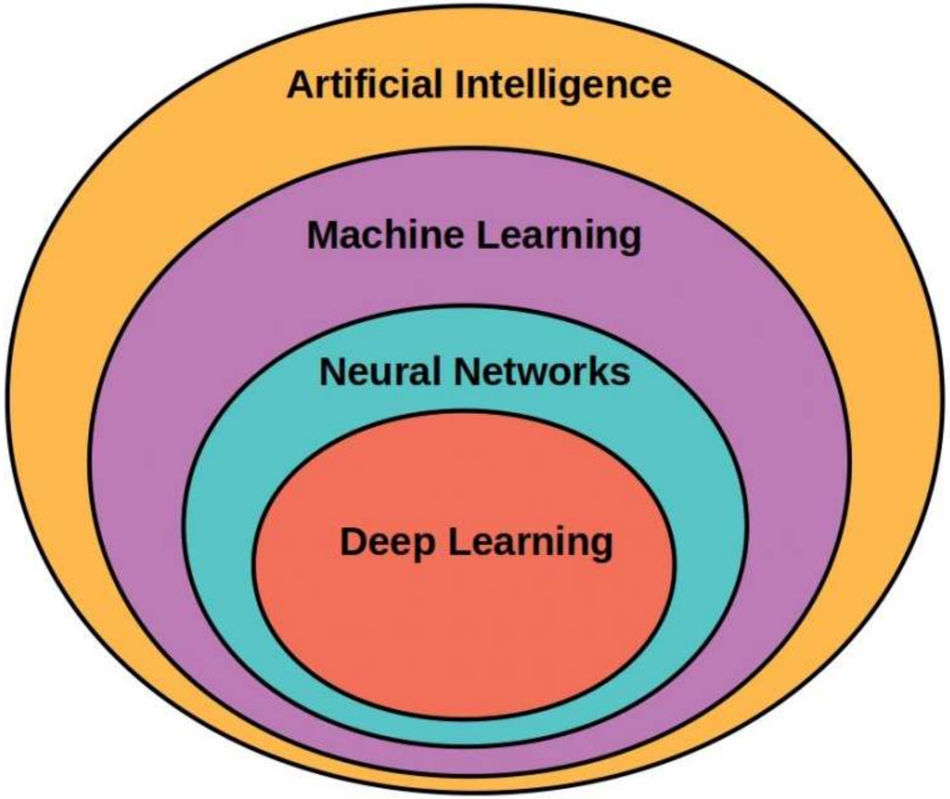
Politecnico di Torino
1859
Dipartimento di Ingegneria dell'Ambiente, del Territorio e delle Infrastrutture

Nicola Baldo
Polytechnic Department of Engineering and Architecture
University of Udine, Italy

Topics of the lecture:

- ✓ Machine Learning & ANN overview
- ✓ Case study n.1
- ✓ Case study n.2
- ✓ Case study n.3
- ✓ Final Remarks

Artificial Intelligence vs Machine Learning vs Artificial Neural Networks vs Deep Learning

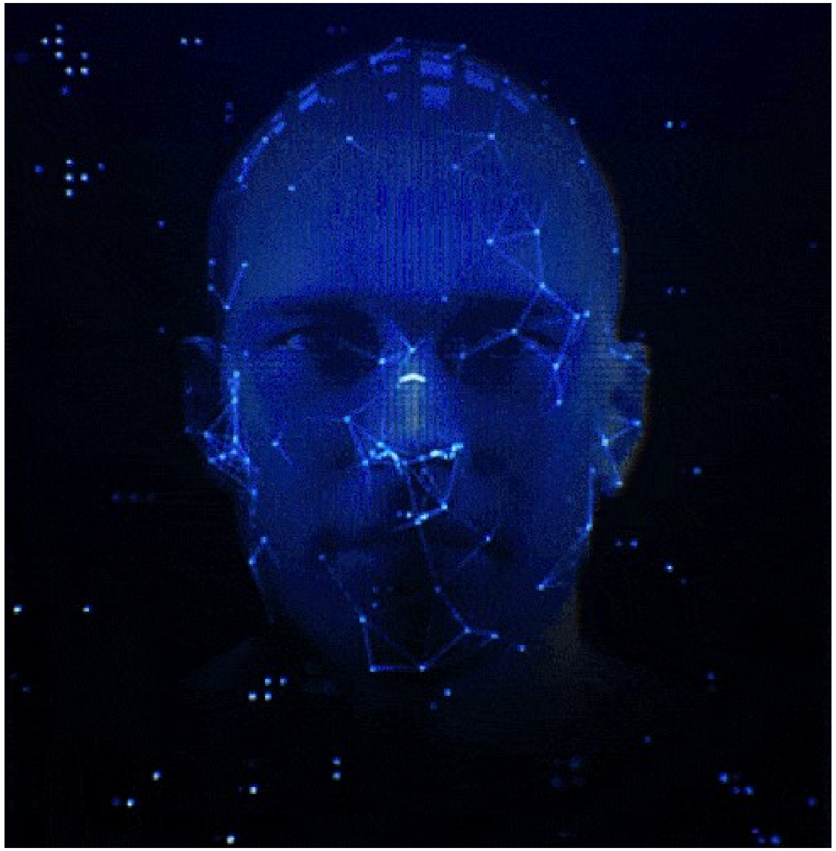


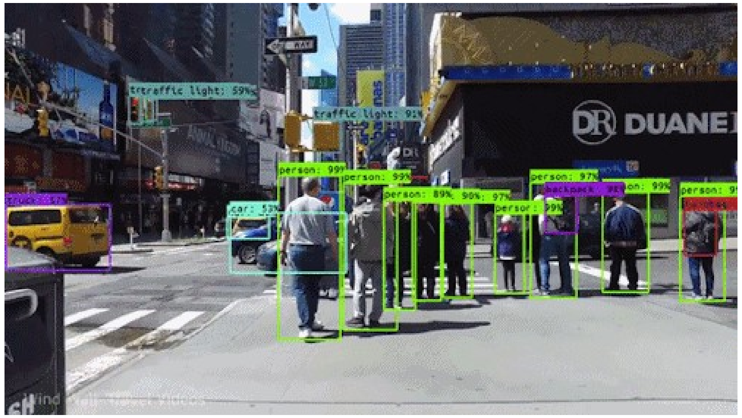
Machine Learning: a data-driven approach

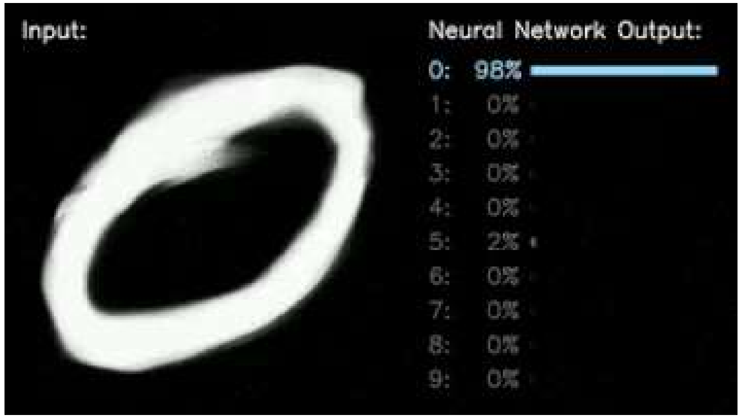
Politecnico di Torino
Dipartimento di Ingegneria dell'Ambiente, del Territorio e delle Infrastrutture

Nicola Baldo
University of Udine

Machine Learning applications: Face Recognition, Computer Vision, Image Classification







Artificial Neural Networks & Pavement Engineering

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e delle Infrastrutture

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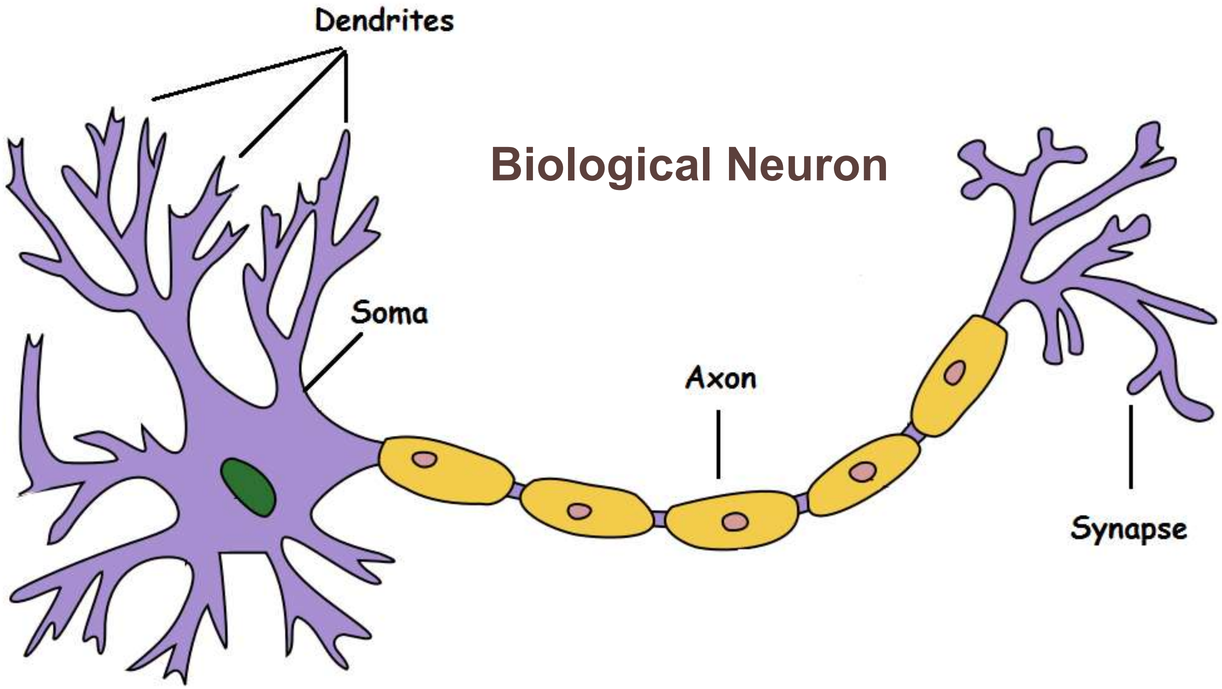
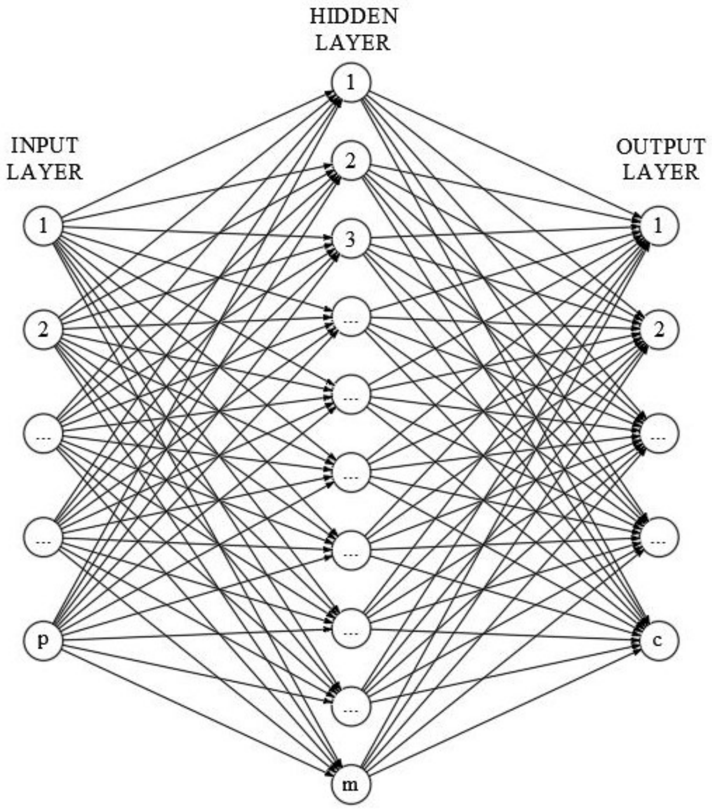
Artificial Neural Network: inspired by biological brain

Biological Neural Network Biological Brain

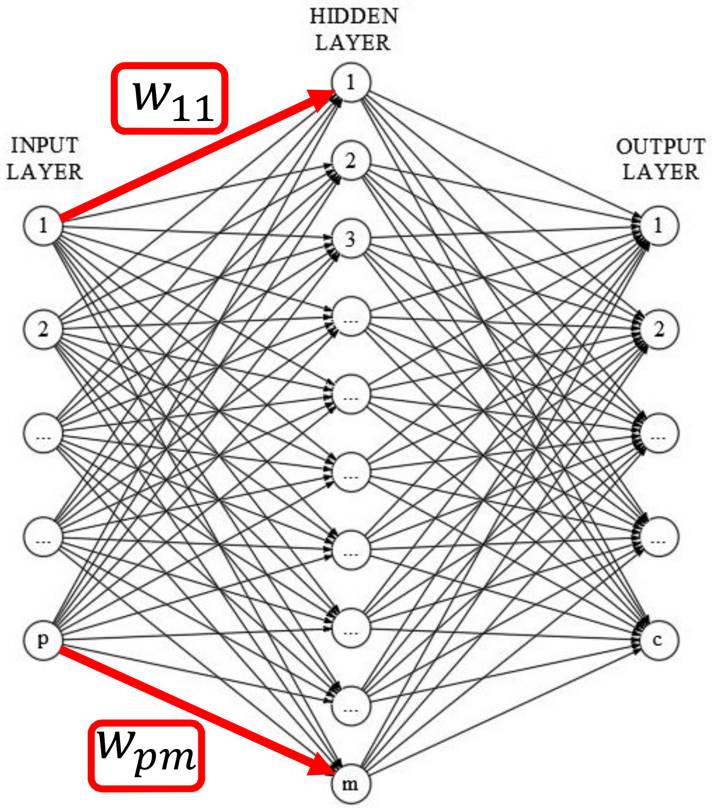
Artificial Neural Network: inspired by biological brain



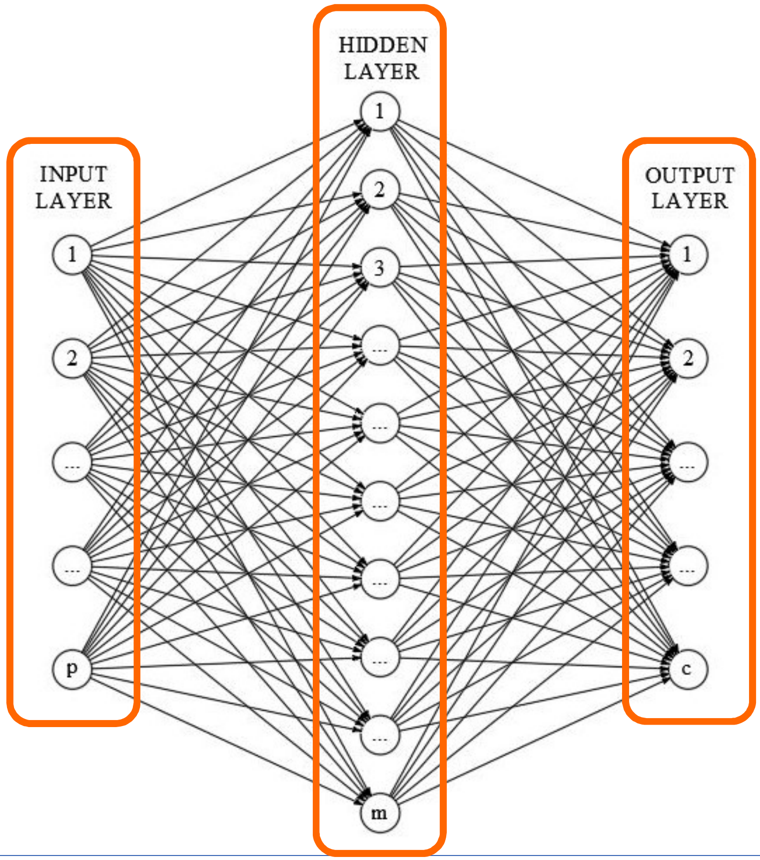
Feedforward Network



Feedforward Network



Feedforward Network

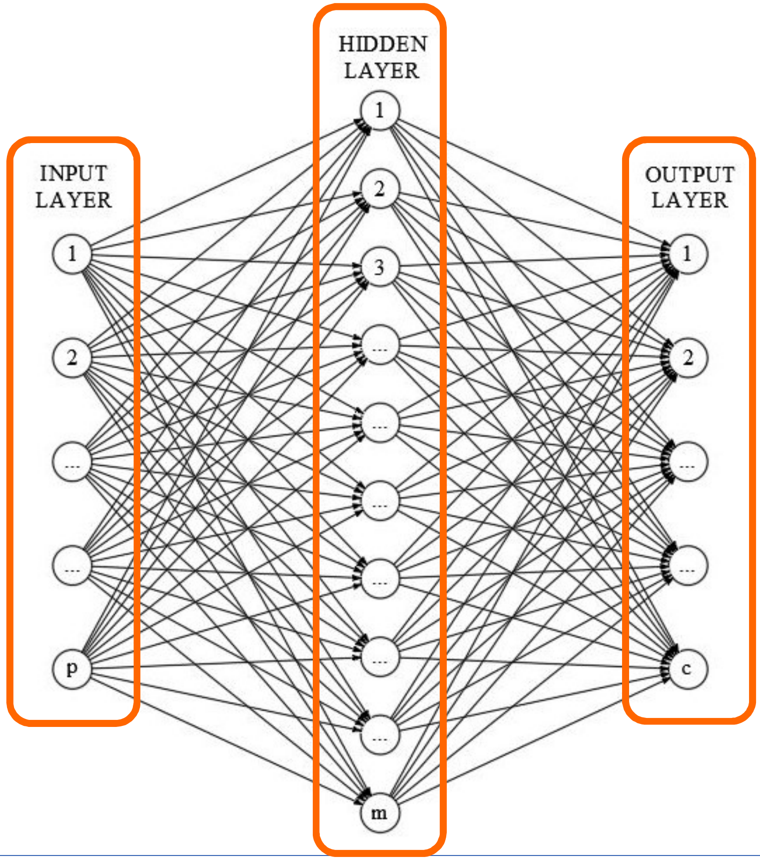


Neurons work in parallel and are organized into interconnected layers.

