BIO-UPTAKE

Digital Tools for Efficient Biomaterials Design & Manufacturing

AIMEN / SIMCOM – 09/Feb/2026

Contents

Digital Platform

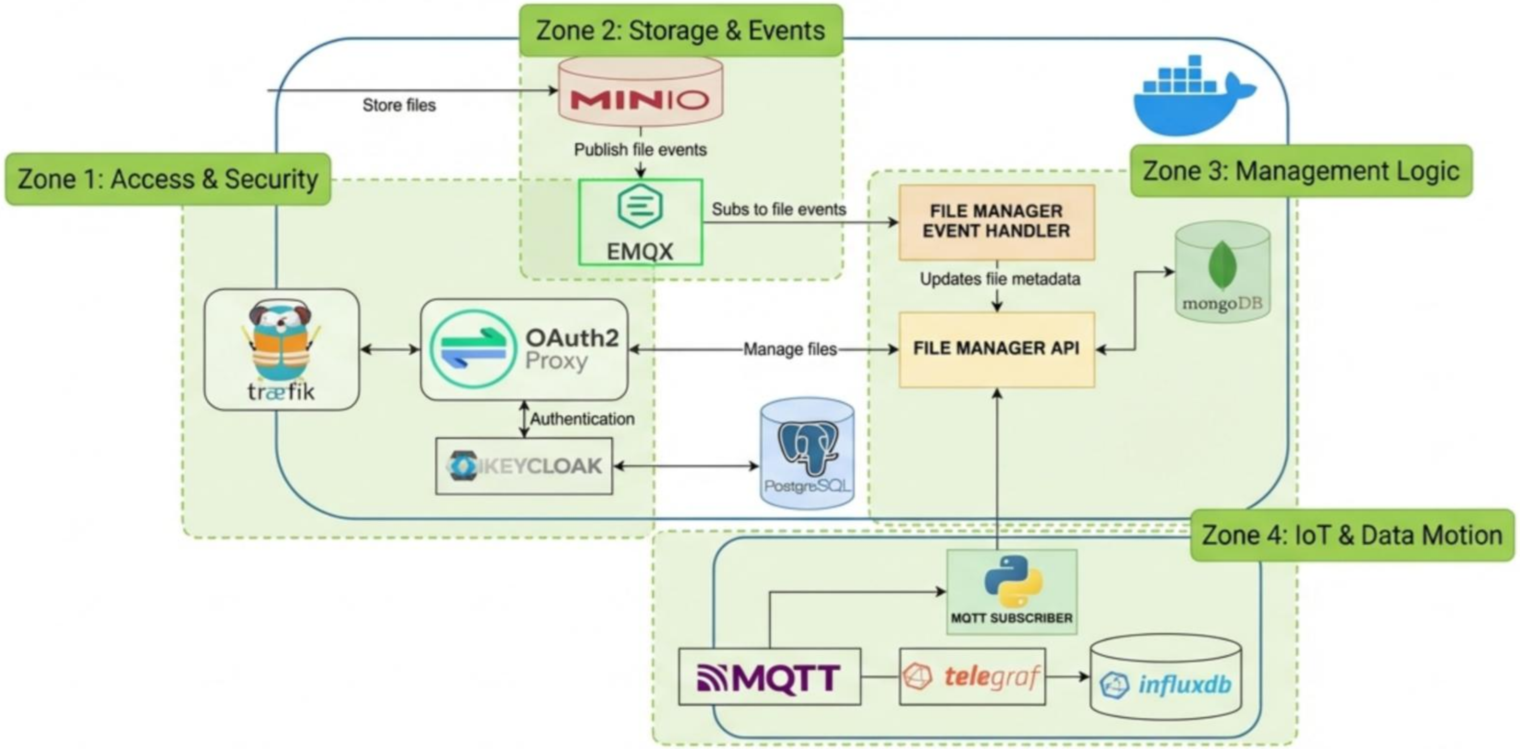
Digital Platform

Core Mission: The Digital Platform (DP) is the cornerstone designed to optimize manufacturing processes, ensuring product quality, process interoperability, and seamless information flow across the value chain.

Target Industries: Construction, Medical, and Packaging.

Key Capability: Serves as an end-to-end digital system supporting the production of flexible, high-performance biobased end-products.

Requirement	Implementation Component
Security & Access Control	Keycloak + OAuth2Proxy
Data Integrity	File Manager + MinIO (Hashing)
Efficient Data Collection	MQTT Protocol
Scalable Storage	MinIO Distributed Storage
Easily Deployable	Docker Containerization
Interoperability	Open Standards (JSON/XML)



