IMPaCT

EPSRC Centre for Doctoral Training in Innovative Metal Processing (IMPaCT)

Using Deep Neural Network with small dataset to Predict Solidification Cracking Susceptibility of Stainless Steels

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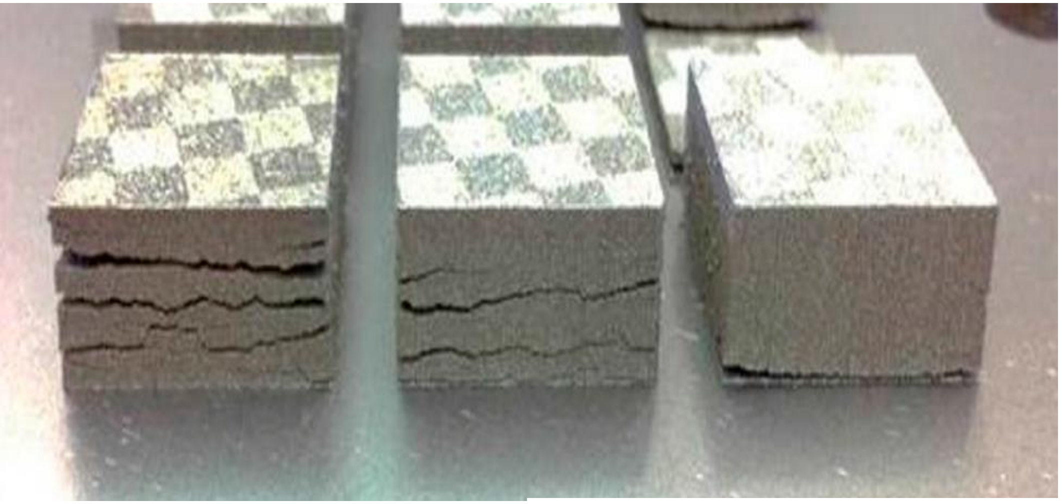
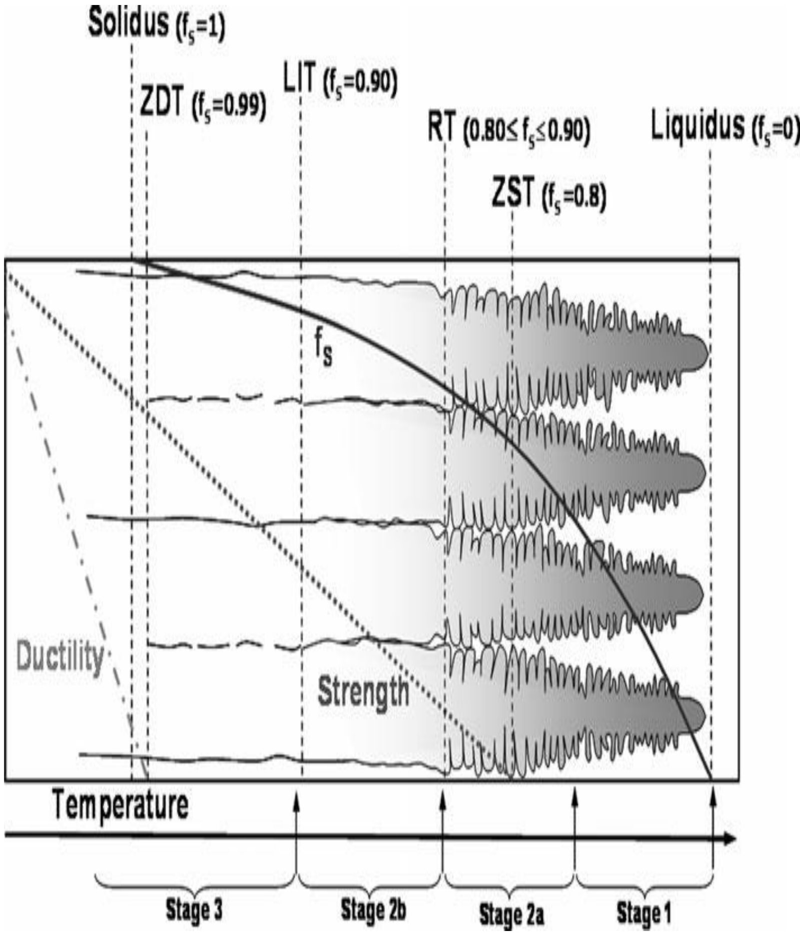
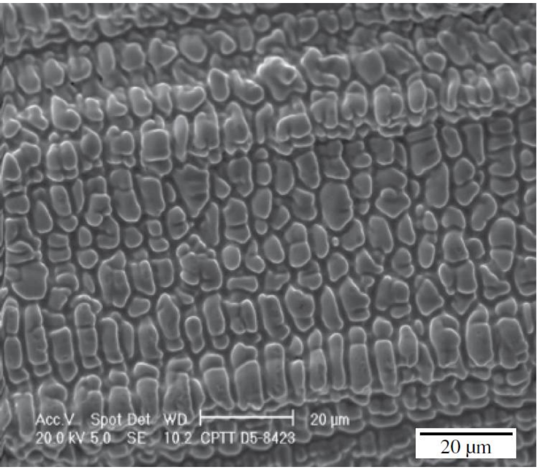
Outlines

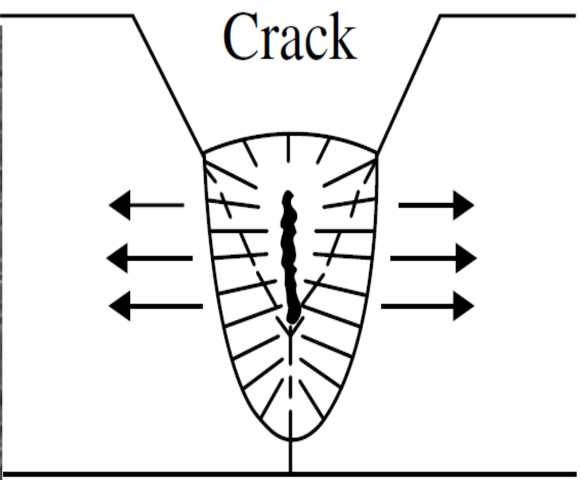
1 Solidification Cracking Susceptibility (SCS)
2 Neural Network (NN)
3 Work Routes
4 Prediction of Stainless Steel SCS Using NN
5 Conclusions

Solidification cracking in AM, casting & welding





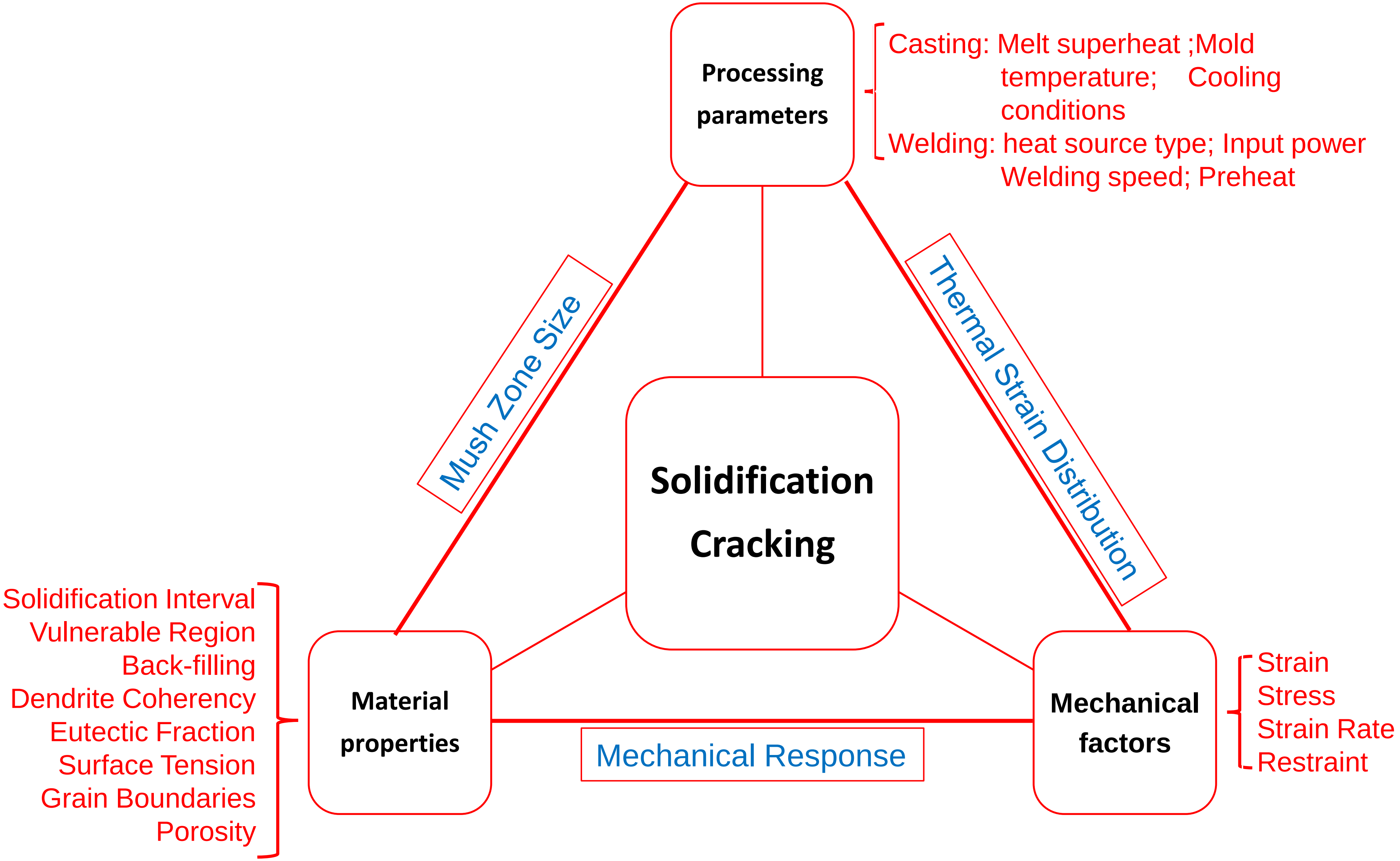




W. J. Sames, F. A. List, S. Pannala, R. R. Dehoff & S. S. Babu (2016): The metallurgy and processing science of metal additive manufacturing, International Materials Reviews
John C. Lippold(2015): Welding Metallurgy and Weldability,

Santillana, B., et al.,MMTA, 2012. 43(13); Lee Aucott, PhD thesis University of :Leicester