Each layer is characterized by a different function and a different number of neurons.

Neurons in the same layer can not communicate with each other.

Feedforward Network

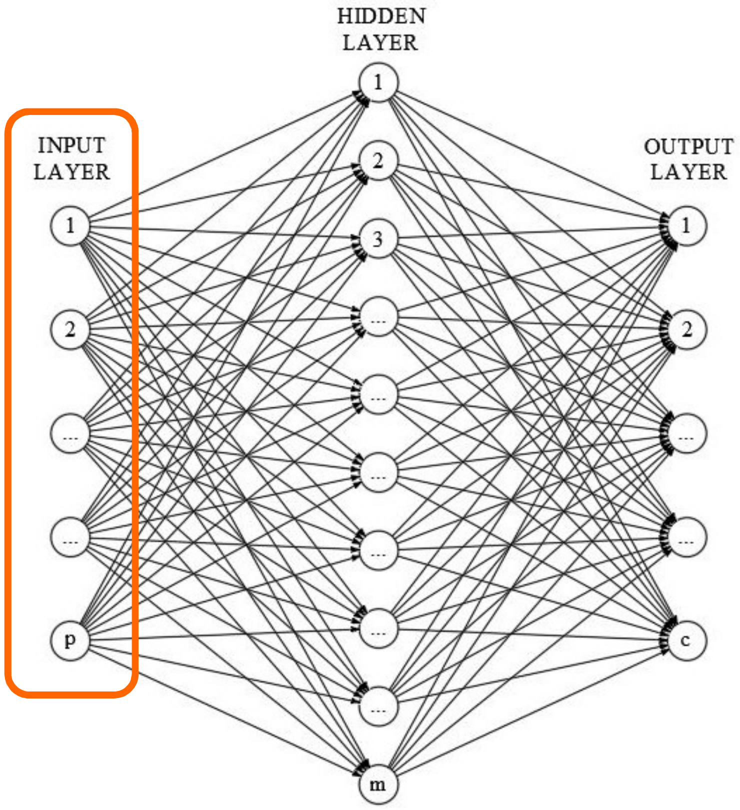


Shallow Neural networks: architecture characterized by only one hidden layer.

Deep learning model: neural network characterized by more than one hidden layers.

Feedforward networks: Information flows only in one direction.

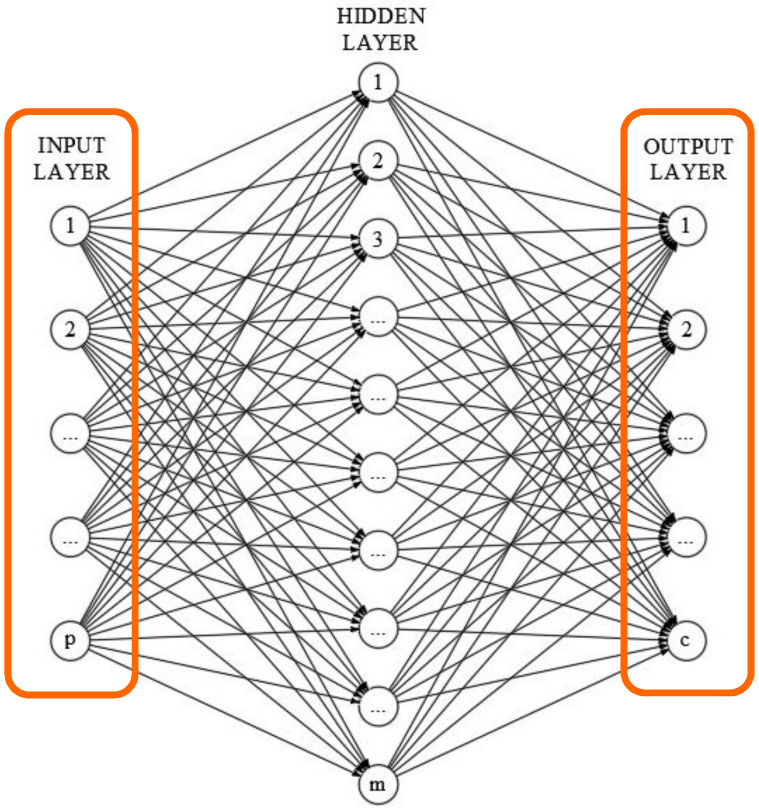
Feedforward Network



Input layer

$$\bar{\boldsymbol{x}}_{\boldsymbol{i}} = (x_{1i}, x_{2i}, \dots, x_{pi})$$
$$i = 1, \dots, n$$

Feedforward Network



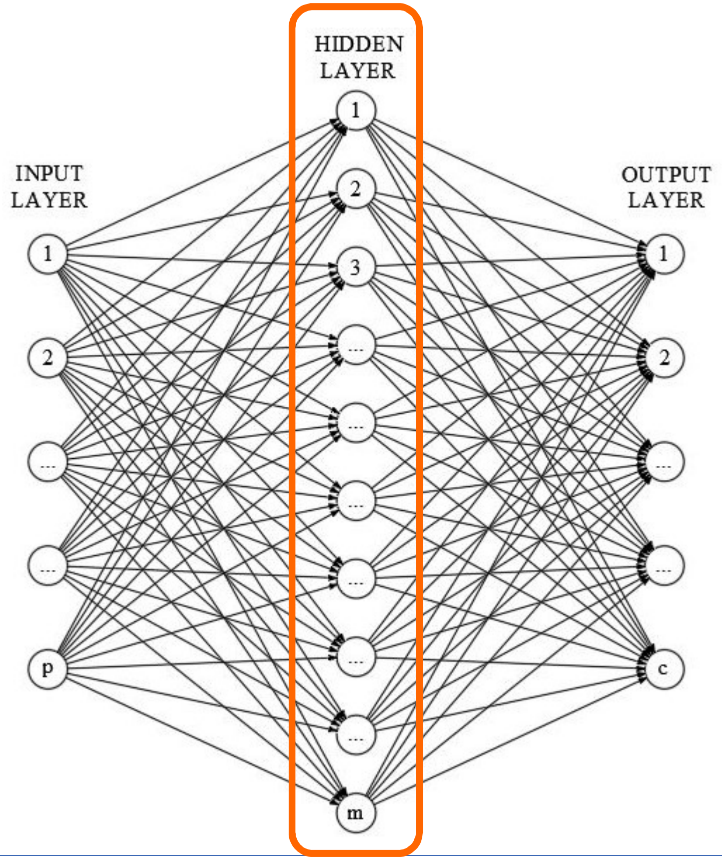
Input layer

$$\bar{\boldsymbol{x}}_{\boldsymbol{i}} = \left(x_{1i}, x_{2i}, \dots, x_{pi}\right)$$
$$i = 1, \dots, n$$

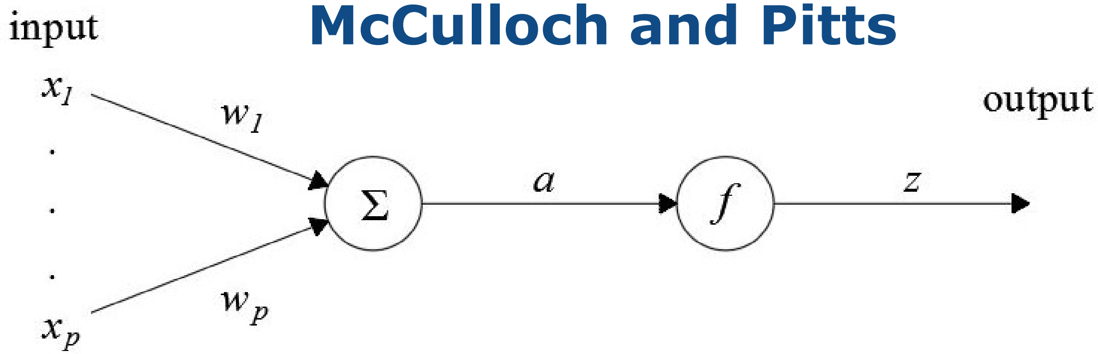
Output layer

$$\bar{\boldsymbol{y}}_{\boldsymbol{i}} = \left(y_{1i}, y_{2i}, \dots, y_{ci}\right)$$
$$i = 1, \dots, n$$

Feedforward Network



Artificial Neuron: mathematical model by McCulloch and Pitts



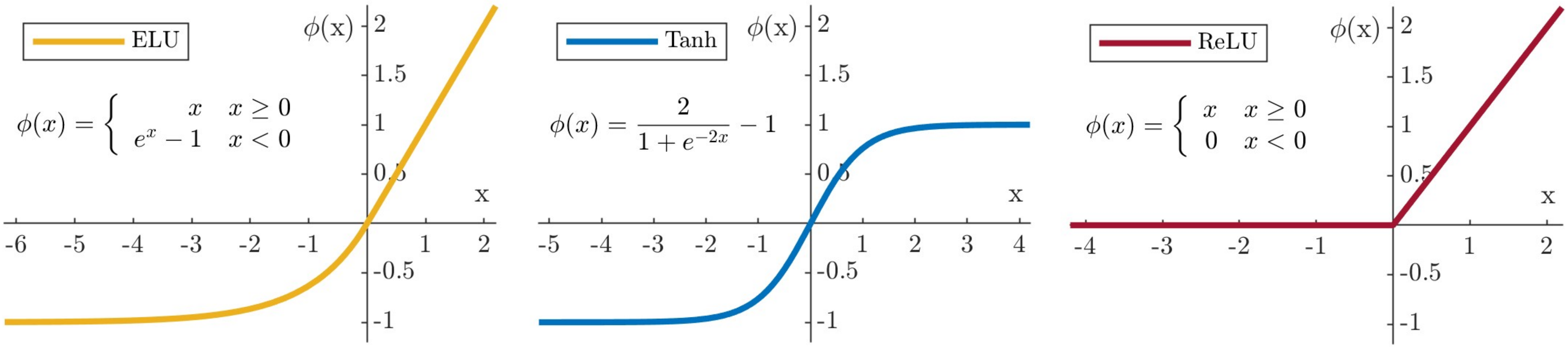
$$a = \sum_{i=0}^{p} w_i x_i$$

$$z = f(a) = f\left(\sum_{i=0}^{p} w_i x_i\right)$$

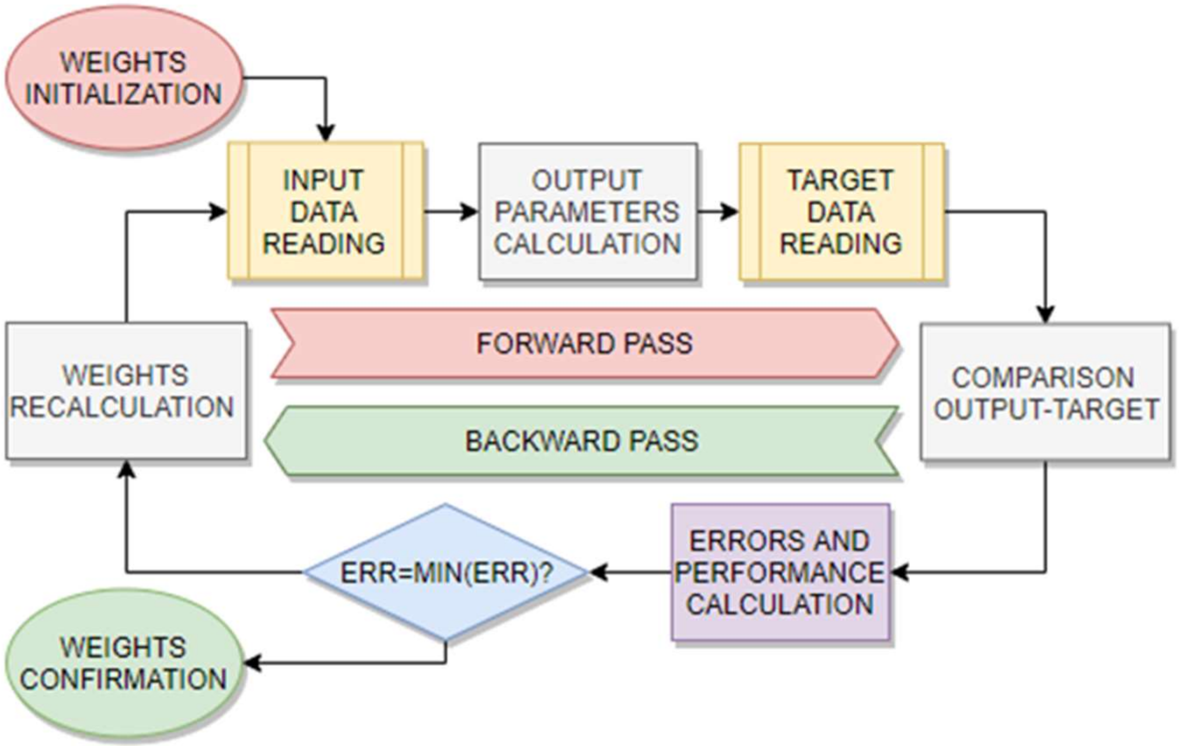
Transfer Function

Hyperbolic tangent function

$$f(a) = \frac{e^{a} - e^{-a}}{e^{a} + e^{-a}} = \frac{2}{1 + e^{-2a}} - 1$$



Training procedure

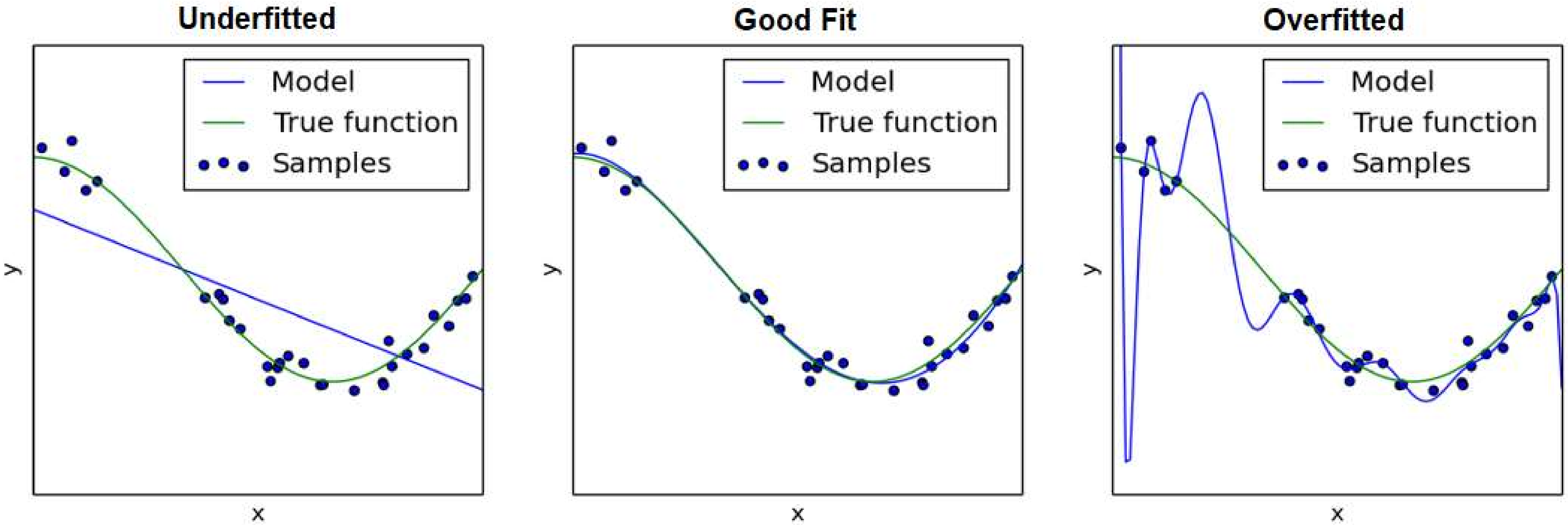


The weights of the connections are defined through a "**training**" process.

