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http://www.msm.cam.ac.uk/phase-trans/

Hot-Strength of Ferritic Creep-Resistant Steels

Comparison of Neural Network and Genetic Programming

Strength of Ferritic Steels?

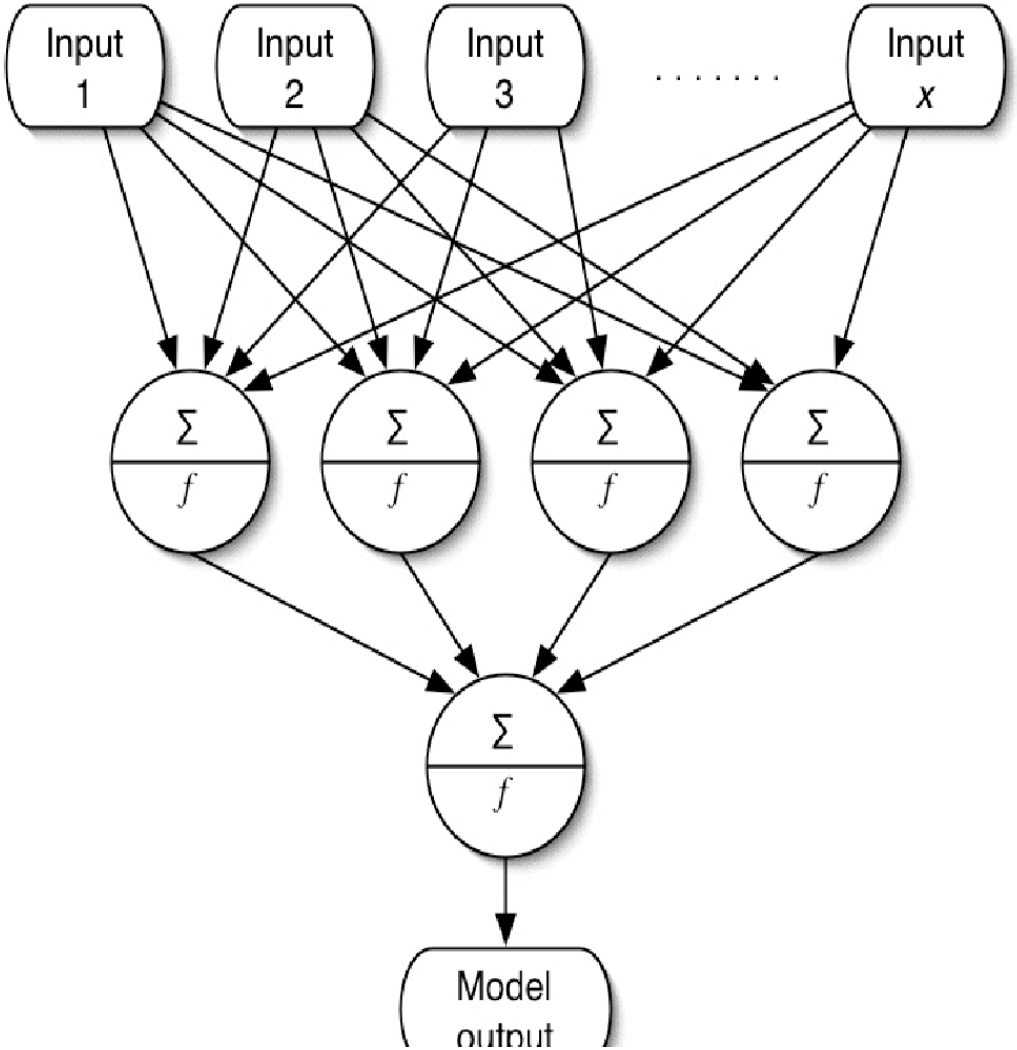
Neural networks

Neural networks in a Bayesian framework used to model the hot-strength of ferritic steels