Three interactive factors



Processing parameters

Casting: Melt superheat ;Mold temperature; Cooling conditions

Welding: heat source type; Input power Welding speed; Preheat

Mush Zone Size

Thermal Strain Distribution

Solidification Cracking

Material properties

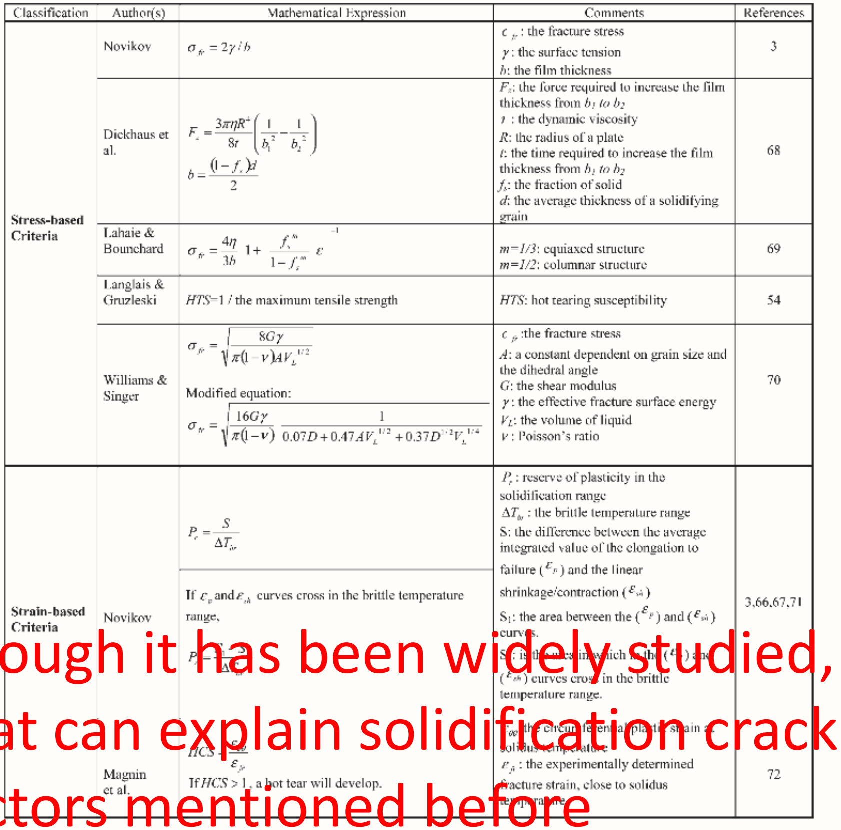
Solidification Interval
Vulnerable Region
Back-filling
Dendrite Coherency
Eutectic Fraction
Surface Tension
Grain Boundaries
Porosity

Mechanical Response

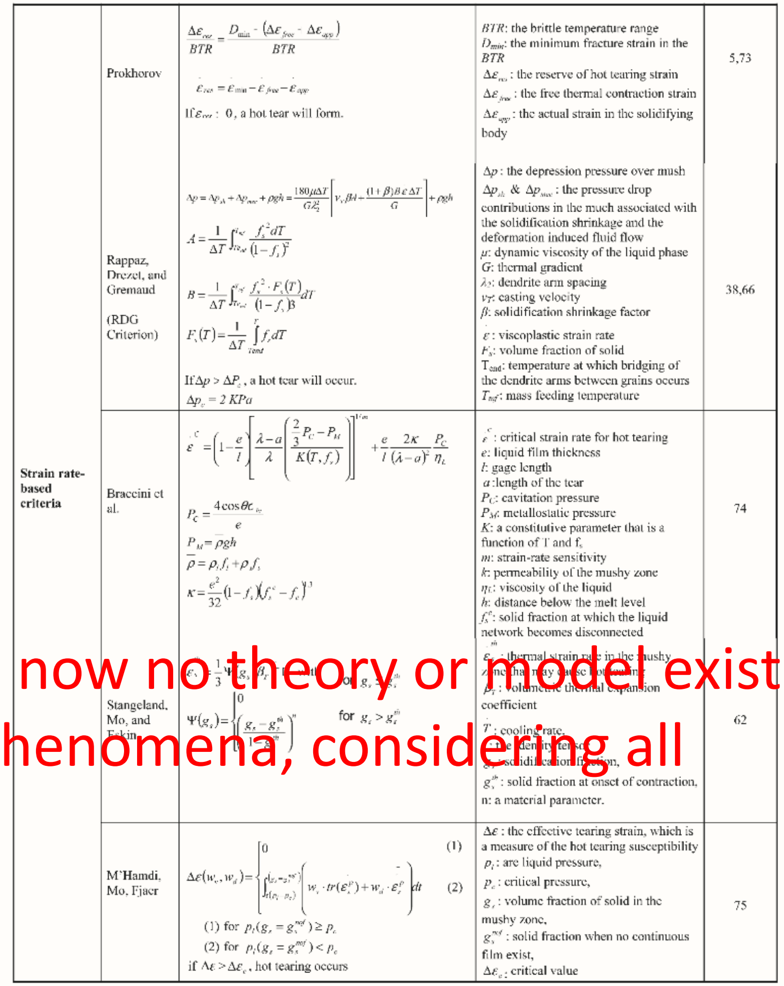
Mechanical factors

Strain
Stress
Strain Rate
Restraint

The limit of theories and models

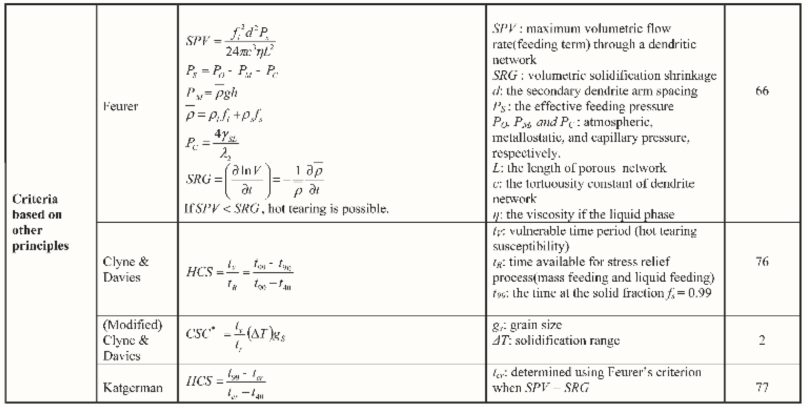


Classification	Author(s)	Mathematical Expression	Comments	References
Stress-based Criteria	Novikov	$\sigma_{fr} = 2\gamma / b$	c_{fr}: the fracture stress γ: the surface tension b: the film thickness	3
	Dickhaus et al.	$F_z = \frac{3\pi\eta R^4}{8t}\left(\frac{1}{b_1^2} - \frac{1}{b_2^2}\right)$ $b = \frac{(1-f_s)d}{2}$	F_z: the force required to increase the film thickness from b_1 *to* b_2 η : the dynamic viscosity R: the radius of a plate t: the time required to increase the film thickness from b_1 *to* b_2 f_s: the fraction of solid d: the average thickness of a solidifying grain	68
	Lahaie & Bounchard	$\sigma_{fr} = \frac{4\eta}{3b}\ 1 + \ \frac{f_s^m}{1-f_s^m}\ \varepsilon^{\ -1}$	$m=1/3$: equiaxed structure $m=1/2$: columnar structure	69
	Langlais & Gruzleski	HTS=1 / the maximum tensile strength	HTS: hot tearing susceptibility	54
	Williams & Singer	$\sigma_{fr} = \sqrt{\frac{8G\gamma}{\pi(1-\nu)AV_L^{1/2}}}$ Modified equation: $\sigma_{fr} = \sqrt{\frac{16G\gamma}{\pi(1-\nu)}\frac{1}{0.07D+0.47AV_L^{1/2}+0.37D^{1/2}V_L^{1/4}}}$	c_{fr} :the fracture stress A: a constant dependent on grain size and the dihedral angle G: the shear modulus γ: the effective fracture surface energy V_L: the volume of liquid ν : Poisson's ratio	70
Strain-based Criteria	Novikov	$P_r = \frac{S}{\Delta T_{br}}$ If ε_p and ε_{sh} curves cross in the brittle temperature range, $P_r = \frac{S_1}{\Delta T_{br}}$	P_r : reserve of plasticity in the solidification range ΔT_{br} : the brittle temperature range S: the difference between the average integrated value of the elongation to failure (ε_F) and the linear shrinkage/contraction (ε_{sh}) S$_1$: the area between the (ε_F) and (ε_{sh}) curves. S$_1$: is the area in which the (ε_F) and (ε_{sh}) curves cross in the brittle temperature range.	3,66,67,71
	Magnin et al.	$HCS = \frac{\varepsilon_{\theta\theta}}{\varepsilon_{fr}}$ If $HCS > 1$, a hot tear will develop.	$\varepsilon_{\theta\theta}$: the circumferential plastic strain at solidus temperature ε_{fr} : the experimentally determined fracture strain, close to solidus temperature	72



	Prokhorov	$\frac{\Delta\varepsilon_{res}}{BTR} = \frac{D_{min} - (\Delta\varepsilon_{free} - \Delta\varepsilon_{app})}{BTR}$ $\dot\varepsilon_{res} = \dot\varepsilon_{min} - \dot\varepsilon_{free} - \dot\varepsilon_{app}$ If ε_{res} : 0, a hot tear will form.	BTR: the brittle temperature range D_{min}: the minimum fracture strain in the BTR $\Delta\varepsilon_{res}$: the reserve of hot tearing strain $\Delta\varepsilon_{free}$: the free thermal contraction strain $\Delta\varepsilon_{app}$: the actual strain in the solidifying body	5,73
	Rappaz, Drezet, and Gremaud (RDG Criterion)	$\Delta p = \Delta p_{sh} + \Delta p_{mec} + \rho gh = \frac{180\mu\Delta T}{G\lambda_2^2}\left[v_T\beta A + \frac{(1+\beta)B\dot\varepsilon\Delta T}{G}\right] + \rho gh$ $A = \frac{1}{\Delta T}\int_{T_{end}}^{T_{mf}} \frac{f_s^2 dT}{(1-f_s)^2}$ $B = \frac{1}{\Delta T}\int_{T_{end}}^{T_{mf}} \frac{f_s^2 \cdot F_s(T)}{(1-f_s)^3} dT$ $F_s(T) = \frac{1}{\Delta T}\int_{Tend}^{T} f_s dT$ If $\Delta p > \Delta P_c$, a hot tear will occur. $\Delta p_c = 2\ KPa$	Δp : the depression pressure over mush Δp_{sh} & Δp_{mec} : the pressure drop contributions in the much associated with the solidification shrinkage and the deformation induced fluid flow μ: dynamic viscosity of the liquid phase G: thermal gradient λ_2: dendrite arm spacing v_T: casting velocity β: solidification shrinkage factor $\dot\varepsilon$: viscoplastic strain rate F_s: volume fraction of solid T$_{end}$: temperature at which bridging of the dendrite arms between grains occurs T_{mf}: mass feeding temperature	38,66
Strain rate-based criteria	Braccini et al.	$\dot\varepsilon^c = \left(1-\frac{e}{l}\right)\left[\frac{\lambda-a}{\lambda}\left(\frac{\frac{2}{3}P_C - P_M}{K(T,f_s)}\right)\right]^{1/m} + \frac{e}{l}\frac{2\kappa}{(\lambda-a)^2}\frac{P_C}{\eta_L}$ $P_C = \frac{4\cos\theta c_{lv}}{e}$ $P_M = \bar\rho gh$ $\bar\rho = \rho_l f_l + \rho_s f_s$ $\kappa = \frac{e^2}{32}(1-f_s)(f_s^c - f_s)^3$	$\dot\varepsilon^c$: critical strain rate for hot tearing e: liquid film thickness l: gage length a :length of the tear P_C: cavitation pressure P_M: metallostatic pressure K: a constitutive parameter that is a function of T and f$_s$ m: strain-rate sensitivity k: permeability of the mushy zone η_L: viscosity of the liquid h: distance below the melt level f_s^c: solid fraction at which the liquid network becomes disconnected	74
	Stangeland, Mo, and Eskin	$\dot\varepsilon_v^{th} = \frac{1}{3}\Psi(g_s)\beta_T\dot T$ [illegible] for $g_s \le g_s^{th}$ $\Psi(g_s) = \begin{cases} 0 \\ \left(\frac{g_s - g_s^{th}}{1-g_s^{th}}\right)^n & \text{for } g_s > g_s^{th} \end{cases}$	$\dot\varepsilon_v^{th}$: thermal strain rate in the mushy zone that may cause hot tearing β_T : volumetric thermal expansion coefficient $\dot T$: cooling rate, [illegible] : the identity tensor, g_s: solidification fraction, g_s^{th} : solid fraction at onset of contraction, n: a material parameter.	62
	M'Hamdi, Mo, Fjaer	$\Delta\varepsilon(w_v, w_d) = \begin{cases} 0 & (1) \\ \int_{t(p_l=p_c)}^{t(g_s=g_s^{nf})}\left(w_v \cdot tr(\dot\varepsilon_s^p) + w_d \cdot \bar{\dot\varepsilon}_s^p\right)dt & (2) \end{cases}$ (1) for $p_l(g_s = g_s^{nf}) \ge p_c$ (2) for $p_l(g_s = g_s^{nf}) < p_c$ if $\Delta\varepsilon > \Delta\varepsilon_c$, hot tearing occurs	$\Delta\varepsilon$: the effective tearing strain, which is a measure of the hot tearing susceptibility p_l : are liquid pressure, p_c : critical pressure, g_s : volume fraction of solid in the mushy zone, g_s^{nf} : solid fraction when no continuous film exist, $\Delta\varepsilon_c$: critical value	75

