AI and ML techniques for generation and assessment of products properties data.

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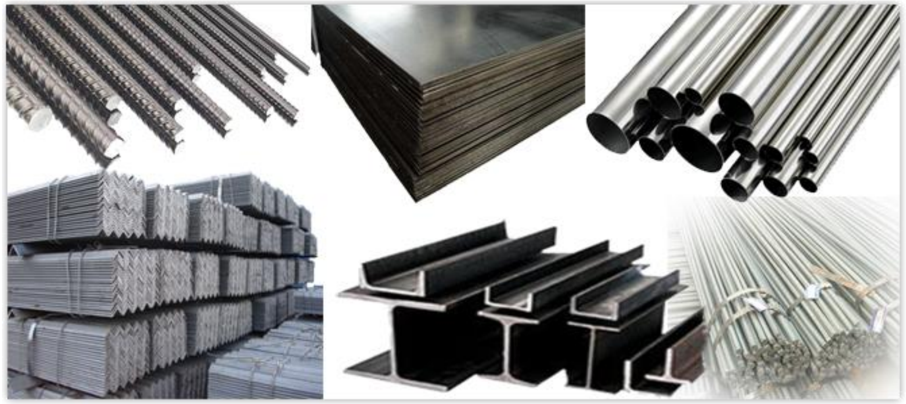
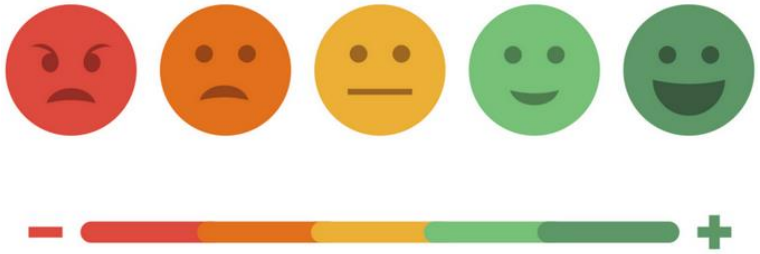
Outline

- The **importance** of steel quality data and their reliability
- The **role of AI** techniques
- AI for the **generation** of quality data
- AI for the **assessment** of quality data
- Conclusions

Introduction
Quality data & reliability

Quality data





- the guarantee of the **fulfillment of products requirements** is an essential point in customer-supplier relation

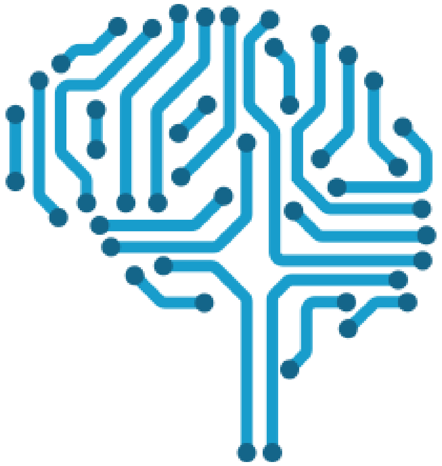
- Providing **reliable** quality data may determine **customer choice**

The *cost* of quality data

- Quality data are not free: either **DT** or **NDT** they cost **time** and **money**
- Sometimes partial (products are not uniform..), as samples
- Reduces overall reliability of provided quality data

- ***Over-quality*** is not the solution

Can Artificial Intelligence & Co. be helpful?



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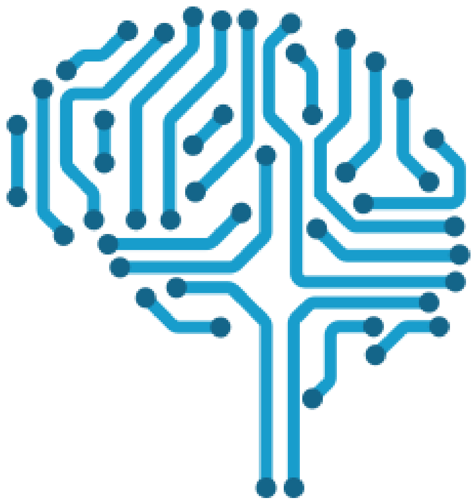


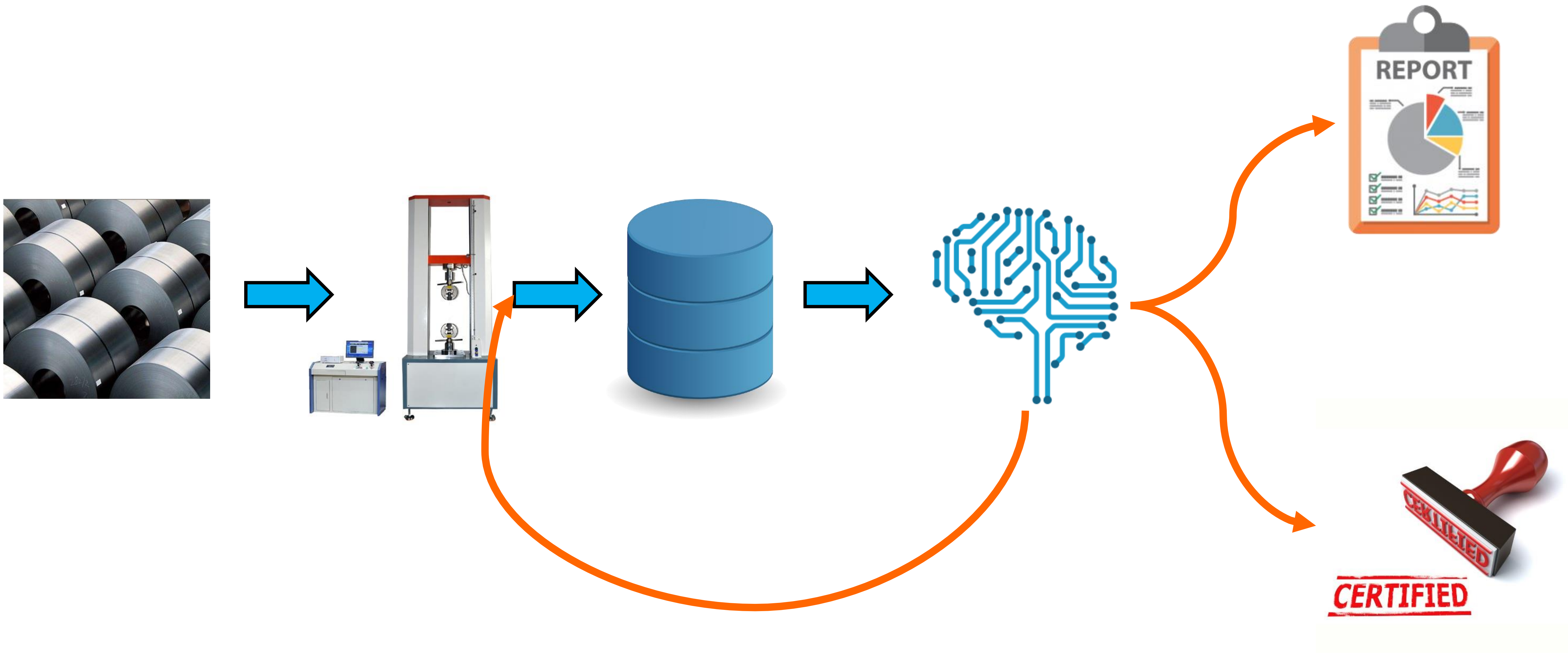
The potential

- No **cost** (more or less)
- Fast
- **Data** driven *but also* human **expertise** flavoured

Things to take into account

- **Need data** and real tests to be tuned
- **Reliability** of **training data** is central
- **Reliability** of **models** and **results** is even more central