Neural network: non-linear method of regression

Data fitted to a function to capture complex relations between inputs and output

Three layer neural network



- input variables

- hidden units

- bias

- output

General form of neural network

y – output

w – weight

h – hidden unit

θ – bias

x – inputs

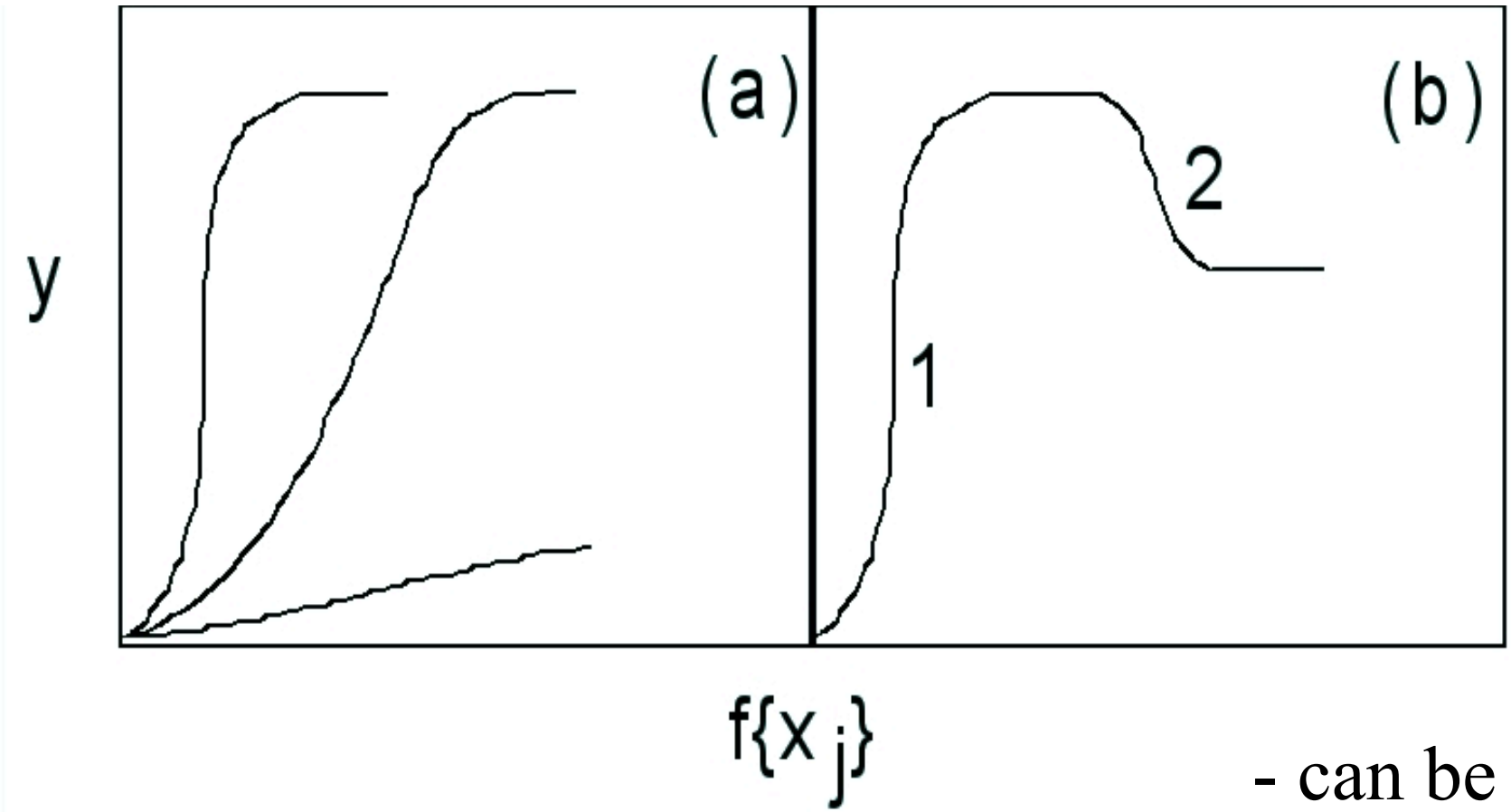
i, j – subscripts

$$y = \sum_i w_i^{(2)} h_i + \theta^{(2)}$$

$$h_i = \tanh\left(\sum_j w_{ij}^{(1)} x_j + \theta_i^{(1)} \right)$$

Hyperbolic tangents

- transfer function
