

Thermo Mechanical Modeling of Continuous Casting with Artificial Neural Network

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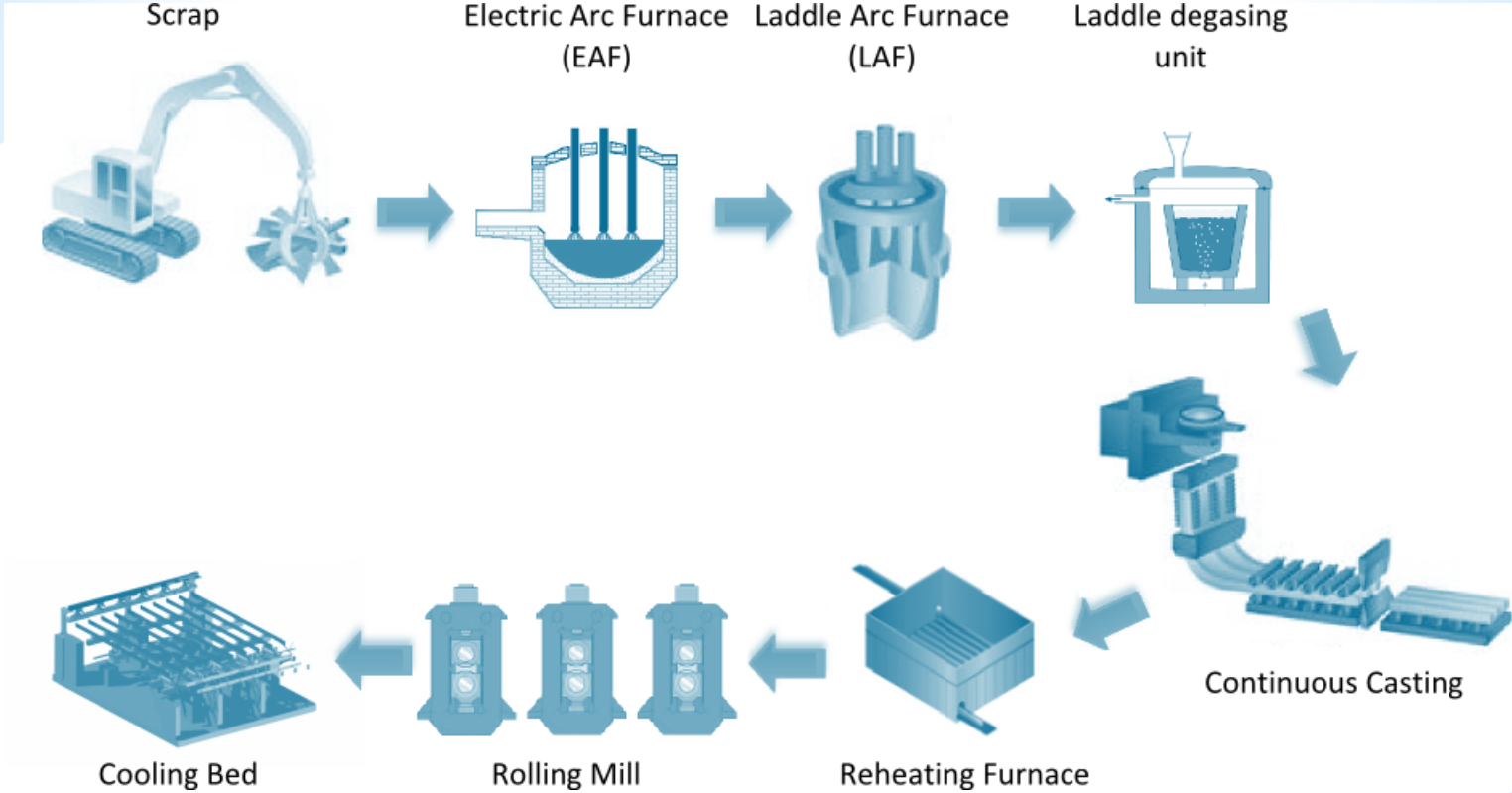
Scope

- Continuous casting of steel and its physics
- Approximative numerical models based on artificial neural network (ANN)
- Modelling of continuous casting of steel by ANN
- Conclusions and future work

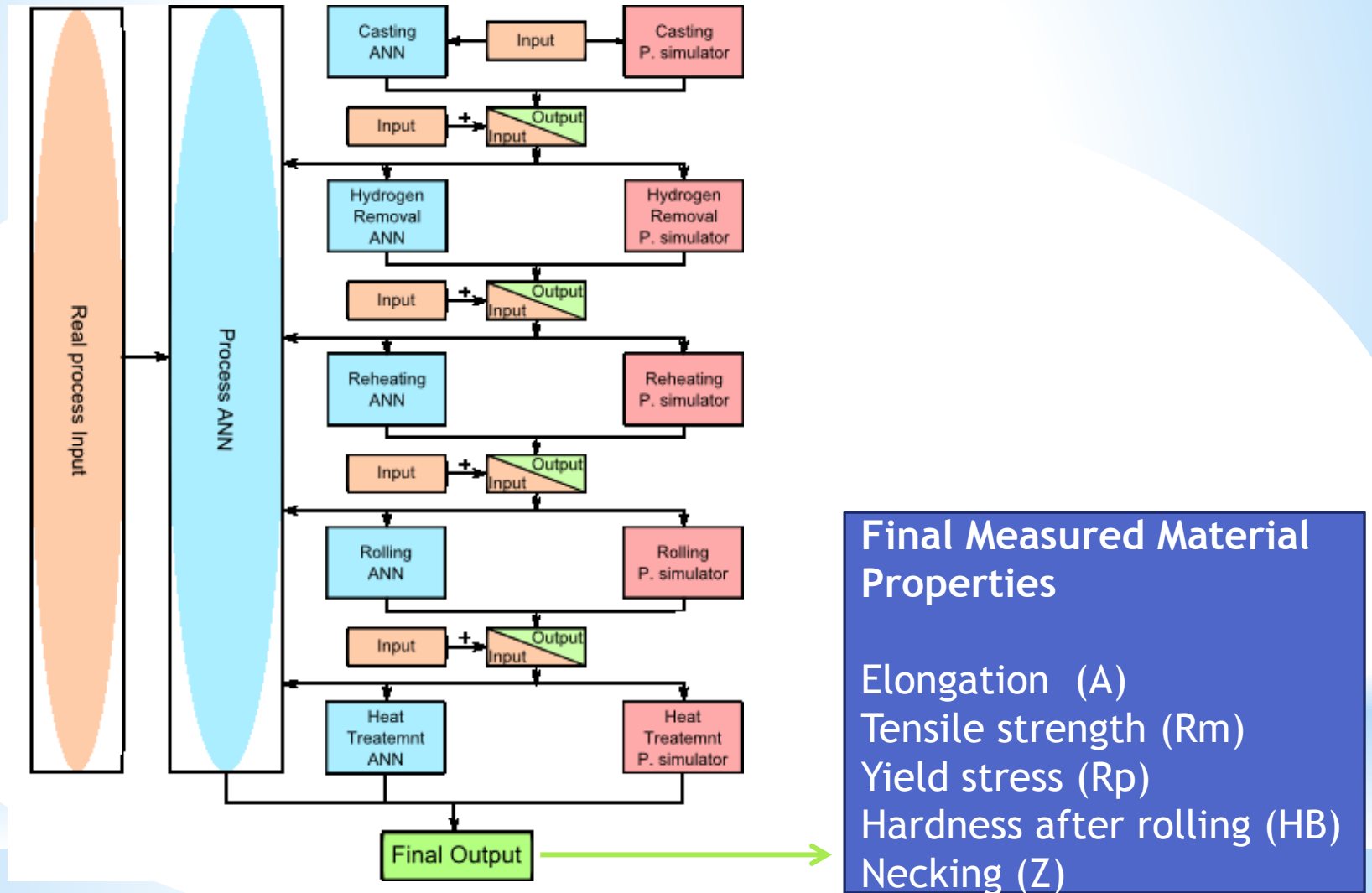
Goals

- Introduction to steel process modelling
- Introduction and motivation for ANN modelling
- Assessment of physical and ANN modelling of continuous casting of steel

Steel Production Process Path



Steel Production Simulation Scheme

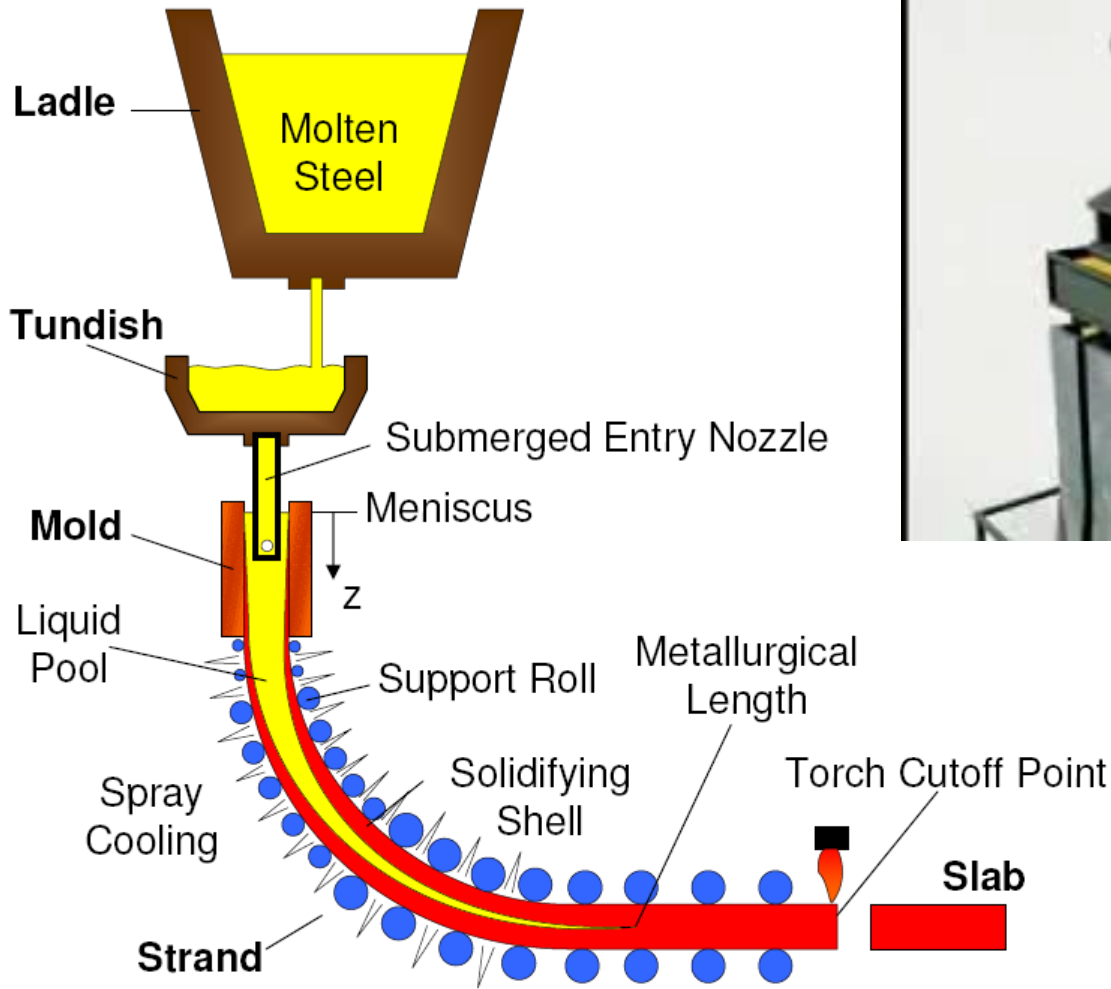


Continuous Casting of Steel

- Process was developed in the 1950s
- The most common process for production of steel
- 90% of all steel grades are produced by this technique
- Types
 - Vertical, horizontal, curved, strip casting
- Typical products
 - Billets, blooms, slab, strip