AI for quality data: the direction



Generating reliable quality data
Through AI

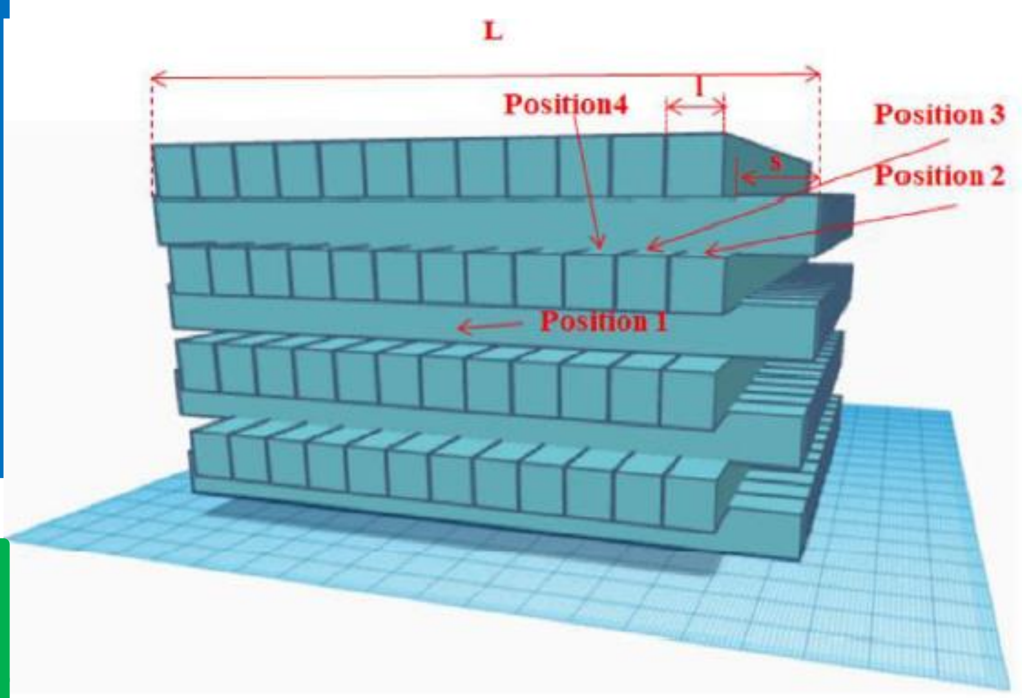
Quality data generation – Residual hydrogen

Motivation

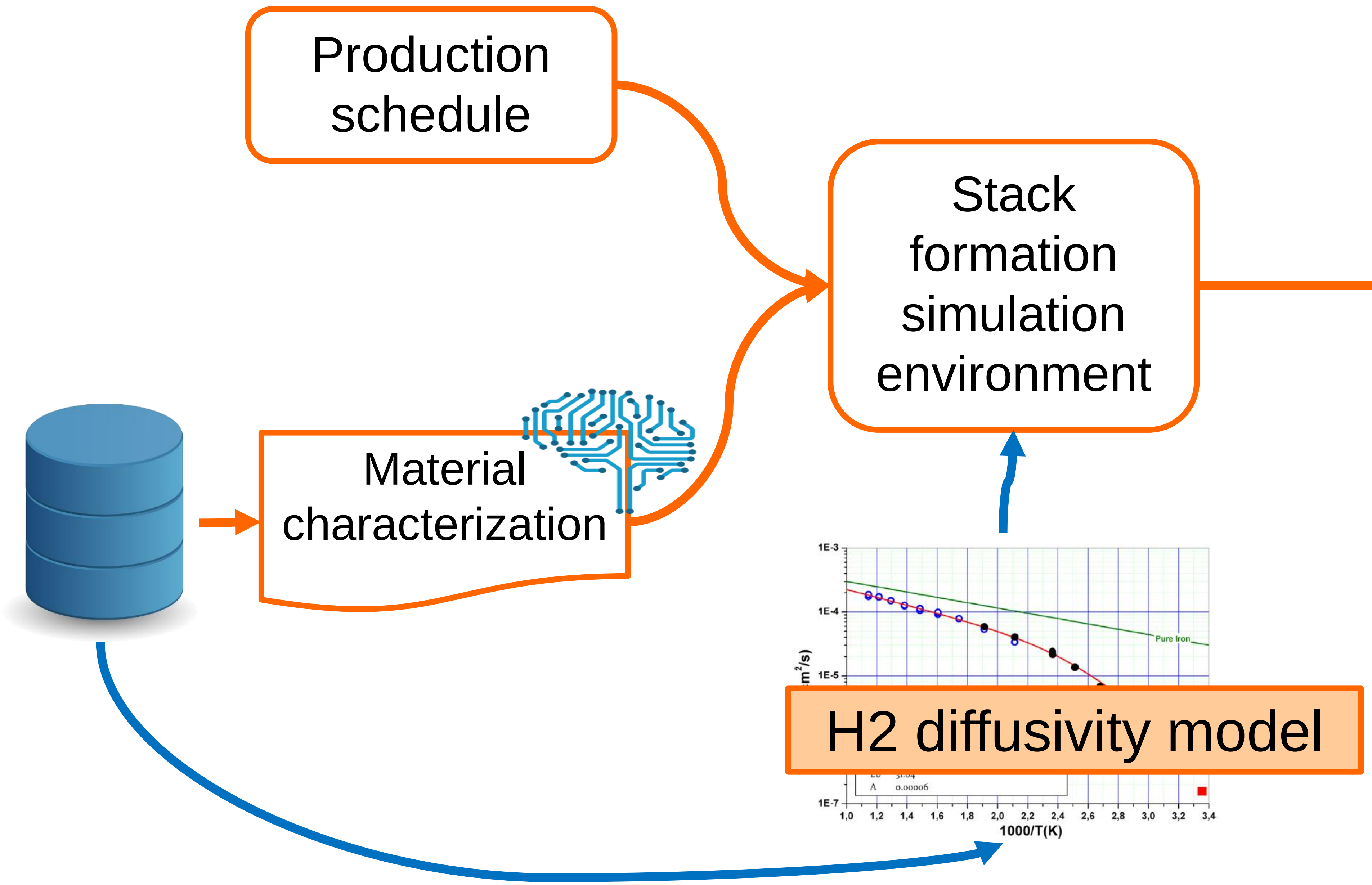
- Hydrogen content is **detrimental** (cracks)
- Not always avoidable (vacuum degassing)
- **Cooling** determines final content of H2
- Which are the billets with dangerous H2 content?

The need of quality data

- Target: no defective products to customers
- Destructive, partial, time consuming test