In supervised learning, weights are progressively adjusted to minimize the difference between experimental targets and network output, using **backpropagation** algorithms:

- **Gradient Descent**
- **Levenberg–Marquardt**
- **Bayesian Regularization**

Training process: Underfitting & Overfitting



Backpropagation Algorithm: Bayesian Regularization

$$\boldsymbol{W}^{e+1} = \boldsymbol{W}^{e} - [\boldsymbol{J}^{T}(\boldsymbol{W}^{e})\boldsymbol{J}(\boldsymbol{W}^{e}) + \boldsymbol{\mu}_{e}\boldsymbol{I}]^{-1}\boldsymbol{J}^{T}(\boldsymbol{W}^{e})\boldsymbol{v}(\boldsymbol{W}^{e})$$

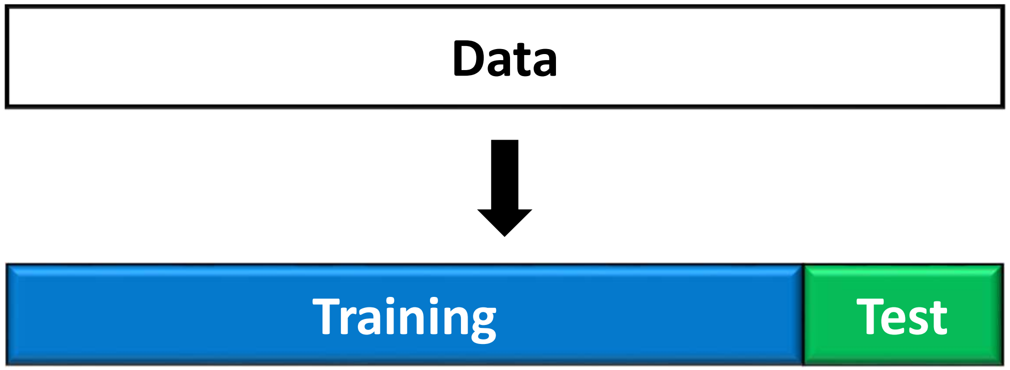
$\boldsymbol{W}$	*Matrix of weights and biases*
$\boldsymbol{e}$	*Generic iteration with* $e \in \{1, \cdots, E\}$
$\boldsymbol{J}$	*Jacobian matrix of training loss function* $F(\cdot)$ *with respect to* $\boldsymbol{W}^{e}$
$\boldsymbol{\mu}$	*Learning step size*
$\boldsymbol{I}$	*Identity matrix*
$\boldsymbol{v}$	*Network errors vector*

$$F(\widehat{\boldsymbol{y}}(\boldsymbol{W}^{e}), \boldsymbol{y}, \boldsymbol{W}^{e}) = \beta \|\widehat{\boldsymbol{y}}(\boldsymbol{W}^{e}) - \boldsymbol{y}\|_{2}^{2} + \alpha \|\boldsymbol{W}^{e}\|_{2}^{2}$$

$\boldsymbol{y}$	*Experimental target vector*
$\widehat{\boldsymbol{y}}$	*Predicted output vector*
$\boldsymbol{\alpha}$	*Regularization parameters set according to David MacKay's approach*
$\boldsymbol{\beta}$	

Training process: Data set partition

Hold-out Method



Possibility of running into overfitting phenomenon

With regard to the hold-out method, it is worth pointing out that such a practice has two major drawbacks when the number of observations is small: first, some relevant patterns may be excluded from the training set; second, the training-test splitting makes the model sensitive to the randomness of data in the training set.

k-fold Cross-Validation

k-fold Cross-Validation is a resampling technique used to elaborate an actual model on a limited data sample. It consists in dividing the data sample in k-partitions. Each sub-sample is used once as validation set and k-1 times as training set.

Randomly Mix Dataset

↓

Split Dataset into k = 5 folds

↓

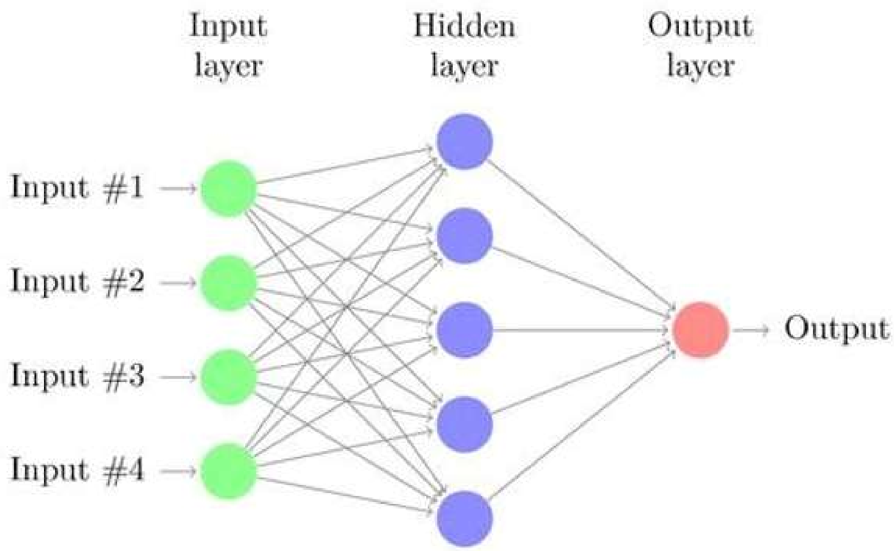
	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	
Split 1	Test	Train	Train	Train	Train	**Test Score 1**
Split 2	Train	Test	Train	Train	Train	**Test Score 2**
Split 3	Train	Train	Test	Train	Train	**Test Score 3**
Split 4	Train	Train	Train	Test	Train	**Test Score 4**
Split 5	Train	Train	Train	Train	Test	**Test Score 5**

↓

Average the scores obtaining the general performance of the model

ANN Optimization

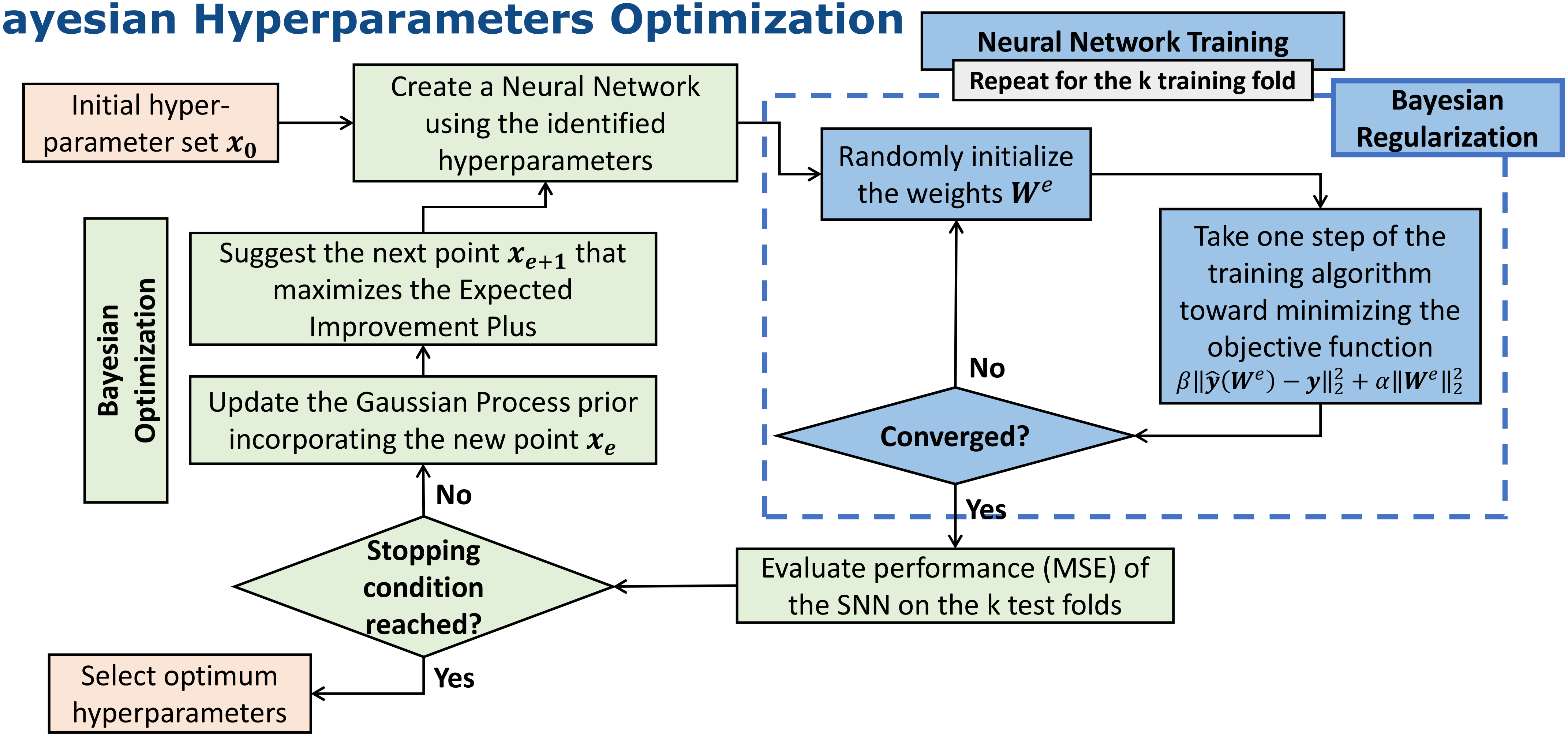
ANNs models are often based on a network structure set “a priori”.



The search for the optimal network architecture is one of the most difficult tasks in ANN studies and consists of tuning the model settings, called hyperparameters, that yield the best performance score on a validation data-set.

Standard methods are based on random or grid search.

Bayesian Hyperparameters Optimization



Case study n.1

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Periodica Polytechnica Civil Engineering

Road Pavement Asphalt Concretes for Thin Wearing Layers: A Machine Learning Approach towards Stiffness Modulus and Volumetric Properties Prediction

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Introduction and Scope

- The goal of this research was to implement a data-driven methodology to predict, by means of ANNs, stiffness and volumetric properties of Asphalt Concretes for **VERY THIN** road pavement wearing **LAYERS** (AC-VTL) starting from few compositional variables.

- The experimental data analyzed in this study resulted from investigations carried out at the Highway Engineering Laboratory, Aristotle University of Thessaloniki.

Asphalt Concretes for Very Thin Layers: AC-VTL

- due to its low thickness, requires lesser amount of materials, hence lowers the total cost and **minimizes the quantities of** hard and durable **aggregates** coming **from natural** non-renewable **resources**;
- provides a **noise reducing surface** (reduction -3 dB to -4 dB in comparison to conventional dense asphalt concrete surface);
- due to its gap-graded gradation, provides a pavement surface with very good surface characteristics, such as very **good macrotexture** and (with the use of hard and durable aggregates) very **good skid resistance**;
- provides a pavement surface with a certain drainage ability, hence reduction of water spray;
- no modifications are required by the conventional mixing plants in order to produce AC-VTL.

Materials and Design

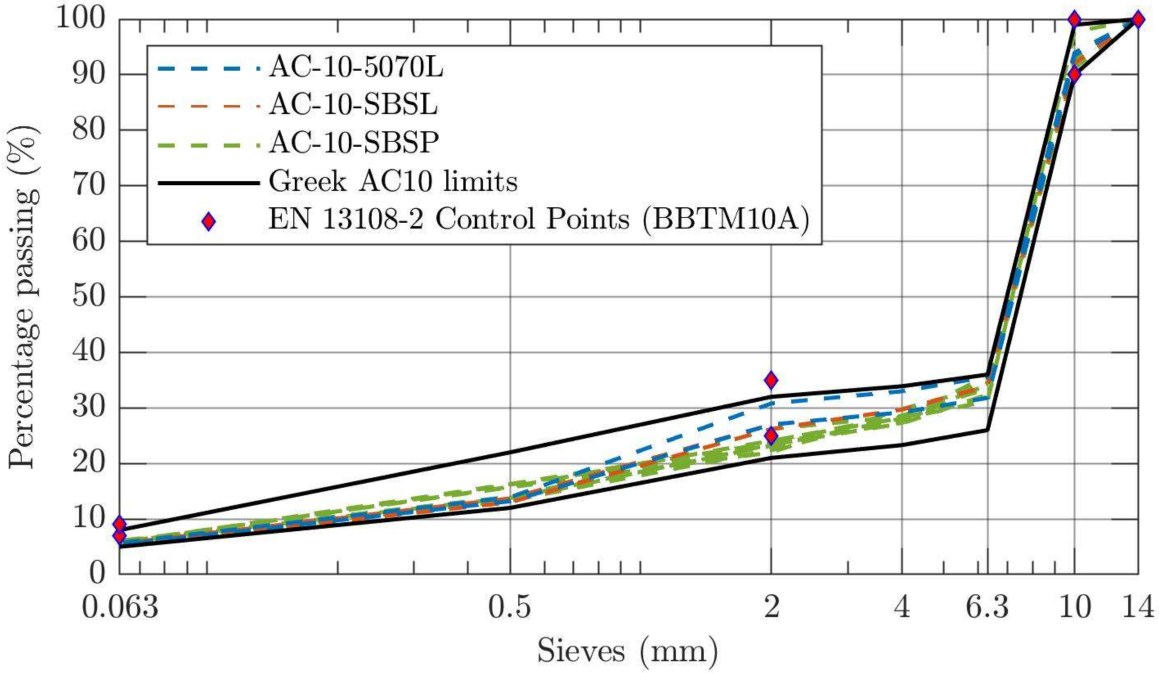
AC-VTLs were produced using **<u>diabase aggregates</u>** coming from three different quarries located in Greece.

Property	Value
Los Angeles coefficient (%), EN 1097-2	25
Polished Stone value (%), EN 1097-8	55 to 60
Flakiness index (%), EN 933-3	< 25
Sand Equivalent (%), EN 933-8	> 55
Methylene blue value (mg/g), EN 933-9	< 10 (range of values 6.7 to 8.3)

Materials and Design

Property	Bitumen type	
	50/70	SBS Modified
Penetration (0.1 x mm), EN 1426	64	45
Softening point (°C), EN 1427	45.6	78.8
Elastic recovery (%), EN 13398	–	97.5
Fraas breaking point (°C), EN 12593	– 7.0	– 15.0
After aging		
Retained penetration	–	84
Difference in softening point (°C)	–	– 2.4

Materials and Design



AC-10-5070	30 specimens laboratory-produced using conventional 50/70 bitumen
AC-10-SBSL	30 specimens laboratory-produced using SBS modified bitumen
AC-10-SBSP	32 specimens plant-produced using SBS modified bitumen

Experimental Data AC-10-5070

Cat. Var.	B_C (%)	% 6.3	% 0.063	IT-CY (MPa)	Va (%)	VMA (%)	Cat. Var.	B_C (%)	% 6.3	% 0.063	IT-CY (MPa)	Va (%)	VMA (%)
1	4.12	31.84	5.35	2939	15.7	23.3	1	4.76	35.62	5.71	2750	11.6	20.8
1	4.12	31.84	5.35	2708	15.9	23.5	1	4.76	35.62	5.71	2749	10.7	20.1
1	4.12	31.84	5.35	2944	15.4	23.0	1	5.39	35.62	5.71	2399	9.3	20.1
1	4.76	31.84	5.35	2445	14.2	23.2	1	5.39	35.62	5.71	2355	10.2	20.8
1	4.76	31.84	5.35	2586	14.2	23.1	1	5.39	35.62	5.71	2336	7.1	18.2
1	4.76	31.84	5.35	2441	14.9	23.8	1	6.02	35.62	5.71	1939	7.4	19.7
1	5.39	31.84	5.35	1962	11.1	21.7	1	6.02	35.62	5.71	1964	8.6	20.7
1	5.39	31.84	5.35	1945	11.3	21.8	1	6.02	35.62	5.71	1956	5.5	18.0
1	5.39	31.84	5.35	1921	11.6	22.1	1	5.35	35.62	5.71	2421	9.4	20.0
1	6.02	31.84	5.35	1775	9.3	21.3	1	5.35	35.62	5.71	2354	10.2	20.8
1	6.02	31.84	5.35	1886	9.4	21.4	1	5.35	35.62	5.71	2342	7.2	18.1
1	6.02	31.84	5.35	1965	9.4	21.4	1	6.00	35.62	5.71	1965	7.4	19.7
1	4.12	35.62	5.71	3276	12.7	20.6	1	6.00	35.62	5.71	1957	8.7	20.7
1	4.12	35.62	5.71	3116	17.1	24.5	1	6.00	35.62	5.71	1948	5.5	18.0
1	4.12	35.62	5.71	3227	12.7	20.6							
1	4.76	35.62	5.71	2760	9.6	19.1							