Though it has been widely studied, until now no theory or model exist that can explain solidification cracking phenomena, considering all factors mentioned before



Criteria based on other principles	Feurer	$SPV = \frac{f_l^2 d^2 P_s}{24\pi c^3\eta L^2}$ $P_S = P_O - P_M - P_C$ $P_M = \bar\rho gh$ $\bar\rho = \rho_l f_l + \rho_s f_s$ $P_C = \frac{4\gamma_{SL}}{\lambda_2}$ $SRG = \left(\frac{\partial \ln V}{\partial t}\right) = -\frac{1}{\bar\rho}\frac{\partial\bar\rho}{\partial t}$ If $SPV < SRG$, hot tearing is possible.	SPV : maximum volumetric flow rate(feeding term) through a dendritic network SRG : volumetric solidification shrinkage d: the secondary dendrite arm spacing P_S: the effective feeding pressure P_O, P_M, *and* P_C : atmospheric, metallostatic, and capillary pressure, respectively. L: the length of porous network c: the tortuousity constant of dendrite network η: the viscosity if the liquid phase	66
	Clyne & Davies	$HCS = \frac{t_V}{t_R} = \frac{t_{99} - t_{90}}{t_{90} - t_{40}}$	t_V: vulnerable time period (hot tearing susceptibility) t_R: time available for stress relief process(mass feeding and liquid feeding) t_{99}: the time at the solid fraction $f_s = 0.99$	76
	(Modified) Clyne & Davies	$CSC^* = \frac{t_v}{t_r}(\Delta T)g_s$	g_s: grain size ΔT: solidification range	2
	Katgerman	$HCS = \frac{t_{99} - t_{cr}}{t_{cr} - t_{40}}$	t_{cr}: determined using Feurer's criterion when $SPV = SRG$	77

Li, S. & Apelian, D. HOT TEARING OF ALUMINUM ALLOYS A CRITICAL LITERATURE REVIEW. International Journal of Metalcasting, 2011, 5

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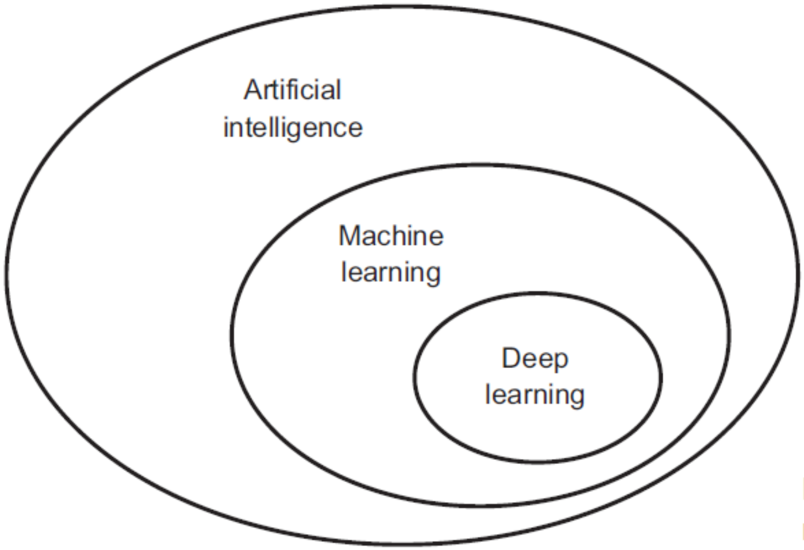
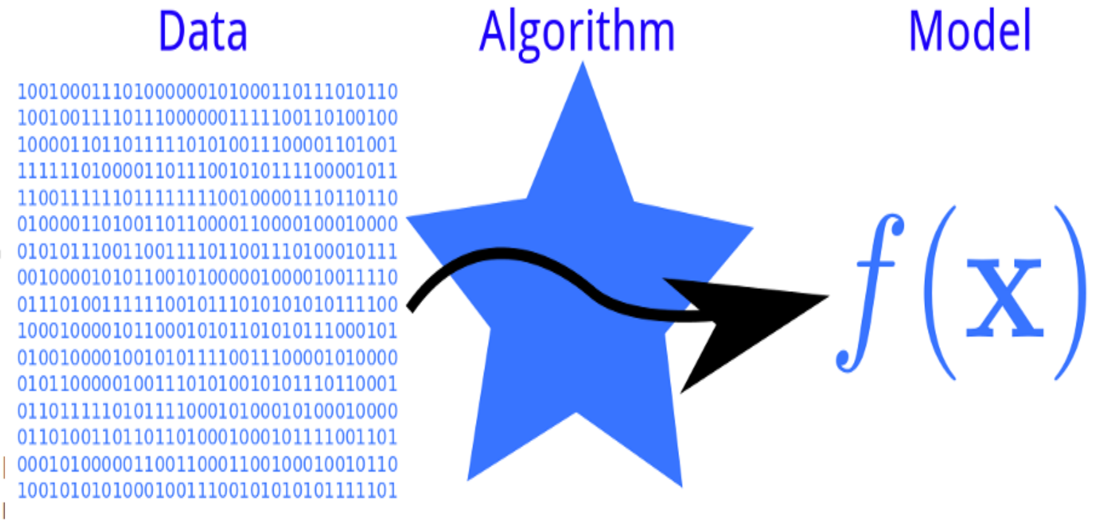
Neural Network

NN a data based and data driven method

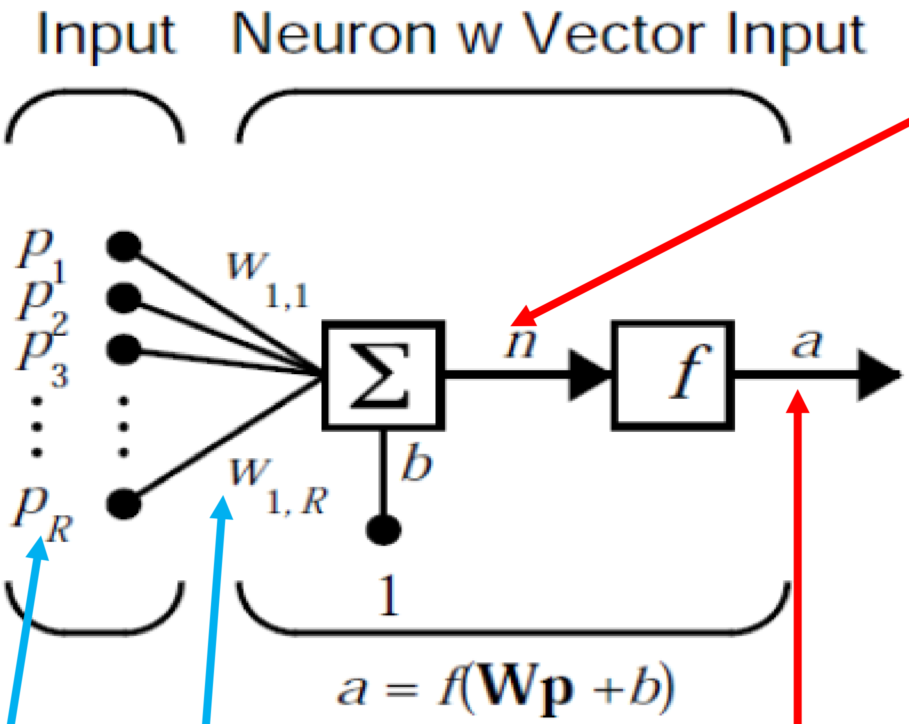
Deep learning (deep neural network)