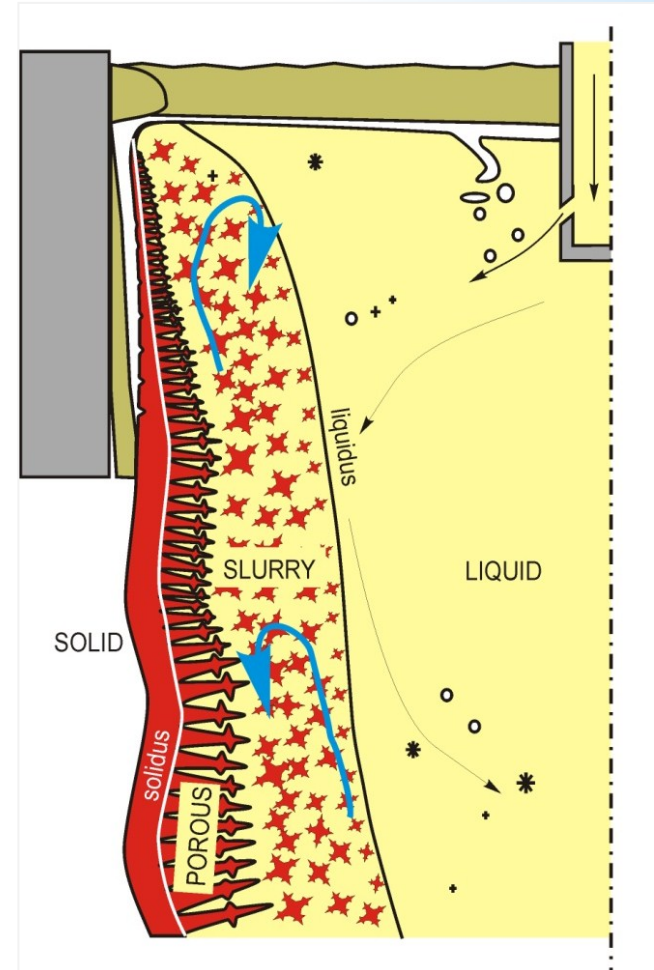
Continuous Casting of Steel



Characteristic Regimes in a Solidifying Continuous Casting

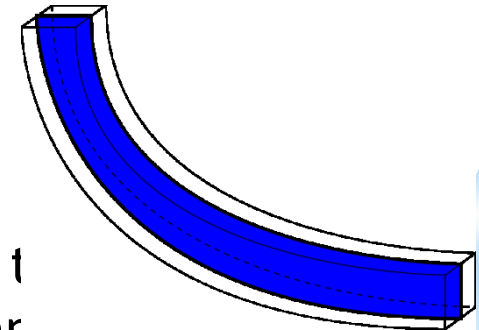
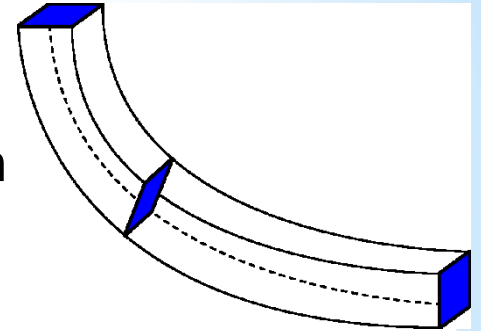
•Regimes

- LIQUID** (liquid, particles, inclusions,...)
- SLURRY** (equiaxed dendrites + liquid)
- POROUS** (columnar dendrites + liquid)
- SOLID** (dendrites)



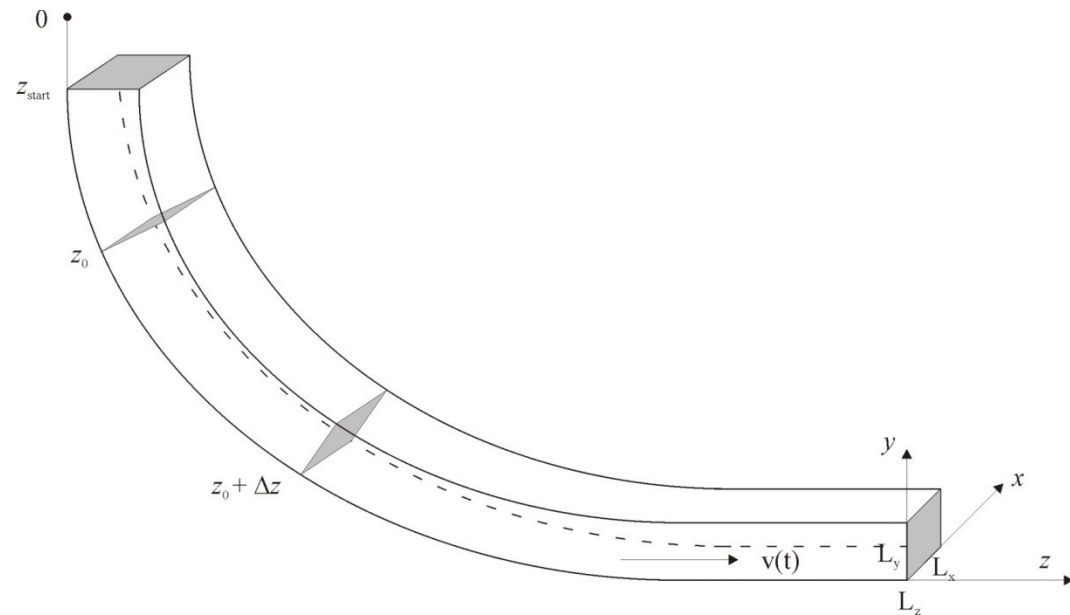
Numerical models of the Continuous Casting

- **Thermal models**
 - Describes heat transfer with solidification
 - Casting velocity is constant for all phases
 - Using slice model
- **Fluid models**
 - Turbulent fluid flow on a fixed geometry
 - Modeling of the turbulent flow involves solving additional two transport equations
- **Thermo-fluid models**
 - Involves the solution of the fluid flow with heat transfer, solidification and species transport
 - Much more complex to numerically implement



Slice Model

- Slice traveling schematics in the billet
 - Fast calculation time
 - x-y cross sectional slice is moving from top horizontal to bottom vertical position
 - Temperature and boundary condition are assumed as time dependent