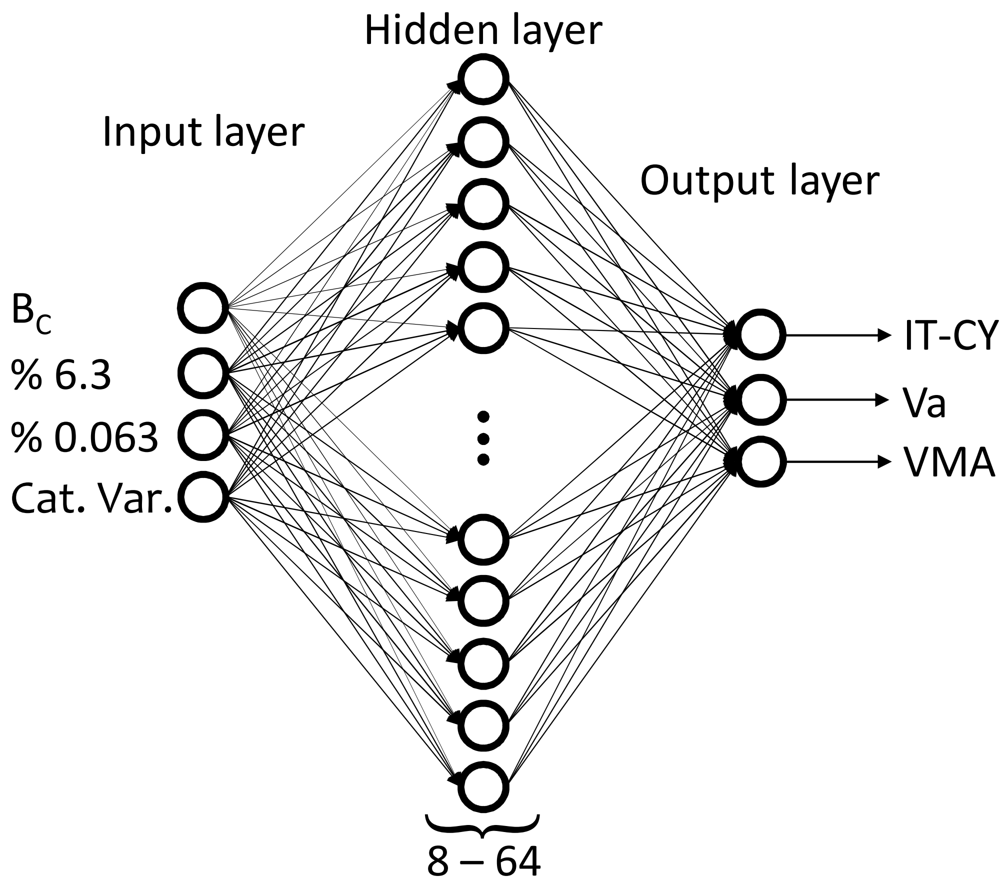
Experimental Data AC-10-SBSL

Cat. Var.	B_C (%)	% 6.3	% 0.063	IT-CY (MPa)	Va (%)	VMA (%)	Cat. Var.	B_C (%)	% 6.3	% 0.063	IT-CY (MPa)	Va (%)	VMA (%)
2	4.41	33.87	5.30	3197	15.6	24.5	2	4.12	31.84	5.60	3356	15.7	23.3
2	4.41	33.87	5.30	3067	17.0	25.8	2	4.12	31.84	5.60	3384	15.3	23.0
2	4.41	33.87	5.30	3278	16.4	25.3	2	4.76	31.84	5.60	3105	14.1	23.1
2	4.79	33.87	5.30	3066	15.6	15.6	2	4.76	31.84	5.60	3085	13.9	23.0
2	4.79	33.87	5.30	3044	16.3	16.3	2	4.76	31.84	5.60	3078	14.2	23.2
2	4.79	33.87	5.30	2931	13.2	13.2	2	5.39	31.84	5.60	2856	11.1	21.7
2	5.11	33.87	5.30	2840	14.4	24.9	2	5.39	31.84	5.60	2854	11.1	21.7
2	5.11	33.87	5.30	2976	13.1	23.8	2	5.39	31.84	5.60	2841	11.2	21.8
2	5.11	33.87	5.30	2873	15.0	25.5	2	6.02	31.84	5.60	2424	8.9	21.1
2	5.48	33.87	5.30	3226	11.9	23.5	2	6.02	31.84	5.60	2451	8.9	21.0
2	5.48	33.87	5.30	2928	13.2	24.6	2	6.02	31.84	5.60	2456	9.4	21.5
2	5.48	33.87	5.30	3093	12.6	24.1	2	6.10	31.84	5.60	2422	7.9	20.4
2	5.86	31.84	5.60	3123	10.9	23.4	2	6.10	31.84	5.60	2438	8.6	21.0
2	5.86	31.84	5.60	3091	10.9	23.5	2	6.10	31.84	5.60	2468	8.6	20.9
2	5.86	31.84	5.60	3358	12.3	24.6							
2	4.12	31.84	5.60	3452	15.6	23.2							

Experimental Data AC-10-SBSP

Cat. Var.	B_C (%)	% 6.3	% 0.063	IT-CY (MPa)	Va (%)	VMA (%)	Cat. Var.	B_C (%)	% 6.3	% 0.063	IT-CY (MPa)	Va (%)	VMA (%)
3	5.58	33.87	5.63	3382	9.5	18.5	3	5.29	35.00	5.58	3332	13.5	22.2
3	5.58	33.87	5.63	3446	9.3	18.3	3	5.29	35.00	5.58	3388	13.3	21.6
3	5.58	33.87	5.63	3260	9.6	18.7	3	5.29	35.00	5.58	3316	13.6	22.4
3	5.58	33.87	5.63	3617	9.1	18.1	3	5.29	35.00	5.58	3786	13.2	22.6
3	5.27	31.17	5.87	3362	14.1	22.5	3	5.42	32.43	5.37	2862	10.6	20.3
3	5.27	31.17	5.87	3458	13.5	22.2	3	5.42	32.43	5.37	2913	10.5	19.5
3	5.27	31.17	5.87	3421	13.9	22.3	3	5.42	32.43	5.37	2809	10.8	19.3
3	5.27	31.17	5.87	3380	13.9	22.7	3	5.42	32.43	5.37	2896	10.7	19.7
3	5.47	32.02	5.77	2810	10.3	19.5	3	5.15	33.92	5.89	3935	15.2	23.9
3	5.47	32.02	5.77	2842	10.0	18.5	3	5.15	33.92	5.89	4145	14.8	23.2
3	5.47	32.02	5.77	2826	10.1	18.6	3	5.15	33.92	5.89	4197	14.3	22.9
3	5.47	32.02	5.77	2827	10.1	18.6	3	5.15	33.92	5.89	4036	15.0	23.5
3	5.74	33.50	6.12	2655	8.2	16.8	3	5.35	35.77	5.24	3309	12.0	20.5
3	5.74	33.50	6.12	3940	7.1	15.9	3	5.35	35.77	5.24	3296	12.1	21.2
3	5.74	33.50	6.12	3612	7.4	16.1	3	5.40	34.53	5.68	2853	11.1	19.9
3	5.74	33.50	6.12	3448	7.6	16.3	3	5.40	34.53	5.68	2865	11.0	19.9

Artificial Neural Network



Transfer Function	Equation	Graph
Exponential Linear	$\varphi(x) = \begin{cases} \alpha(e^x - 1) & x \le 0 \\ x & x > 0 \end{cases}$	
Hyperbolic Tangent	$\varphi(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$	

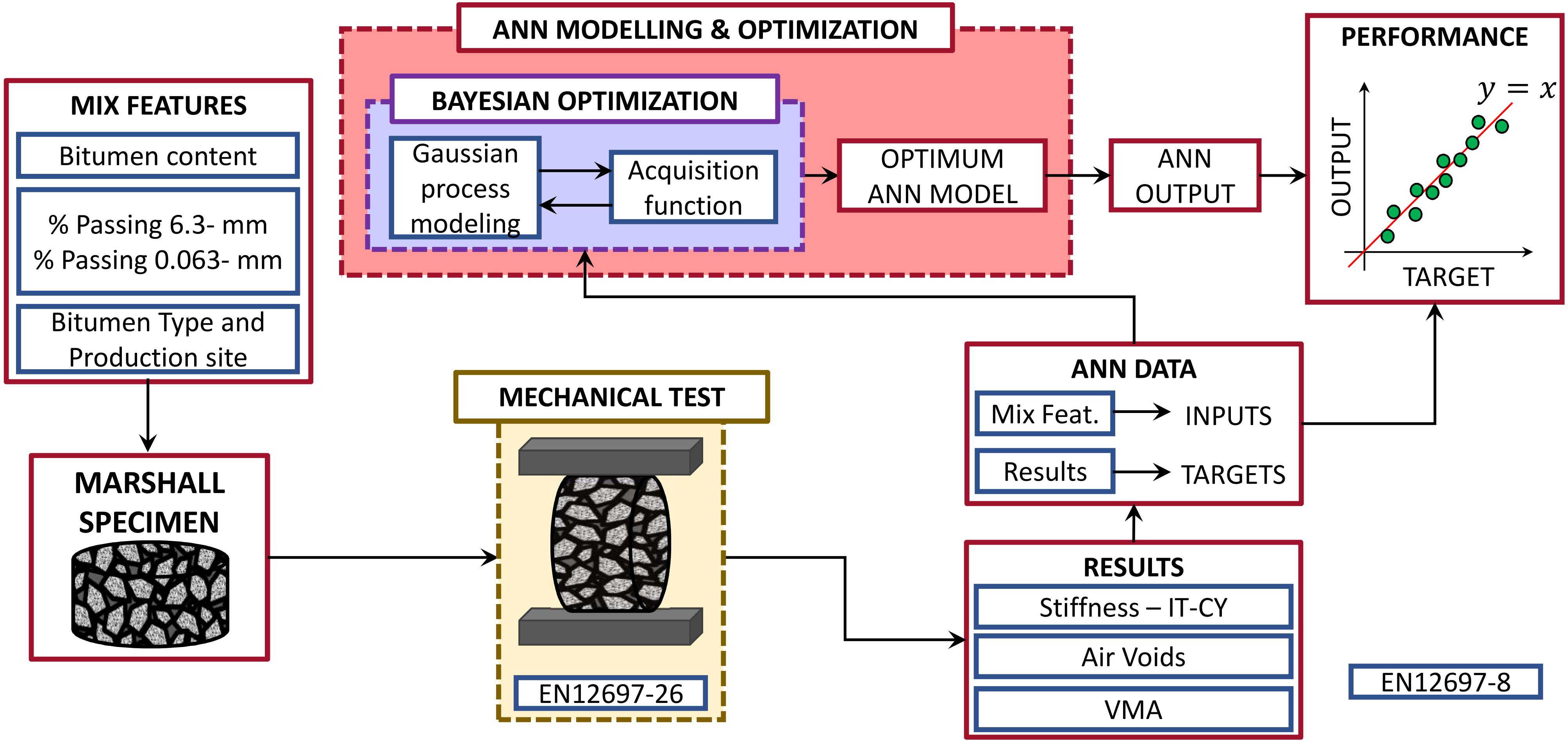
Input	Description
B_C	Bitumen content (by weight)
% 6.3	% passing at 6.3 mm sieve
% 0.063	% passing at 0.063 mm sieve
Cat. Var.	Categorical variable

Output	Description
IT-CY	Stiffness modulus
Va	Air voids content
VMA	Voids in the mineral aggregate

Hyperparameters Definition

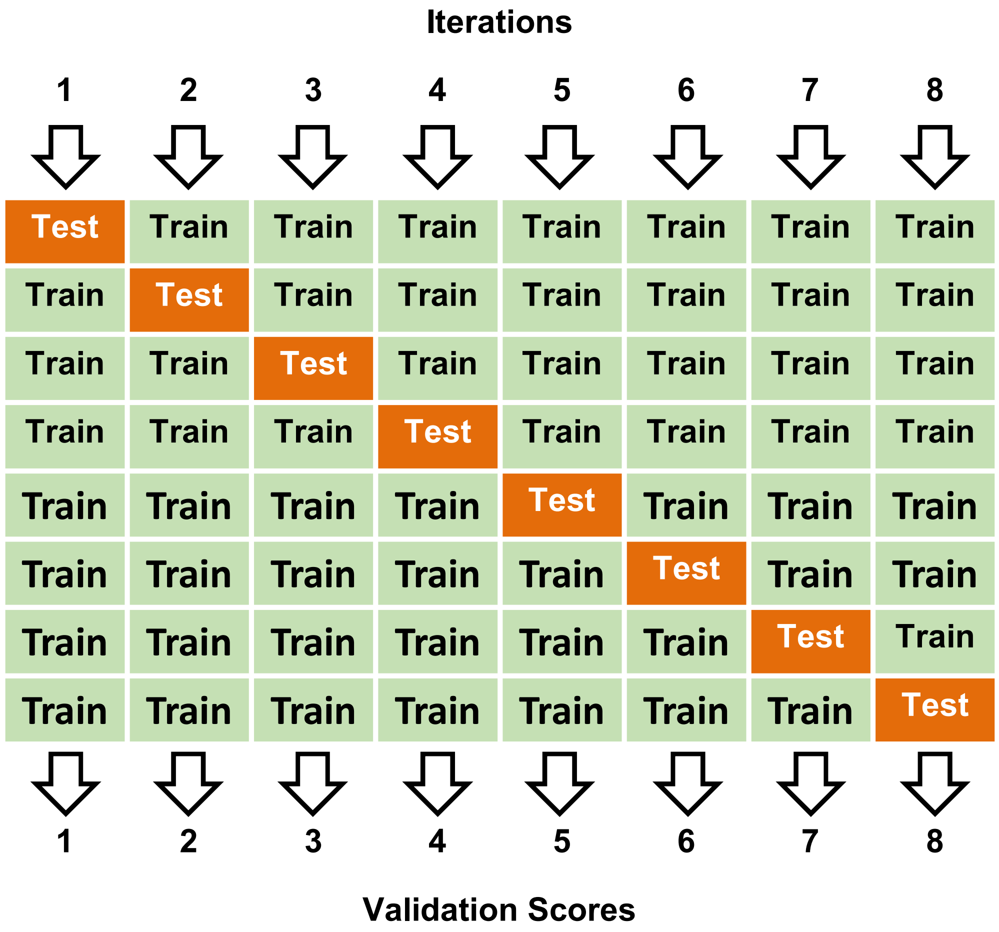
	Hyperparameter	Symbol	Variation Interval
Network Topology	Neurons in the hidden layer	N	$\{8, \cdots, 64\}$
	Transfer Function	act	$\{ELU, Tanh\}$
Learning Algorithm	Learning Rate	μ	$[10^{-4}, 10^{-2}]$
	Increasing factor	μ_{inc}	$[10^{1}, 10^{3}]$
	Decreasing factor	μ_{dec}	$[10^{-3}, 10^{-1}]$
	Maximum Learning Rate	μ_{max}	$[10^{6}, 10^{8}]$
	Learning Algorithm Iterations	E	$\{500, \cdots, 5000\}$

Step-by-step Procedure



k-fold Cross-Validation

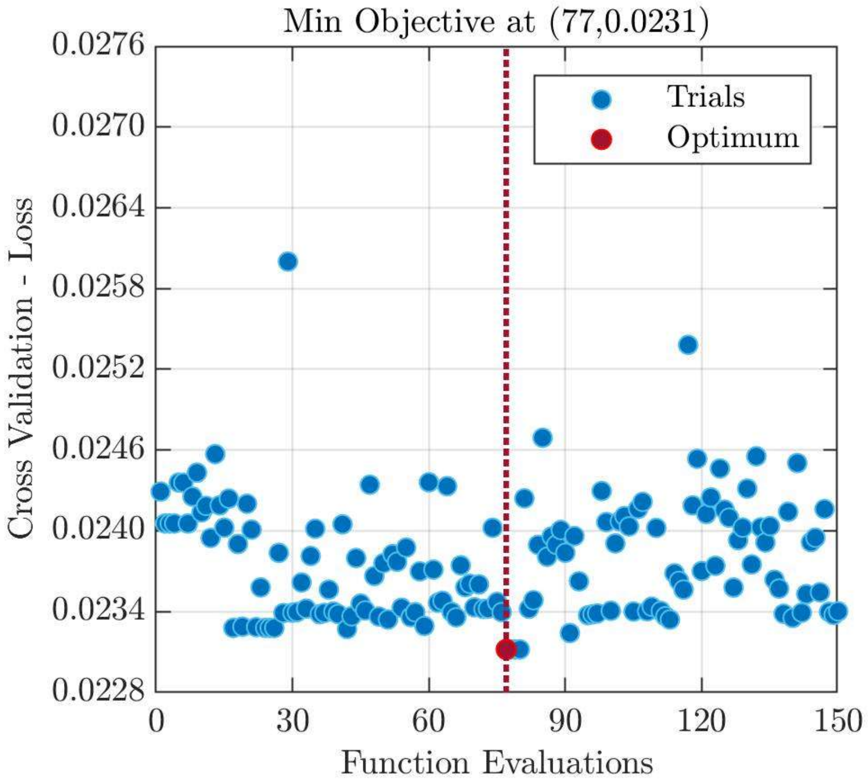
k-fold Cross-Validation is a resampling technique used to elaborate an actual model on a limited data sample. It consists in dividing the data sample in k-partitions. Each sub-sample is used once as validation set and k-1 times as training set. It was decided to give a k-value equal to 8, consistently with the relevant literature. This procedure is iteratively repeated 8 times; finally, the average of the 8 validation scores is given as general performance of the model.