Problems of multiple variables and complexity, e.g. solidification cracking





The basic unit of neural network



$$n = \begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,R} \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_R \end{bmatrix} + b$$

$$= W_{1\times R}\, p_{R\times 1} + b$$

$$= W_{1,1}p_1 + W_{1,2}p_2 + \cdots + W_{1,R}p_R + b$$

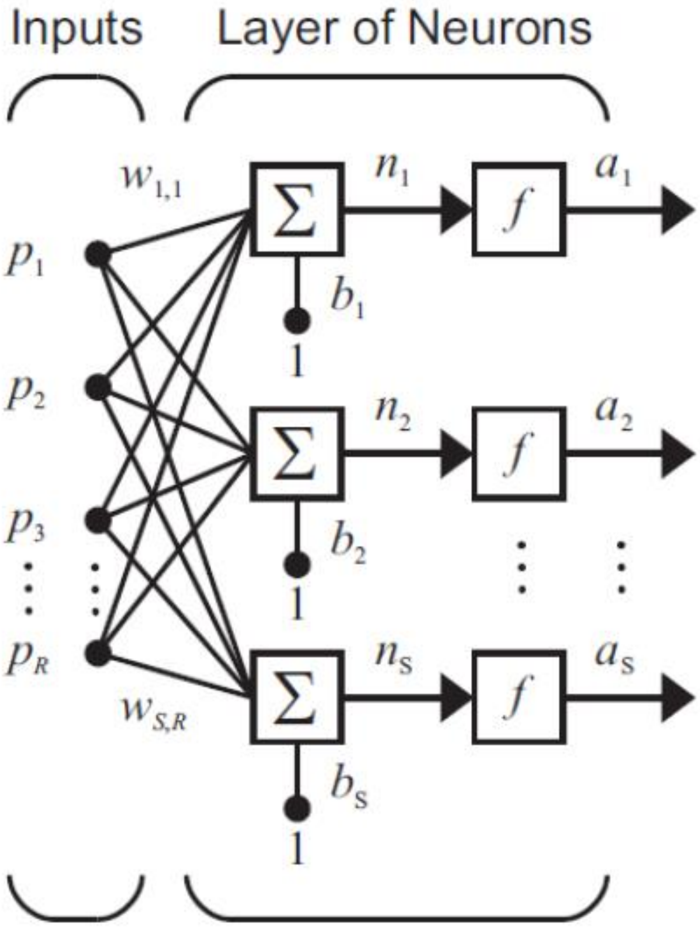
number of input: R

$$\mathrm{p} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_R \end{bmatrix} \quad \mathrm{W} = \begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,R} \end{bmatrix}$$

$$a = f(n) = f\left(\begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,R} \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_R \end{bmatrix} + b \right)$$

$$= f(W_{1,1}p_1 + W_{1,2}p_2 + \cdots + W_{1,R}p_R + b)$$

S-neuron, one-layer network



$$\mathbf{a} = \mathbf{f}(\mathbf{Wp} + \mathbf{b})$$

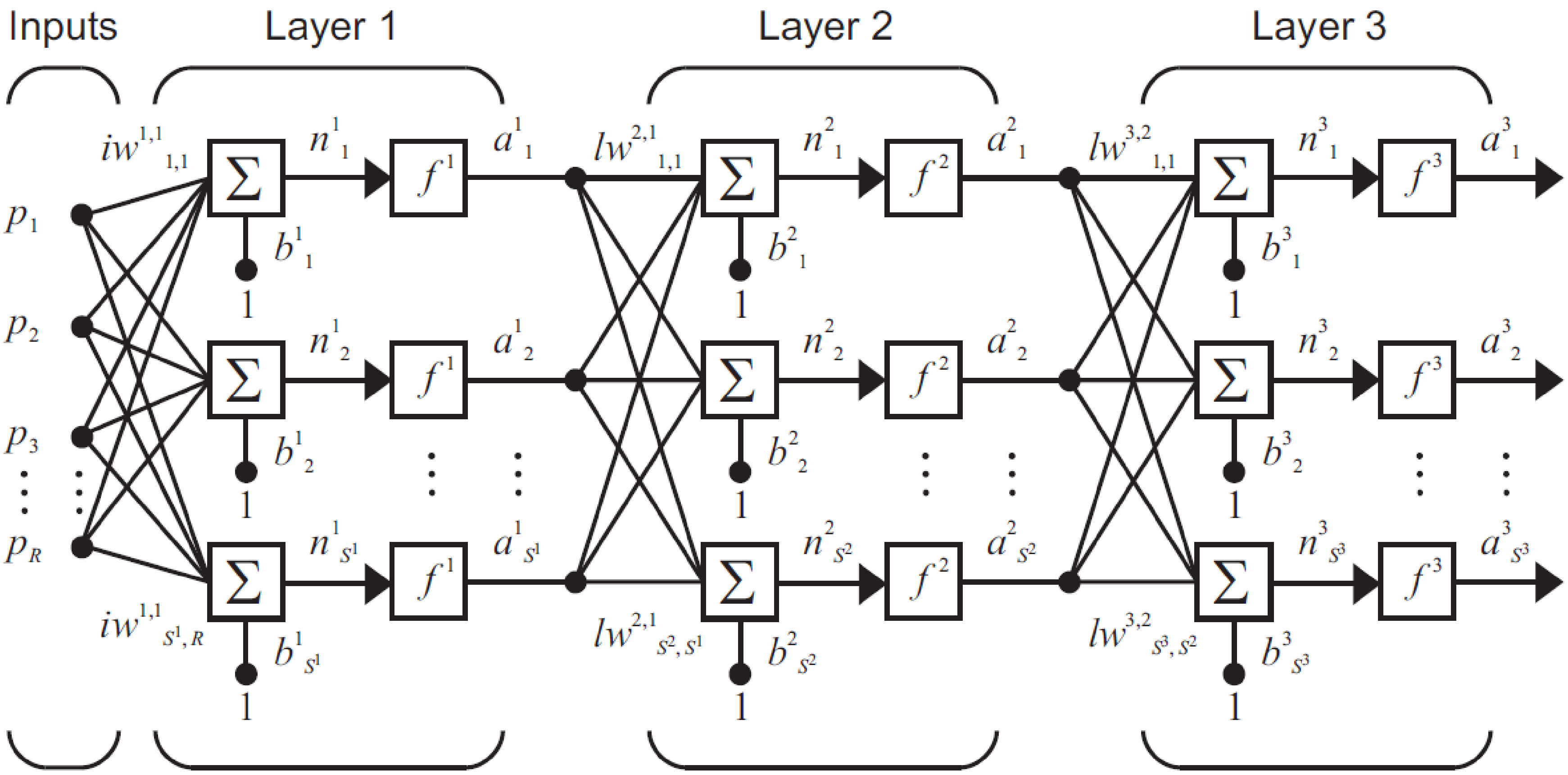
$$\mathrm{W} = \begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,R} \\ W_{2,1} & W_{2,2} & \cdots & W_{2,R} \\ \vdots & \vdots & \cdots & \vdots \\ W_{S,1} & W_{S,2} & \cdots & W_{S,R} \end{bmatrix}$$

$$\mathrm{p} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_R \end{bmatrix}, b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_S \end{bmatrix}, n = \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_S \end{bmatrix}, a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_S \end{bmatrix}$$

$$n = \begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,R} \\ W_{2,1} & W_{2,2} & \cdots & W_{2,R} \\ \vdots & \vdots & \cdots & \vdots \\ W_{S,1} & W_{S,2} & \cdots & W_{S,R} \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_R \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_S \end{bmatrix}$$

$$\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_S \end{bmatrix} = f\left(\begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,R} \\ W_{2,1} & W_{2,2} & \cdots & W_{2,R} \\ \vdots & \vdots & \cdots & \vdots \\ W_{S,1} & W_{S,2} & \cdots & W_{S,R} \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_R \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_S \end{bmatrix} \right)$$

Three-layers Network



$$\mathbf{a}^1 = \mathbf{f}^1(\mathbf{IW}^{1,1}\mathbf{p}+\mathbf{b}^1) \qquad \mathbf{a}^2 = \mathbf{f}^2(\mathbf{LW}^{2,1}\mathbf{a}^1+\mathbf{b}^2) \qquad \mathbf{a}^3 = \mathbf{f}^3(\mathbf{LW}^{3,2}\mathbf{a}^2+\mathbf{b}^3)$$

$$\mathbf{a}^3 = \mathbf{f}^3(\mathbf{LW}^{3,2}\mathbf{f}^2(\mathbf{LW}^{2,1}\mathbf{f}^1(\mathbf{IW}^{1,1}\mathbf{p}+\mathbf{b}^1)+\mathbf{b}^2)+\mathbf{b}^3)$$

Beale, M.H., M.T. Hagan, and H.B. Demuth, Neural Network Toolbox™ User's Guide.
2016: The Mathworks Inc.

Training process

Changing NN’s parameters θ (i.e. weights w and bias b) to minimize mse (mean square error) and msw (mean square weight, in order to improve generalization)

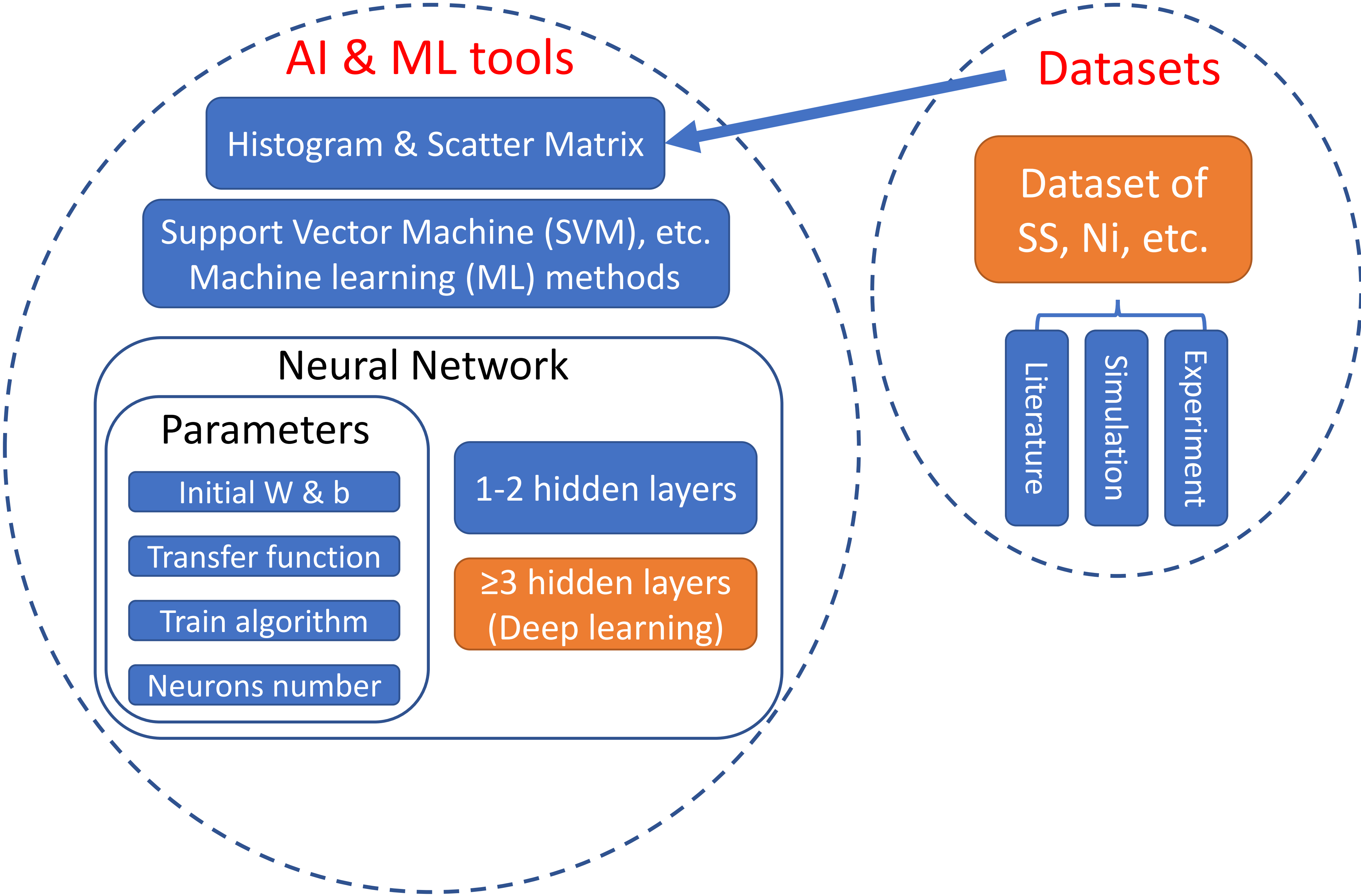
$$\boxed{\text{mse}} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad \boxed{\text{msw}} = \frac{1}{n}\sum_{j=1}^{n}W_j^2$$

$$\mathbf{J(\theta)} = \text{msereg} = \gamma\,\text{mse} + (1-\gamma)\,\text{msw}$$

Backpropagation algorithm (most popular one in training)

Training/testing dataset: evaluate the reliability of a NN

3 Work Routes



AI & ML tools

Histogram & Scatter Matrix

Support Vector Machine (SVM), etc.
Machine learning (ML) methods

Neural Network

Parameters

- Initial W & b
- Transfer function
- Train algorithm
- Neurons number

1-2 hidden layers

≥3 hidden layers (Deep learning)

Datasets

Dataset of SS, Ni, etc.