Quality data generation – Residual hydrogen

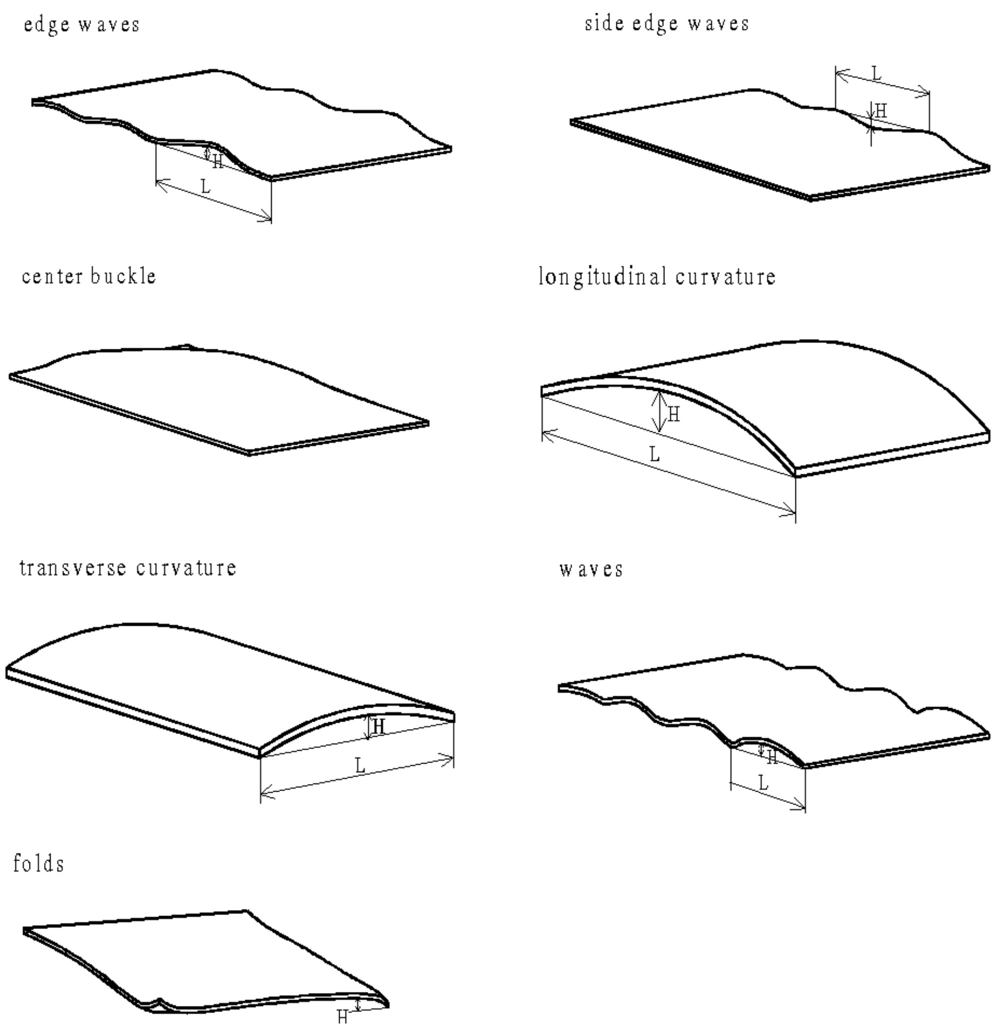


Column / Row	21	22	23	24	25	26	27
33	0.6	0.8	1.1	1.6	2.5	4.0	5.8
32	0.4	0.6	0.8	1.3	2.2	3.7	5.7
31	0.3	0.4	0.7	1.1	1.9	3.4	5.6
30	0.2	0.3	0.5	0.9	1.6	3.1	5.5
29	0.2	0.2	0.4	0.7	1.4	2.9	5.4
28	0.1	0.2	0.3	0.6	1.3	2.7	5.4
27	0.1	0.1	0.3	0.5	1.1	2.5	5.3

Achievements:

- **Position** and H2 content of risky billets
- Possibility of **optimization**

Flatness defects detection through DNN



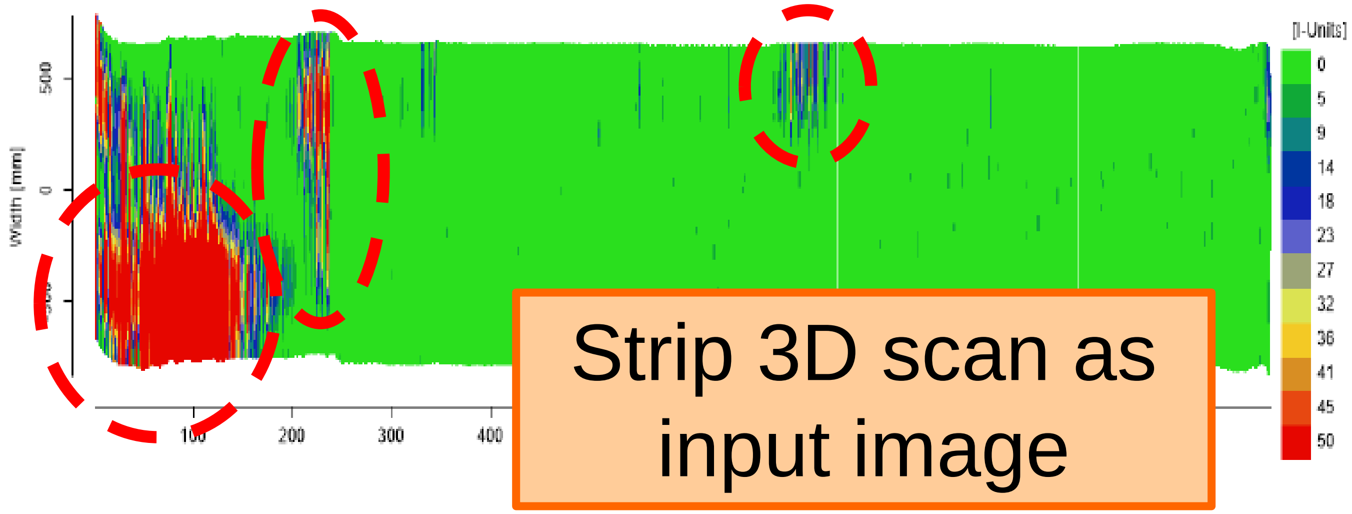
Flatness defects

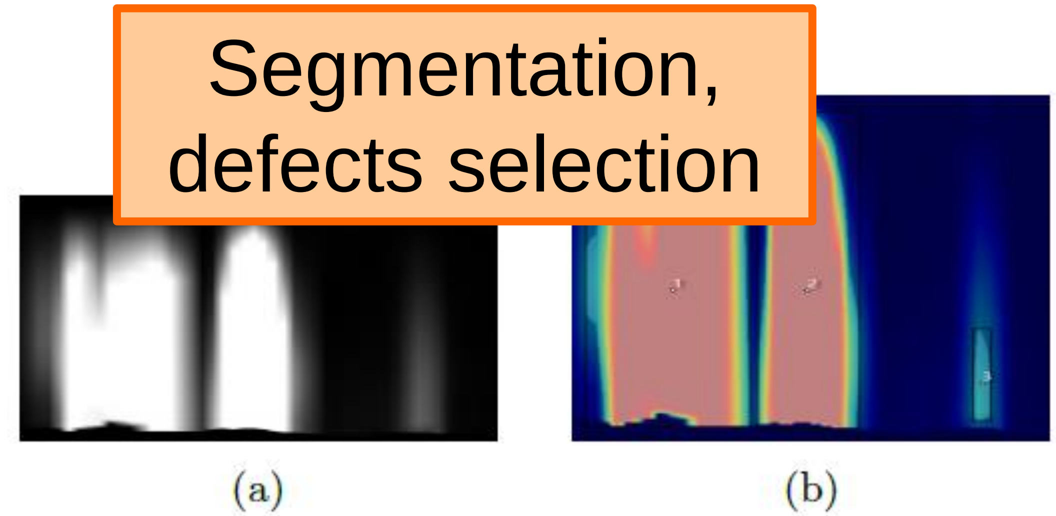
- Important **quality** information
- Not only the **presence** but also the **type** and **position**
- *Downgrading* type is affected