Results and discussion

Feature	Bounded Domain	Selected Value
N	$\{8, \dots, 64\}$	22
act	$\{Tanh, ELU\}$	$Tanh$
μ	$[10^{-4}, 10^{-2}]$	2.02×10^{-3}
μ_{inc}	$[10^{1}, 10^{3}]$	1.18×10^{2}
μ_{dec}	$[10^{-3}, 10^{-1}]$	1.07×10^{-2}
μ_{max}	$[10^{6}, 10^{8}]$	4.52×10^{7}
E	$\{500, \dots, 5000\}$	2922

$$F : X_N \times X_{act} \times X_\mu \times X_{\mu_{inc}} \times X_{\mu_{dec}} \times X_{\mu_{max}} \times X_E$$



Results and discussion

Fold	Loss (MSE)	R-Pearson coefficient		
		ITSM	Va	VMA
1	0.0172	0.9780	0.9523	0.9374
2	0.0318	0.9654	0.9332	0.9204
3	0.0181	0.9952	0.9413	0.9535
4	0.0273	0.9109	0.9746	0.9630
5	**0.0520**	**0.8698**	**0.8826**	**0.8470**
6	0.0130	0.9856	0.9863	0.9674
7	0.0209	0.9569	0.9470	0.9440
8	**0.0047**	**0.9731**	**0.9975**	**0.9931**
	Average over the 8 test folds			
	0.0231	0.9544	0.9519	0.9407

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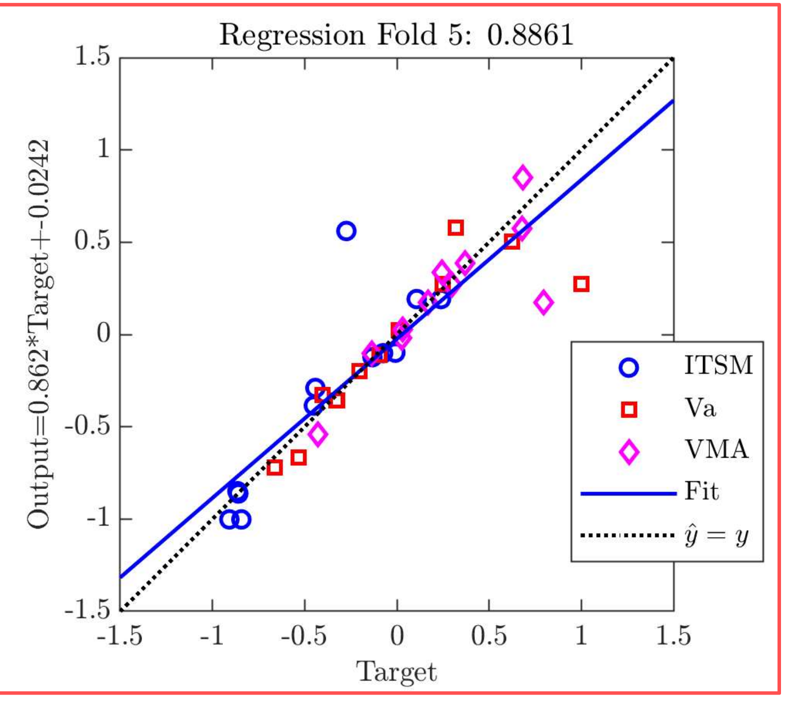

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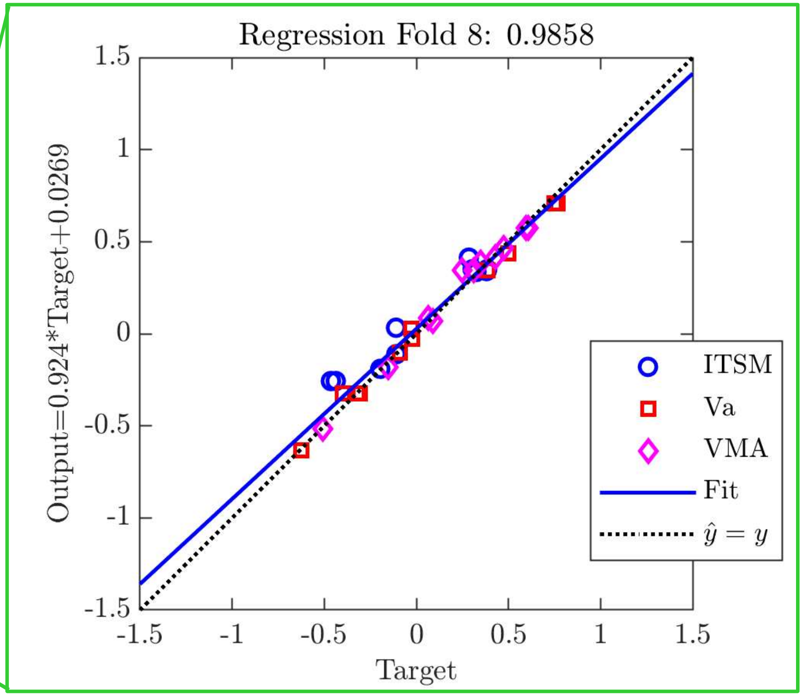

Remarks case study n.1

- It has been feasible to predict simultaneously Stiffness Modulus, Va and VMA, starting from bitumen content, a couple of grading curve data and “the type of mix” categorical variable.
- The best predictions accuracy has been achieved for the Stiffness Modulus.
- The number of artificial neurons in the hidden layer, as well as the hyperparameters values related to the learning algorithm, resulted different with respect to those suggested by empirical rules.

Case study n.2

coatings

MDPI

Article

Stiffness Data of High-Modulus Asphalt Concretes for Road Pavements: Predictive Modeling by Machine-Learning

Nicola Baldo [1,*], Matteo Miani [1], Fabio Rondinella [1], Jan Valentin [2], Pavla Vackcová [2] and Evangelos Manthos [3]

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2 Faculty of Civil Engineering, Czech Technical University, Thákurova 7, 166 29 Prague, Czech Republic; jan.valentin@fsv.cvut.cz (J.V.); pavla.vackova@fsv.cvut.cz (P.V.)
3 Department of Civil Engineering, University Campus, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece; emanthos@civil.auth.gr
* Correspondence: nicola.baldo@uniud.it; Tel.: +39-0432-558-745

Introduction and Scope

- The goal of this study was to predict, by means of ANNs, the stiffness of High-Modulus Asphalt Concretes (HMAC) on the basis of selected input parameters.
- A set of 38 variants of HMAC mixtures was available.
- All mixtures were characterized by a gradation 0–22 mm and had to fulfill requirements set in Czech technical specifications TP 151.
- Hard paving grade bitumen 20/30, conventional binder 50/70 or PMB 25/55-60 were used.
- Some mix variants contained between 10% and 30% RAP.

Experimental data set
(VMT stands for Vysokým Modulem Tuhosti, i.e., HMAC in Czech)

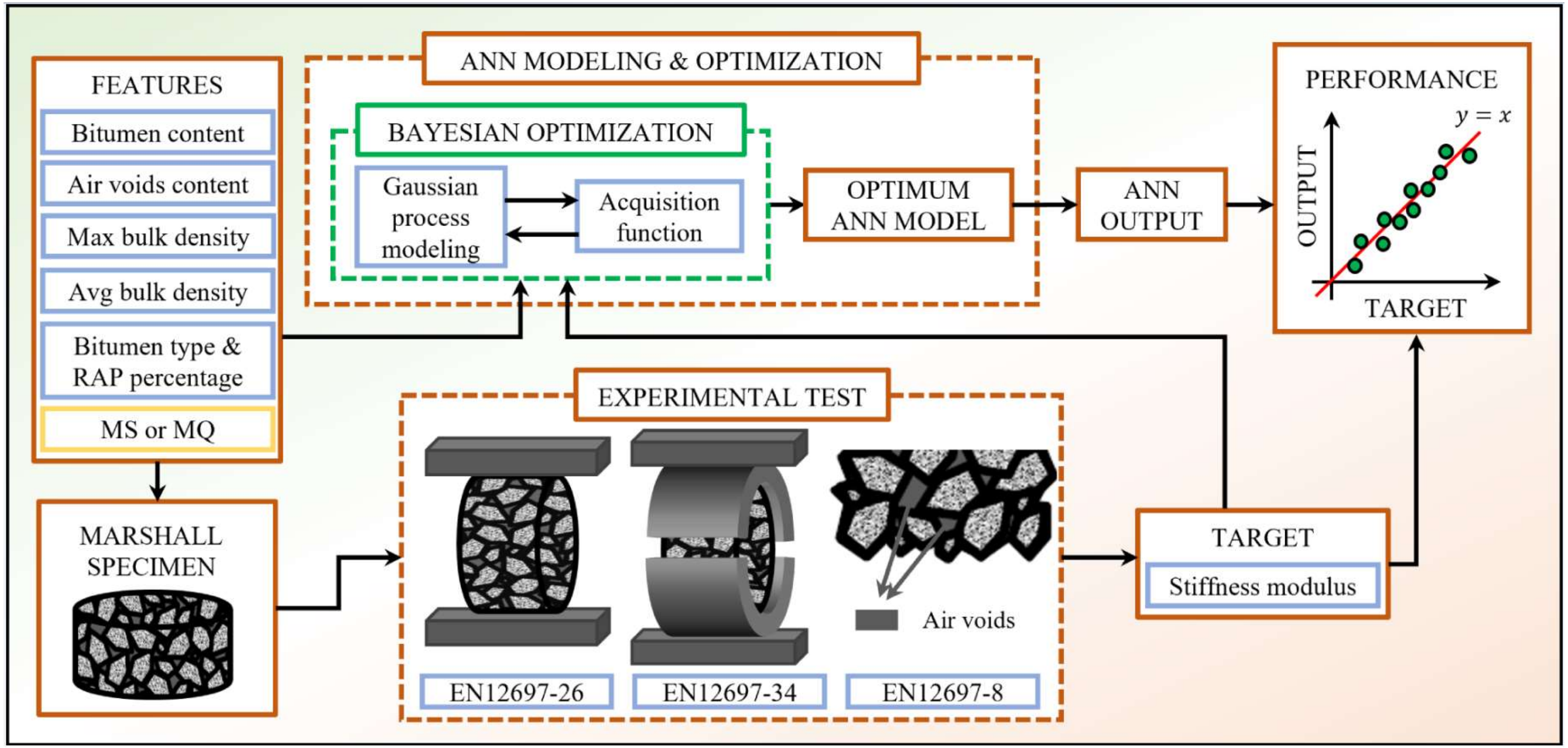
Mix	Bitumen Type	ID	Bulk Density	Max Bulk Density	Binder Content	Voids Content	Maximum Strength	Marshall Stability	Marshall Flow	IT-CY 15 °C
			(g/cm^3)	(g/cm^3)	(%)	(%)	kN	kN	(0.1 mm)	(MPa)
VMT 22 with 30% RA var. 5.1	50/70	M3	2.547 2.554 2.538	2.617	5.1 5.1 5.1	2.7 2.4 3.0	17.1 17.2 19.6	19.7 20.0 21.9	71 55 45	13,171 11,659 13,242
VMT 22 with 30% RA. var. 4.8	50/70	M3	2.538 2.535 2.539	2.607	4.8 4.8 4.8	2.6 2.8 2.6	17.4 14.8 22.7	19.9 16.9 25.5	58 47 61	12,739 13,287 13,217
VMT 22 with 30% RA (Froněk)	50/70	M3	2.549 2.539 2.548	2.602	4.8 4.8 4.8	2.0 2.4 2.1	17.4 15.3 16.8	20.2 17.9 19.0	53 63 66	13,025 14,267 13,325
VMT 22 with 30% RA (Froněk)	50/70	M3	2.553 2.548 2.548	2.626	4.6 4.6 4.6	2.8 3.0 3.0	20.6 18.6 20.2	20.7 21.0 23.4	51 54 50	15,871 15,666 16,707
VMT 22 with 20% RA (Froněk-3)	50/70	M4	2.473 2.495 2.477	2.639	4.8 4.8 4.8	6.3 5.4 6.1	18.1 20.2 21.5	19.0 21.6 22.3	34 34 46	12,729 12,282 14,101
VMT 22 with 20% RA (PKB-A)	50/70	M4	2.397 2.421 2.412	2.496	4.4 4.4 4.4	4.0 3.0 3.4	14.2 13.4 12.2	13.6 13.4 12.4	48 50 51	8666 9064 8135
VMT 22 with 10% RA (PKB-101)	50/70	M5	2.358 2.351 2.355	2.559	4.6 4.6 4.6	7.9 8.1 8.0	12.1 15.3 12.8	11.4 14.1 14.5	35 37 34	8950 9339 9311
VMT 22 with 10% RA (PKB-102)	50/70	M5	2.341 2.343 2.323	2.559	4.5 4.5 4.5	8.5 8.4 9.2	17.1 17.1 15.1	16.2 16.1 14.2	90 80 96	9203 9142 9361

Stiffness prediction based on Marshall test results

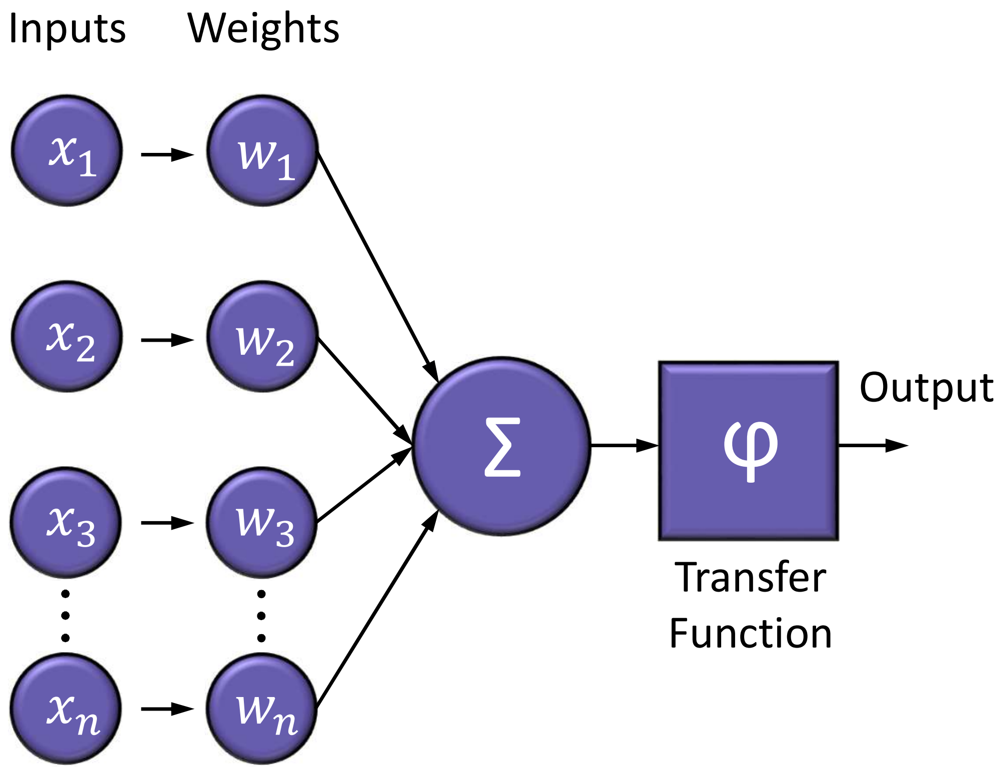
Marshall test
(EN 12697-34)
Empirical

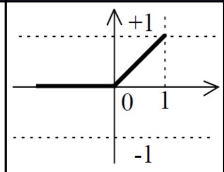
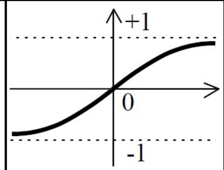
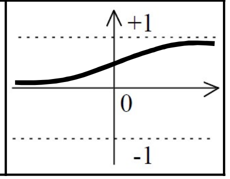
Stiffness Modulus test
(EN 12697-26)
Performance based

The Procedure



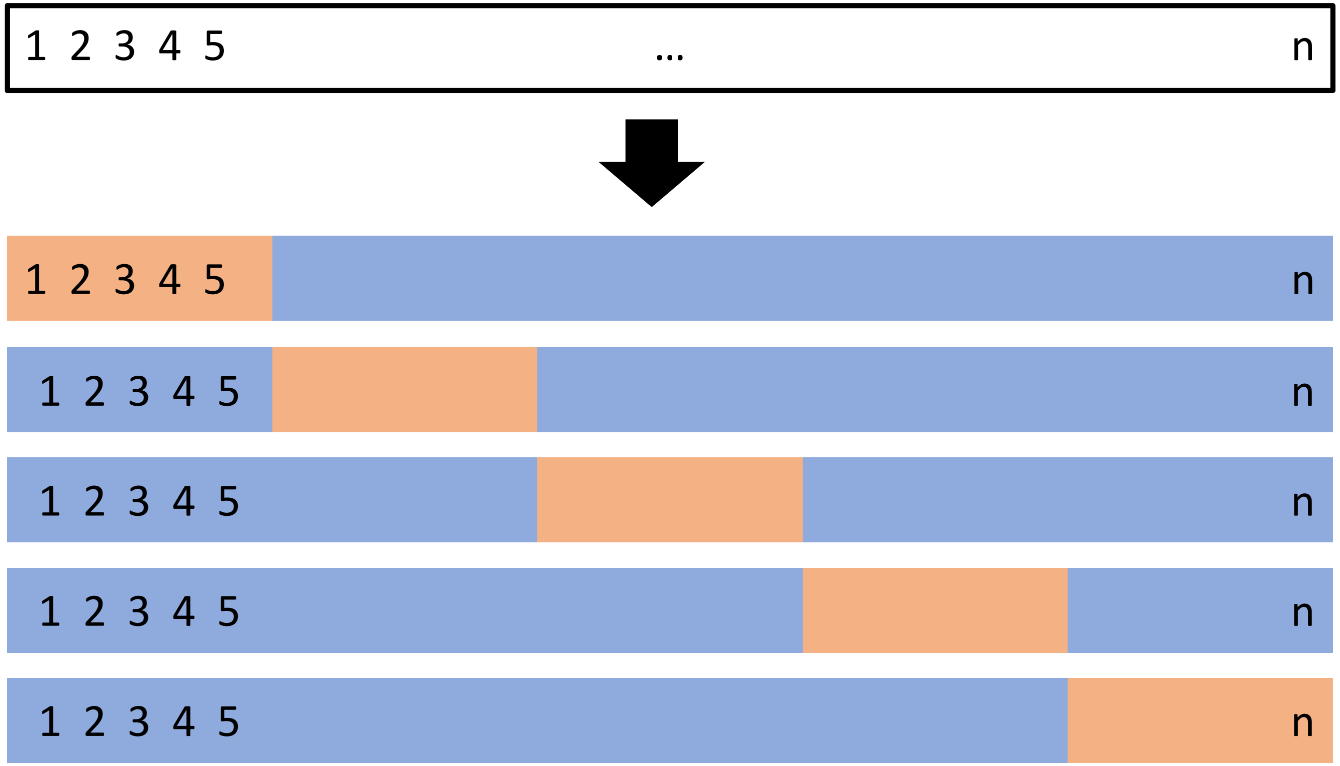
Hidden Neuron



Transfer Function	Equation	Graph
Rectified Linear	$\varphi(x) = \begin{cases} 0 & x \le 0 \\ x & x > 0 \end{cases}$	
Hyperbolic Tangent	$\varphi(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$	
Logistic Sigmoid	$\varphi(x) = \dfrac{1}{1 + e^{-x}}$	

The k-fold Cross Validation

A set of n observations is randomly split into five non-overlapping groups. Each of these fifths acts as a validation set (shown in beige), and the remainder as a training set (shown in blue). The test error is estimated by averaging the five resulting MSE estimates.