- Literature
- Simulation
- Experiment

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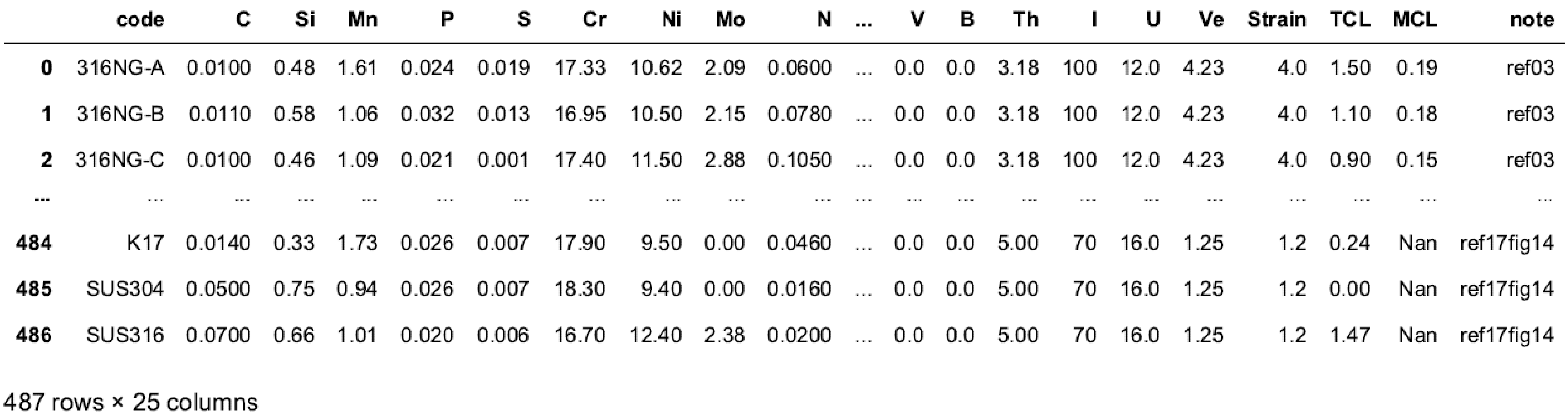
Stainless Steel Varestraint Test Dataset



	code	C	Si	Mn	P	S	Cr	Ni	Mo	N	...	V	B	Th	I	U	Ve	Strain	TCL	MCL	note
0	316NG-A	0.0100	0.48	1.61	0.024	0.019	17.33	10.62	2.09	0.0600	...	0.0	0.0	3.18	100	12.0	4.23	4.0	1.50	0.19	ref03
1	316NG-B	0.0110	0.58	1.06	0.032	0.013	16.95	10.50	2.15	0.0780	...	0.0	0.0	3.18	100	12.0	4.23	4.0	1.10	0.18	ref03
2	316NG-C	0.0100	0.46	1.09	0.021	0.001	17.40	11.50	2.88	0.1050	...	0.0	0.0	3.18	100	12.0	4.23	4.0	0.90	0.15	ref03
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
484	K17	0.0140	0.33	1.73	0.026	0.007	17.90	9.50	0.00	0.0460	...	0.0	0.0	5.00	70	16.0	1.25	1.2	0.24	Nan	ref17fig14
485	SUS304	0.0500	0.75	0.94	0.026	0.007	18.30	9.40	0.00	0.0160	...	0.0	0.0	5.00	70	16.0	1.25	1.2	0.00	Nan	ref17fig14
486	SUS316	0.0700	0.66	1.01	0.020	0.006	16.70	12.40	2.38	0.0200	...	0.0	0.0	5.00	70	16.0	1.25	1.2	1.47	Nan	ref17fig14

487 rows × 25 columns

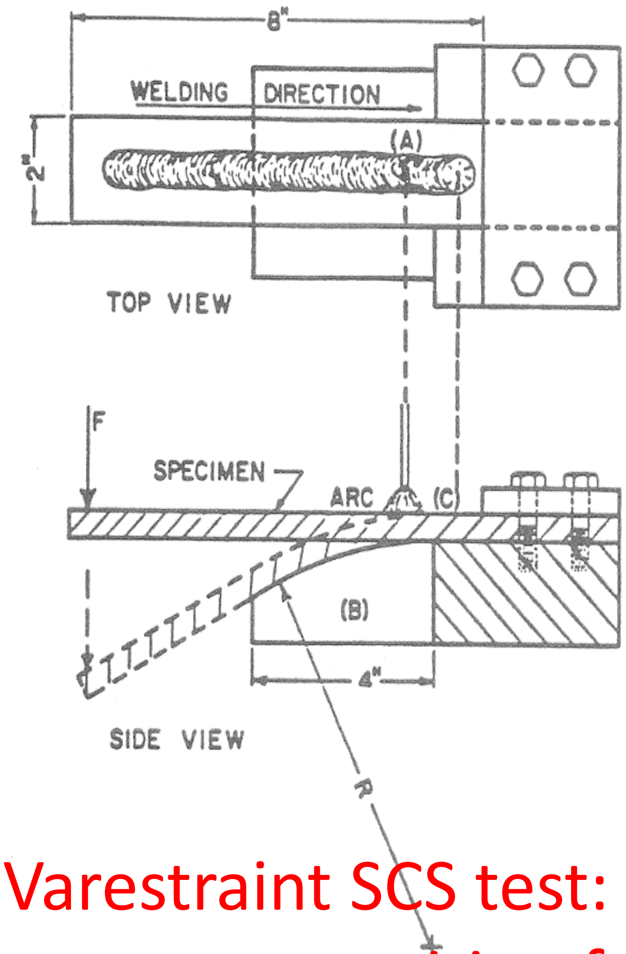
487 testing data： 487*22 matrix

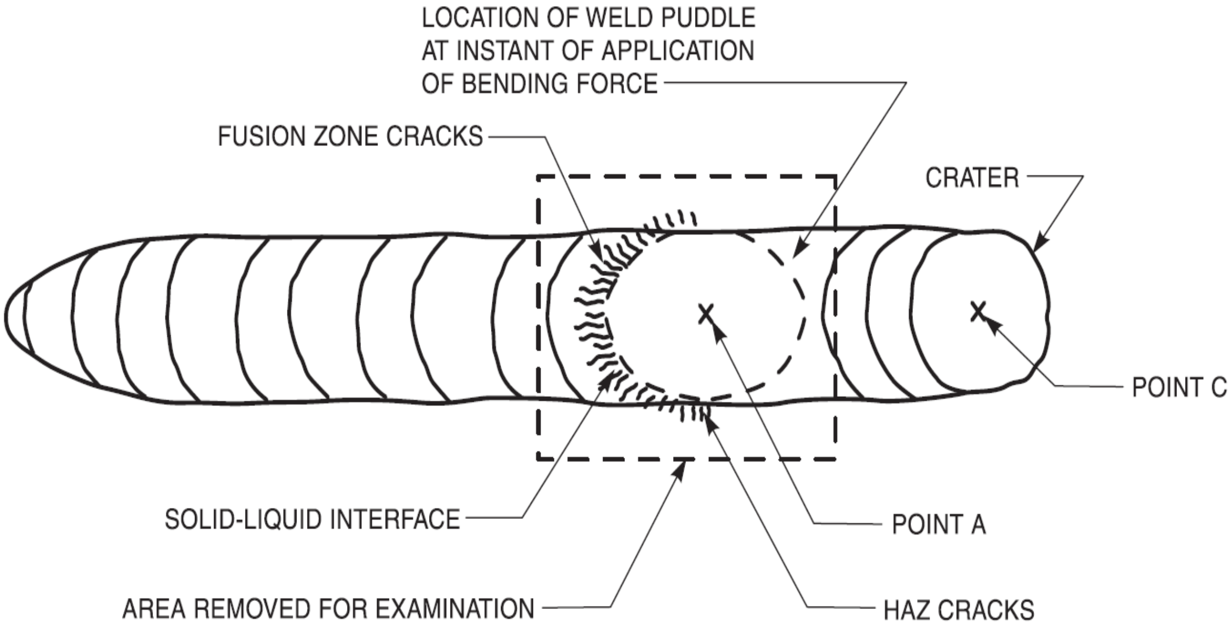
21 input: composition and test parameters

1 output: TCL

Weldability Varestraint Test

Lundin: WRC509 Weldability and hot ductility behavior of nuclear grade austenitic stainless steels