- very flexible



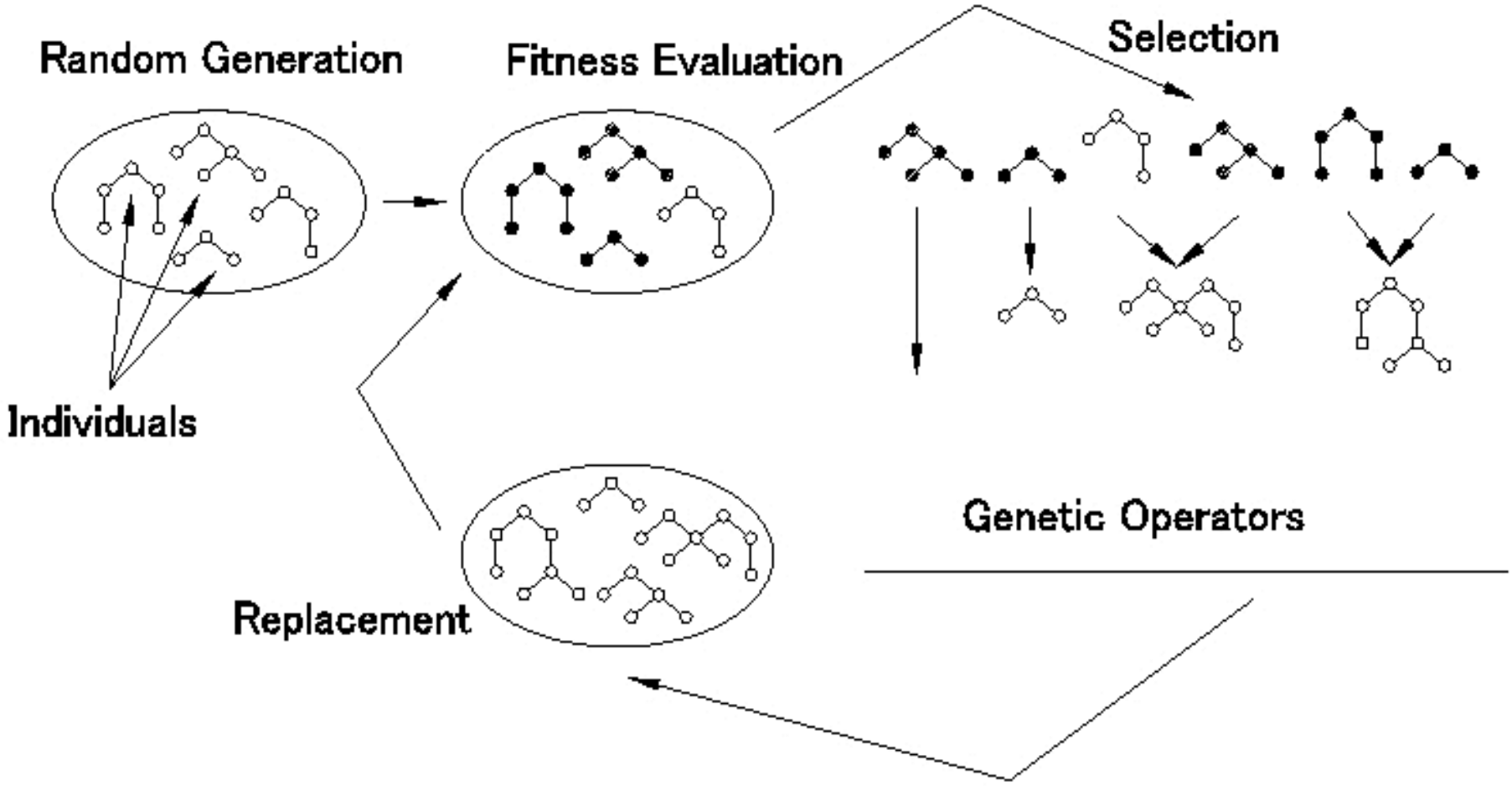
- can be combined

Genetic programming

Machine learning technique to optimise a population of computer programs

Program may be an expression, formula, plan, control strategy, decision tree or learning model

Genetic programming evolution cycle



Genetic programming functions

- arithmetic (+, -, *, /)
- elementary (exp, log, power, ...)
- trigonometric (sin, cos, tan, ...)

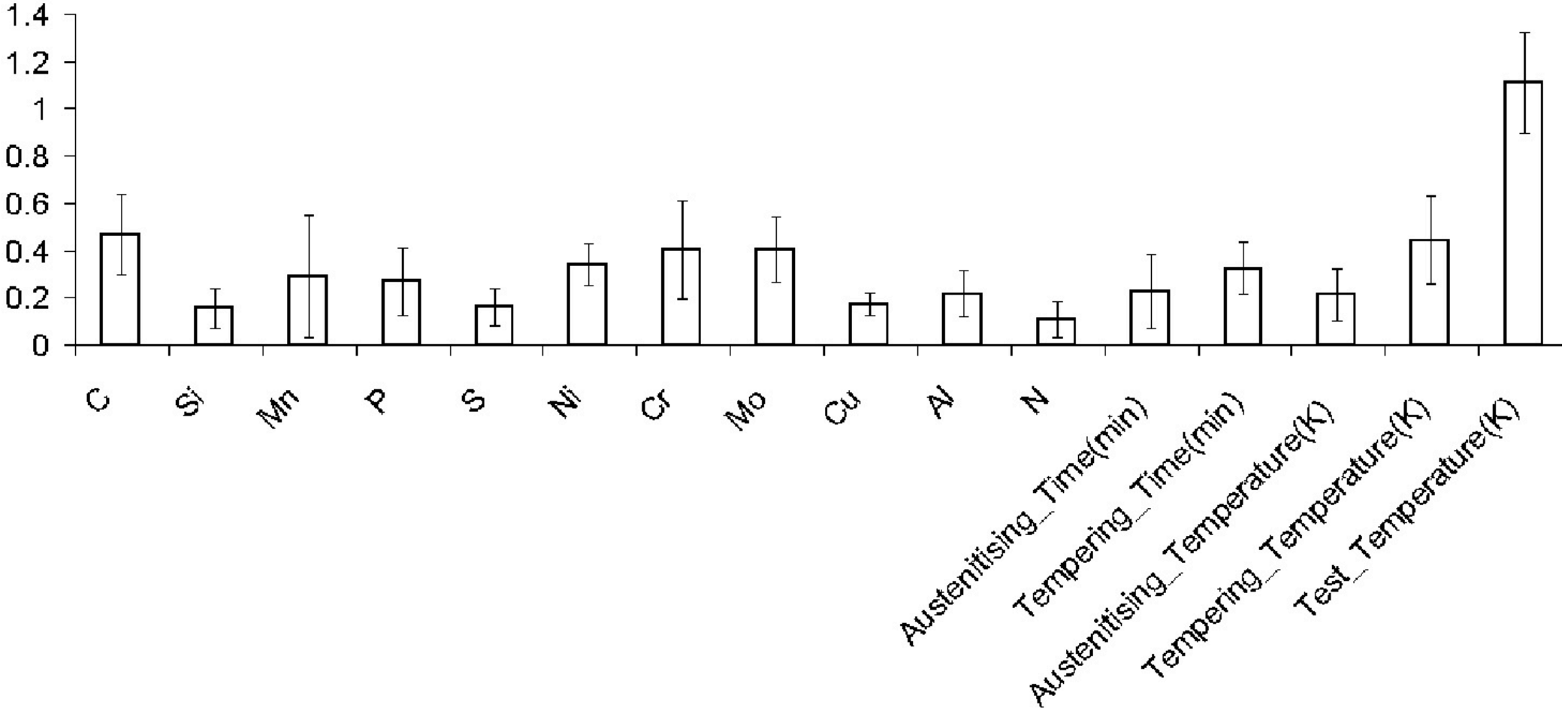
- genetic operators (mutation, …)