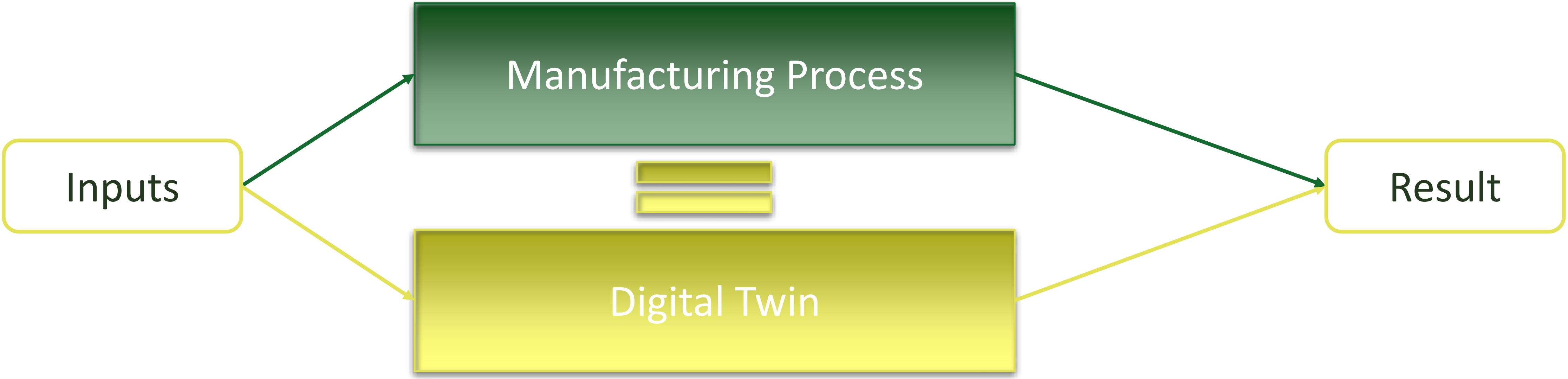
A containerized, microservices-based architecture designed for scalability and security

Hybrid Twins

Hybrid Twins

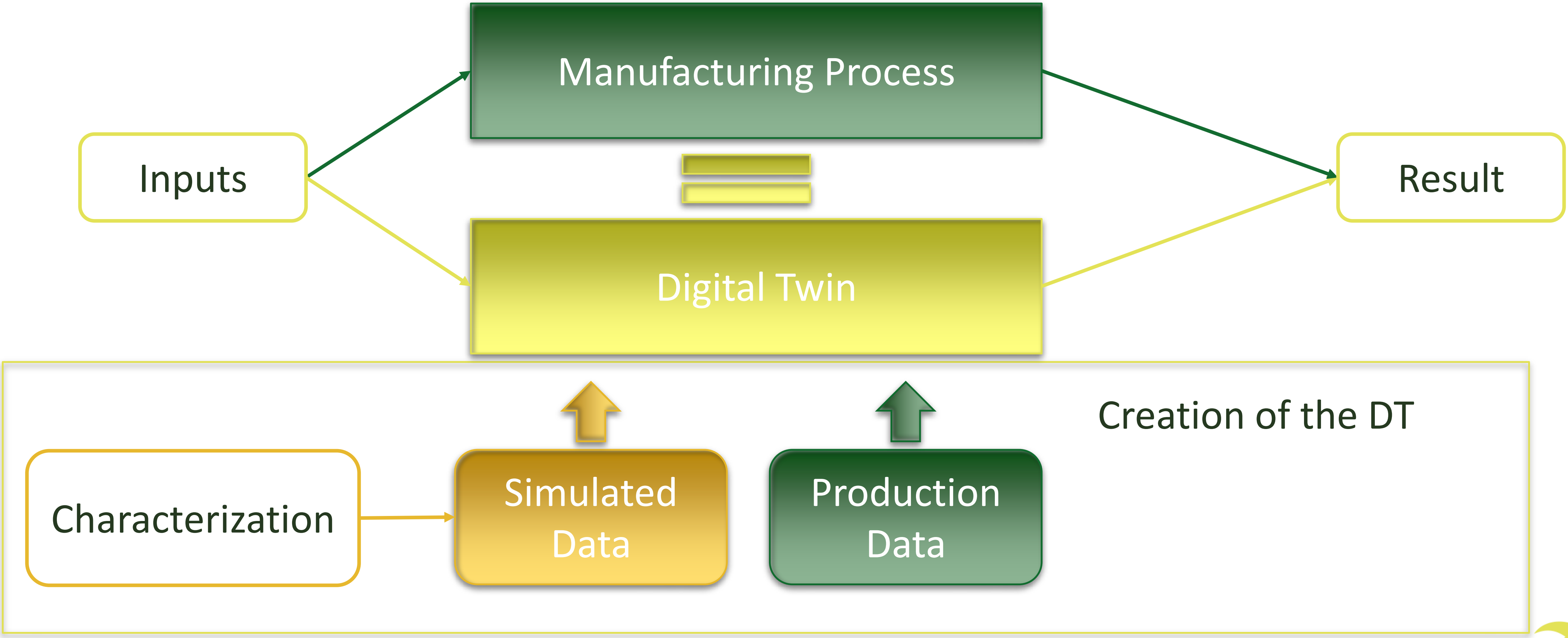
1 - What is a digital twin ?

- Modelization of a process, product, infrastructure (Statistical, physical simulation,…)
- Useful for maintenance prediction, process optimization, traceability



Hybrid Twins

2 - What is it Hybrid in this situation?