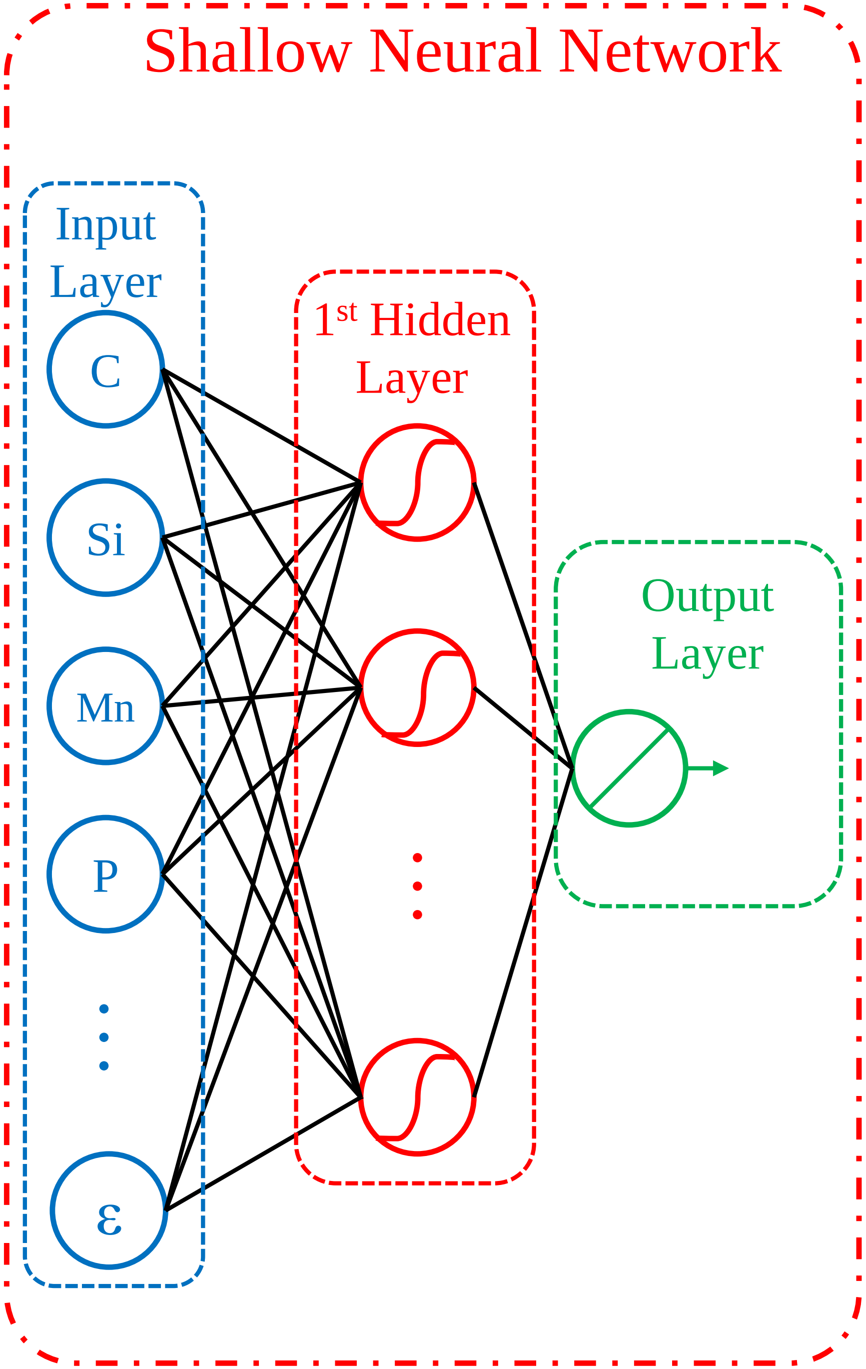


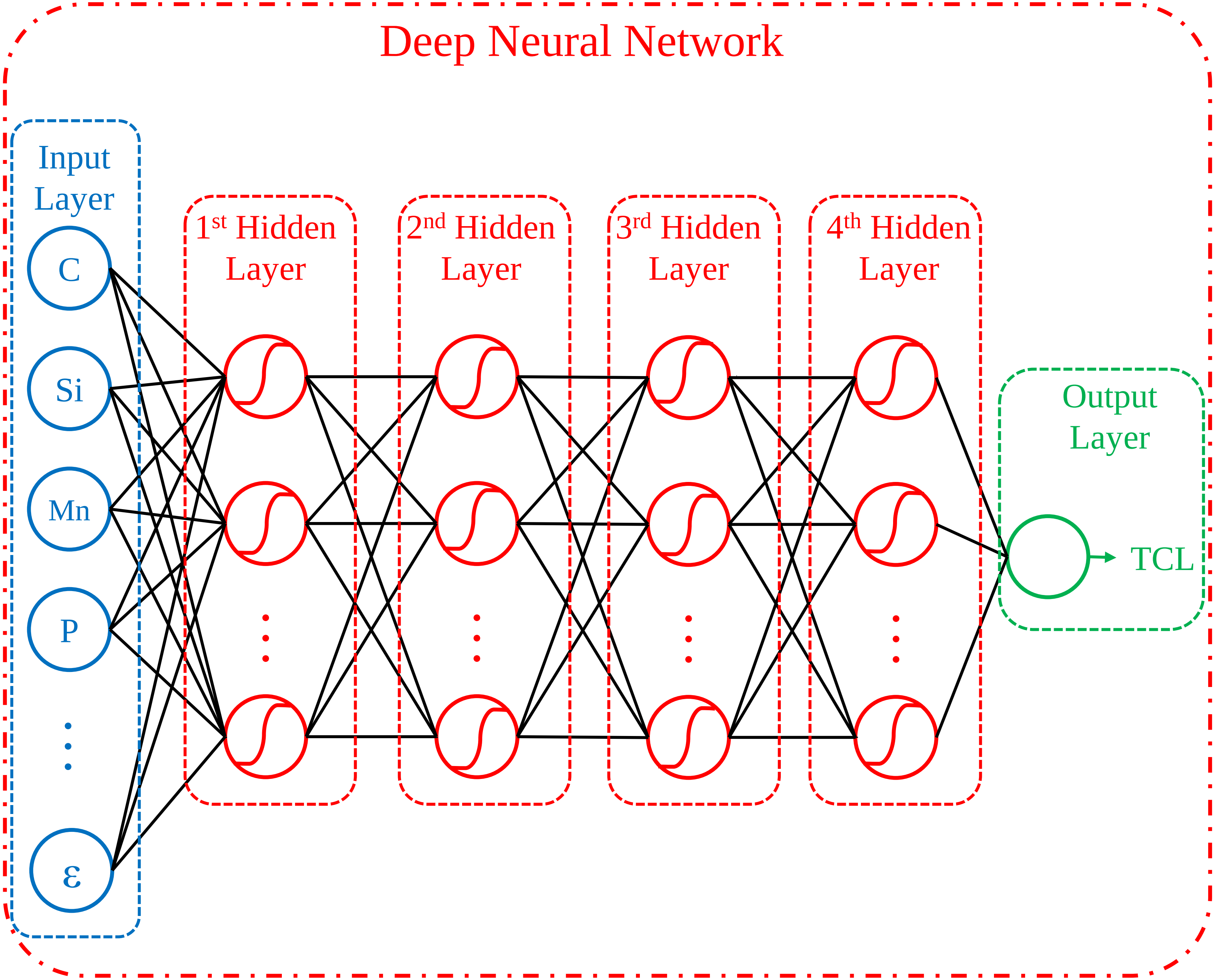


TOP SURFACE OF TEST WELD SHOWING LOCATION OF ARC, WELD PUDDLE, SOLID-LIQUID INTERFACE AT INSTANT OF APPLICATION OF BENDING FORCE AND WELD METAL AND HEAT-AFFECTED ZONE HOT CRACKS.

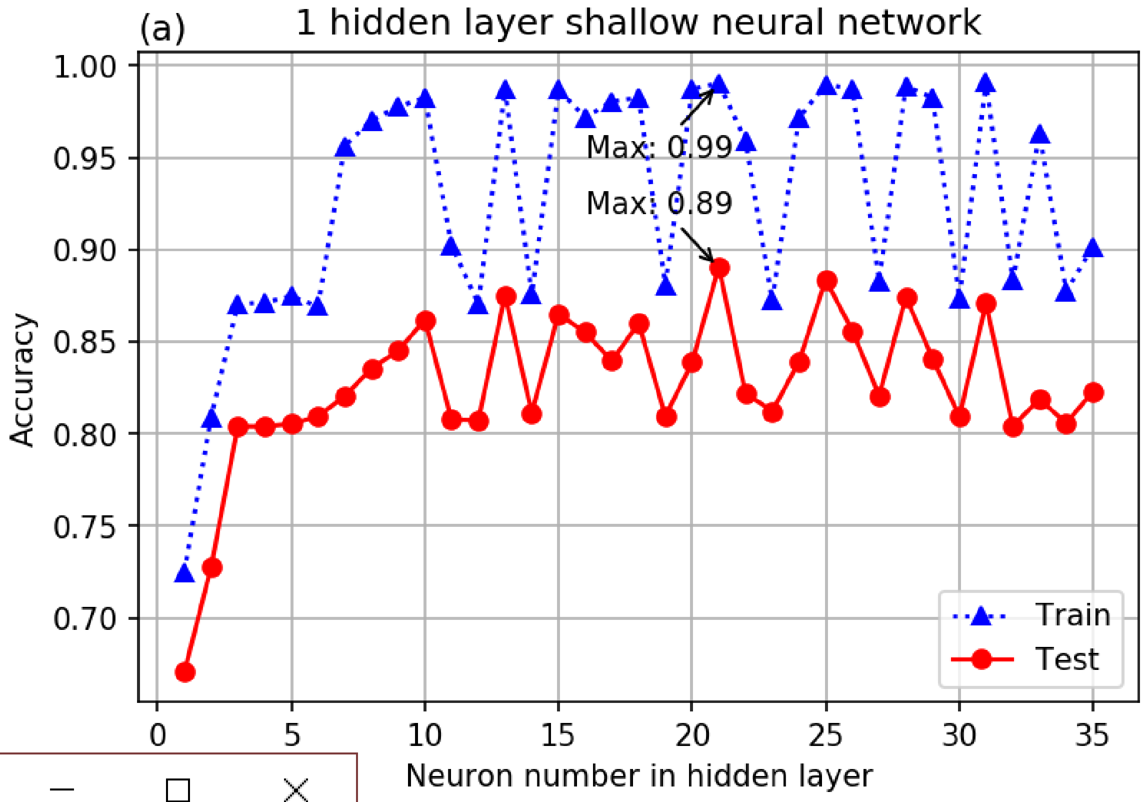
Varestraint SCS test: include three type factors in one test : composition factors, processing parameters, and strain

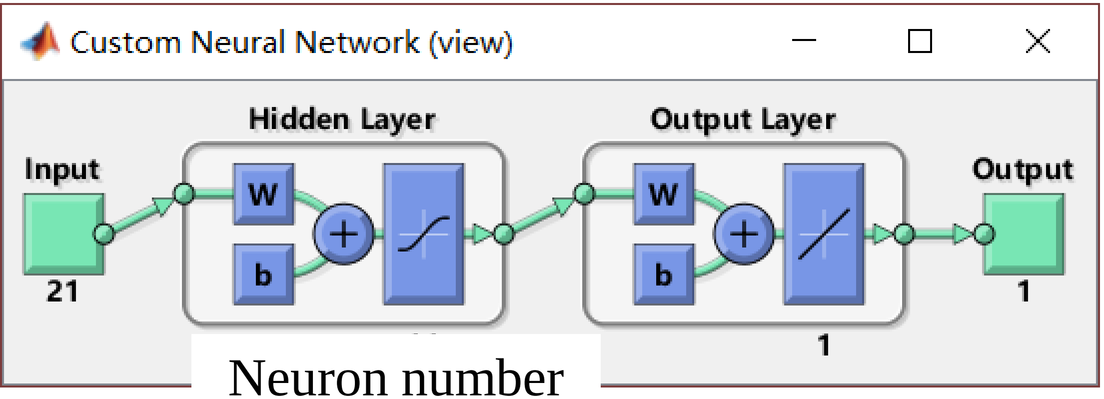
Total crack length (TCL): indicator for SCS


Shallow Neural Network
Input Layer
C
Si
Mn
P
ε
1st Hidden Layer
Output Layer


Deep Neural Network
Input Layer
C
Si
Mn
P
⋮
ε
1st Hidden Layer
2nd Hidden Layer
3rd Hidden Layer
4th Hidden Layer
Output Layer
TCL