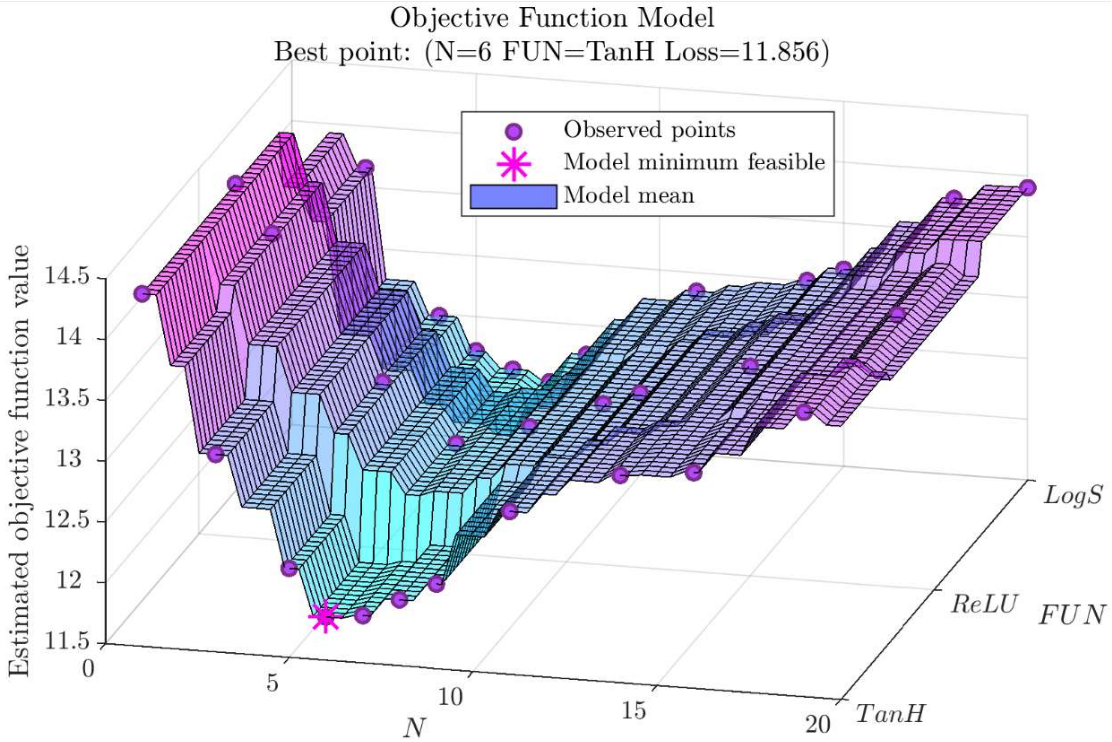


Results

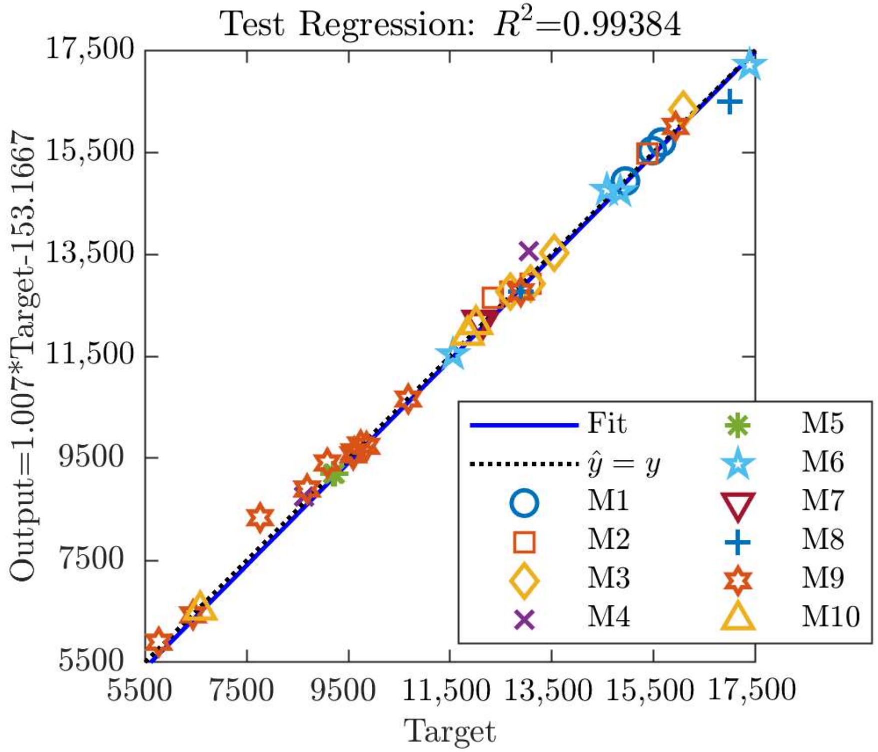
In general, the addition of the empirical mechanical parameters among the predictors of the stiffness modulus improved the prediction accuracy compared to the use of mixes' composition parameters alone, as shown by the model evaluation functions: in particular, the values of the R^2_{adj} parameter, a modified version of R^2 which assesses the effect of adding predictors to a model, increase with the use of MS or MQ, showing that the new independent term improves the model more than would be expected by chance, but the percentage gain in model accuracy is really paltry. In fact, although the percentage variation in MAE between MIX_{SNN} and MS_{SNN} is +23.4%, in terms of R^2_{adj} the gain is only +0.29% and therefore such that it may not justify the use of additional data, such as any results of the Marshall test.

ID	Features	N	ϕ	$f(\cdot)$	MAE	RMSE	R^2	R^2_{adj}
MIX_{SNN}	5	6	TanH	12.093	209.12	293.56	0.9909	0.9894
MS_{SNN}	6	6	TanH	11.856	160.17	241.54	0.9938	0.9923
MQ_{SNN}	6	8	LogS	12.373	174.91	272.61	0.9922	0.9902

Results



Objective Function Model
Best point: (N=6 FUN=TanH Loss=11.856)
Observed points
Model minimum feasible
Model mean
Estimated objective function value
14.5
14
13.5
13
12.5
12
11.5
0
5
10
15
20
N
TanH
ReLU
LogS
FUN



Test Regression: R^2=0.99384
Output=1.007*Target-153.1667
17,500
15,500
13,500
11,500
9500
7500
5500
Target
Fit
$\hat{y} = y$
M1
M2
M3
M4
M5
M6
M7
M8
M9
M10

Remarks case study n.2

- It has been feasible to fit experimental data of asphalt concretes partially made with RAP.
- The inclusion in the input data of Marshall Stability or Quotient values, allows to improve the prediction accuracy of the Stiffness Modulus.
- For each of the neural models analyzed, the Bayesian optimization procedure has identified a different combination of hidden neurons and transfer functions.

Case study n.3

sustainability

MDPI

Article

Mechanical Characterization of Industrial Waste Materials as Mineral Fillers in Asphalt Mixes: Integrated Experimental and Machine Learning Analysis

Nitin Tiwari [1,2,*], Nicola Baldo [3,*], Neelima Satyam [2] and Matteo Miani [3]

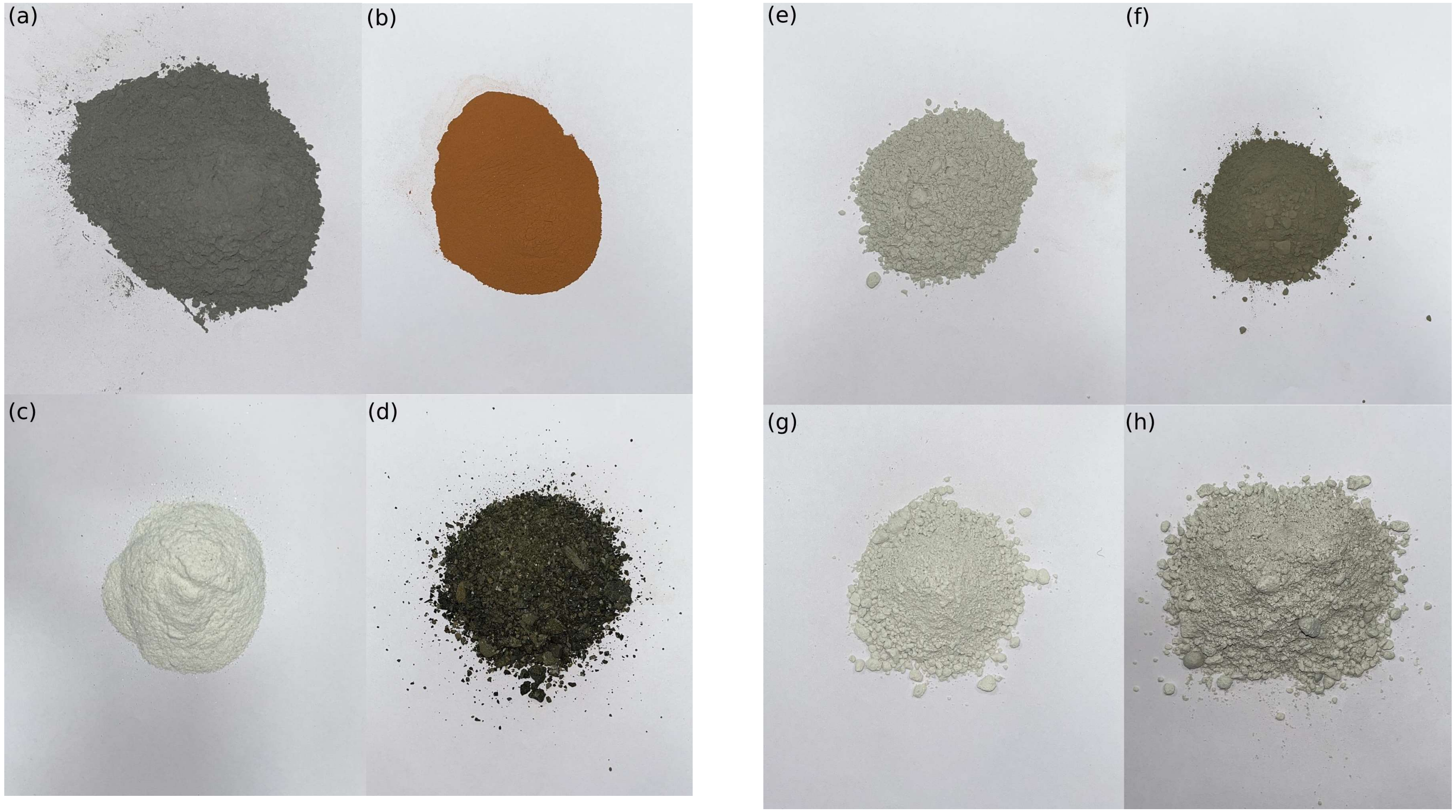
1 Lyles School of Civil Engineering, Purdue University, West Lafayette, IN 47907, USA
2 Department of Civil Engineering, Indian Institute of Technology Indore, Indore 452020, India; neelima.satyam@iiti.ac.in
3 Polytechnic Department of Engineering and Architecture (DPIA), University of Udine, 33100 Udine, Italy; matteo.miani@phd.units.it
* Correspondence: tiwari50@purdue.edu (N.T.); nicola.baldo@uniud.it (N.B.)

Introduction

This case study regards the feasibility of using seven different materials as alternative filler instead of ordinary Portland cement (OPC) in road pavement base layers, namely **rice husk ash** (RHA), **brick dust** (BD), **marble dust** (MD), **stone dust** (SD), **fly ash** (FA), **limestone dust** (LD), and **silica fume** (SF).

The experimental data were processed through artificial neural networks (ANNs), using k-fold cross validation resampling technique.

Materials and Design



RHA (a), BD (b), MD (c), SD (d), FA (e), OPC (f), LD (g), and SF (h) filler materials.

Materials and Design

Properties of the investigated mineral fillers.

Test parameter	Mineral Filler Type							
	RHA	BD	MD	SD	FA	OPC	LD	SF
Specific gravity (g/cm^3)	2.02	2.56	2.69	2.69	2.32	3.04	2.65	2.20
MBV (g/kg)	4.72	6.25	4.45	3.67	3.86	3.00	3.75	3.85
German filler (g)	65	40	70	85	75	85	97	94
FM	3.21	5.17	2.12	5.38	3.77	4.96	3.03	1.96
Surface area (m^2/g)	2.31	2.69	4.37	2.70	2.19	1.75	2.70	16.45
PH	10.86	8.67	8.50	12.57	7.30	12.90	10.22	6.98
SiO_2 (%)	89.67	39.55	0.60	82.37	48.24	21.43	0.48	93.5
CaO (%)	1.88	12.88	55.60	2.79	13.40	66.58	96.57	0.89
Al_2O_3 (%)	1.62	15.71	0.40	8.23	24.15	3.01	0.41	0.08
MgO (%)	0.97	3.29	0.10	1.47	1.46	1.39	0.46	0.82
Fe_2O_3 (%)	1.06	14.05	0.20	5.27	6.48	4.68	0.32	0.50
Particle shape	Honeycombed	Subangular particles	Subangular particles	Angular particles	Rounded	Granular/ subangular particles	Granular particles	Spherically shaped

Materials and Design

Crushed quartz aggregate properties

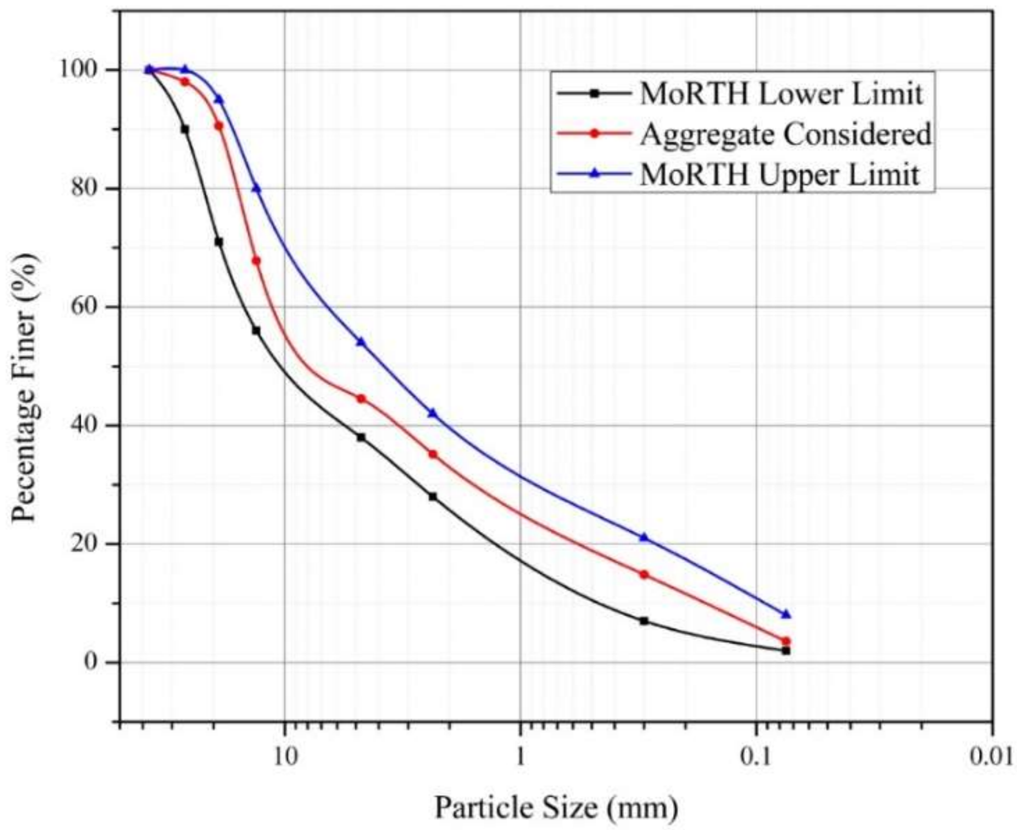
Test Parameters	Specified Limit (MoRTH)	Test Results	Test Method
Cleanliness (Dust) (%)	Max 5 %	3	IS 2386 Part I
Bulk Specific gravity (g/cm3)	2-3	2.68	IS 2386 Part III
Percent wear by Los Angeles abrasion (%)	Max 35 %	10.6	IS 2386 Part IV
Soundness loss by sodium sulphate solution (%)	Max 12%	3.4	IS 2386 Part V
Soundness loss by magnesium sulphate solution (%)	Max 18%	3.7	IS 2386 Part V
Flakiness and Elongation Index (%)	Max 35%		IS 2386 Part I
– 20 mm		27.93	
– 10 mm		32.13	
Impact Strength (%)	Max 27%		IS 2386 Part IV
– 20 mm		4.15	
– 10 mm		5.91	
Water Absorption (%)	Max 2%	1.67	IS 2386 Part III

Materials and Design

Aggregate type, grain size distribution, and bitumen type have been kept constant for all the asphalt concretes investigated in order to assess only the effect of the different filler materials on the physical-mechanical response of the mixes.

Four levels of waste mineral filler have been considered, namely, 4.0%, 5.5%, 7.0%, and 8.5%, by volume of mix; OPC has been used with the same contents as a comparative term.

Marshall compaction and stability, Indirect Tensile Strenght, Cantabro Abrasion Loss, modified Lottman test.



Design gradation curve and MoRTH limits.