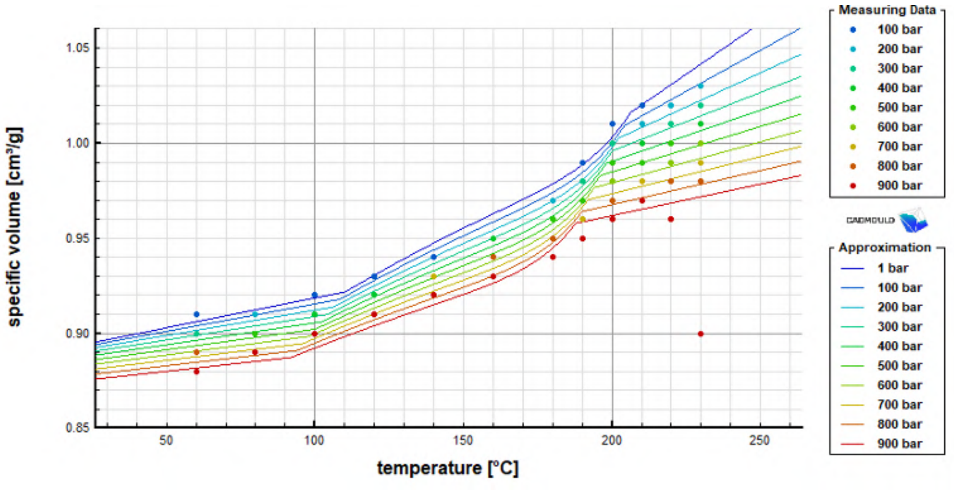


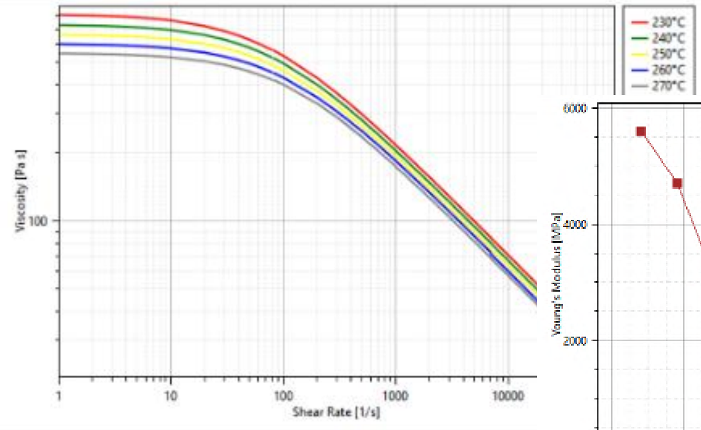
Hybrid Twins

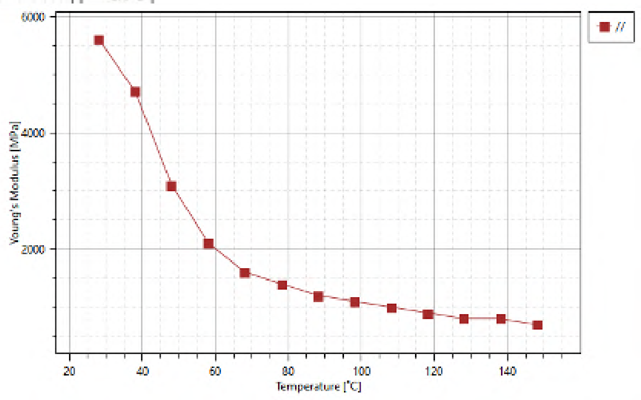
3 – How is it inserted in the Bio-Uptake Project?

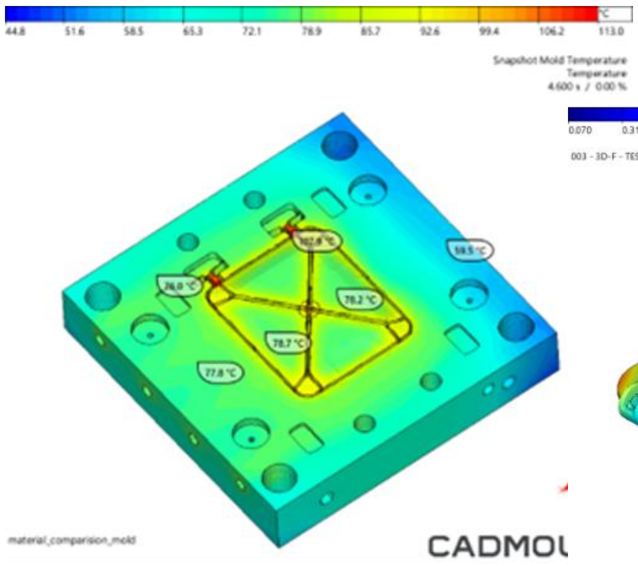
- Infrastructure for future production projects (applicable to other industries).
- Used directly in Decision Support System for Product Design.
- Using Finished Element Method Simulations, validation of part design and production feasibility.