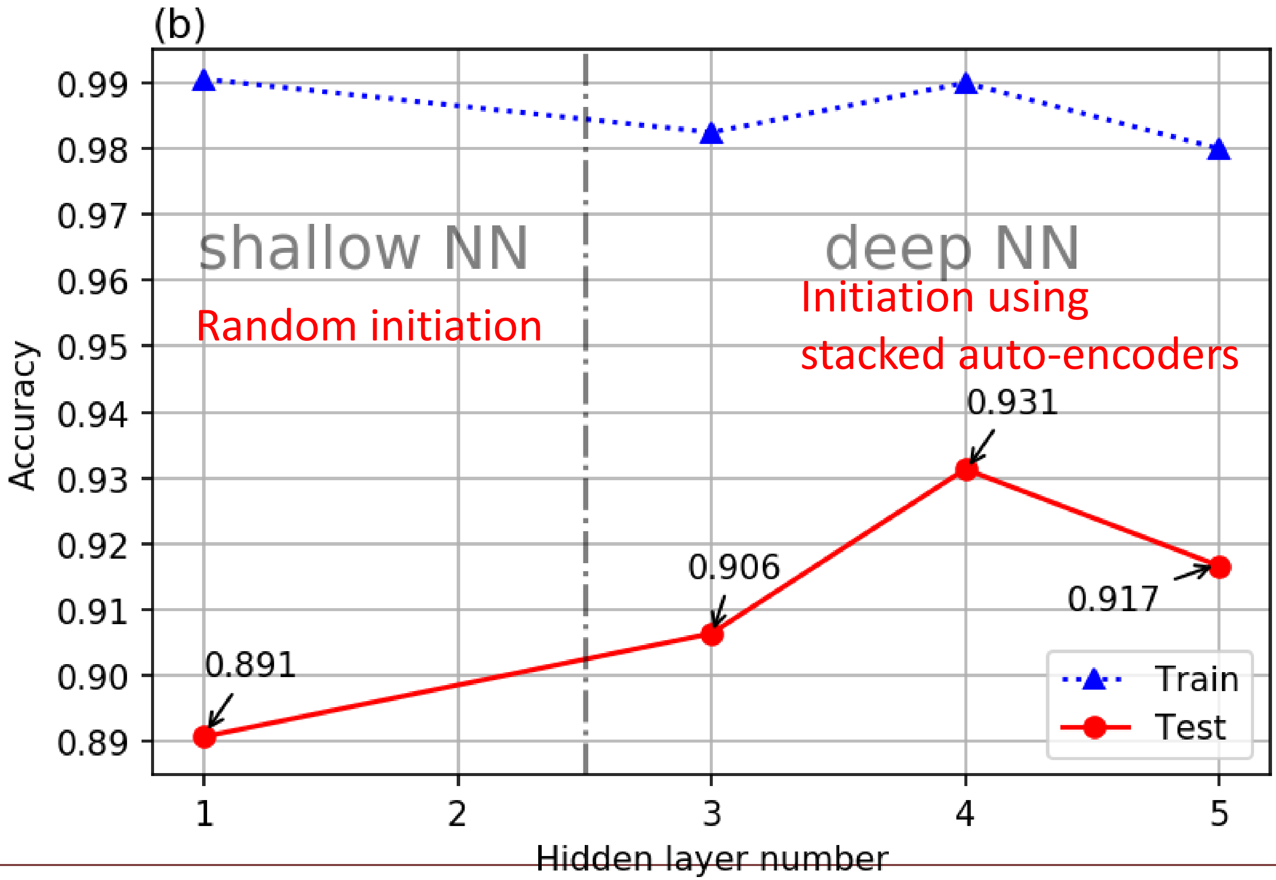
Accuracy vs. Neuron Number (1 Hidden Layer SNN)



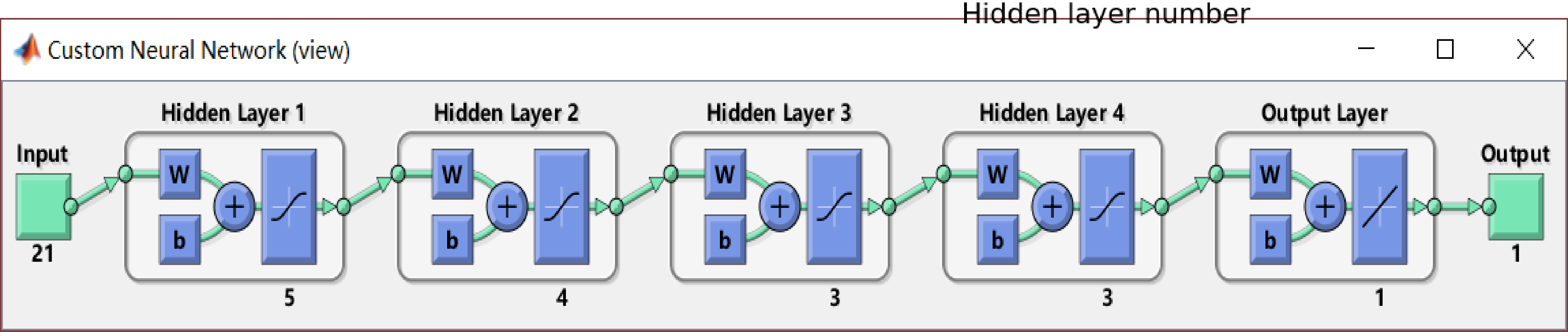


Neuron number
1-35

Accuracy vs. Depth of Neural Network



The structure of deep neural network:
Using the 21 inputs- (5-4-3-3) - 1output DNN as an example



The equations and its weights & bias of the optimal DNN

$W^{(1)}$																					$b^{(1)}$
0.21302	-0.13728	-0.29130	0.30728	-0.22614	-0.18915	0.08463	0.83295	-0.09320	0.06928	0.04505	0.12717	0.27171	-0.08078	0.40400	0.07463	0.89075	0.27322	0.25324	-0.64984	0.07199	0.40058
-0.08141	0.11454	0.28791	-0.47611	-0.14114	1.15287	-0.12534	0.89128	-0.62873	0.03279	0.00436	0.54762	-0.76461	0.02923	0.57712	0.07656	-0.14809	-0.65051	1.11834	0.39843	0.12635	0.80163
-0.96144	-0.05044	-0.33331	-0.79264	0.36823	-0.01755	-0.09935	0.20156	-0.92305	0.68631	-0.15720	-0.28002	0.02075	-1.10695	-0.36385	0.55782	0.06162	-0.58075	-0.26965	-0.03545	1.72419	1.18896
-0.28734	-0.39078	-0.53766	-0.37878	0.18985	0.24885	0.20358	-0.21241	0.19951	-0.01238	0.25977	0.06853	0.91162	0.21018	-0.42271	0.11499	-0.64558	0.23226	-1.04965	-0.49250	0.21684	0.67331
-0.33686	0.19210	0.72565	0.67674	0.11436	-0.89480	-1.13927	-0.80494	0.02992	-0.02757	0.20245	-0.74528	0.10759	0.20419	-0.09976	-0.17644	0.49419	0.34569	-0.07508	0.49617	-0.20636	-0.56453
0.59653	0.28000	0.24845	0.00150	-0.36076	-0.48237	0.16221	-0.02181	0.21926	-0.25284	-0.80652	-0.21373	0.72760	-0.56491	0.25185	-0.37342	-0.37807	-0.25855	0.41869	0.18635	-0.68136	-0.05009

$W^{(2)}$						$b^{(2)}$
-0.94332	-1.71903	1.21223	-1.83675	-0.62682	0.75407	-0.11556
0.18031	0.50986	-0.43079	0.39878	0.82744	0.63286	-0.07297
0.30440	0.36401	-0.19122	0.59981	0.41342	0.88375	-0.23361
-0.15303	-0.51368	0.56099	-0.30175	-0.96129	-0.73518	0.06317
0.33916	0.24617	-0.10838	0.53502	0.25802	0.92477	-0.24121

$W^{(3)}$					$b^{(3)}$
2.43093	-0.71937	-0.38082	0.79999	-0.21163	-0.41123
-0.98336	0.91622	0.75527	-0.99166	0.64225	0.11795
0.40206	-0.11321	-0.31942	0.08885	-0.35521	-0.04758
-0.85122	0.59576	0.88247	-0.59981	0.90241	-0.10502

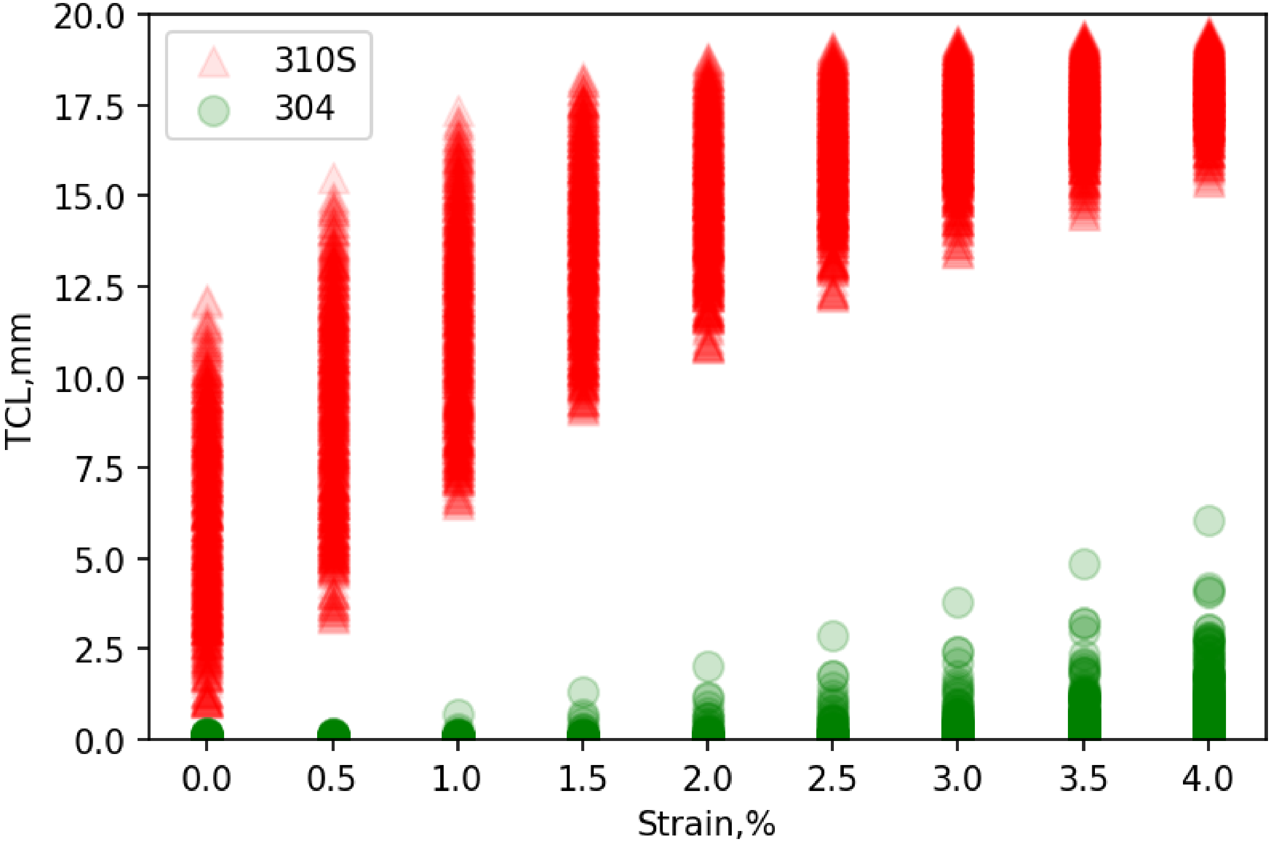
$W^{(4)}$				$b^{(4)}$
-0.04615	0.06806	-0.11679	0.19370	0.00189
0.70474	-0.68250	-0.07769	-0.10960	-0.25479
2.40762	-1.66337	0.62795	-1.60591	-0.32587

$W^{(5)}$			$b^{(5)}$
-0.21672	-0.50473	1.25758	-0.08385

$$h_i^{(1)} = \tanh\left(\sum_j W_{ij}^{(1)} X_j + b_i^{(1)}\right)$$
$$h_i^{(k)} = \tanh\left(\sum_j W_{ij}^{(k)} h_j^{(k-1)} + b_i^{(k)}\right), k = 2,3,4$$
$$Z = h_i^{(5)} = \sum_j W_{ij}^{(5)} h_j^{(4)} + b_i^{(5)}$$

X is the normalized input vector,
Z is the normalized output value,
$h_i^{(k)}$ (k= 1, 2, …, 5) is the output of the kth layer,
$W_{ij}^{(k)}$ and $b_i^{(k)}$ are the weights and bias matrix of the kth layer.