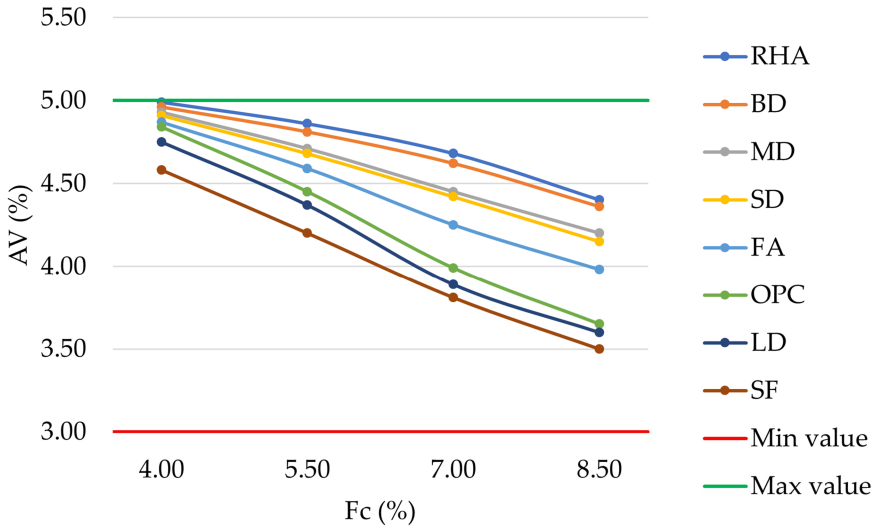
Materials and Design

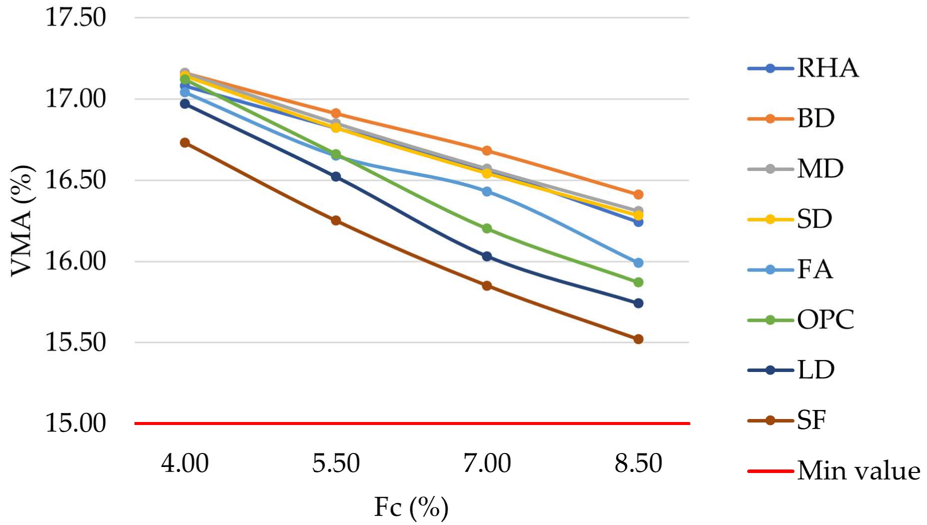
Conventional VG-30 bitumen properties.

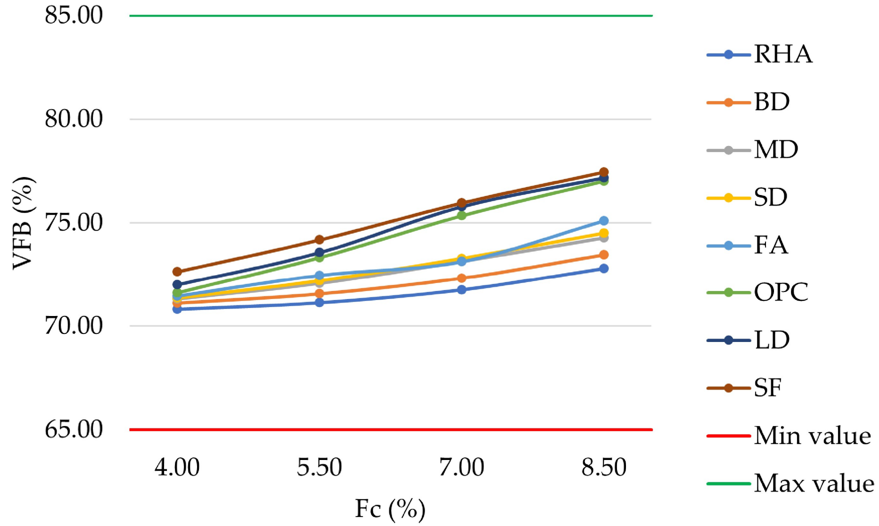
Test Parameters	Specified Limit (MoRTH)	Test Results	Test Method
Absolute Viscosity at 60°C, poises	2400-3600	2855	IS 1206 (P-2)
Kinematic Viscosity at 135°C cSt, Min	350	392	IS 1206 (P-3)
Flash point Cleveland open cup, °C, Min	250	304	IS 1448 (P-69)
Penetration at 25°C, 100gm, 5sec, 1/10 mm, Min	45	49	IS 1203
Softening Point (R&B), °C, Min	47	48	IS 1205
Matter Soluble in trichloroethylene, % by mass, Min	99	99.45	IS 1216
Viscosity Ratio at 60°C, Max	4.0	1.3	IS 1206 (P-2)
Ductility at 25°C, cm after TFOT Min	40	75	IS 1208
Specific Gravity gm/cc	0.97 -1.02	0.987	IS 1202

Results and discussion

VOLUMETRIC PROPERTIES

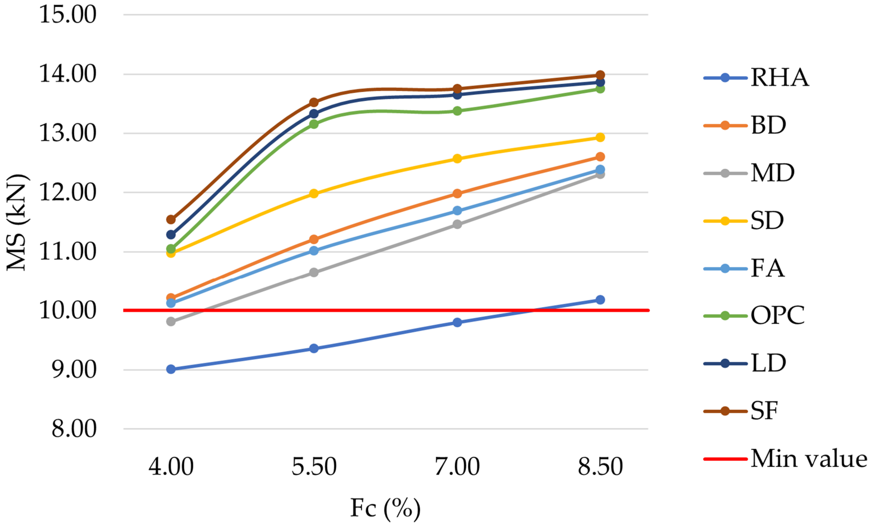


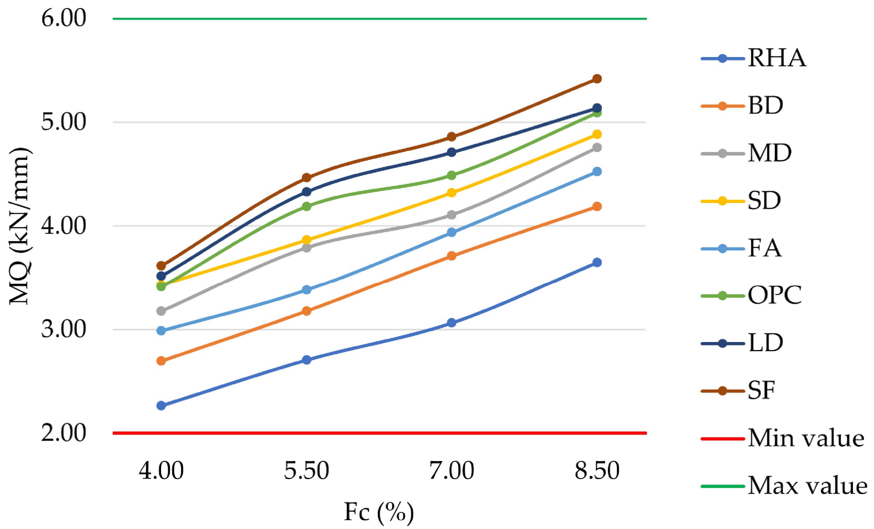


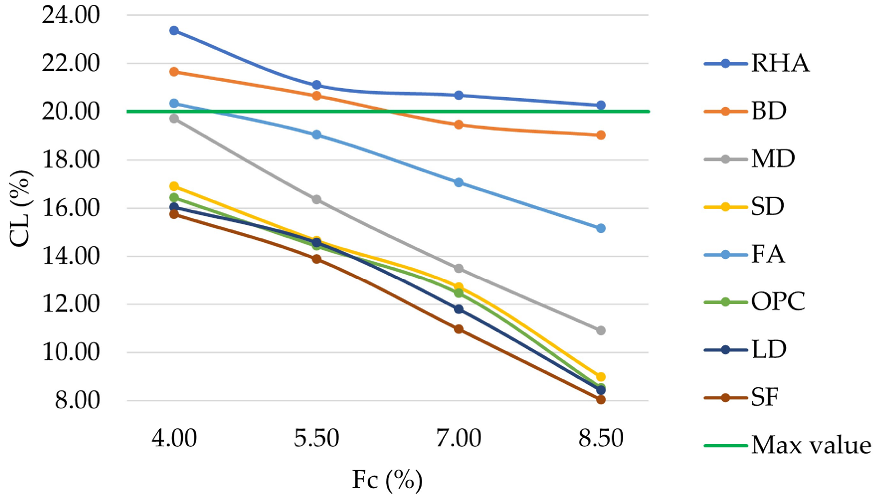


Results and discussion

MARSHALL PARAMETERS and CANTABRO LOSS

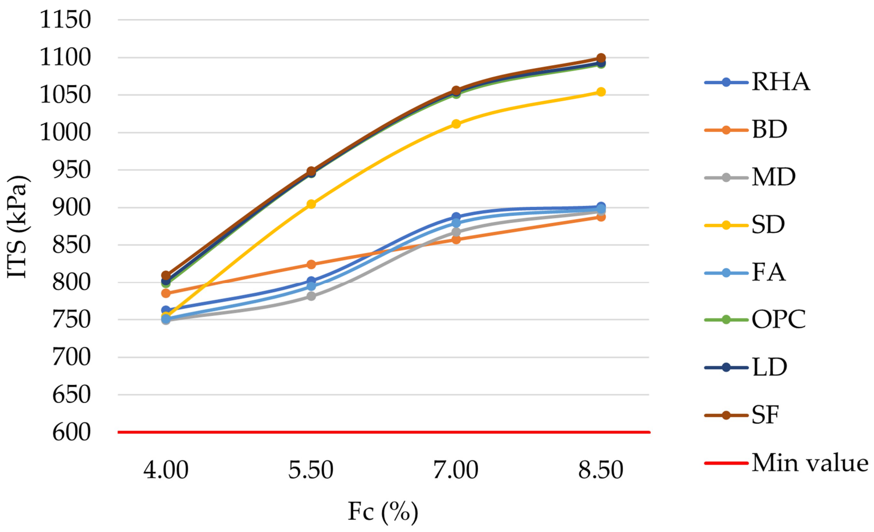


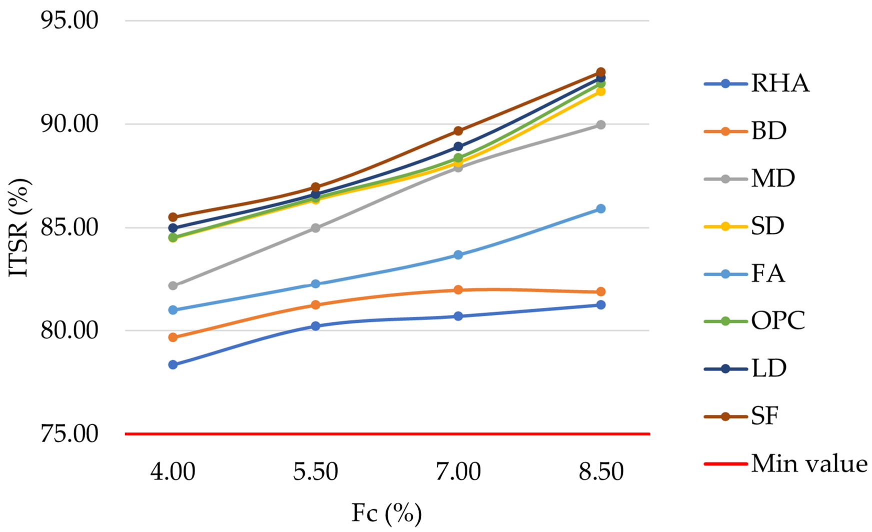




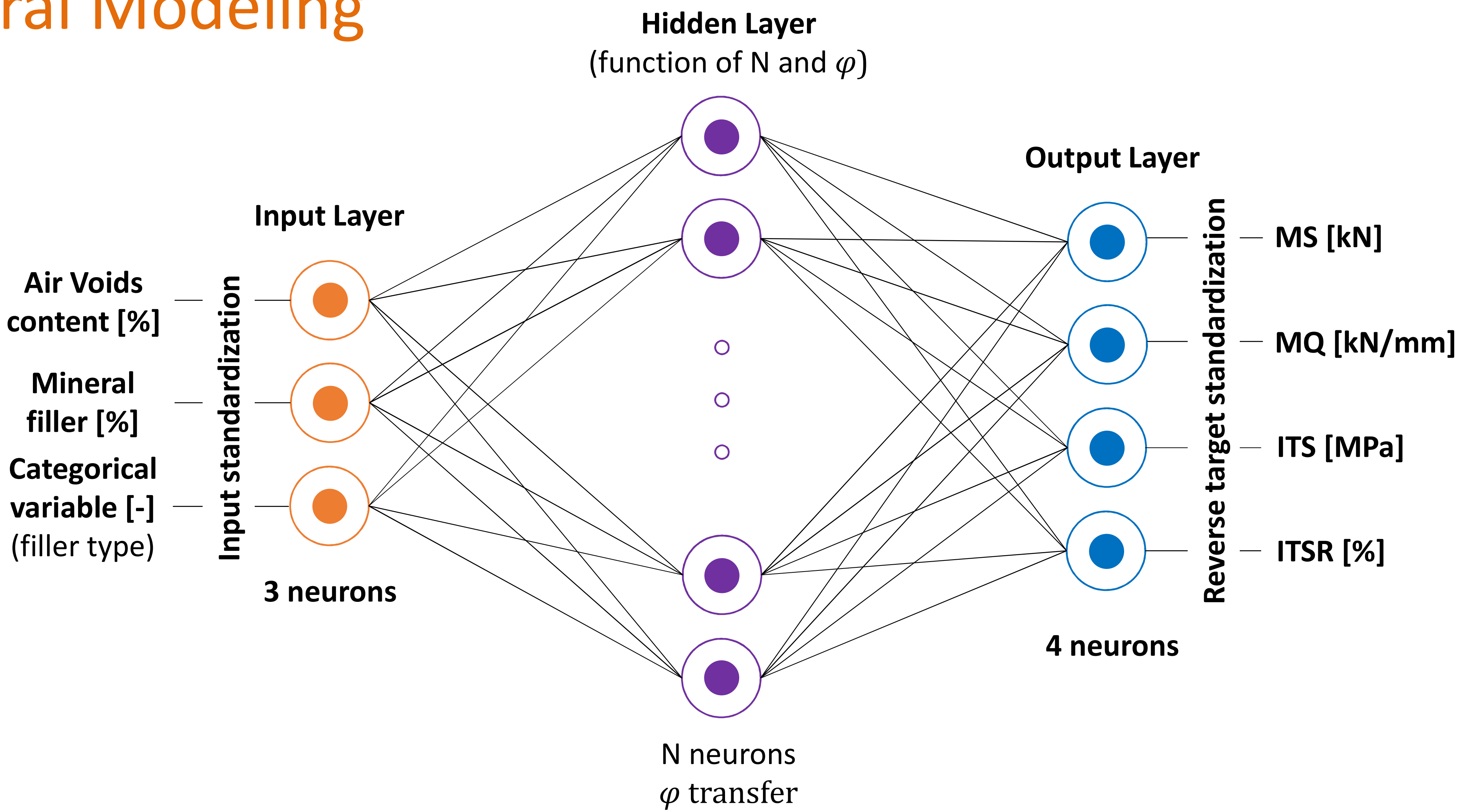
Results and discussion

INDIRECT TENSILE STRENGTH

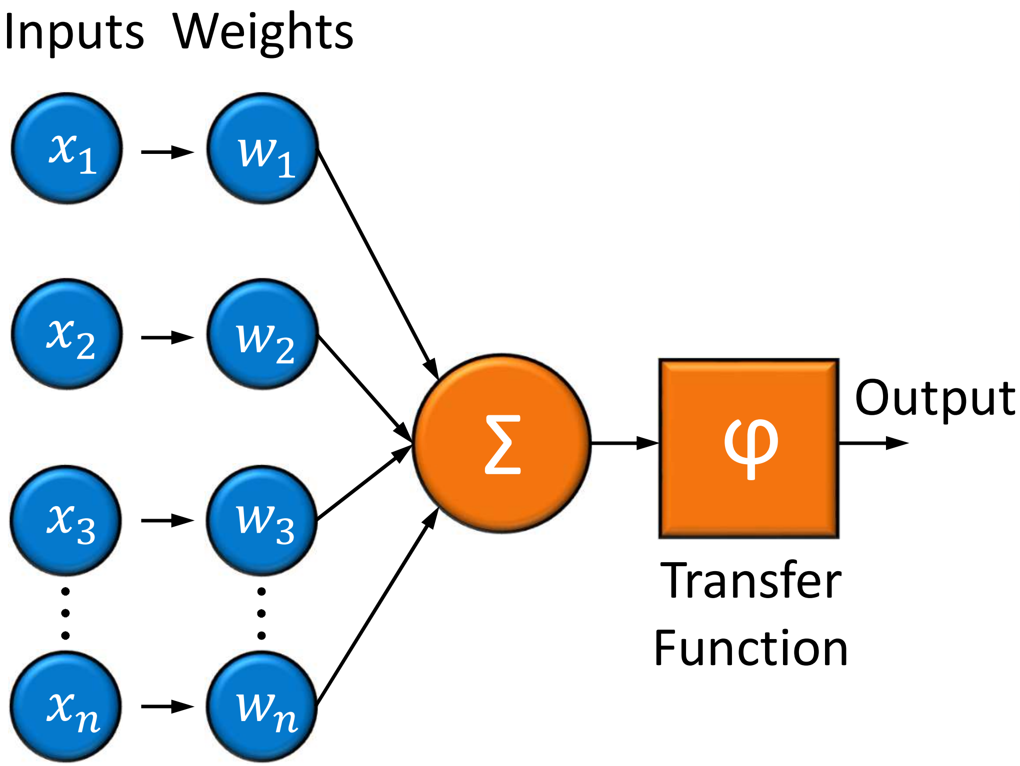




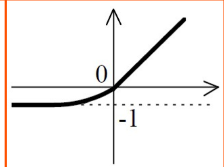
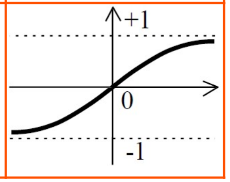
Neural Modeling