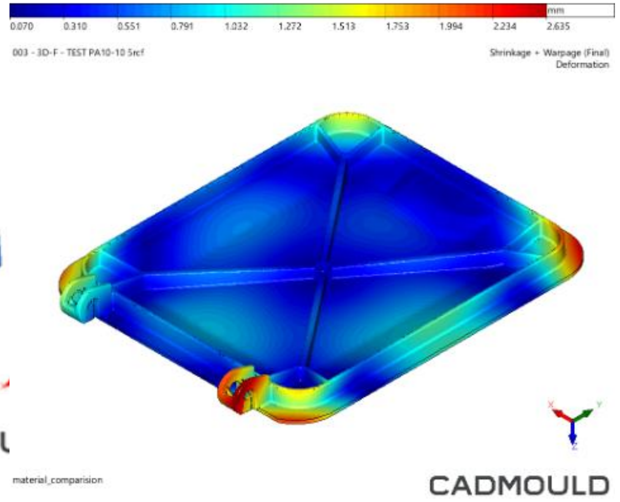
Hybrid Twins

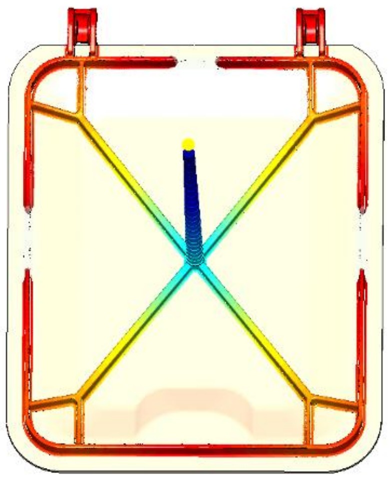


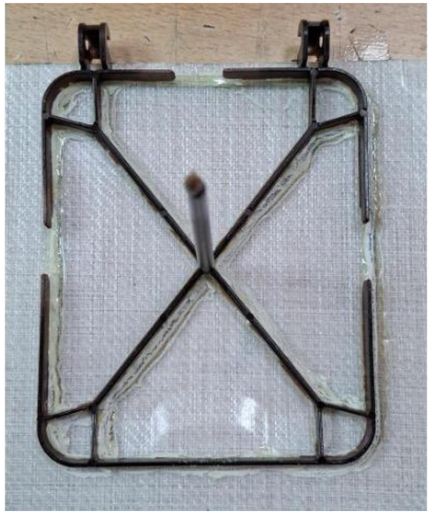












Hybrid Twins

Optimisation parameters for production Trials

Variants			Variable 1	Variable 2	Variable 3	Variable Group 4		Variable 5	Variable Group 6	
ID	Project Generated	Results Available	Filling Time [s]	Packing Time [s]	Packing 1 - Packing / Final Injection Pressure [%]	Inlet Temperature H/C Circuit 1 Time 1 [°C]	Inlet Temperature H/C Circuit 4 Time 1 [°C]	Melt Temperature [°C]	Inlet Temperature H/C Circuit 3 Time 1 [°C]	Inlet Temperature H/C Circuit 2 Time 1 [°C]
▴ Automatic										
1	☑	☑	1,034	7,000	80,000	57,000	57,000	250,000	57,000	57,000
2	☑	☑	2,034	12,000	100,000	72,000	72,000	270,000	72,000	72,000
3	☑	☑	2,034	12,000	100,000	72,000	72,000	270,000	42,000	42,000
4	☑	☑	2,034	12,000	100,000	42,000	42,000	230,000	72,000	72,000
5	☑	☑	2,034	12,000	60,000	42,000	42,000	270,000	72,000	72,000
6	☑	☑	2,034	2,000	100,000	72,000	72,000	230,000	42,000	42,000
7	☑	☑	2,034	2,000	60,000	72,000	72,000	230,000	72,000	72,000
8	☑	☑	2,034	2,000	60,000	42,000	42,000	270,000	42,000	42,000
9	☑	☑	0,034	12,000	100,000	72,000	72,000	270,000	72,000	72,000
10	☑	☑	0,034	12,000	60,000	72,000	72,000	230,000	42,000	42,000
11	☑	☑	0,034	12,000	60,000	42,000	42,000	230,000	42,000	42,000
12	☑	☑	0,034	2,000	100,000	42,000	42,000	270,000	42,000	42,000
13	☑	☑	0,034	2,000	100,000	42,000	42,000	230,000	72,000	72,000
14	☑	☑	0,034	2,000	60,000	72,000	72,000	270,000	72,000	72,000

Variable	Value
Filling time (s)	1.69
Packing time (s)	10
Packing pressure (% of VP Switchover pressure)	70
Melt Temperature (°C)	240
Inlet Temperature fixed side (°C)	65
Inlet Temperature Moveable side (°C)	65