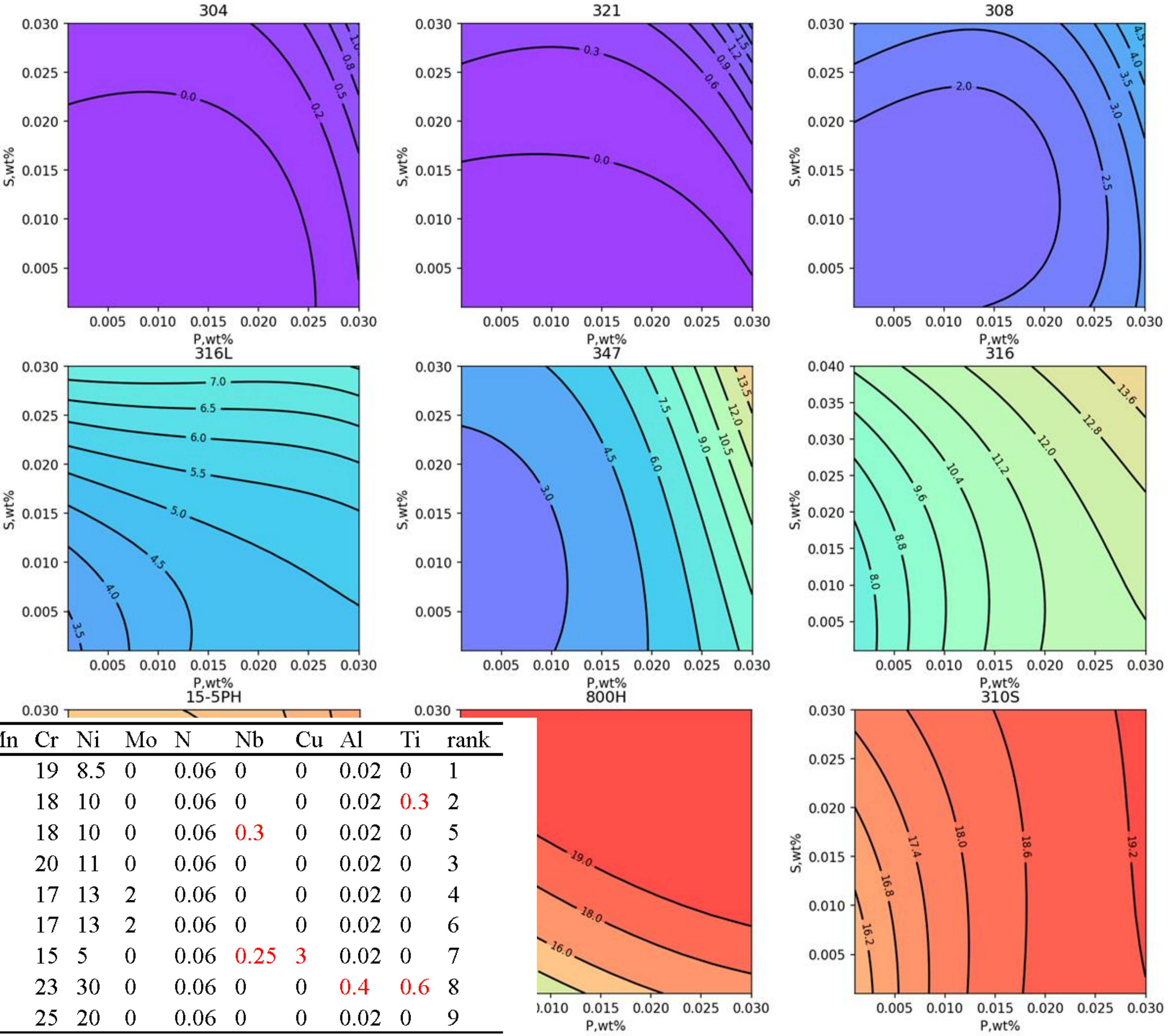
Prediction Using Trained DNN



Small change in composition, Big change in TCL (SCS)

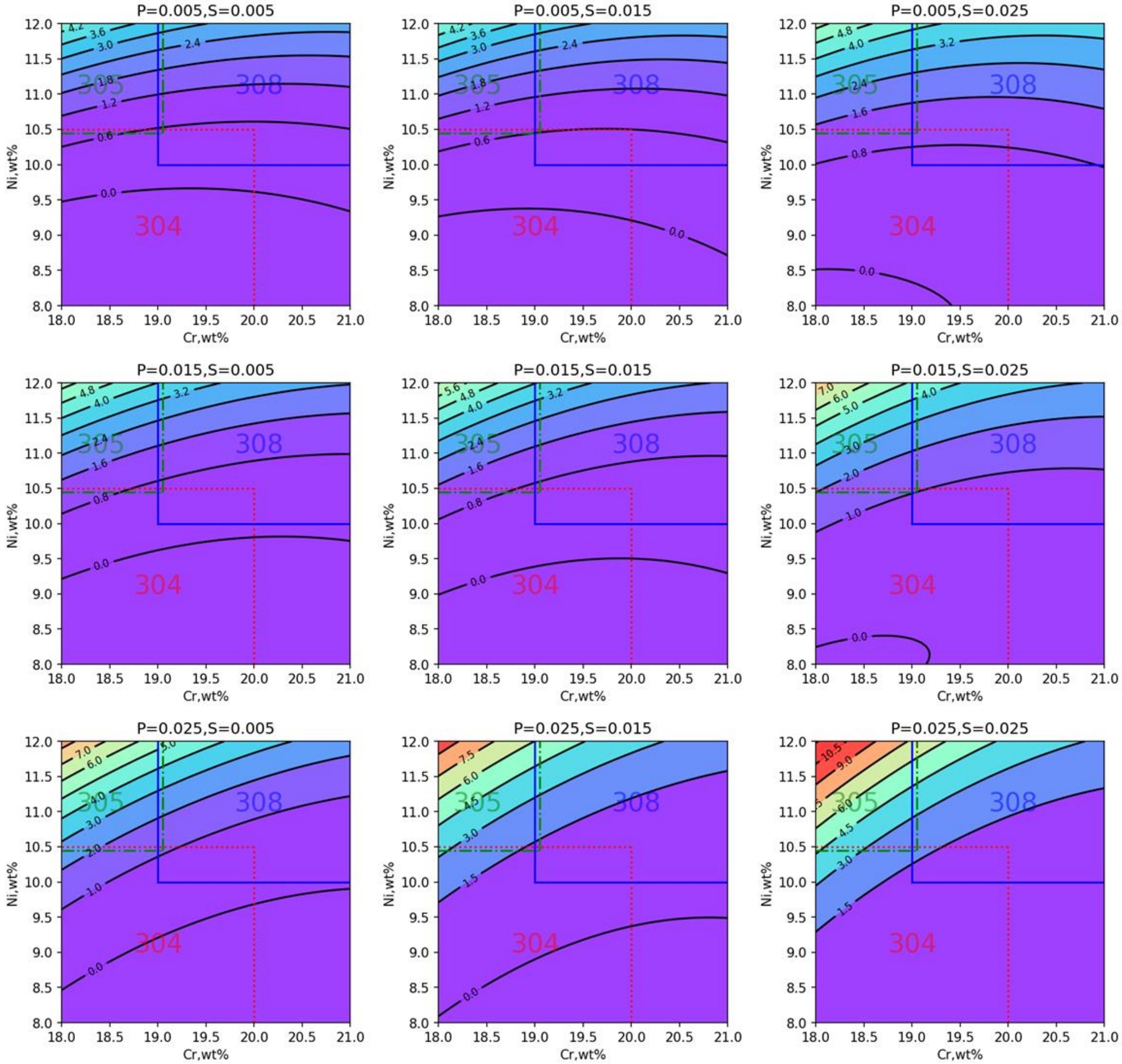
Code	C	Si	Mn	P	S	Cr	Ni	N	Al	Th	I	U	Ve
304	0.06	0.5	1.5	0.005-0.03	0.005-0.03	18-20	8-10.5	0.02	0.02	3.18	100	12	4.23
310S	0.01	0.5	1.5	0.005-0.03	0.005-0.03	24-26	19-22	0.02	0.02	3.18	100	12	4.23

Prediction Using Trained DNN



Code	C	Si	Mn	Cr	Ni	Mo	N	Nb	Cu	Al	Ti	rank
304	0.04	1	1	19	8.5	0	0.06	0	0	0.02	0	1
321	0.04	1	1	18	10	0	0.06	0	0	0.02	0.3	2
347	0.04	1	1	18	10	0	0.06	0.3	0	0.02	0	5
308	0.04	1	1	20	11	0	0.06	0	0	0.02	0	3
316L	0.01	0.5	1	17	13	2	0.06	0	0	0.02	0	4
316	0.06	0.5	1	17	13	2	0.06	0	0	0.02	0	6
15-5PH	0.02	1	1	15	5	0	0.06	0.25	3	0.02	0	7
800H	0.02	1	1	23	30	0	0.06	0	0	0.4	0.6	8
310S	0.02	1	1	25	20	0	0.06	0	0	0.02	0	9

Prediction Using Trained DNN



Conclusions:

1 Increasing neuron number does not improve the prediction accuracy of NN when neuron number larger than a number in one hidden layer NN (last generation one hidden layer SNN)

2 The prediction accuracy of NN can be improved through increasing hidden layer number (using deep learning NN)

3 Multiple variables and nonlinear Problems in material process, e.g. SCS, can be solved using NN

Thank you!