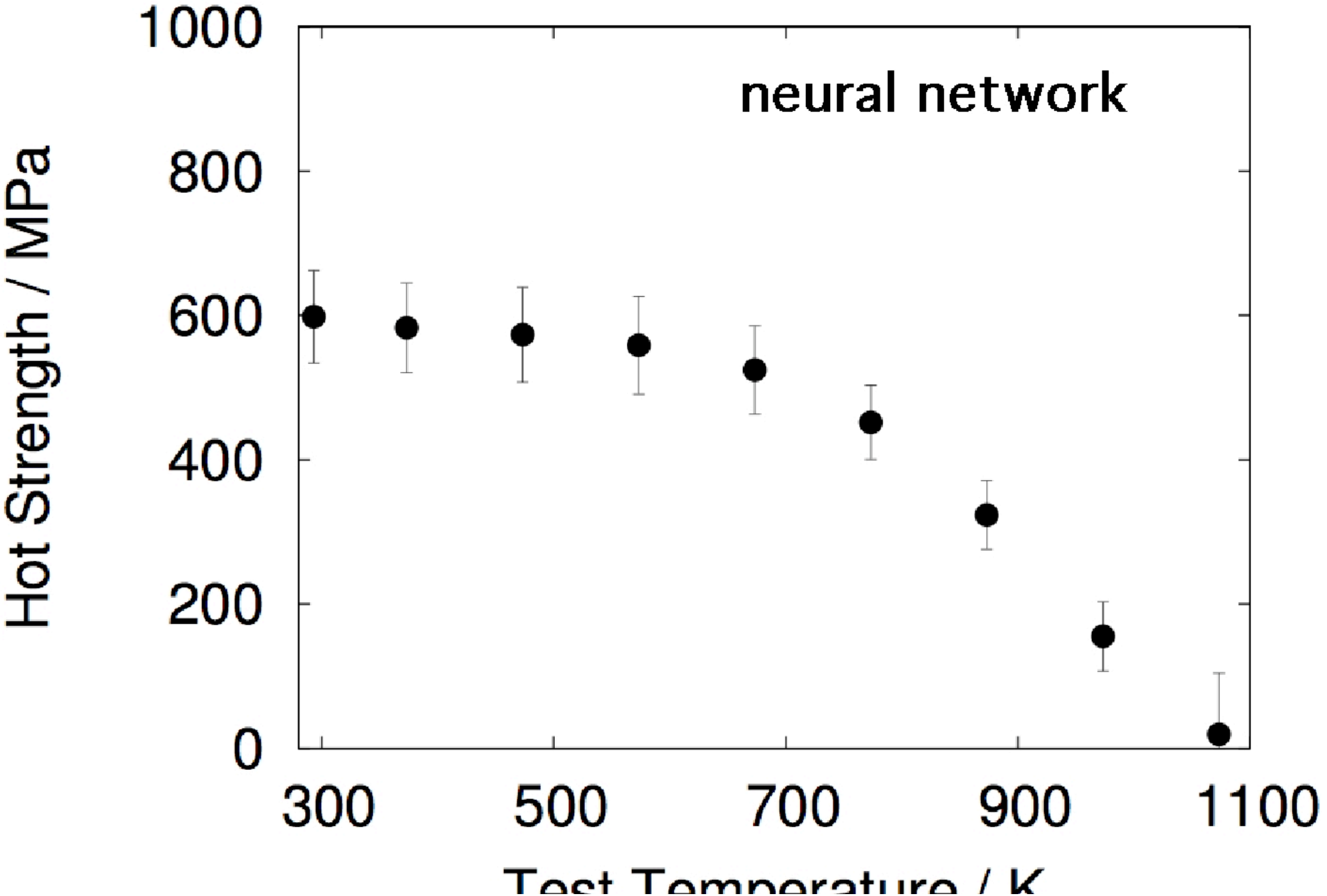
Input variables

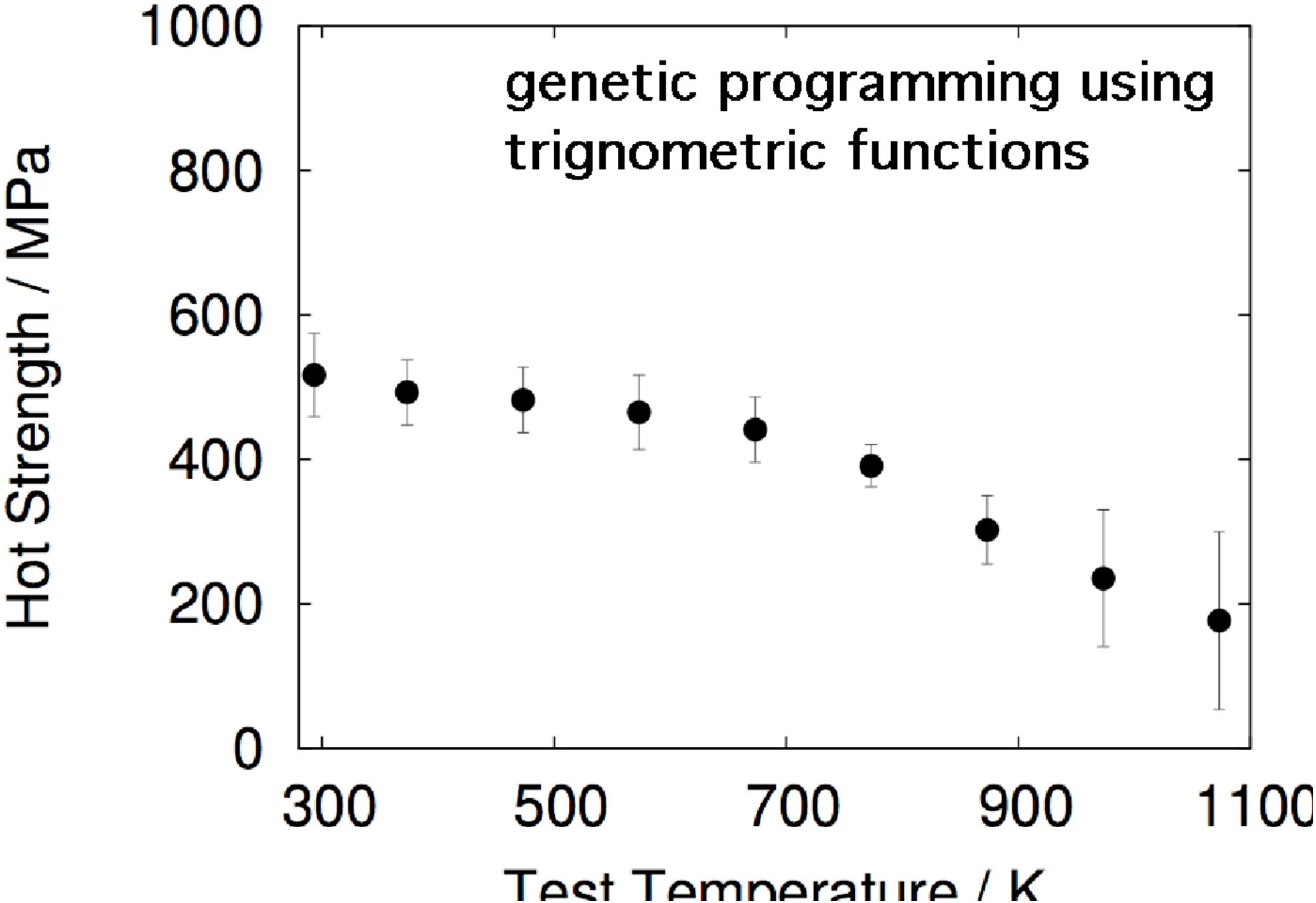
- Al, C, Cu, Cr, Mn, Mo, Ni, N,Si
- Austenitising time and temperature
- Tempering time and temperature
- Test temperature

Variable	Minimum	Maximum
Aluminium / wt%	0.001	0.04
Carbon / wt%	0.09	0.48
Copper / wt%	0.0001	0.25
Chromium / wt%	0.0001	12.38
Manganese / wt%	0.38	1.44
Molybdenum / wt%	0.01	1.05
Nickel / wt%	0.0001	0.6
Nitrogen / wt%	0.001	0.04
Silicon / wt%	0.18	0.86
Austenitising time / min	10	5400
Tempering time / min	30	660
Austenitising temperature / K	1143.15	1243.15
Tempering temperature / K	898.15	1023.15
Test temperature / K	293.15	973.15
Hot strength / MPa	69	660

Significance




neural network
Hot Strength / MPa
1000
800
600
400
200
0
300
500
700
900
1100
Test Temperature / K