Decision Support System for Product

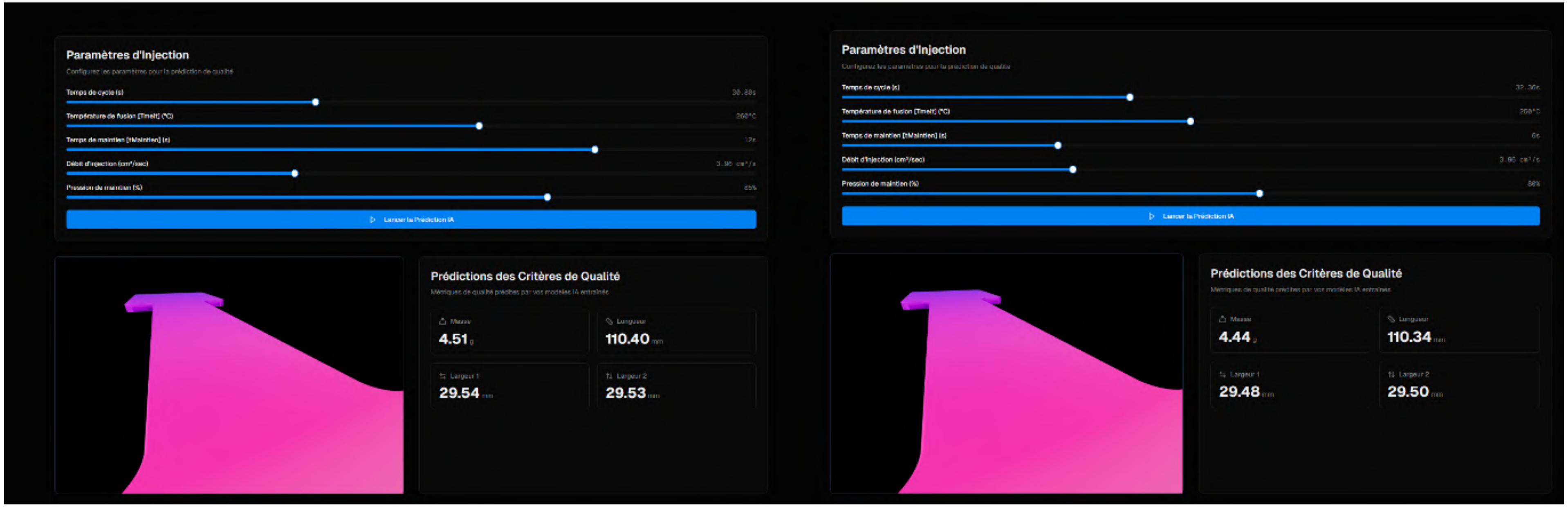
Decision Support System for Product Design

- What is the decision support system
- How is the decision support created
- How is it relevant in the overall bio-uptake project

Decision Support System for Product Design

1 - What is the decision support system

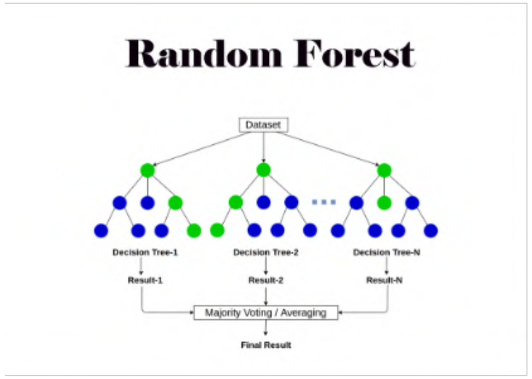
- Python Application with Web API for UI.
- Powered by Deep Learning and FEM Simulation
- Created to help Project managers for product design and new material use.

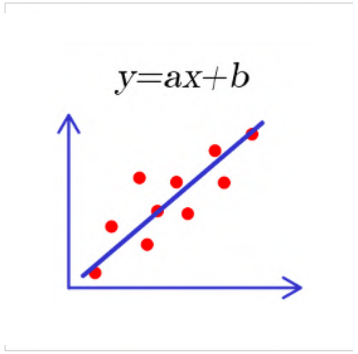


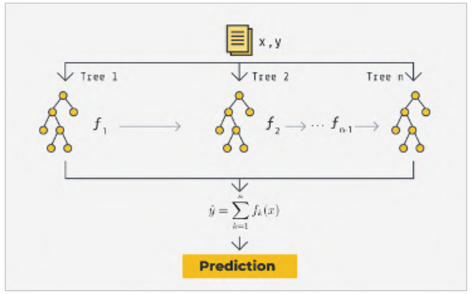
Decision Support System for Product Design

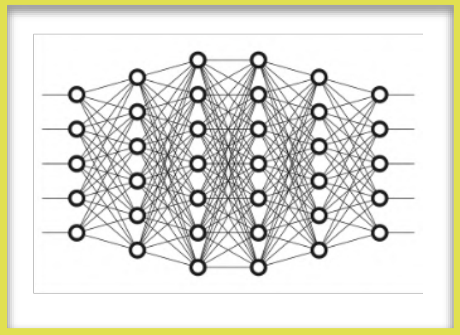
2 - How is the decision support created

Model definition and benchmark







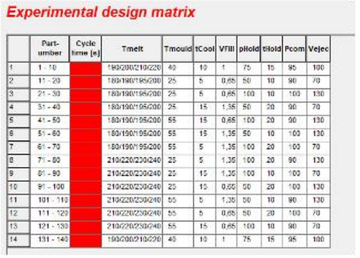


Variable	Modèle	MSE (Train)	MSE (Test)	R² (Train)	R² (Test)
Longueur	Rég. Linéaire	0.000427	–	0.9853	–
Longueur	BPNN1	0.002579	–	0.9911	–
Longueur	BPNN2	0.000275	–	0.9950	–
Longueur	BPNN3	0.000010	0.000012	0.9995	0.9993
Longueur	Random Forest	0.000925	–	0.9531	–
Longueur	XGBoost	0.000275	–	0.9659	–
Largeur 1	Rég. Linéaire	0.001419	–	0.8244	–
Largeur 1	BPNN1	0.001367	–	0.8308	–
Largeur 1	BPNN2	0.000136	–	0.9900	–
Largeur 1	BPNN3	0.000005	0.000007	0.9980	0.9975
Largeur 1	Random Forest	0.001874	–	0.8012	–
Largeur 1	XGBoost	0.001423	–	0.8239	–
Largeur 2	Rég. Linéaire	0.000187	–	0.9632	–
Largeur 2	BPNN1	0.000151	–	0.9702	–
Largeur 2	BPNN2	0.000015	–	0.9900	–
Largeur 2	BPNN3	0.000001	0.000002	0.9998	0.9997
Largeur 2	Random Forest	0.000369	–	0.9423	–
Largeur 2	XGBoost	0.000187	–	0.9777	–
Masse	Rég. Linéaire	0.000087	–	0.9894	–
Masse	BPNN1	0.000061	–	0.9926	–
Masse	BPNN2	0.000005	–	0.9980	–
Masse	BPNN3	0.000001	0.000002	0.9999	0.9998
Masse	Random Forest	0.000113	–	0.9812	–
Masse	XGBoost	0.000063	–	0.9923	–