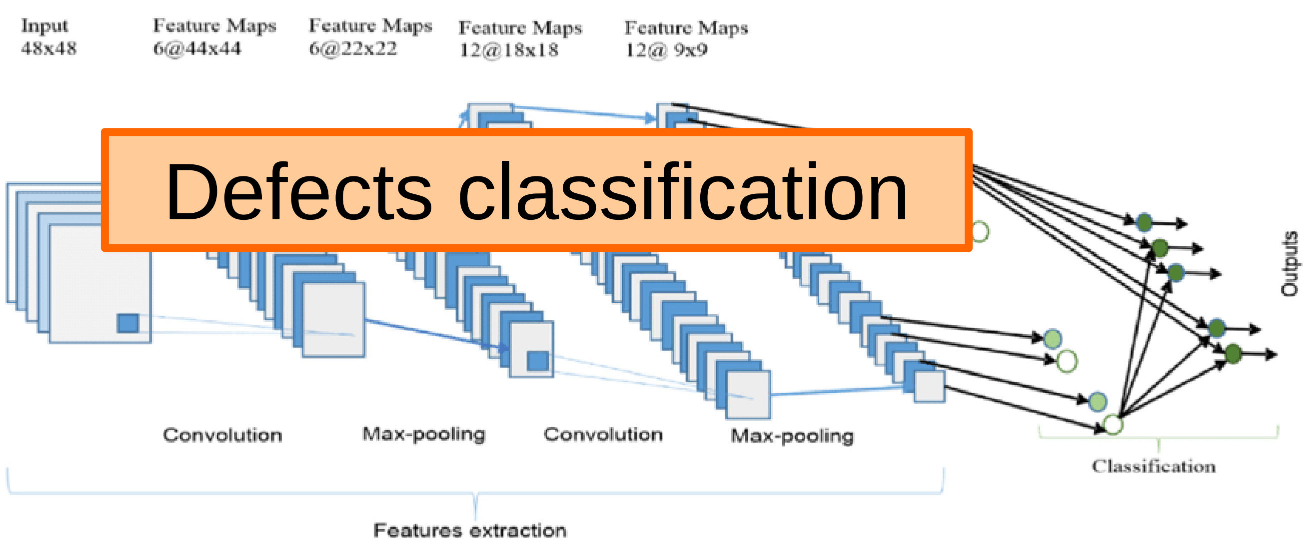
- **Time** and **resources** consuming task performed by **humans**

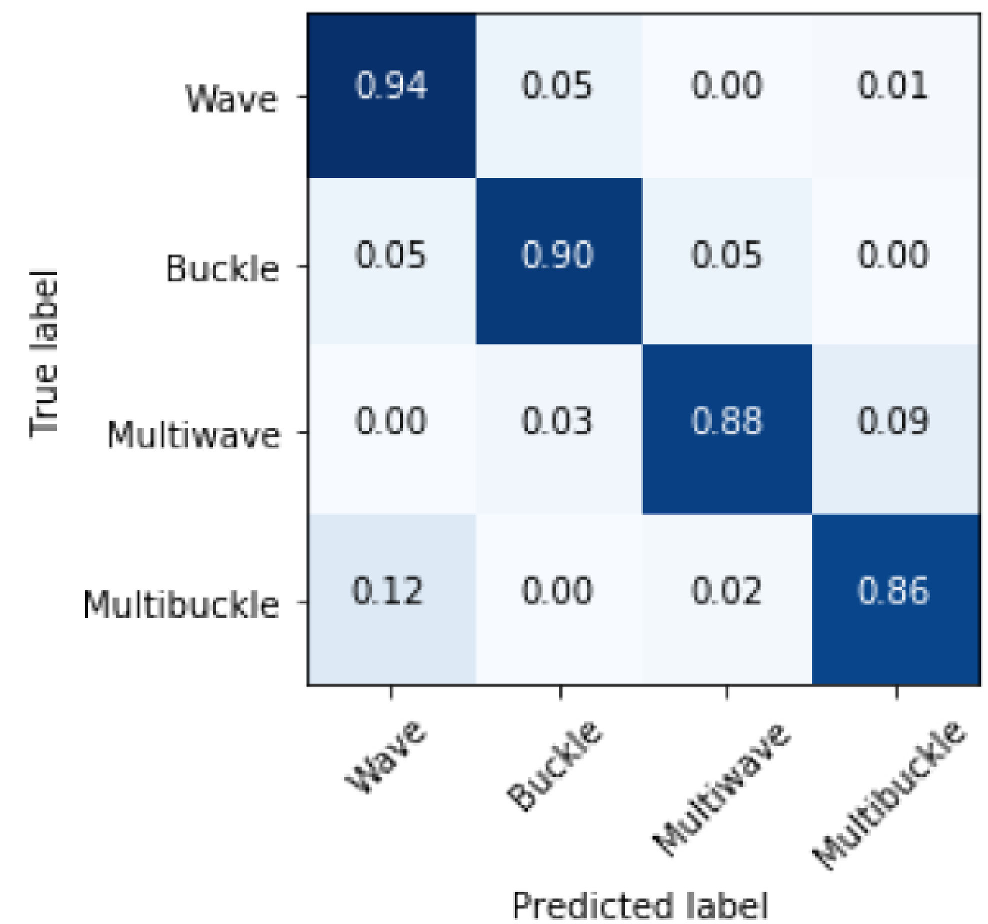
Is automation possible and reliable?