genetic programming using
trignometric functions
Hot Strength / MPa
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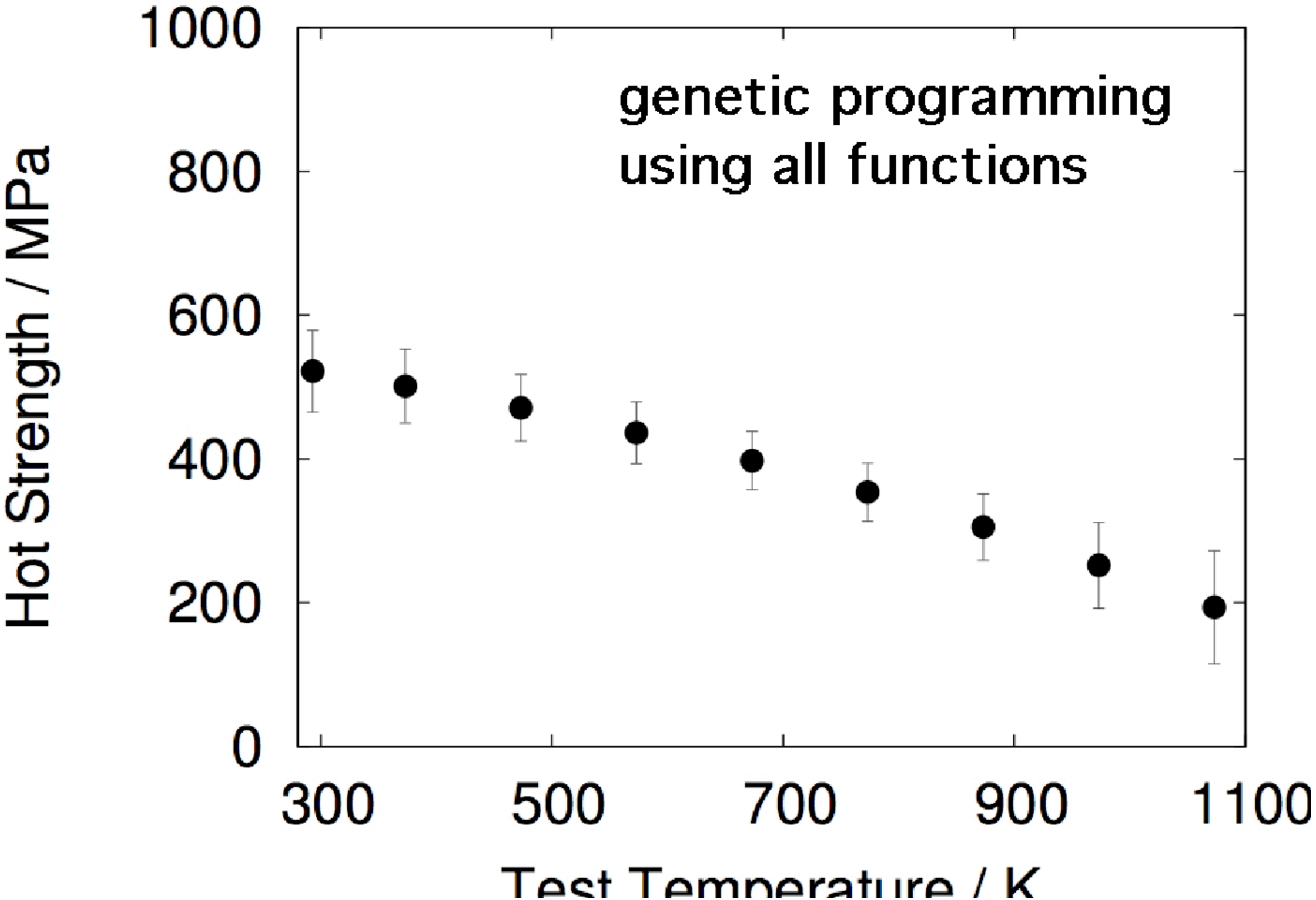
Test Temperature / K