Macroscopic Transport Model

- Governing equations
 - Enthalpy transport

$$\frac{\partial}{\partial t}(\rho h) = \nabla \cdot (k \nabla T)$$

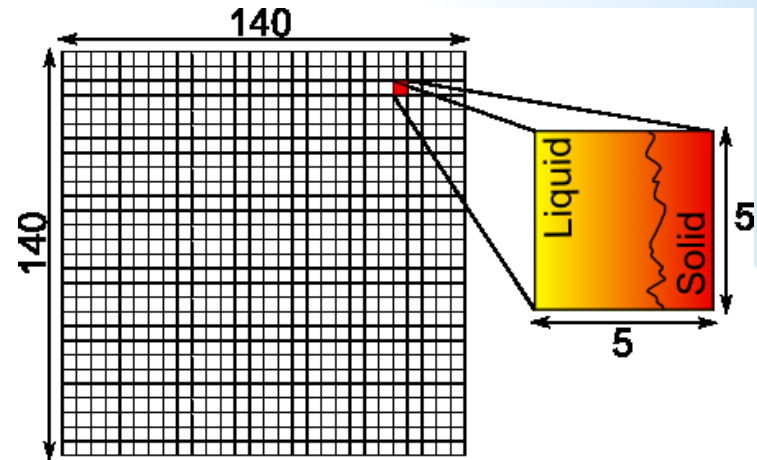
- Mixture and phase enthalpies

$$h = f_L h_L + f_S h_S$$

$$h_L = c_L T + (c_S - c_L) T_{sol} + h_f$$

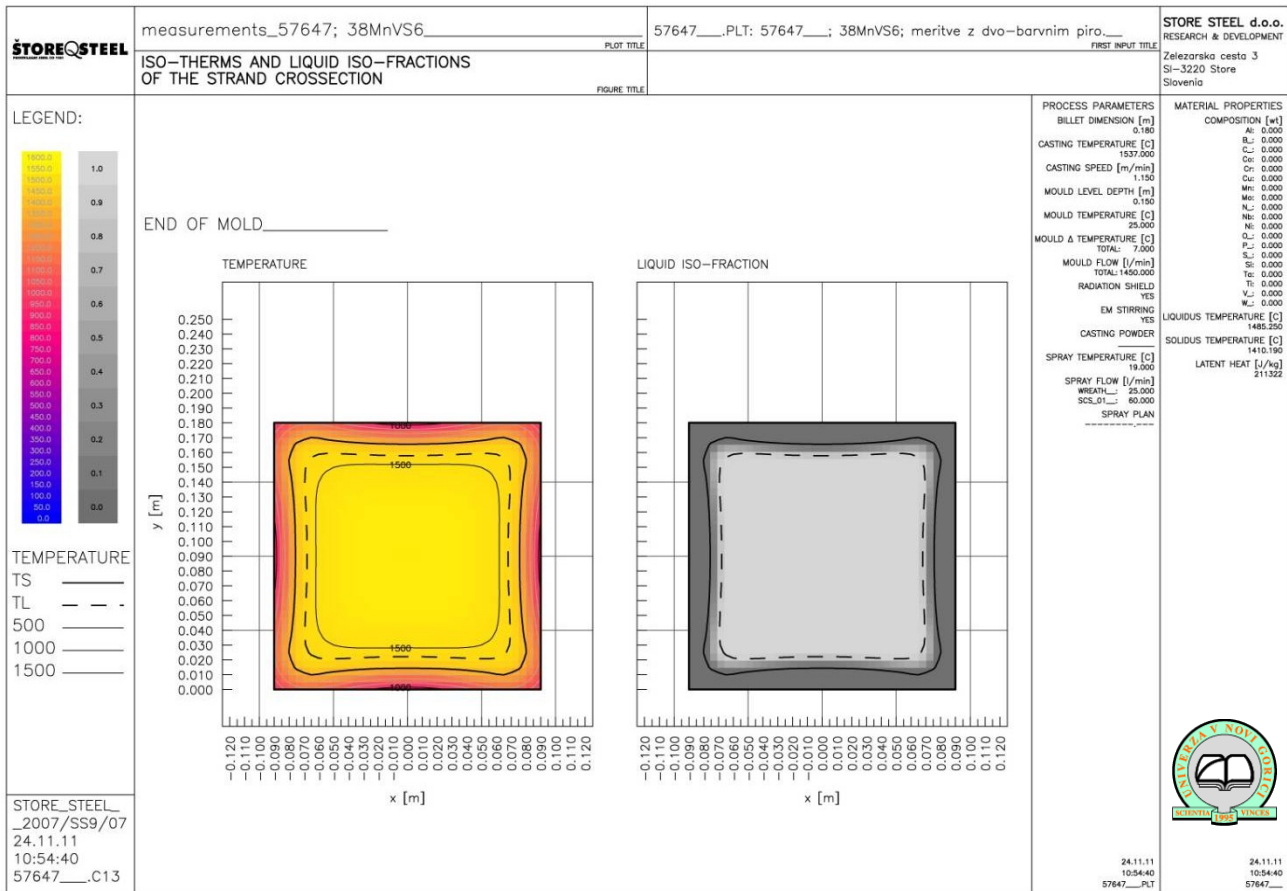
$$h_S = c_S T$$

- Solved based on initial and boundary conditions that relate the enthalpy transport with the process parameters



28 x 28 points

Example of CC Simulation



Artificial Neural Network

Artificial Neural Network - ANN

- An information-processing system that has certain performance characteristic similar to biological neural networks
- Have been developed as generalizations of mathematical models of human cognition
 - Information processing occurs at many simple elements called neurons
 - Signals are passed between neurons over connection links
 - Each link has an associated weight
 - Each neuron applies an activation function

ANN - Types

- Feedforward NN
- Feedforward backpropagation NN
- Self organizing map (SOM)
- Hopfield NN
- Recurrent NN
- Modular NN
- ...

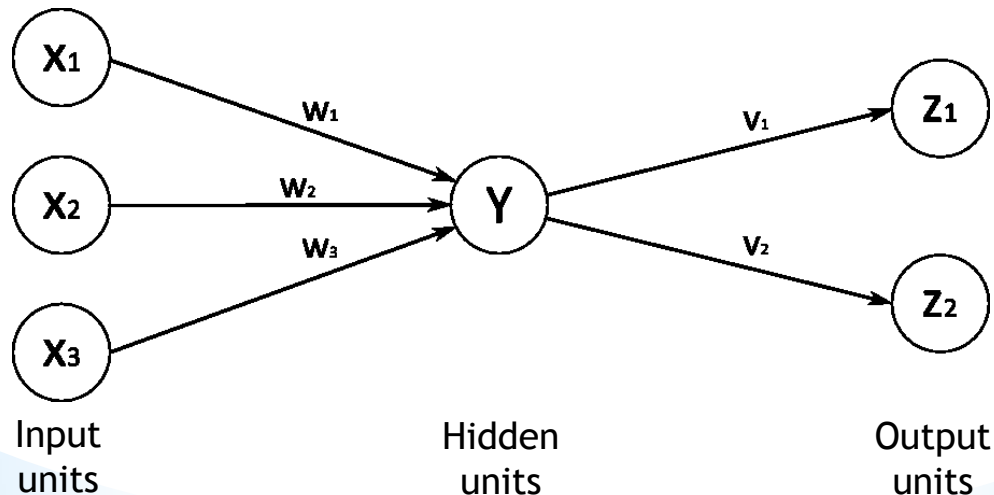
ANN - Examples of Applications

Is an extremely interdisciplinary field

- Signal processing
 - Suppressing noise on a telephone line
- Control
 - Provide steering direction to a trailer truck attempting to back up to a loading dock
- Pattern recognition
 - Recognition of handwritten characters
- Medicine
 - Diagnosis and treatment
- Speech production / recognition, business...

ANN - Characterization

- **Architecture** - pattern of connections between the neurons
- **Training or learning** - method of determining the weights on the connections
- **Activation function**



ANN - Architecture

The arrangement of neurons into layers and the connection patterns between layers

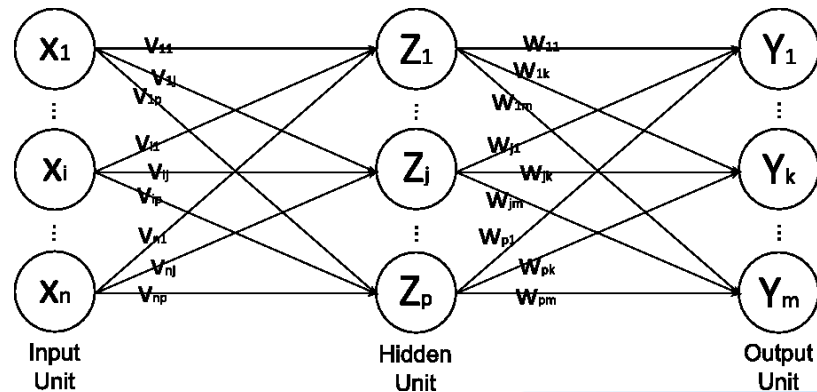
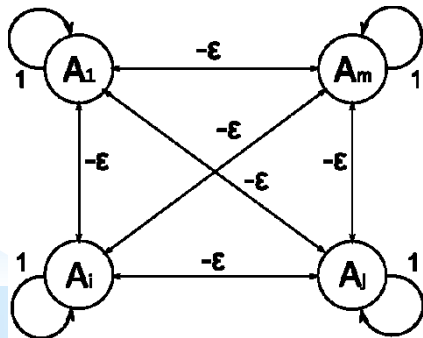
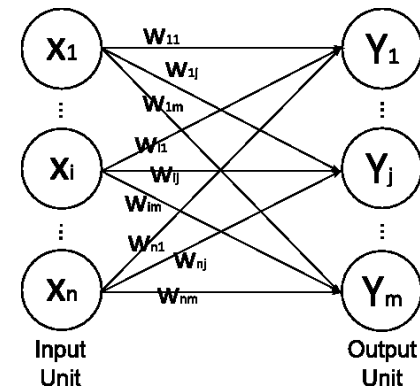
- **Single-layer net**

- Input and output units

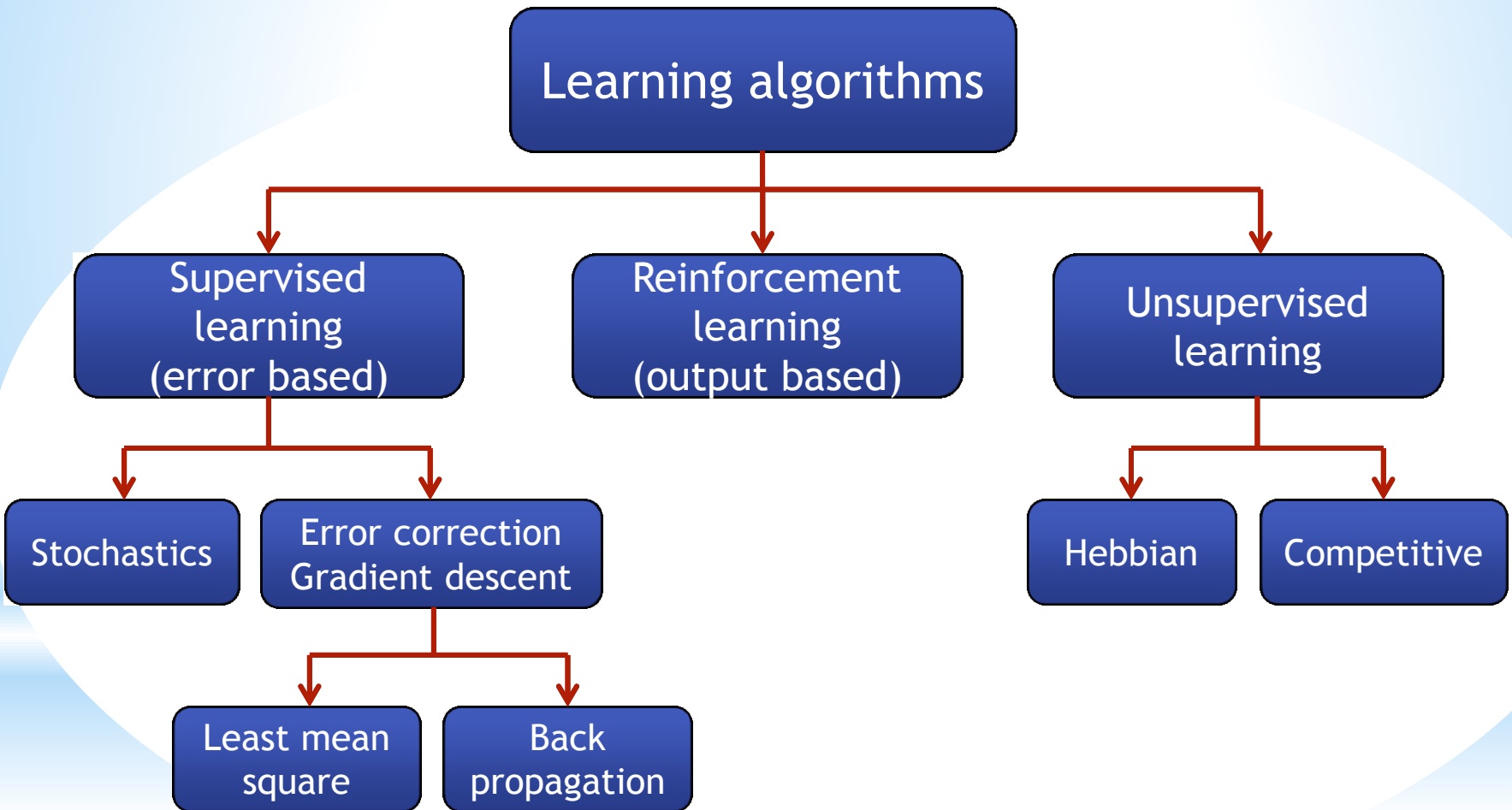
- **Multi-layer net**

- Input, output and hidden units

- **Competitive layer**



ANN - Training or Learning



ANN - Activation Functions

- Typically, the same activation function is used for all neurons in any particular level