Flatness defects detection through DNN

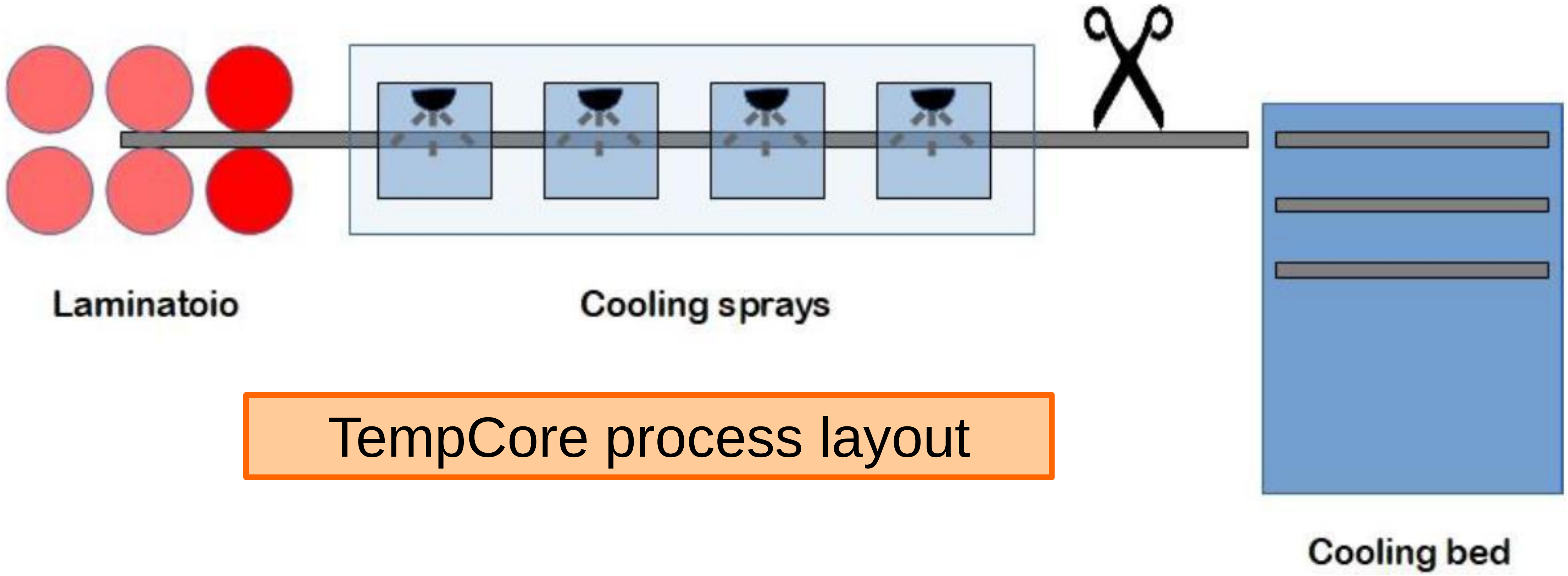








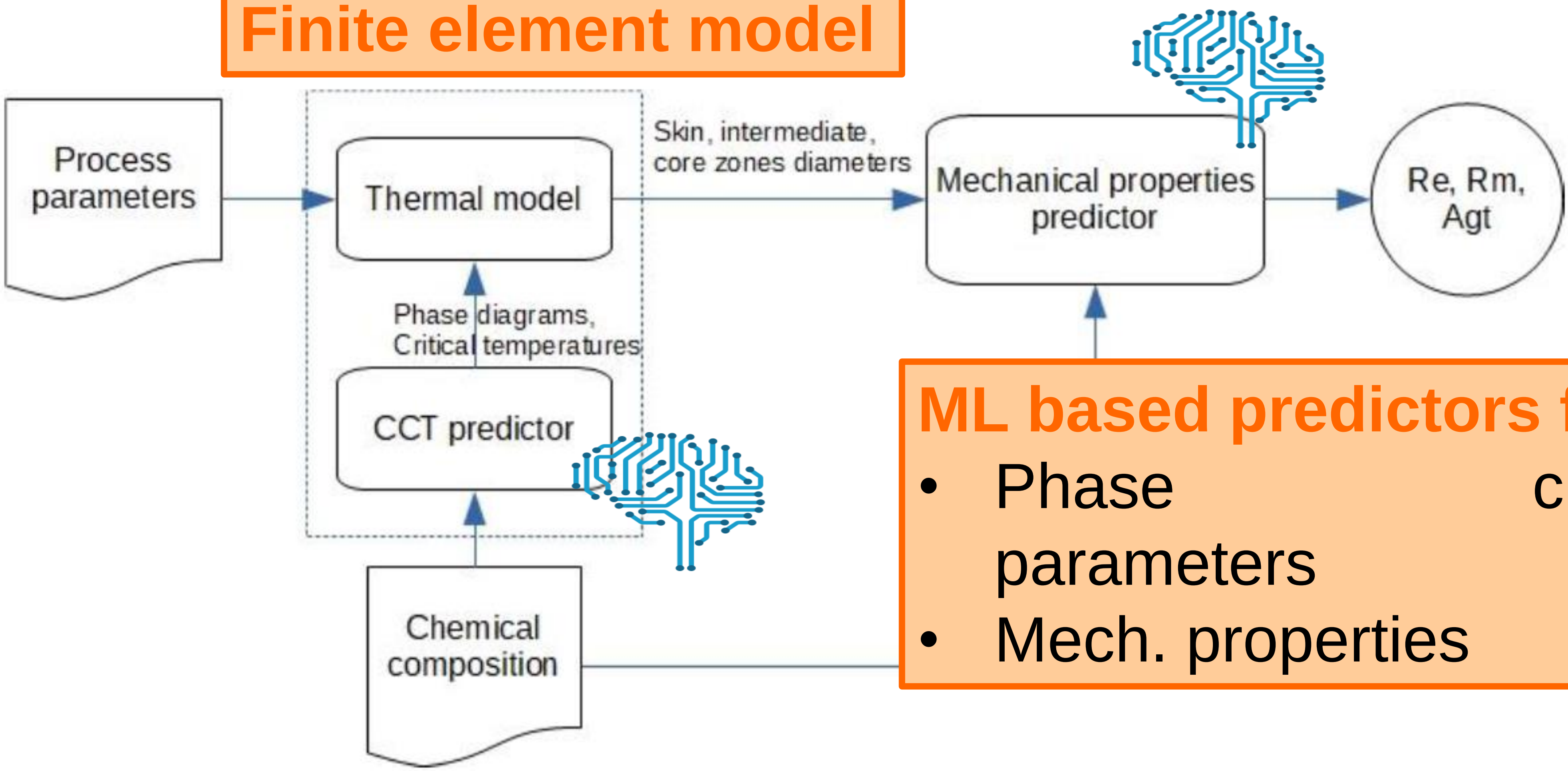
Reinforcing bars mechanical properties prediction



- Reinforcing bars produced through the ***TempCore*** process for achieving high elasticity and resistance
- Complex chemical and physical interaction during cooling
- Different conditions throughout production: how to evaluate all bars features?

Reinforcing bars mechanical properties prediction

Finite element model



ML based predictors for:

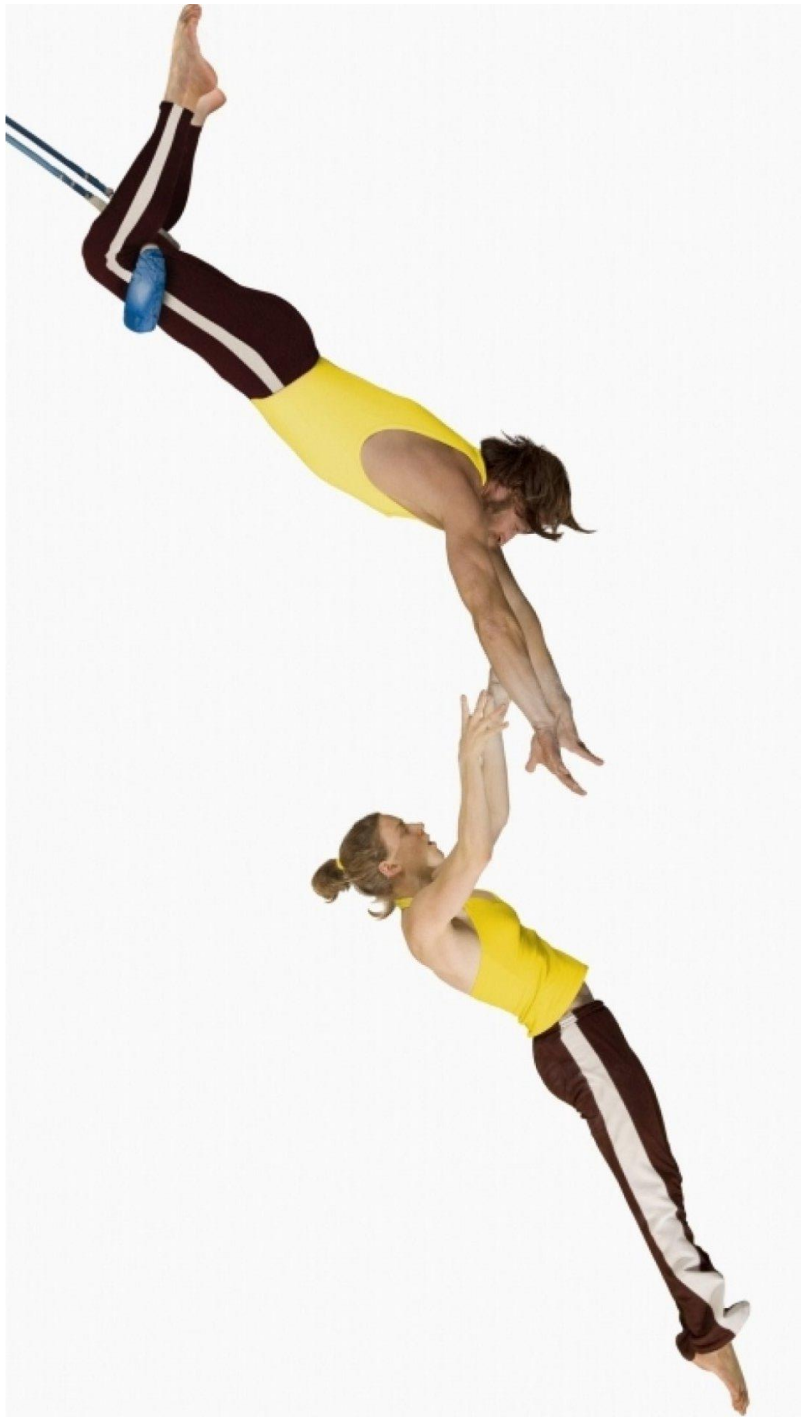
- Phase curves parameters
- Mech. properties

%err	LM	LS	MLP
R_m	1.77	**1.69**	**1.69**
R_e	2.52	**2.37**	2.88
A%	6.13	**6.02**	6.69

- **Satisfactory** on Re and Rm
- Plant set-up can be used for ***optimization*** purpose