Artificial Neuron



Activation functions investigated

Transfer Function	Equation	Graph
Exponential Linear	$\varphi(x) = \begin{cases} \alpha(e^x - 1) & x \le 0 \\ x & x > 0 \end{cases}$	
Hyperbolic Tangent	$\varphi(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$	

k-fold Cross-Validation

Randomly mix the dataset

↓

Split the dataset into k = 4 folds

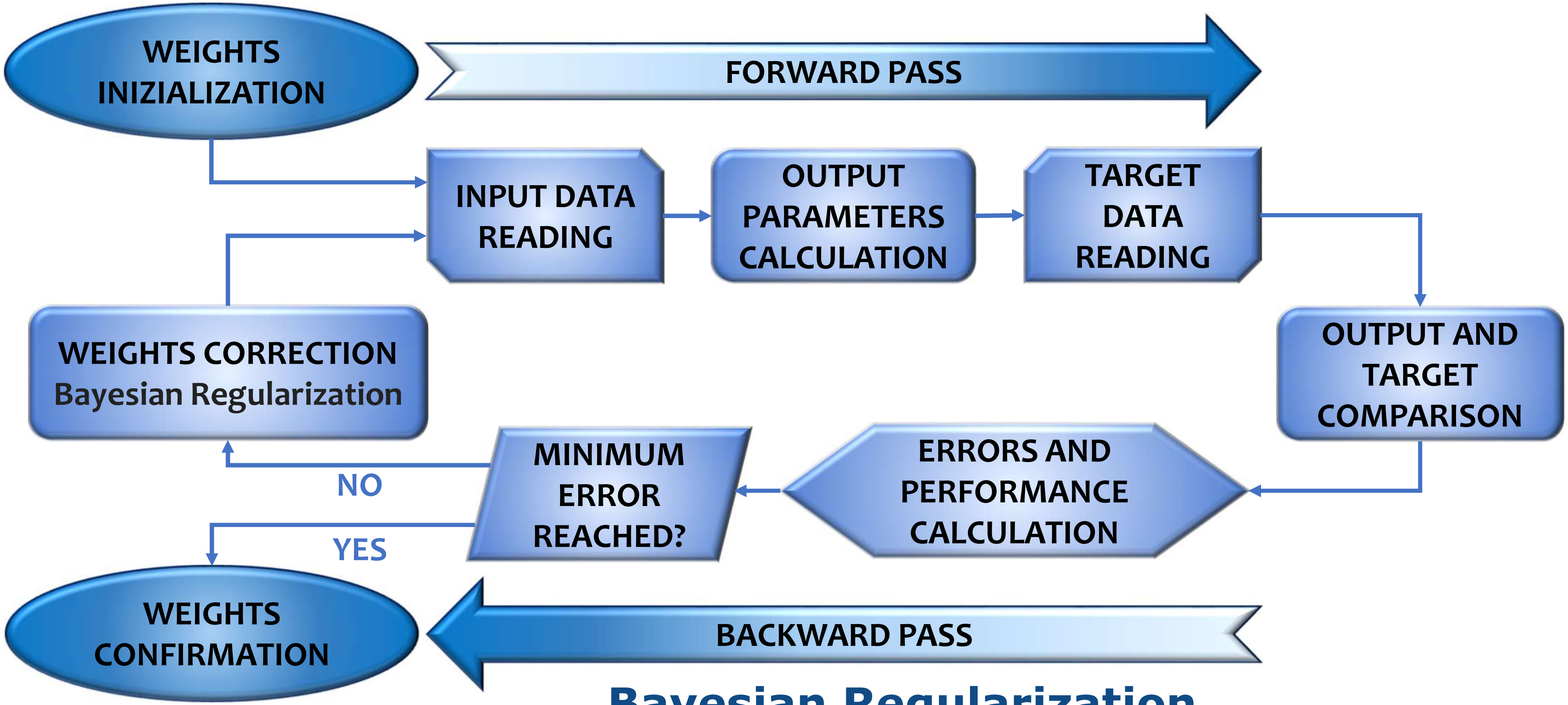
↓

	Fold 1	Fold 2	Fold 3	Fold 4	
Iteration 1	Validation	Train	Train	Train	Validation score 1
Iteration 2	Train	Validation	Train	Train	Validation score 2
Iteration 3	Train	Train	Validation	Train	Validation score 3
Iteration 4	Train	Train	Train	Validation	Validation score 4

↓

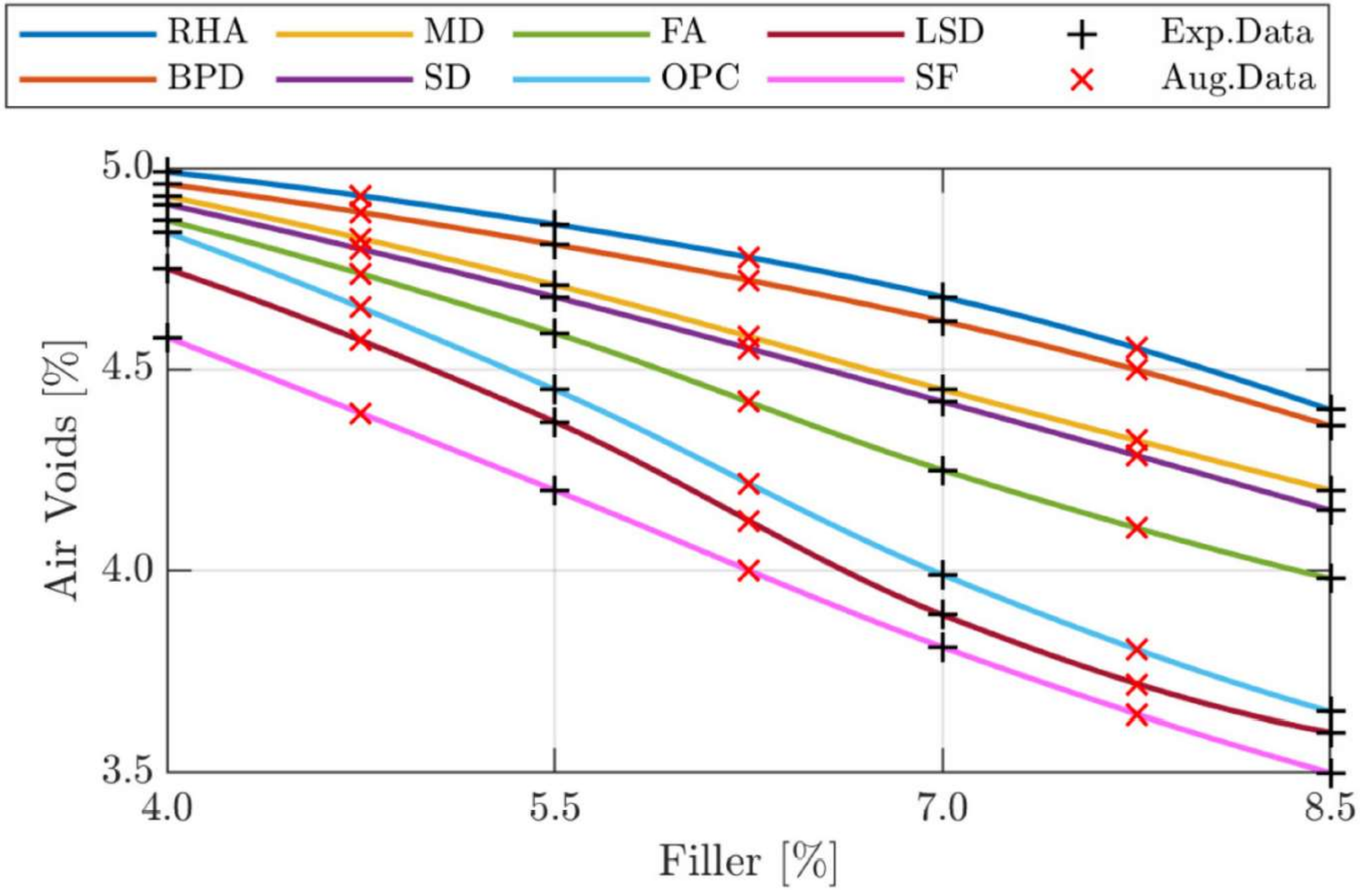
Average the scores obtaining the general performance of the model

Training Process



Bayesian Regularization

Data Augmentation



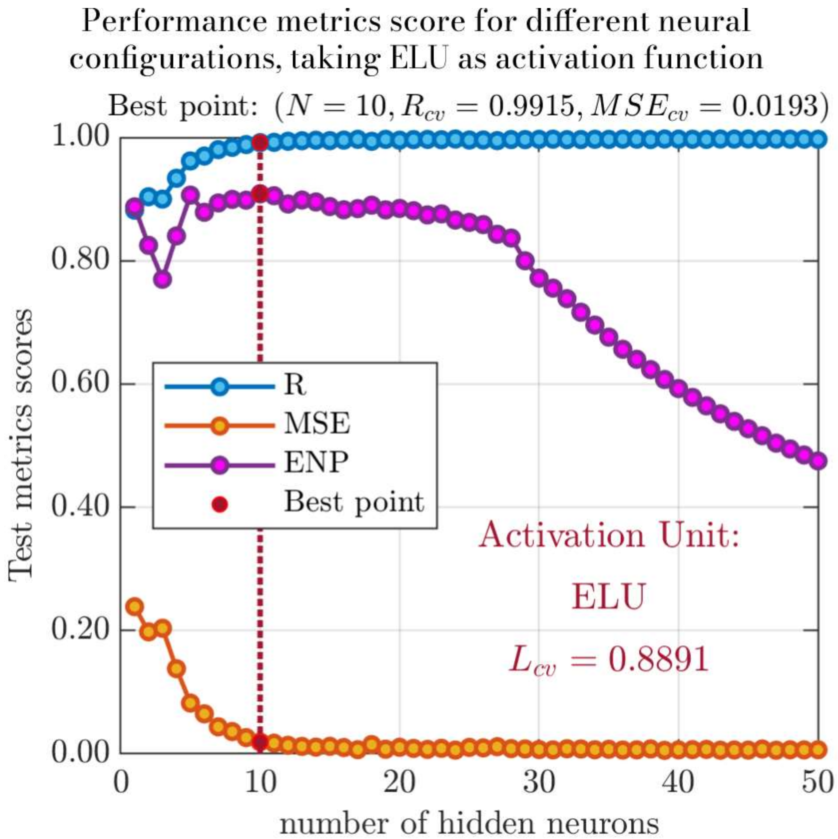
Augmented points (red cross marker) and available experimental points functions (black plus sign marker).

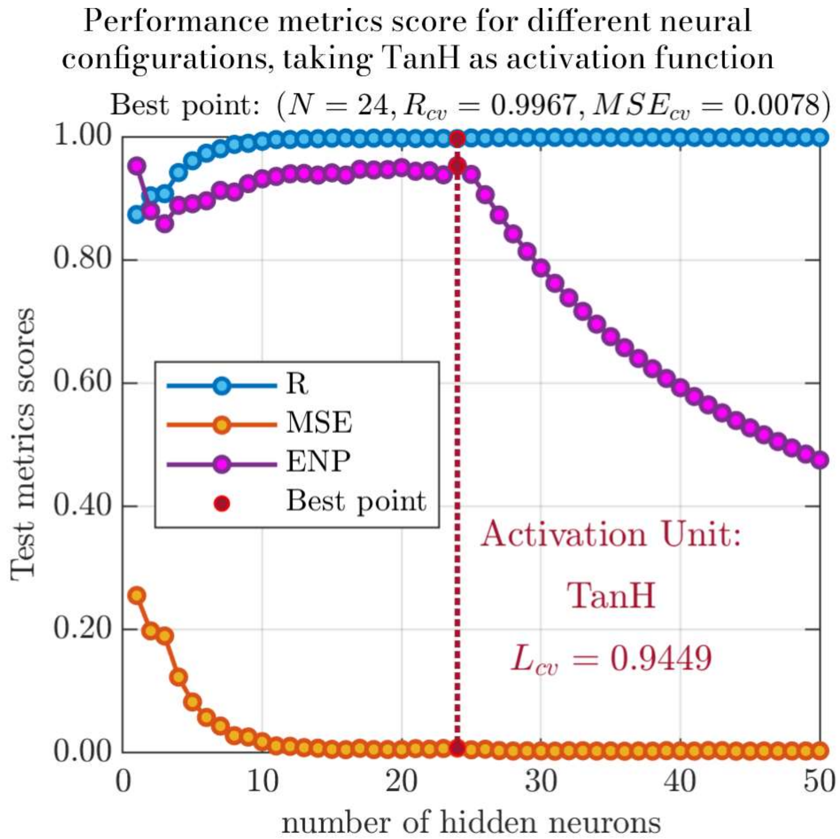
- Synthetic data generation
- Unaltered collected information meaning

Makima Interpolation

$$z(x, y) = \sum_{j=0}^{3} \sum_{k=0}^{3-j} q_{jk} x^j y^k$$

Neural Modeling Results





Remarks case study n.3

- WASTE Fillers can replace conventional filler in asphalt concretes.

- k-folds resampling and MAKIMA data-augmentation methods allow to properly train neural models.

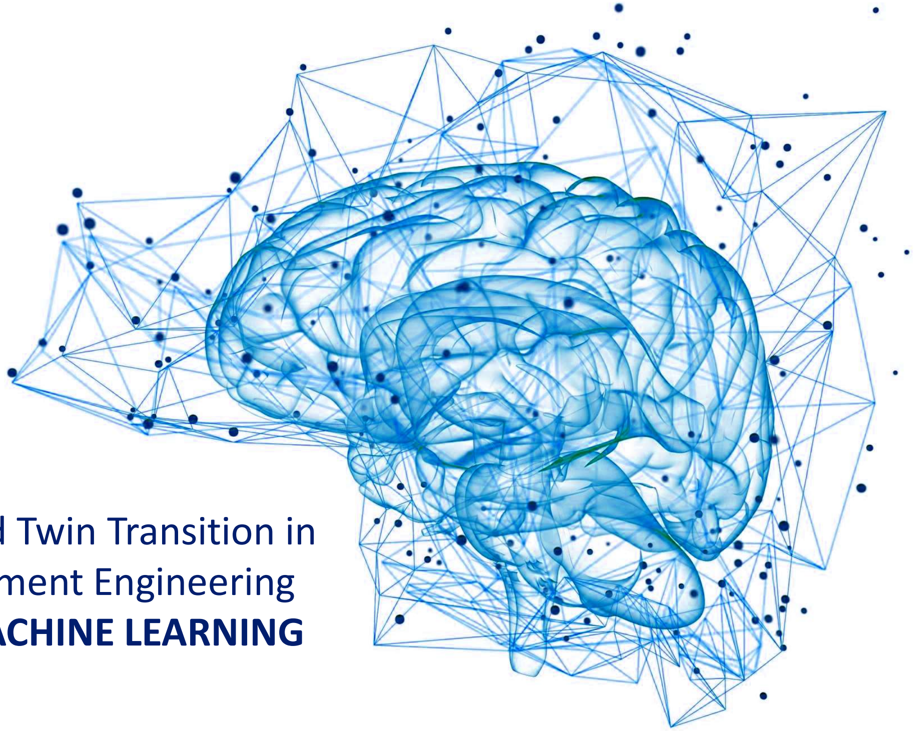
- The Artificial Neural Network architecture should be always optimized.

FINAL REMARKS (1/2)

1. Performance predictions via Machine Learning represent a contribution to *Pavement Engineering Digitalization*.
2. ANN non-linear fitting methods can positively contribute to the laboratory performance evaluation phase of bituminous mixtures, even for mixes with waste materials included in the composition, thus enforcing the *Green Transition* of Pavement Engineering.
3. Laboratory data consistency is a fundamental requisite to ensure neural models prediction accuracy.
4. Prediction accuracy is not based on the complexity of the model, but rather on the optimization of the model.

FINAL REMARKS (2/2)

1. SNNs (Shallow Neural Networks) have been shown to solve pretty well any multi-dimensional input-output fitting problem by providing an optimal number of hidden neurons.
2. The Bayesian optimization represents an effective approach to identify the optimal SNNs architecture and hyperparameters values.
3. The prediction accuracy of a SNNs model is very good, but a physical interpretation of the phenomena cannot be obtained (**BLACK BOX** issue).
4. Fatigue or permanent deformation resistance data should be included in the machine learning modeling, to further enhance the performance evaluation phase of asphalt concretes.



Toward Twin Transition in
Pavement Engineering
by **MACHINE LEARNING**

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