Decision Support System for Product Design

2 - How is the decision support created

Experimental matrix

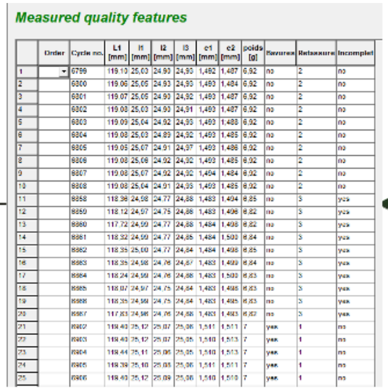


Experimental design matrix

	Part-umber	Cycle time [s]	Tmelt	Tmould	tCool	VFill	pHold	tHold	Pcom	Vejec
1	1 - 10		190/200/210/220	40	10	1	75	15	95	100
2	11 - 20		180/190/195/200	25	5	0,65	50	10	90	70
3	21 - 30		180/190/195/200	25	5	0,65	100	10	100	130
4	31 - 40		180/190/195/200	25	15	1,35	50	20	90	70
5	41 - 50		180/190/195/200	55	15	0,65	100	20	90	130
6	51 - 60		180/190/195/200	55	15	1,35	50	10	100	130
7	61 - 70		180/190/195/200	55	5	1,35	100	20	100	70
8	71 - 80		210/220/230/240	25	5	1,35	100	20	90	130
9	81 - 90		210/220/230/240	25	15	1,35	100	10	100	70
10	91 - 100		210/220/230/240	25	15	0,65	50	20	100	130
11	101 - 110		210/220/230/240	55	5	1,35	50	10	90	130
12	111 - 120		210/220/230/240	55	5	0,65	50	20	100	70
13	121 - 130		210/220/230/240	55	15	0,65	100	10	90	70
14	131 - 140		190/200/210/220	40	10	1	75	15	95	100

Preparation of test specimen on the press

Validation and reinforcement



Measured quality features

	Order	Cycle no.	L1 [mm]	l1 [mm]	l2 [mm]	l3 [mm]	e1 [mm]	e2 [mm]	poids [g]	Bavures	Retassure	Incomplet
1		6799	119.10	25,03	24.90	24,93	1,492	1,487	6,92	no	2	no
2		6800	119.06	25,05	24.93	24,93	1,493	1,484	6,92	no	2	no
3		6801	119.07	25,05	24.90	24,92	1,493	1,487	6,92	no	2	no
4		6802	119.08	25,03	24.90	24,91	1,493	1,487	6,92	no	2	no
5		6803	119.09	25,04	24.92	24,93	1,493	1,488	6,92	no	2	no
6		6804	119.08	25,03	24.89	24,92	1,493	1,485	6,92	no	2	no
7		6805	119.05	25,07	24.91	24,97	1,493	1,486	6,92	no	2	no
8		6806	119.08	25,08	24.92	24,92	1,493	1,485	6,92	no	2	no
9		6807	119.08	25,07	24.92	24,92	1,494	1,484	6,92	no	2	no
10		6808	119.08	25,04	24.91	24,93	1,493	1,485	6,92	no	2	no
11		6858	118.98	24,98	24.77	24,88	1,483	1,494	6,85	no	3	yes
12		6859	118.12	24,97	24.75	24,88	1,483	1,496	6,82	no	3	yes
13		6860	117.72	24,99	24.77	24,88	1,484	1,498	6,82	no	3	yes
14		6861	118.32	24,99	24.77	24,85	1,484	1,500	6,84	no	3	yes
15		6862	118.35	25,00	24.77	24,84	1,484	1,498	6,85	no	3	yes
16		6863	118.35	24,98	24.76	24,87	1,483	1,499	6,84	no	3	yes
17		6864	118.24	24,98	24.76	24,88	1,483	1,500	6,83	no	3	yes
18		6865	118.07	24,97	24.75	24,84	1,483	1,496	6,83	no	3	yes
19		6866	118.35	24,98	24.75	24,84	1,483	1,495	6,83	no	3	yes
20		6867	117.83	24,96	24.76	24,88	1,483	1,483	6,82	no	3	yes
21		6902	118.40	25,12	25.07	25,08	1,511	1,511	7	yes	1	no
22		6903	118.40	25,12	25.07	25,05	1,510	1,513	7	yes	1	no
23		6904	118.44	25,11	25.06	25,05	1,510	1,513	7	yes	1	no
24		6905	118.39	25,10	25.05	25,06	1,511	1,511	7	yes	1	no
25		6906	118.40	25,12	25.09	25,08	1,510	1,510	7	yes	1	no