Assessing the reliability of quality data Through AI

The key role of reliability



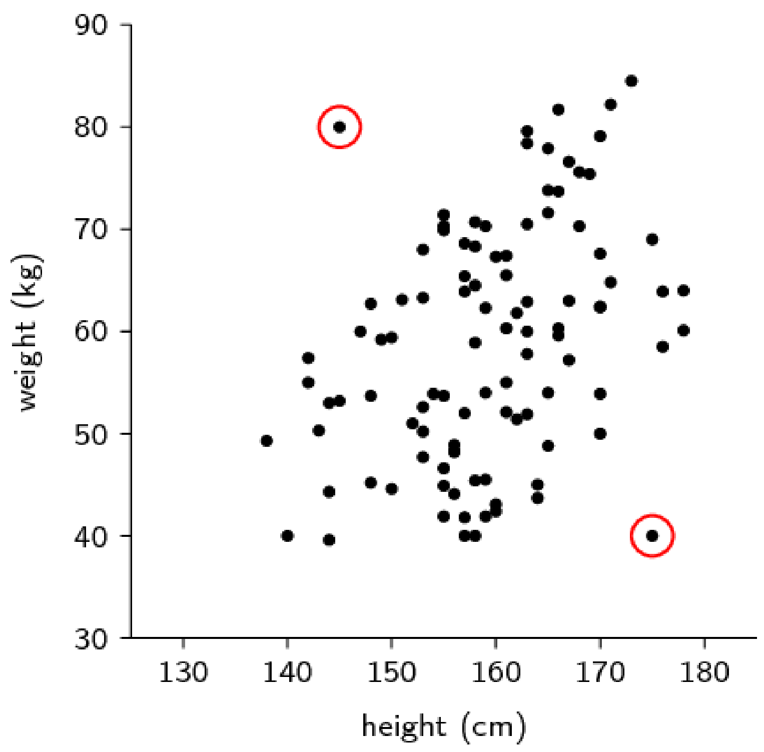
Quality data are nothing without reliability

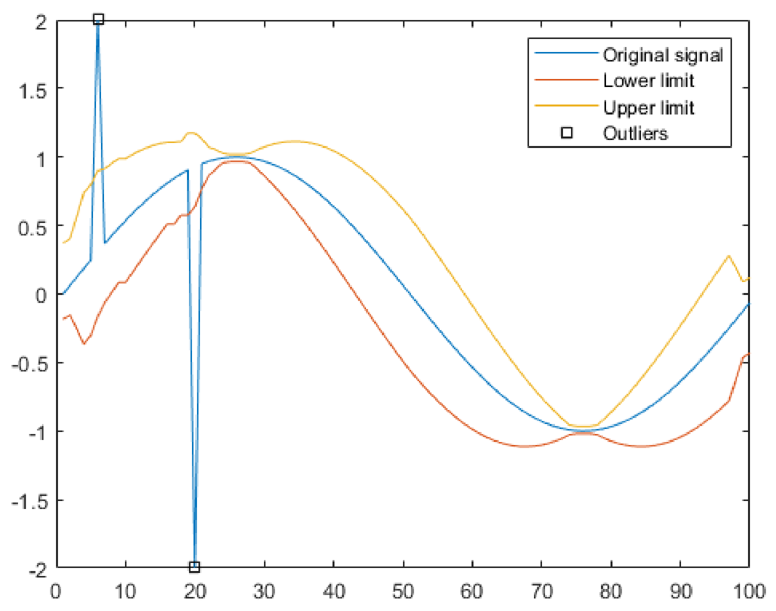
- Are **unreliable** quality data **useful**?
- Producer-customer **intimacy**

We need to be able to **assess** quality data reliability

- Both measured and calculated quality data.

Get rid of outliers in quality data





An **outlier** is a measure that strongly *deviates* from the others.

Highly **detentrimental** in steel quality data

- To share with customer
- To use for estimated quality data

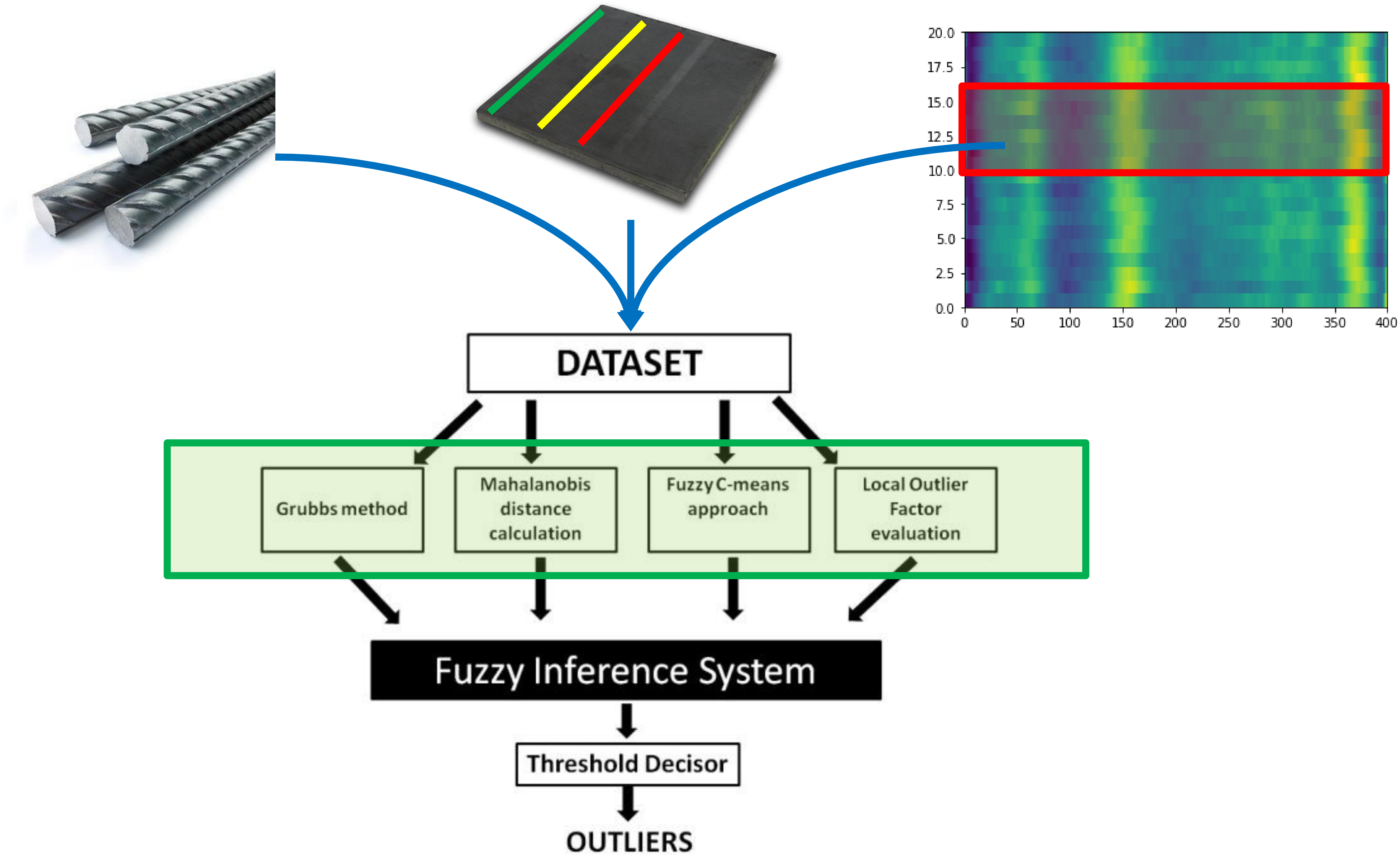
Possible causes:

- Biased tests
- Sensors malfunctions

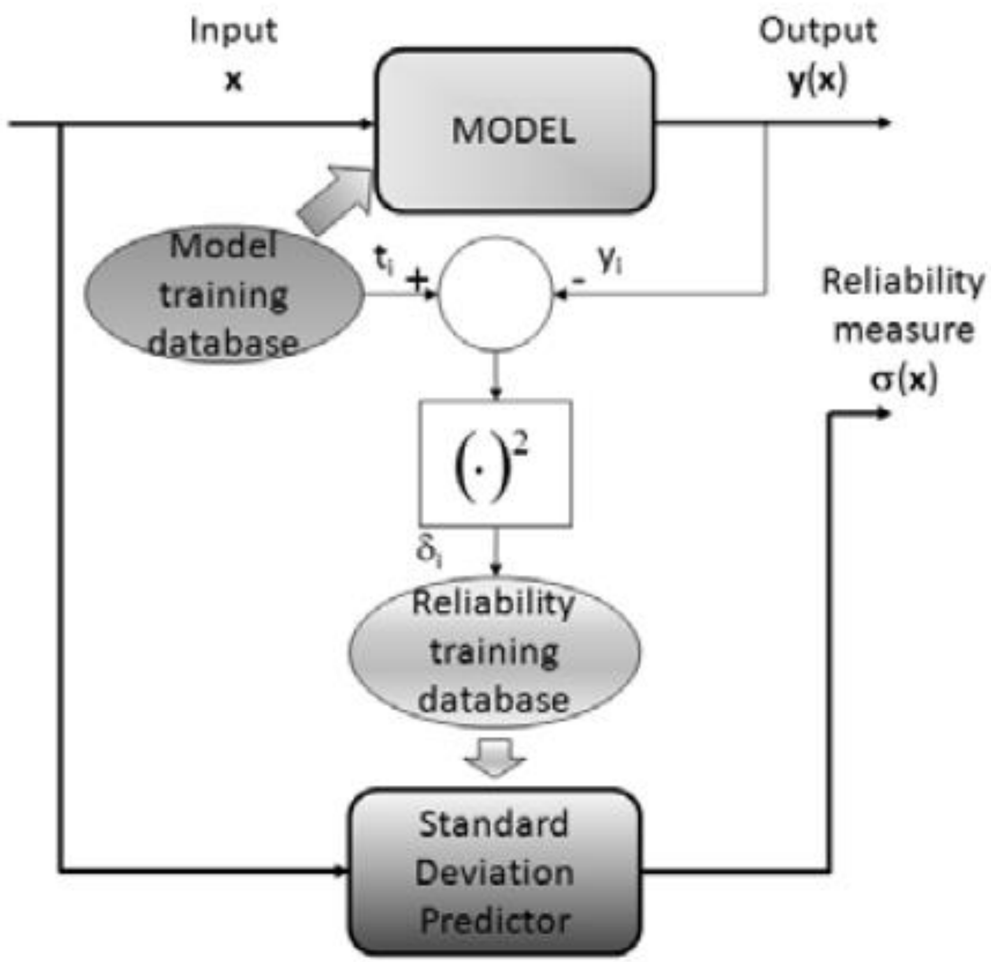
Not always easy! Not always 1D!

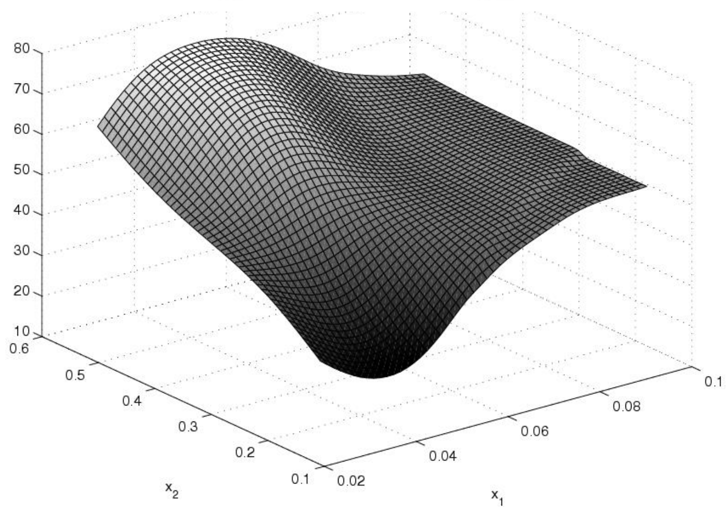
In many steel applications a **multidimensional** approach is required.