- Identity function

$$f(x) = x$$

- Binary step function

- Binary sigmoid

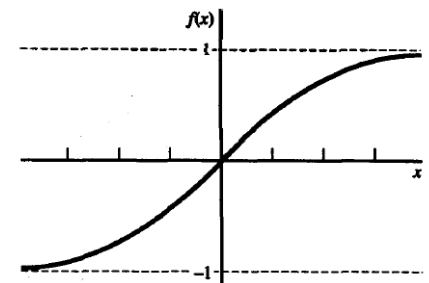
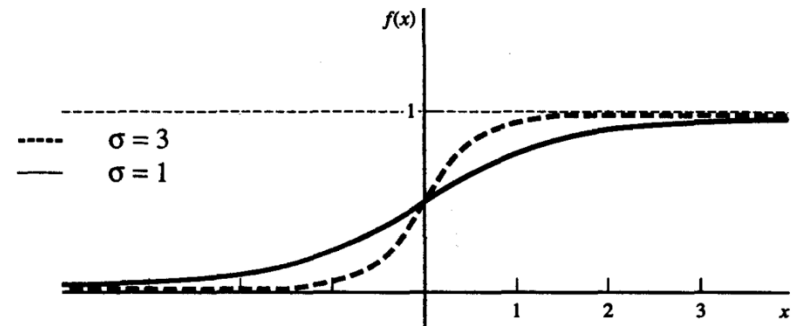
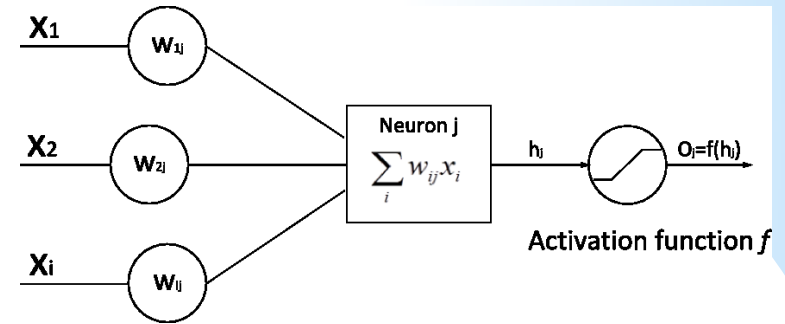
$$f(x) = \frac{1}{1 + \exp(-\sigma x)}$$

- Bipolar sigmoid

$$f(x) = \frac{1 - \exp(-\sigma x)}{1 + \exp(-\sigma x)}$$

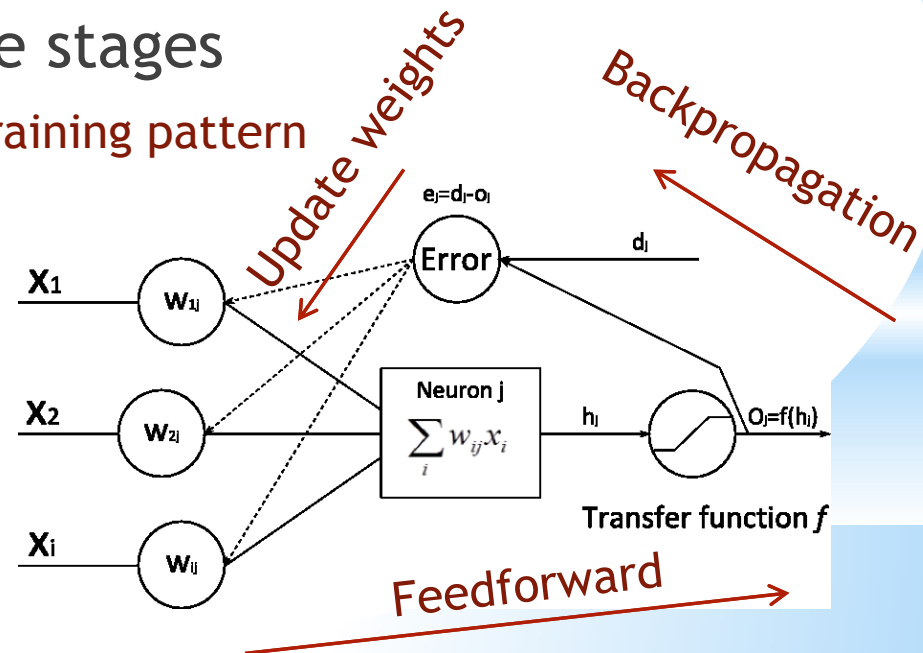
- Hyperbolic tangent

$$f(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)}$$

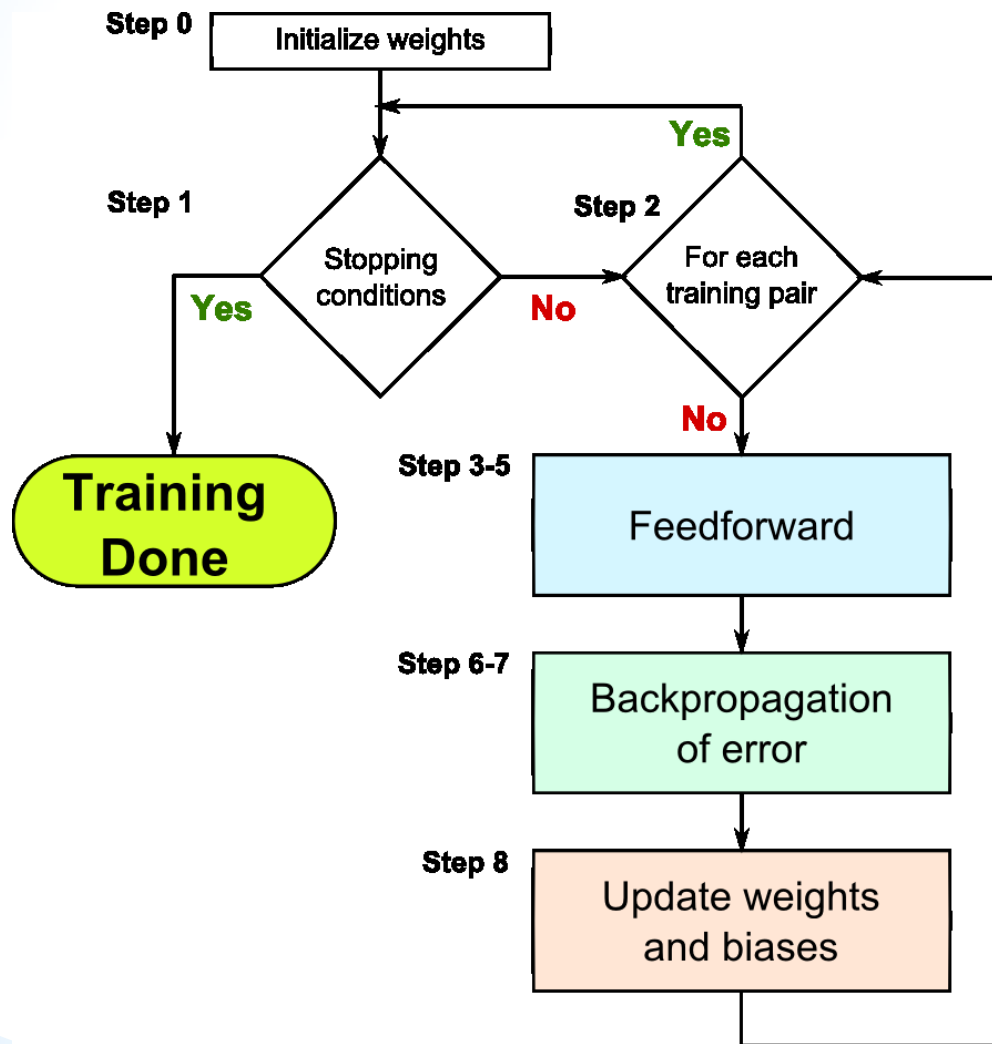


ANN - Feedforward Backpropagation

- A gradient descent method to minimize the total squared error of the output
- A backpropagation (multilayer, feedforward, trained by backpropagation) can be used to solve problems in many areas
- The training involves three stages
 - The feedforward of the input training pattern
 - The calculation and backpropagation of the associated error
 - The adjustment of the weights



ANN -Backpropagation Algorithm



ANN -Backpropagation Algorithm

Feedforward

- Step 3

Each input unit ($X_i, i = 1, \dots, n$) receives input signal and broadcasts the signal to all units in the layer above (hidden layer) x_i

- Step 4

Each hidden unit ($Z_j, j = 1, \dots, p$)

sums its weighted input signals $z_in_j = v_{0j} + \sum_{i=1}^n x_i v_{ij}$

applies its activation function $z_j = f(z_in_j)$

and sends this signals to all units in the layer above (output unit)