genetic programming
using all functions
Hot Strength / MPa
Test Temperature / K
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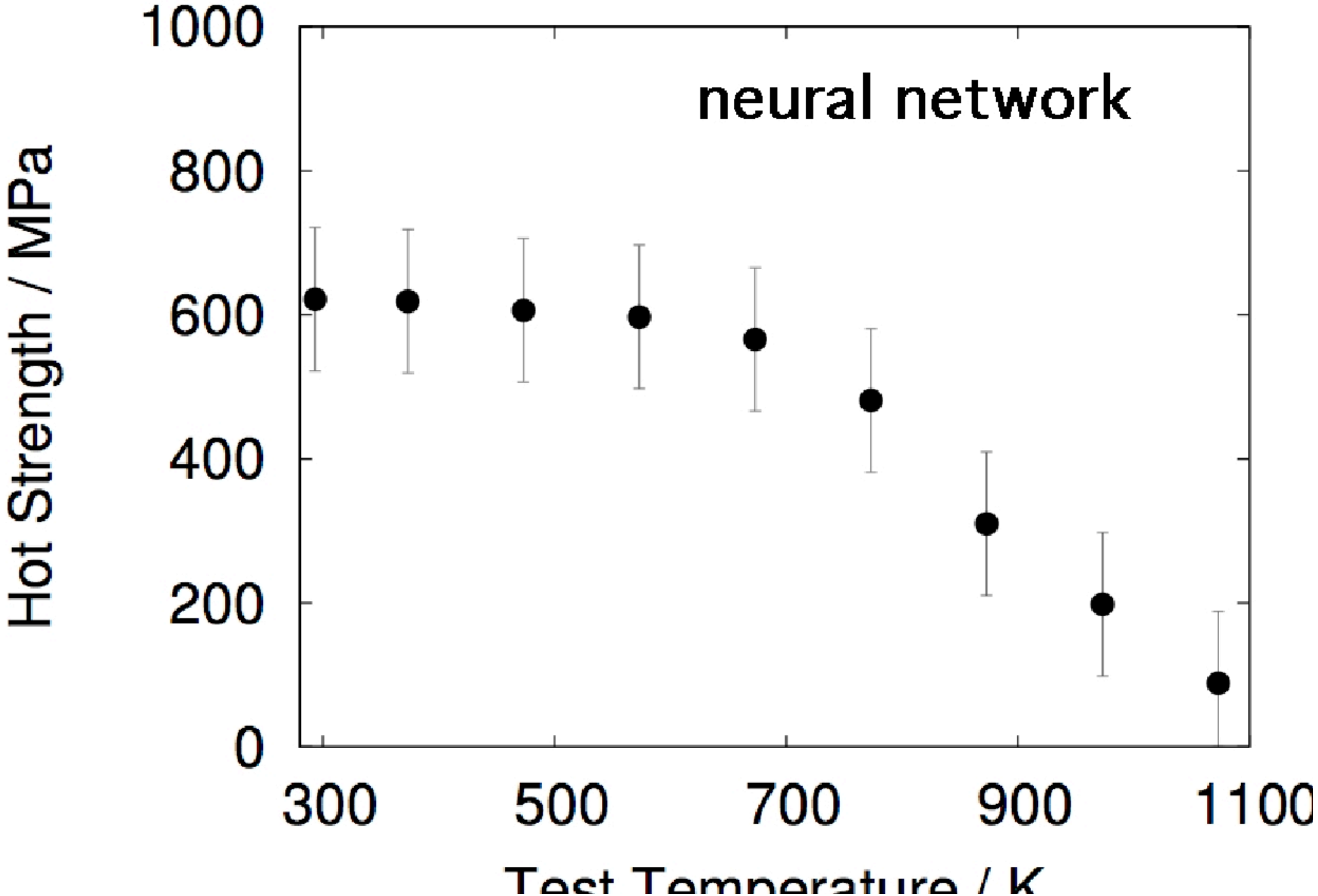
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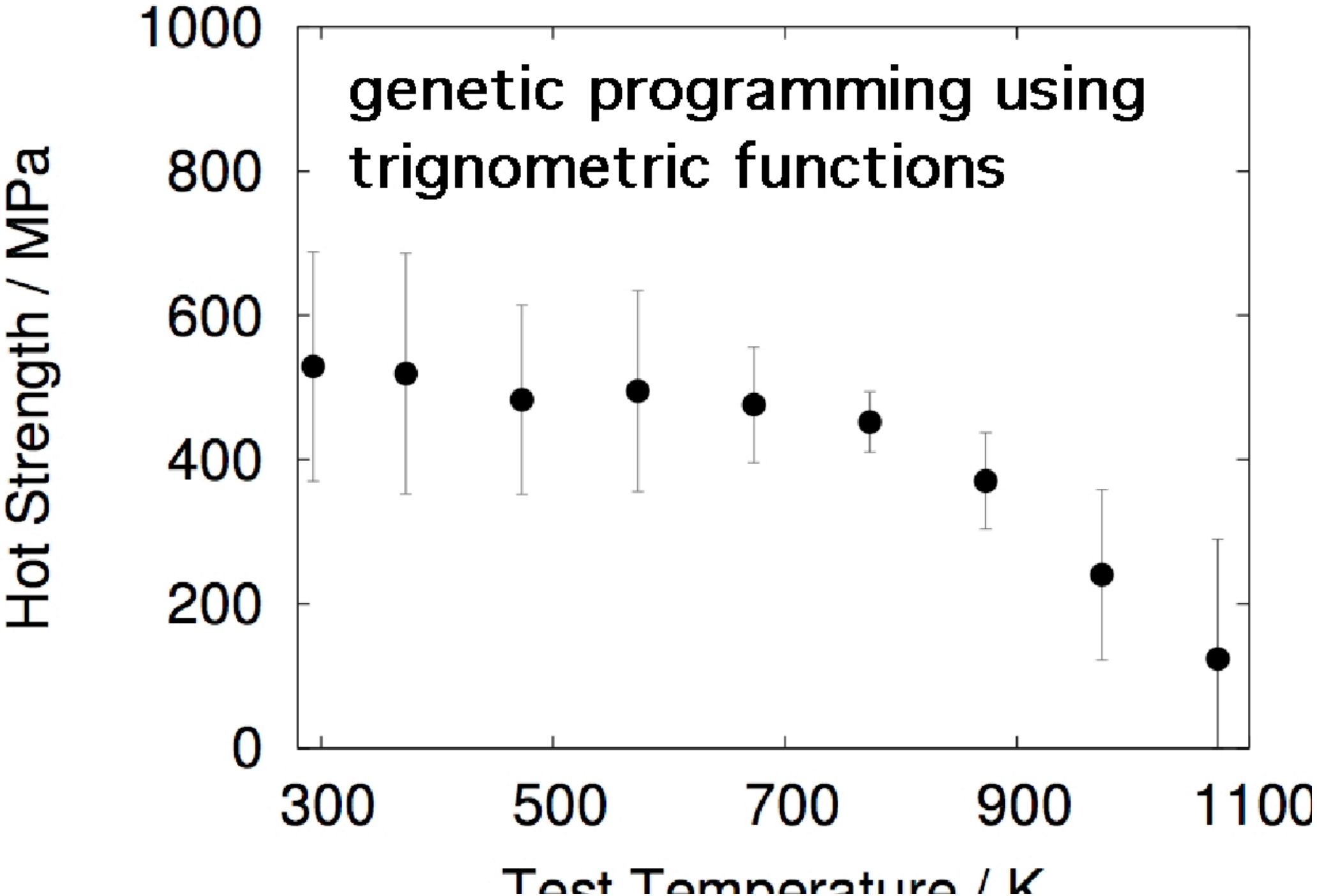
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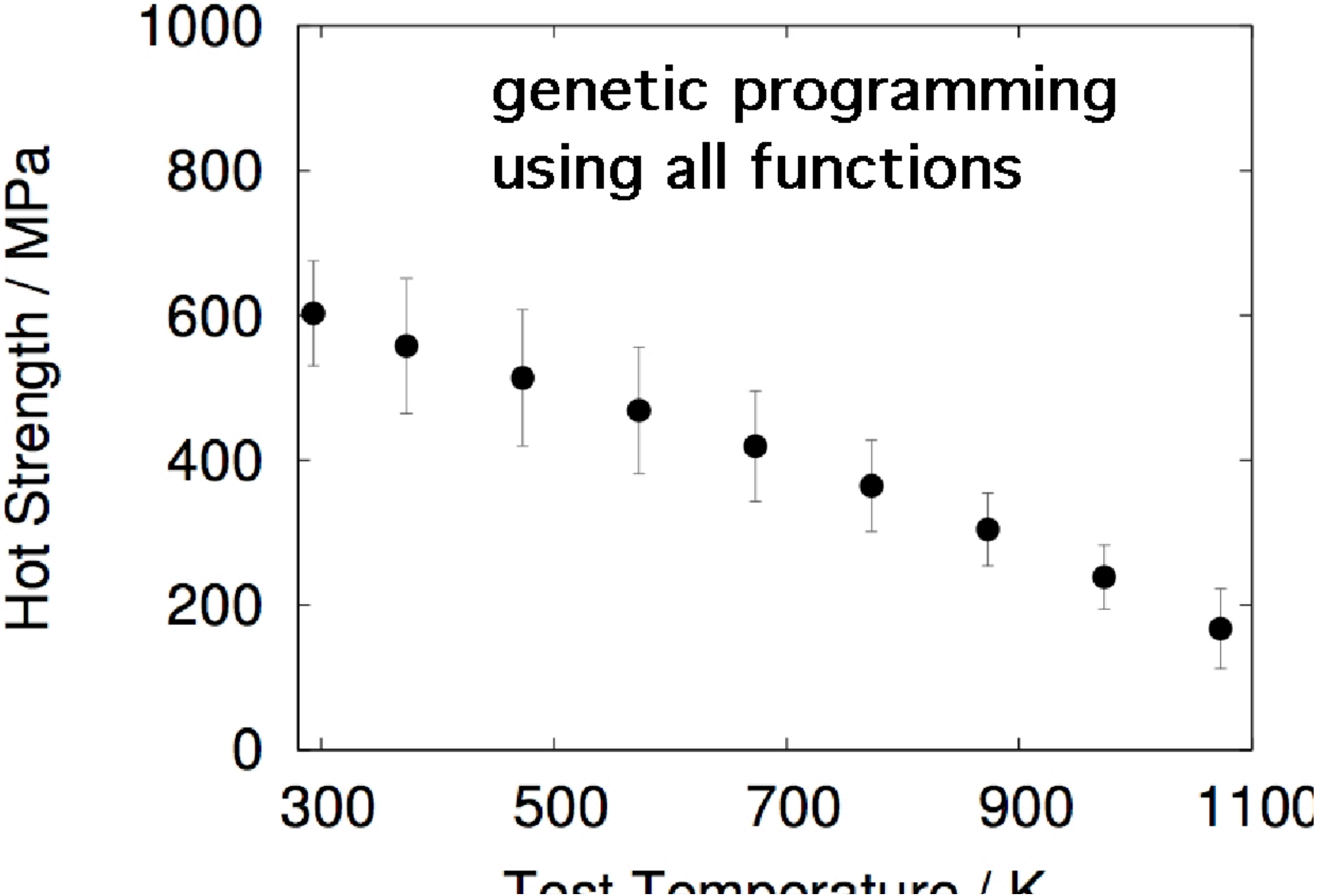
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using all functions
Hot Strength / MPa
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Conclusions

Both methods where similar in capturing the two regimes in the decrease of hot strength

The neural network having a plus in also capturing the slopes correctly

ACKNOWLEDGEMENTS

- Many thanks to professor H. K. D. H. Bhadeshia
- Department of Material Science and Metallurgy
- University of Cambridge
- European Commission under the Marie Curie Early Stage Research Training Programme

Thank you for listening