Outliers detection based on fuzzy merging



Estimating models reliability through ANNs



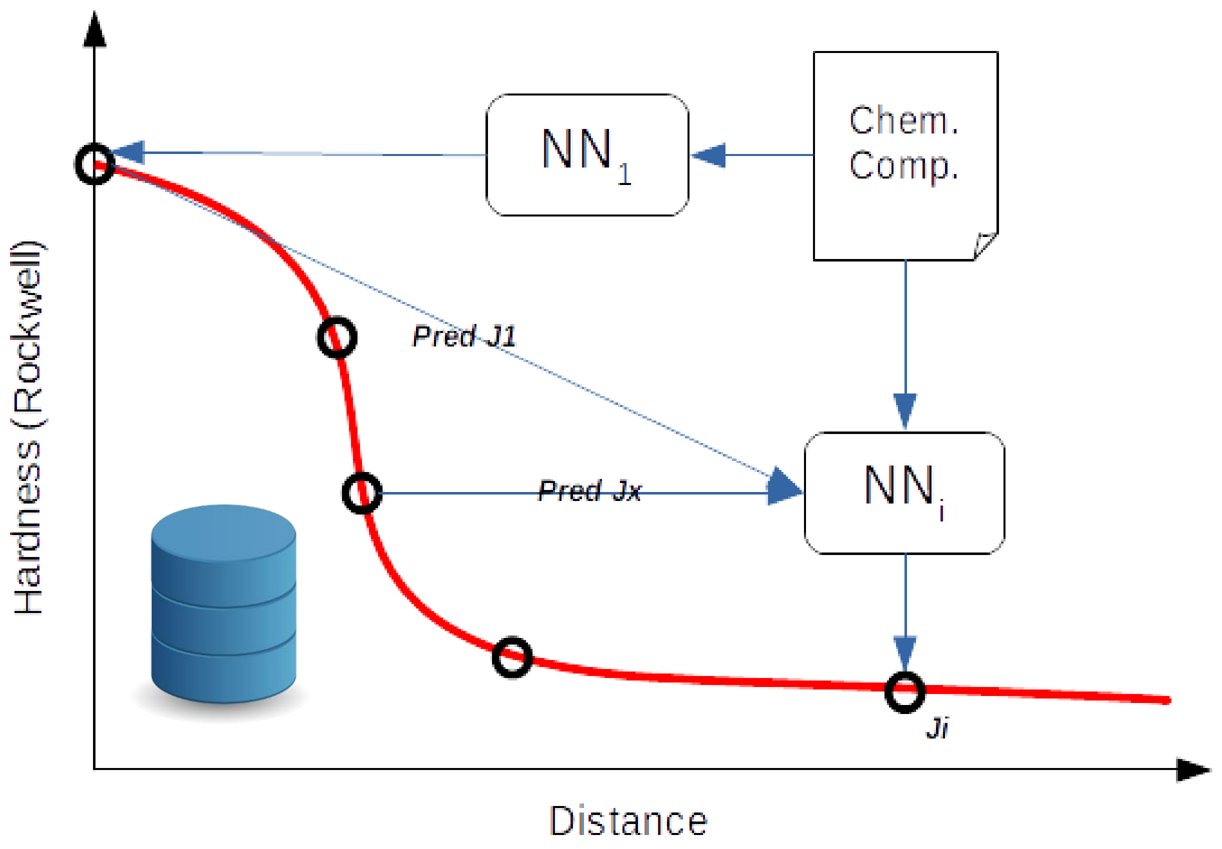


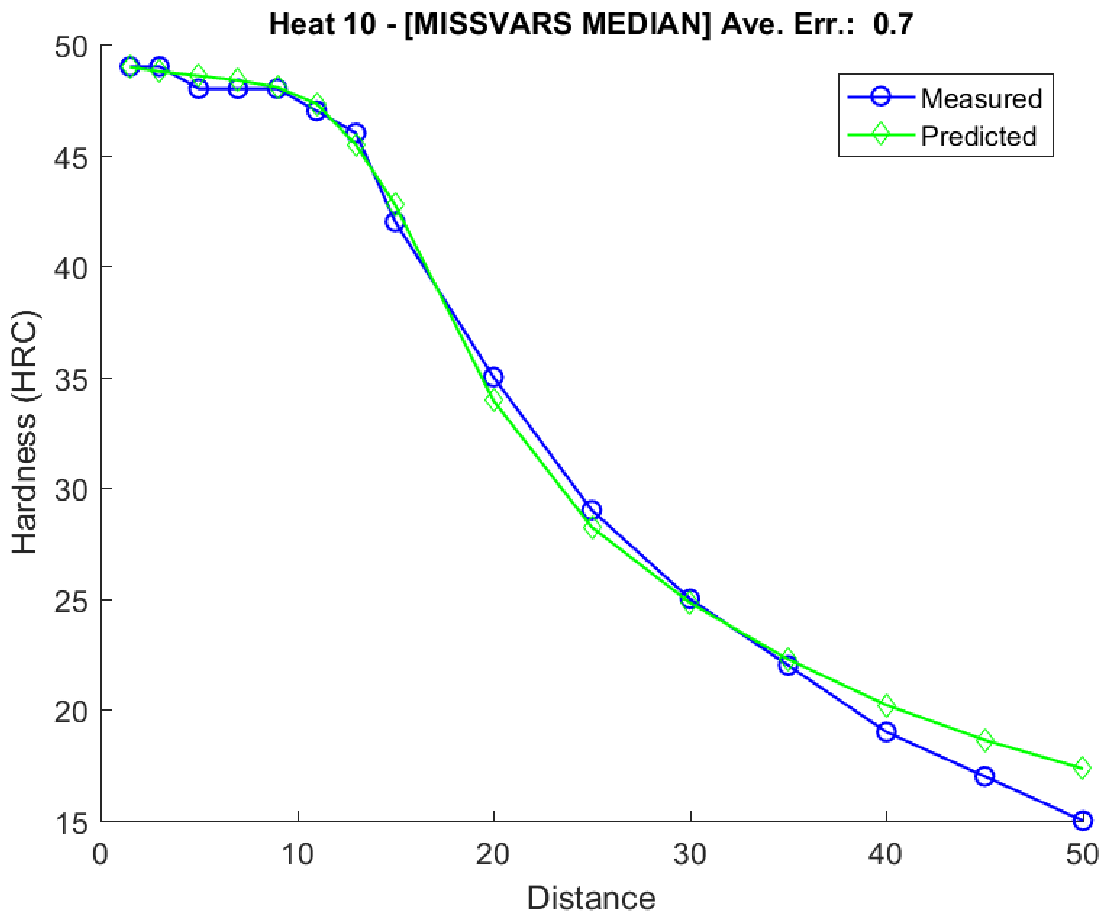
When using a model for quality data estimation, **model reliability** can be punctually *estimated*

- Additional NN
- Point out **favorable/critical** conditions
- No limitation on the model type

Q1	**Q2**	**Q3**	**..**						
R1	R2	R3	..						

A final case study:
the self-conscious Jominy profile predictor





Not just a **performing** Jominy profile predictor

- No need of real test
- Usable for product design

A final case study:
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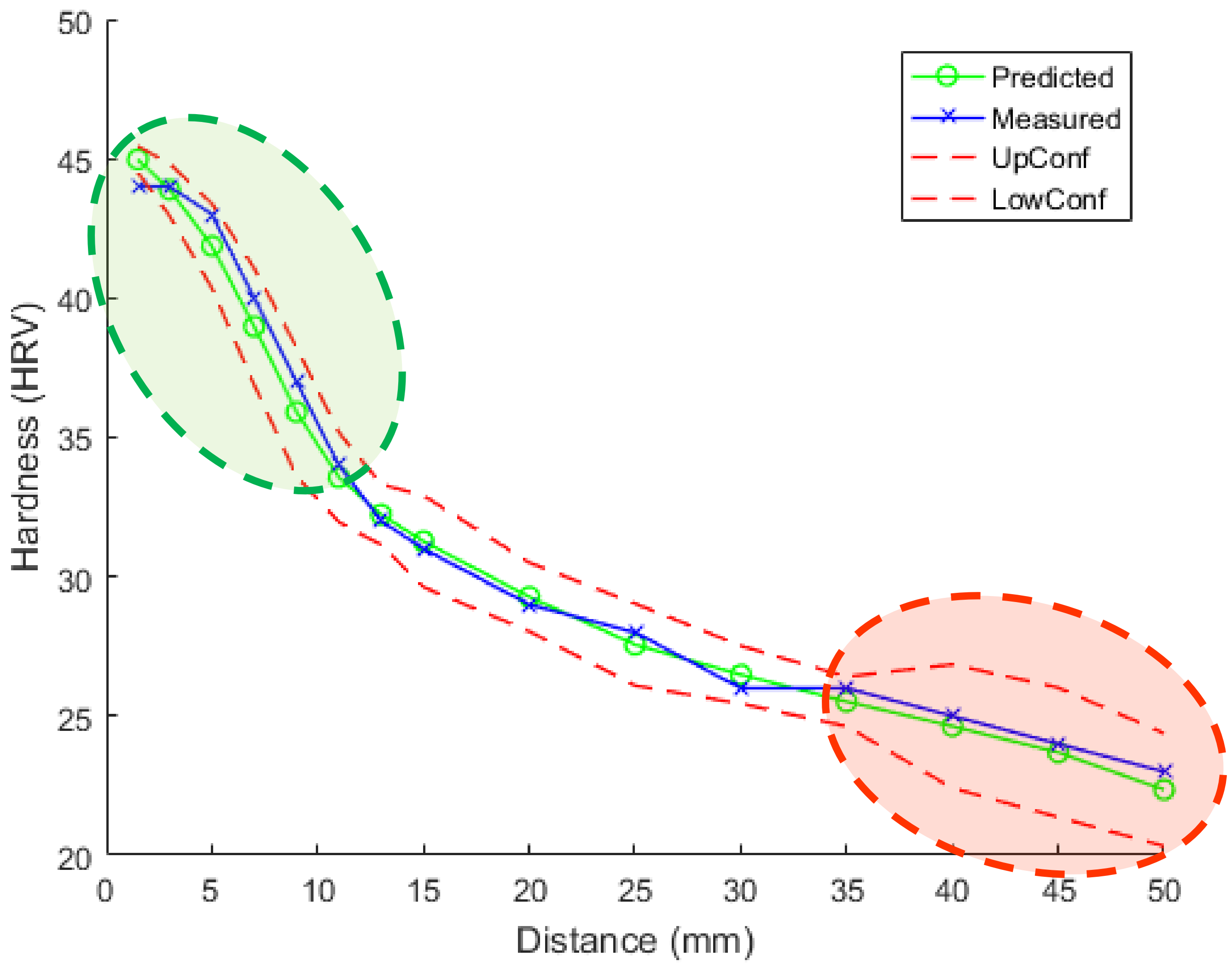

.. But also self-estimation of punctual reliability

- Reliability bounds **adaptive** to model **confidence** in *each point of the profile*
- Determined by **peculiar sample input**
  - Process condition, chem. Composition,..

ICT COISP

To sum up…

- **Quality data** fundamental to
  - Monitor production
  - Relation with customer
- Quality data are not free and their reliability must be granted

- The role of **AI techniques**
  - **Generation** of quality data
    - Save resources, more data, objectivity
  - Improving **reliability**
    - Data integrity, unreliable data detection
    - Assess or produce a reliability measure of quality data

Thank you for your attention.
Time for questions.