- Step 5

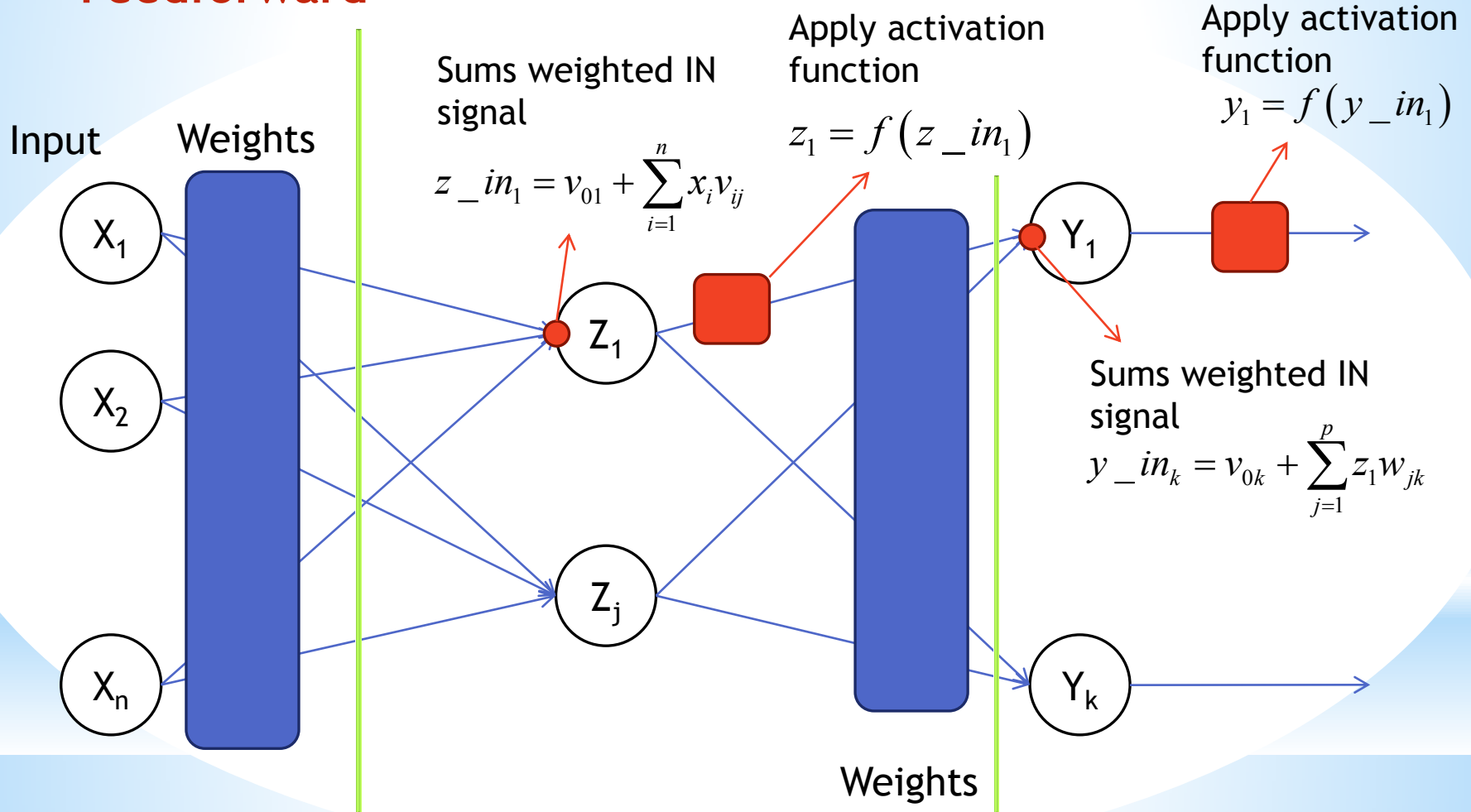
Each output unit ($Y_k, k = 1, \dots, m$)

sums its weighted input signals $y_in_k = w_{0k} + \sum_{j=1}^p z_j w_{jk}$

and applies its activation function $y_k = f(y_in_k)$

ANN - Backpropagation Algorithm

Feedforward



ANN -Backpropagation Algorithm

Backpropagation of errors

• Step 6

Each output unit ($Y_k, k = 1, \dots, m$) receives a target pattern

computes its error information term $\delta_k = (t_k - y_k) f'(y_{in_k})$

calculates its weight correction term $\Delta w_{jk} = \alpha \delta_k z_j$

calculates its bias correction term $\Delta w_{ok} = \alpha \delta_k$

and sends δ_k to units in the layer below

• Step 7

Each hidden unit ($Z_j, j = 1, \dots, p$) sums its delta inputs $\delta_{in_j} = \sum_{k=1}^m \delta_k w_{jk}$

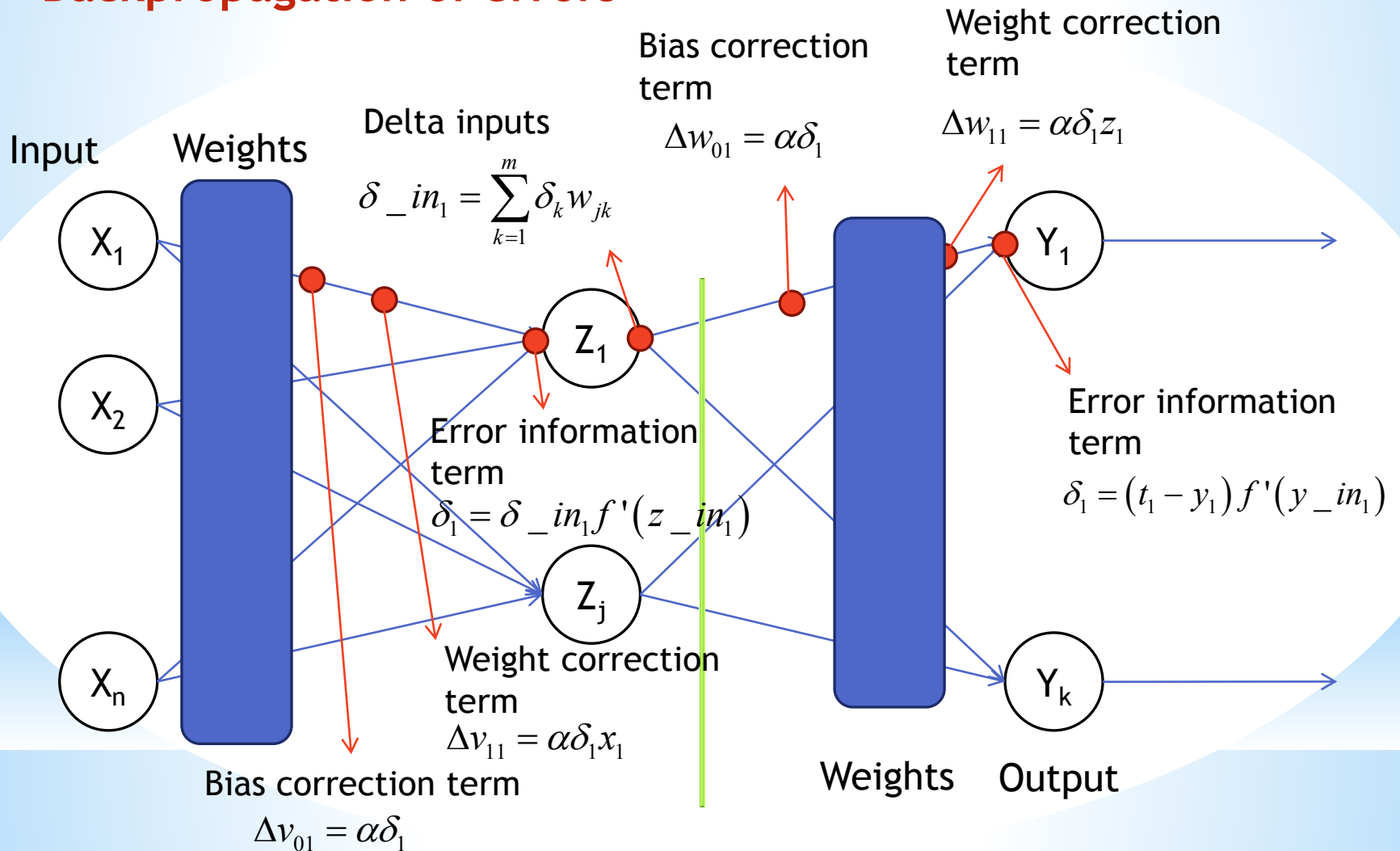
calculates its error correction term $\delta_j = \delta_{in_j} f'(z_{in_j})$

calculates its weight correction term $\Delta v_{ij} = \alpha \delta_j x_i$

and calculates its bias correction term $\Delta v_{0j} = \alpha \delta_j$

ANN - Backpropagation Algorithm

Backpropagation of errors



ANN -Backpropagation Algorithm

Update weights and biases

- **Step 8**

Each output unit ($Y_k, k = 1, \dots, m$) updates its bias and weights ($j = 0, \dots, p$)

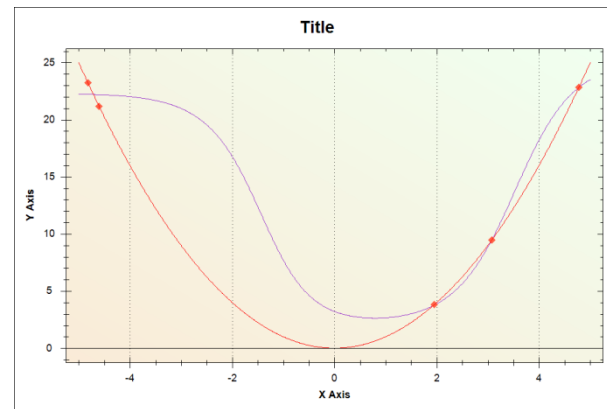
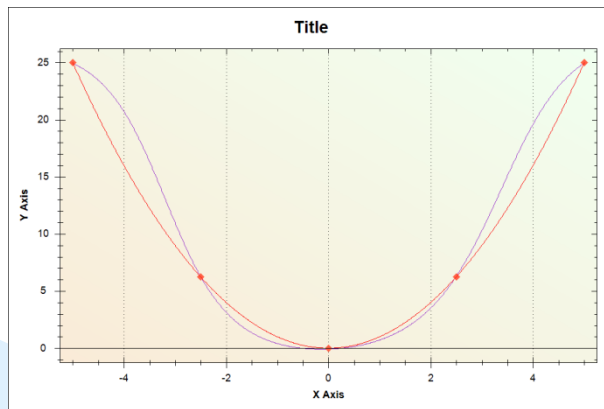
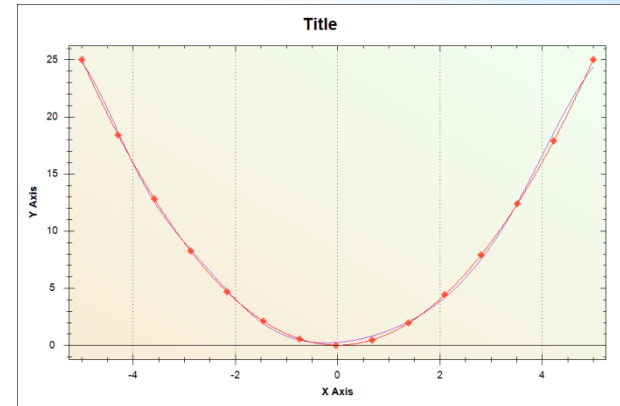
$$w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk}$$