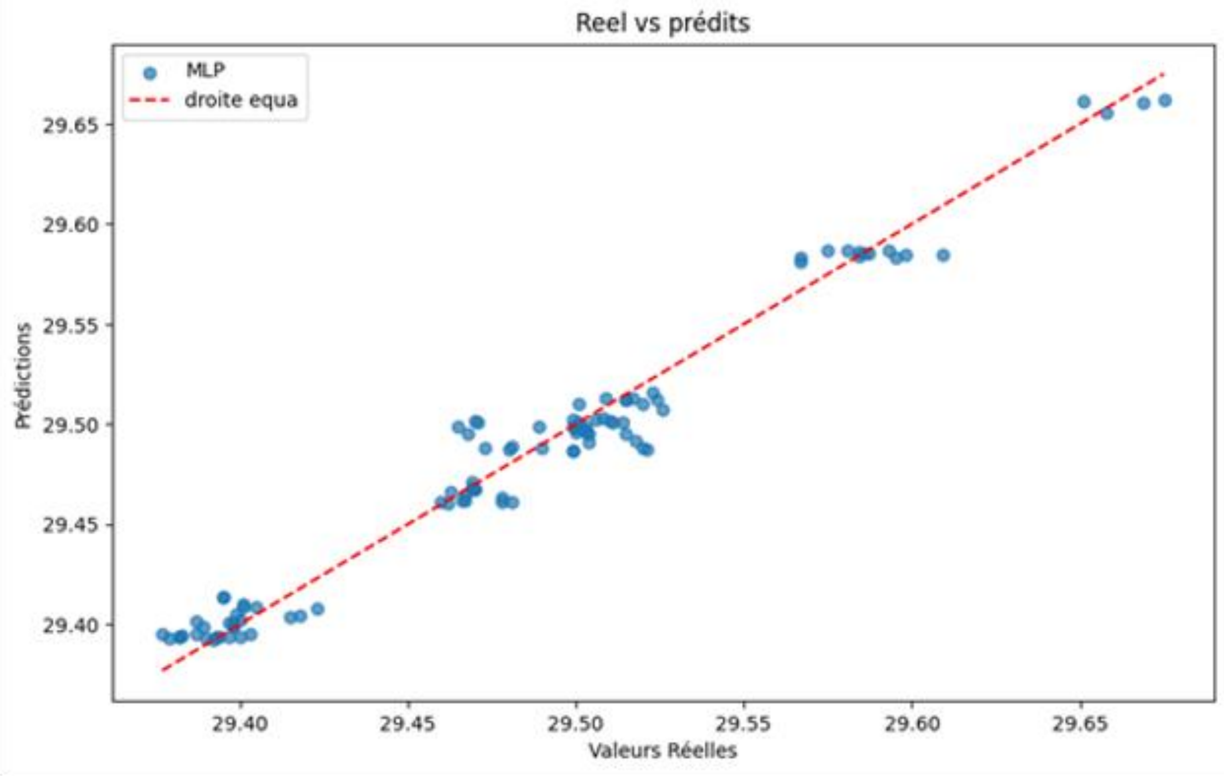
Mesuring quality criterias

Training AI models

Results

Decision Support System for Product Design

2 - How is the decision support created



Adding 20% of real-life measurement enables a closer fitting of the predictive model

Decision Support System for Product Design

3 - How is it relevant in the overall bio-uptake project :

- It enables to test different geometries before touch-ups in the production tools:
  - ribs,
  - thickness change,
  - different production strategies

- Less needs for mould trials:
  - Time gains
  - Material gains

- **Use of new materials** :
  - Once characterized, any material processed can be estimated beforehand

Decision Support System for Manufacturing

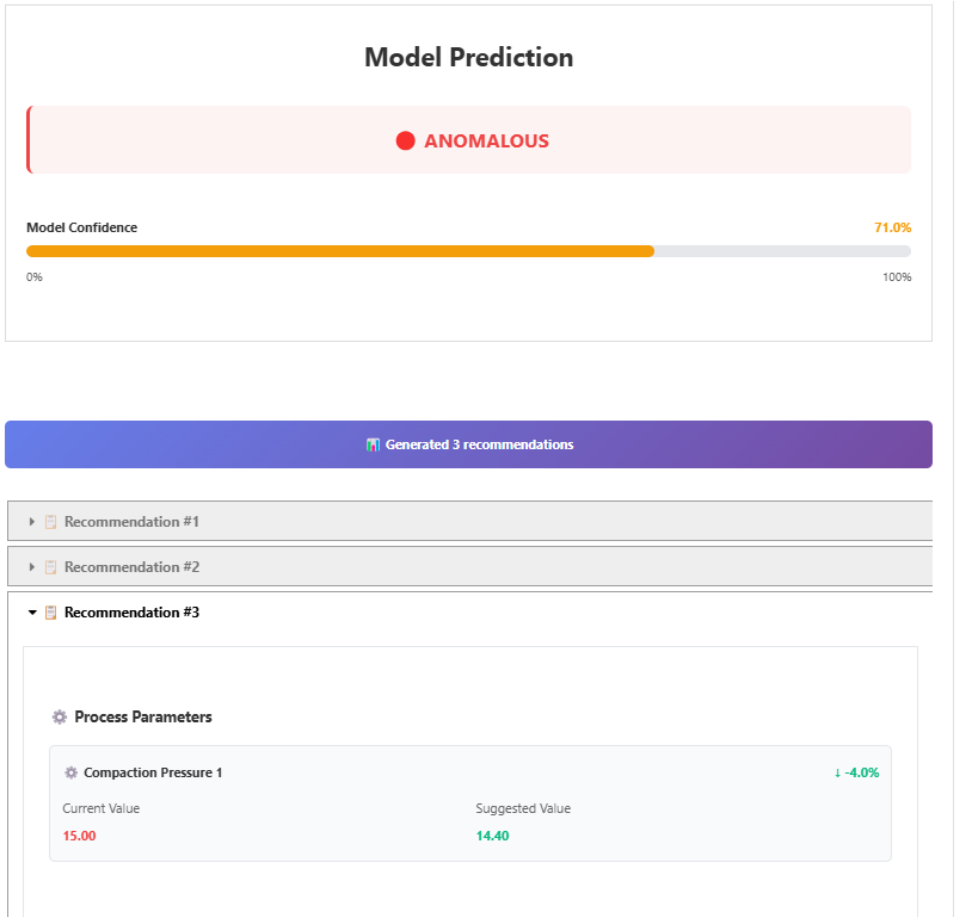
Decision Support System for Manufacturing