Each hidden unit ($Z_j, j = 1, \dots, p$) updates its bias and weights ($i = 0, \dots, n$)

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij}$$

ANN - Training-Data

- Training-data quality
- Sufficient number of training data pairs
- Training data points distribution
- Verification points selection



ANN - Calculation of response

After training, a backpropagation NN is using only the feedforward phase of the training algorithm

- Step1

Initialize weights

- Step2

For $i = 1, \dots, n$ set activation of input unit x_i

- Step3

For $j = 1, \dots, p$ $z_in_j = v_{0j} + \sum_{i=1}^n x_i v_{ij}$ $z_j = f(z_in_j)$

- Step4

For $k = 1, \dots, m$ $y_in_k = w_{0k} + \sum_{j=1}^p z_j w_{jk}$ $y_k = f(y_in_k)$

Modeling of continuous casting of steel by ANN

Physical Simulator Parameters

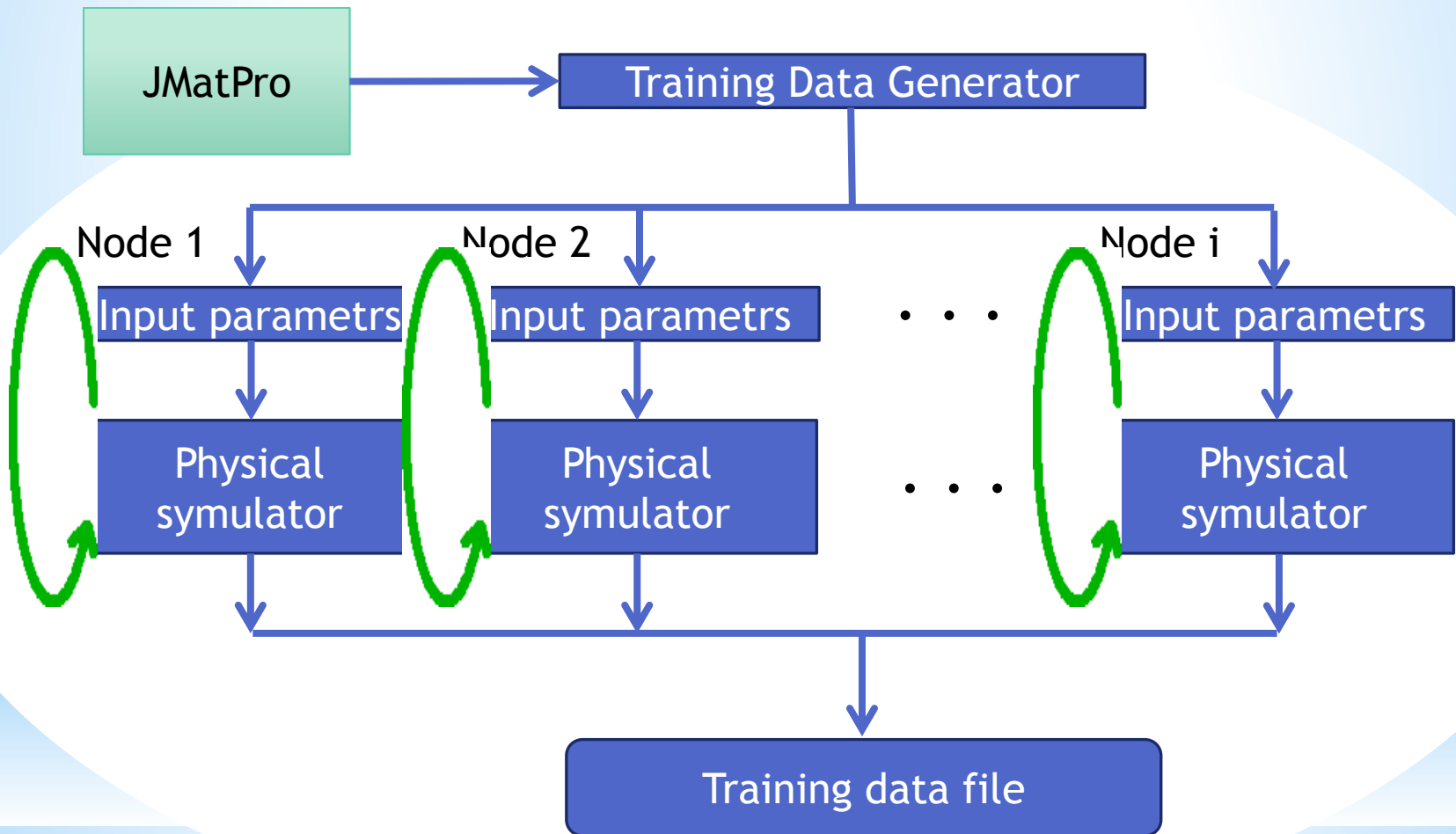
• 21 Input parameters

- Charge number
- Steel type
- Concentration: Cr, Cu, Mn, Mo, Ni, Si, V, C, P, S
- Billet dimension
- Casting temperature
- Casting speed
- Delta temperature
- Cooling flow rate in the mold
- Cooling water temperature in sprays
- Cooling flow rate in wreath spray system
- Cooling flow rate in 1st spray system

• 21 Output parameters

- ML
- DS
- T

Generating Parameters & Outputs

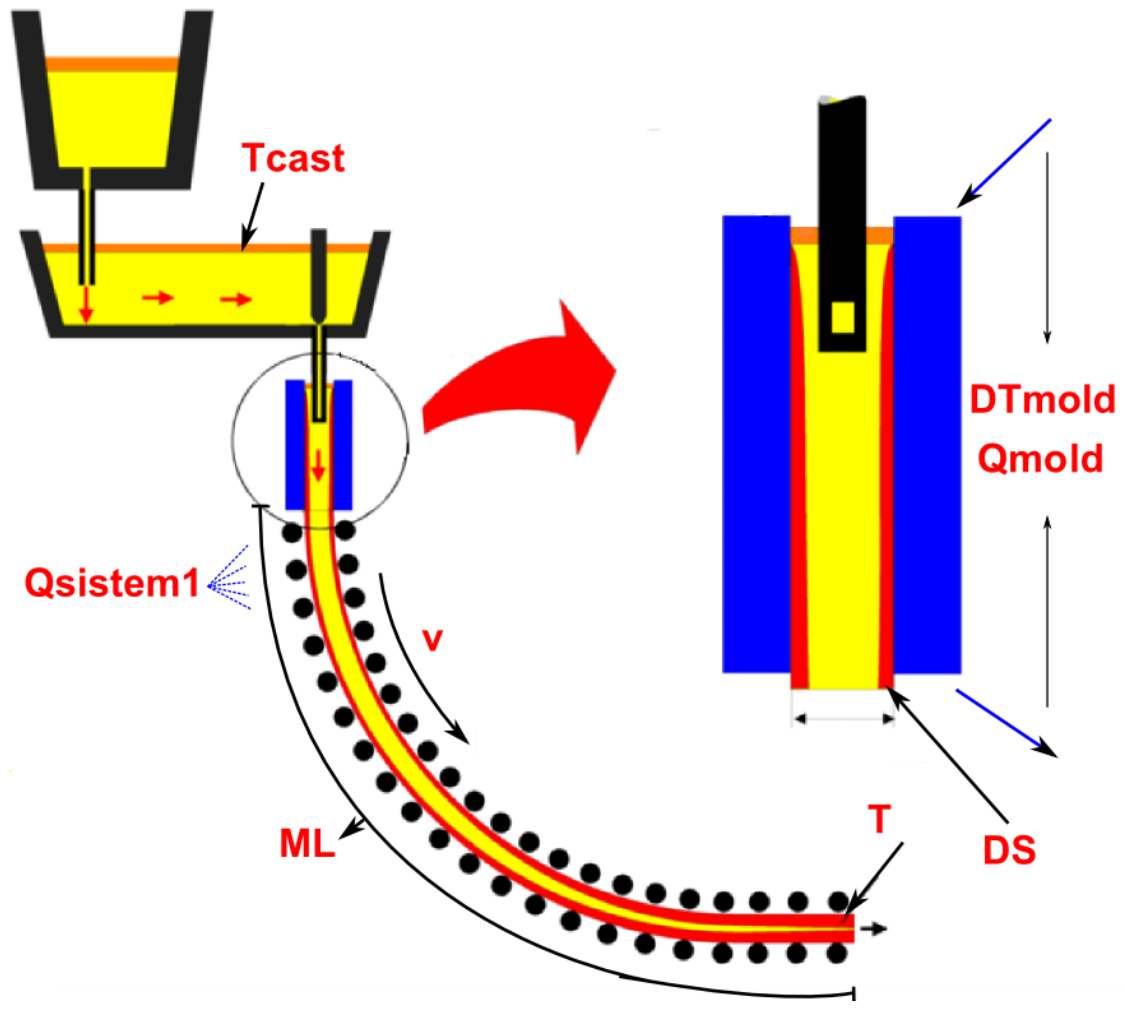


Casting Parameters & Outputs

ID	Name & units	Description	Range in the training set
1	Tcast [°C]	Casting temperature	1515 - 1562
2	v [m/min]	Casting speed	1.03 - 1.86
3	DTmold [°C]	Temperature difference of cooling water in the mold	5 - 10
4	Qmold [l/min]	Cooling flow rate in the mold	1050 - 1446
5	Qwreath [l/min]	Cooling flow rate in wreath spray system	10 - 39
6	Qsistem1 [l/min]	Cooling flow rate in 1st spray system	28 - 75

ID	Name & units	Description & units	Range in the training set
1	ML [m]	Metallurgical length	8.6399 - 12.54
2	DS [m]	Shell thickness at the end of the mold	0.0058875 - 0.0210225
3	T [°C]	Billet surface temperature at straightening start position	1064.5 - 1163.5

Casting Parameters & Outputs

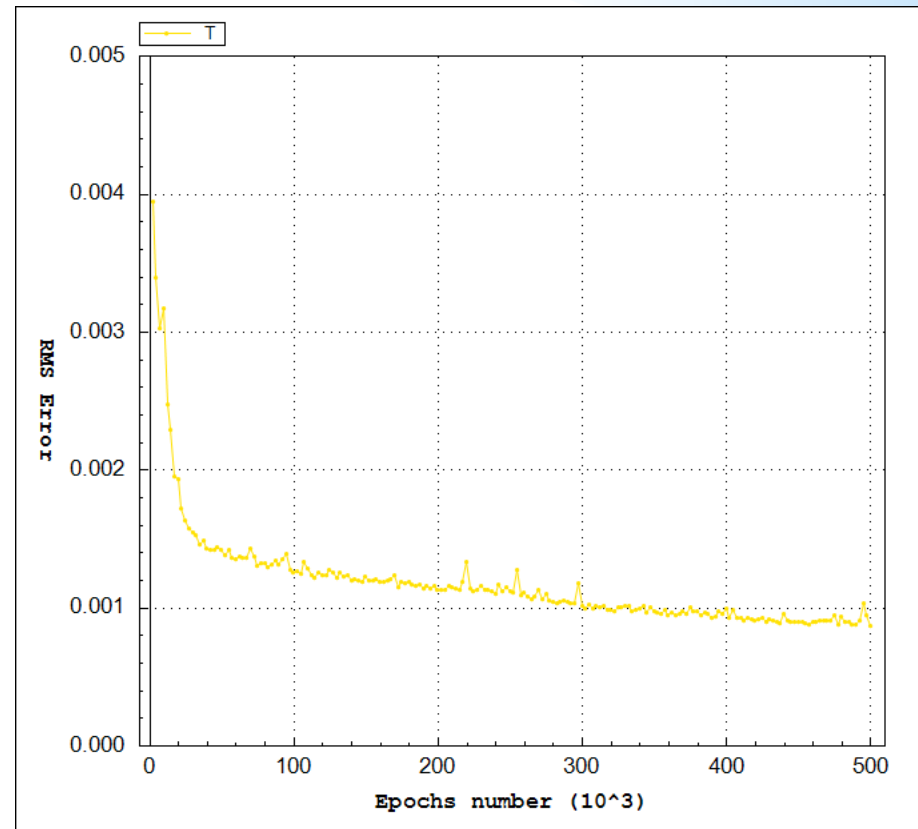
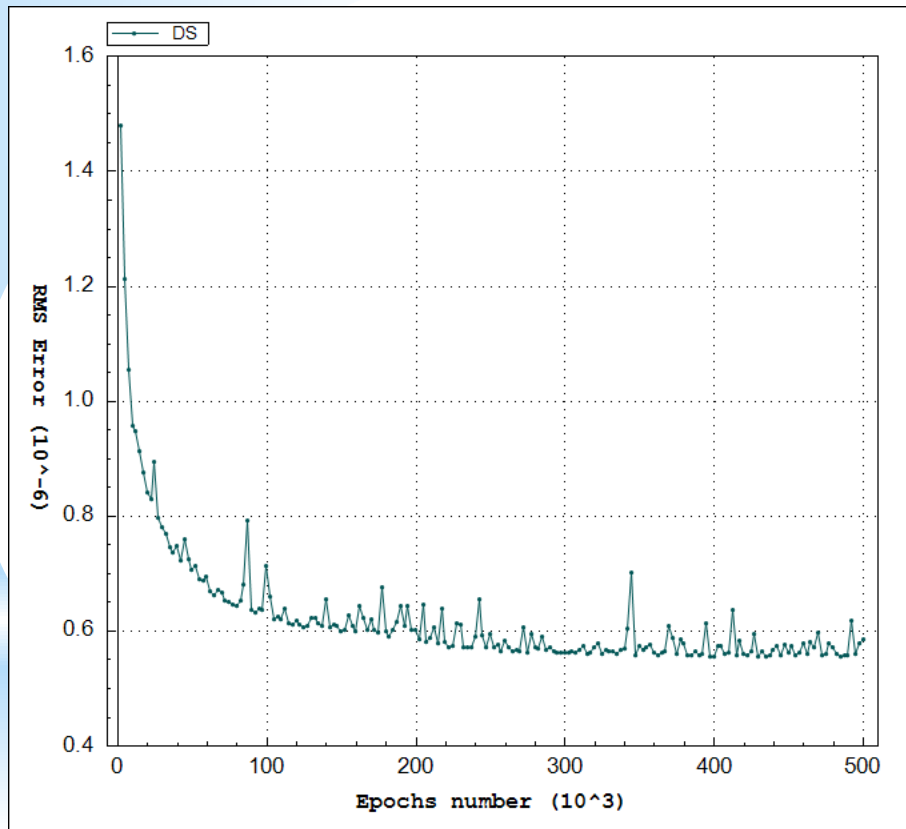


Training the ANN

- NeuronDotNet open source library
- 200000 total IO pairs
 - 100000 training IO pairs
 - 100000 verification IO pairs
- Settings for ANN
 - Epochs 50000
 - Hidden layers 1
 - Neurons in hidden layer 25
 - Learning rate = 0.3
 - Momentum = 0.6

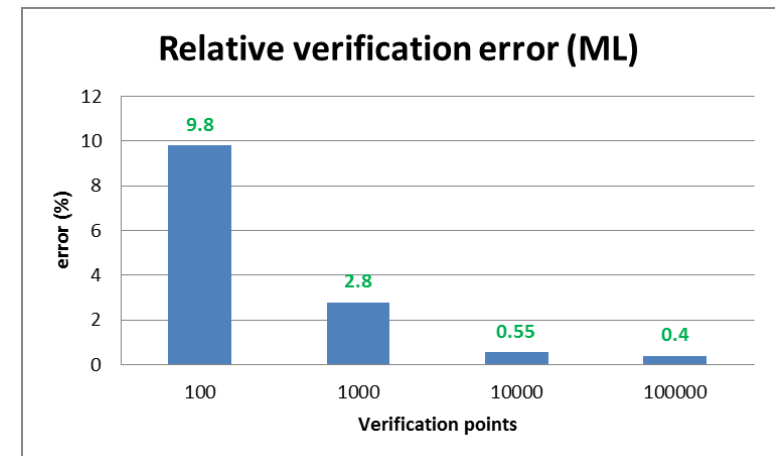
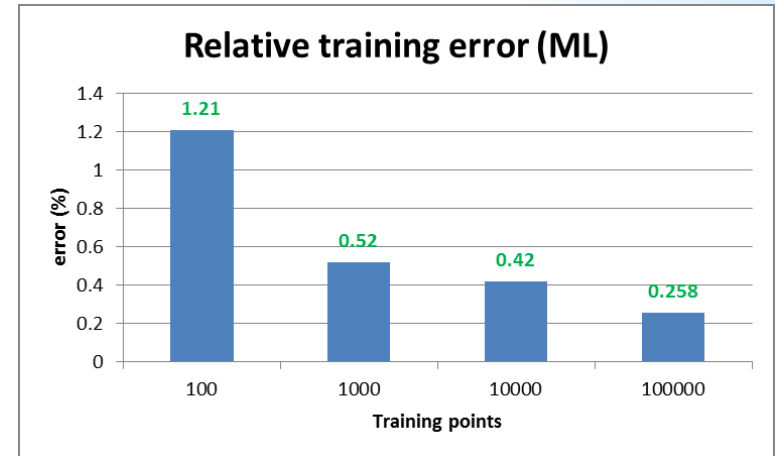
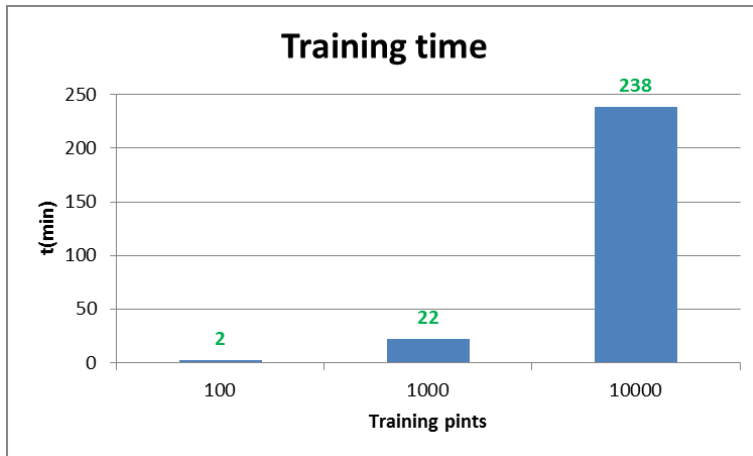
Training the ANN

- RMS errors during training



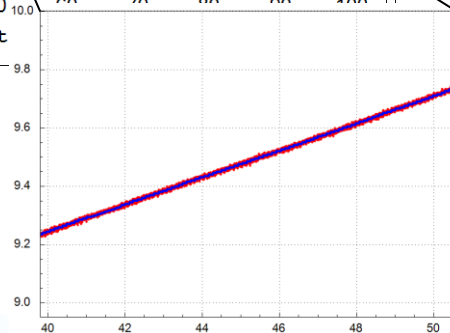
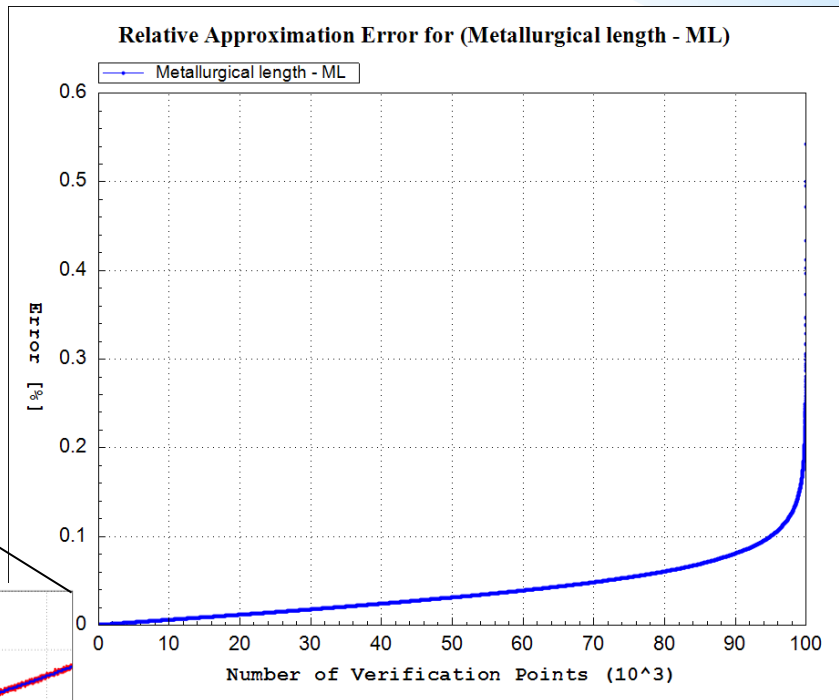
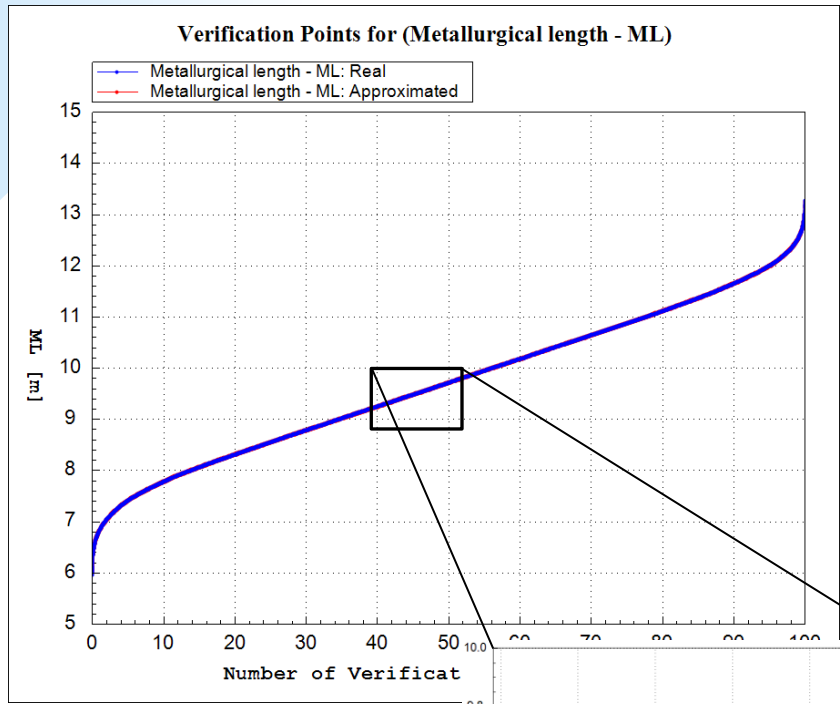
Studies

- Relations between training time, training data and errors



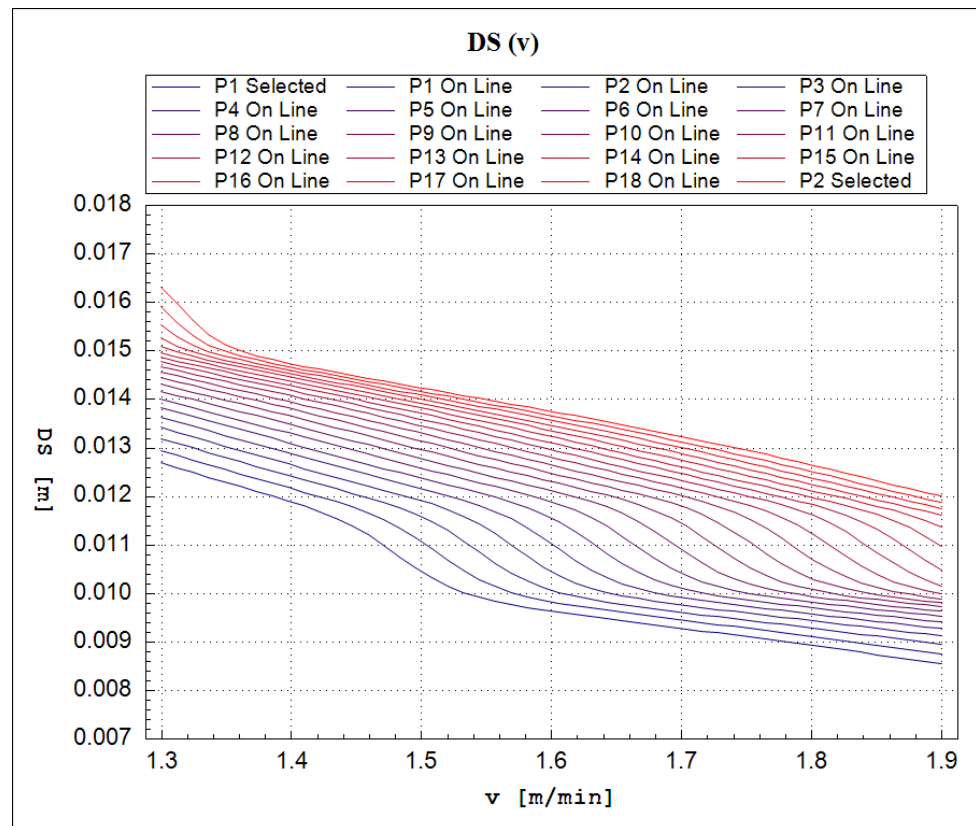
Study of Errors

- Relative errors in verification points



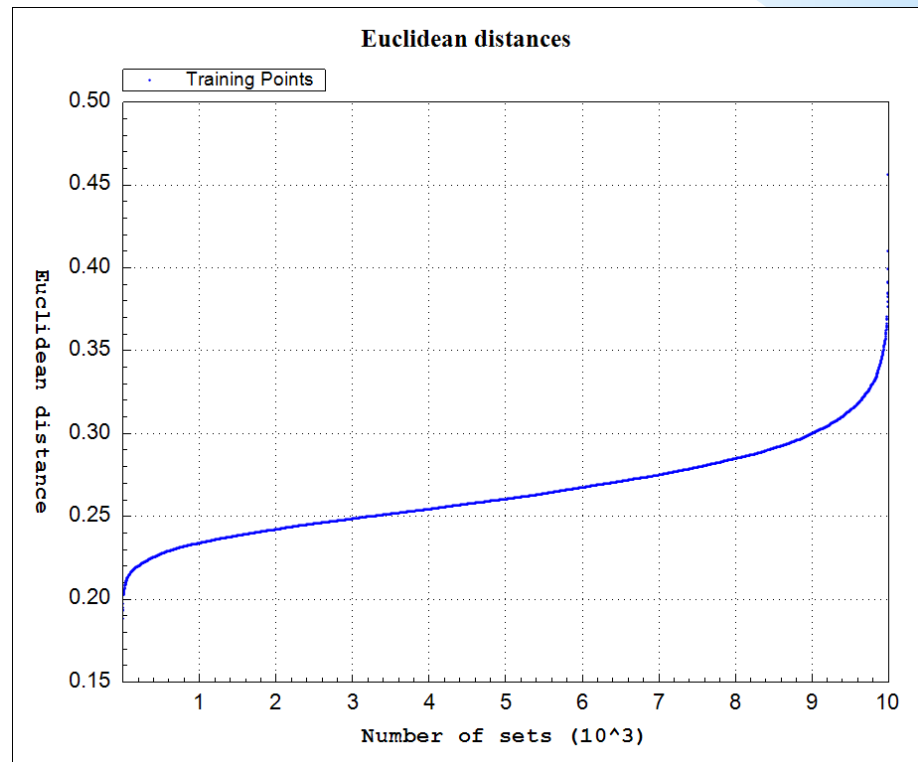
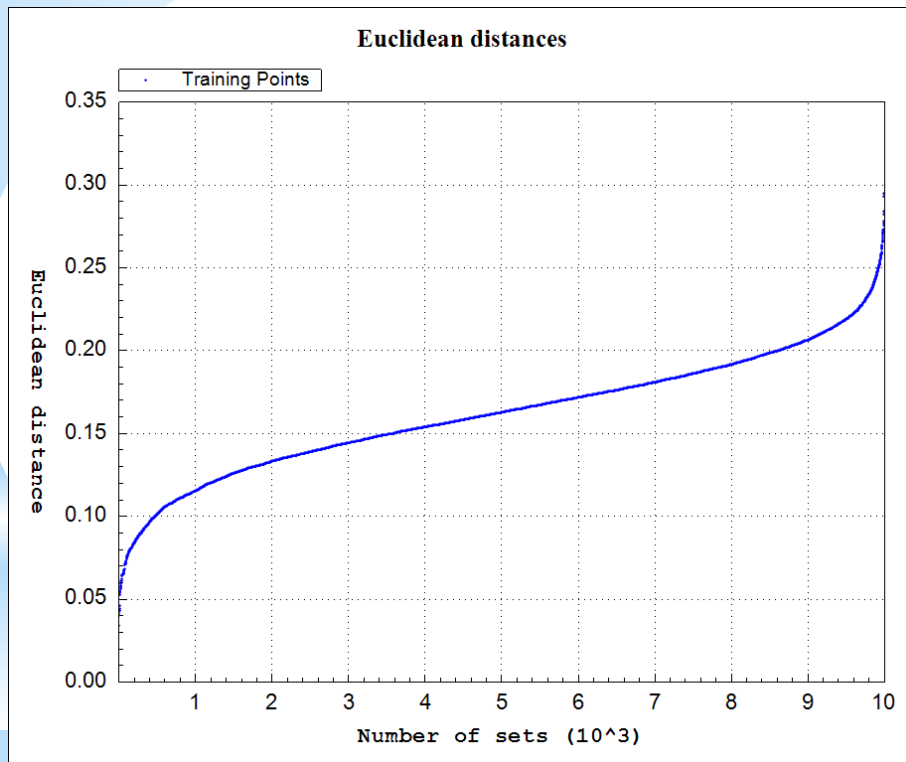
Parametric Studies

- Response around Points on a Line Between Two Points



Study: Uniformity of Training Points Distribution

- Euclidean distances to the N-th point
 - Closest point
 - 9-th closest point



Conclusions and future work

- Dedicated SW framework was developed
- Studies to examine the accuracy of ANN based on physical model
- ANN approximation is much faster than physical simulation

- Complementing physical models with ANNs
- Replacing physical models with ANNs
- Upgrading of the ANN model for continuous casting with the model of the whole production chain
- Development of new methods for checking the quality of training-data

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- I. Grešovnik: IGLib.NET library, <http://www2.arnes.si/~ljc3m2/igor/iglib/>.

Acknowledgements

Prof.dr.Božidar Šarler, dr. Igor Grešovnik, dr. Robert Vertnik

Thank you!