Objectives

Use process parameters to **predict** probability of **defect**

Faster understanding of process: identify which variables increase defect risk

Data-driven **recalibration** decisions, expert-controlled



Decision Support System for Manufacturing

Step 1 – Data analytics

AI learns from:

- Process variables (temperature, pressure…)
- Production runs with quality result (defect / no defect)

Rule: **We need many more production runs than variables**.

- If not → the model memorizes the past
- If yes → the model learns and predicts future production

How to address data limitation

- Feature engineering: combine or summarize variables to reduce complexity
  - e.g. speed1, speed2 > mean speed
  - e.g. target temperature, measured temperature > deviation
- Data augmentation: advanced AI models to generate additional data that is statistically similar to real production.

Decision Support System for Manufacturing

Step 2 – AI model selection

Several model families tested

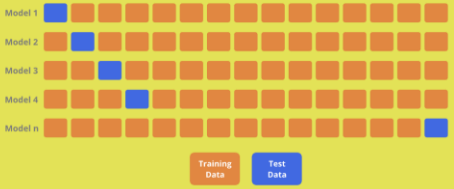
1. Compare different models

There is no universal AI model. Each model makes different assumptions about the process. We look at the same process through different “lenses”.

- Linear models → risk of defect = higher pressure
- Tree-based models → defect risk = high pressure + low humidity, or high temperature and low fibers %
- Neural networks → defect risk = complex interaction of variables

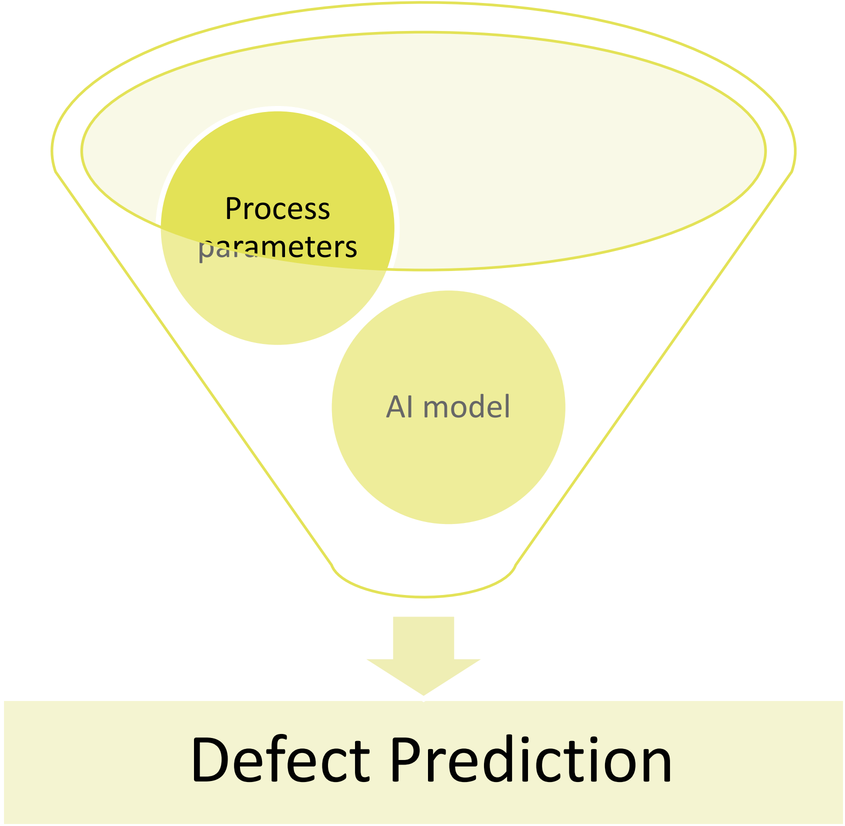
2. Best model = the one that generalizes betters: cross-validation.

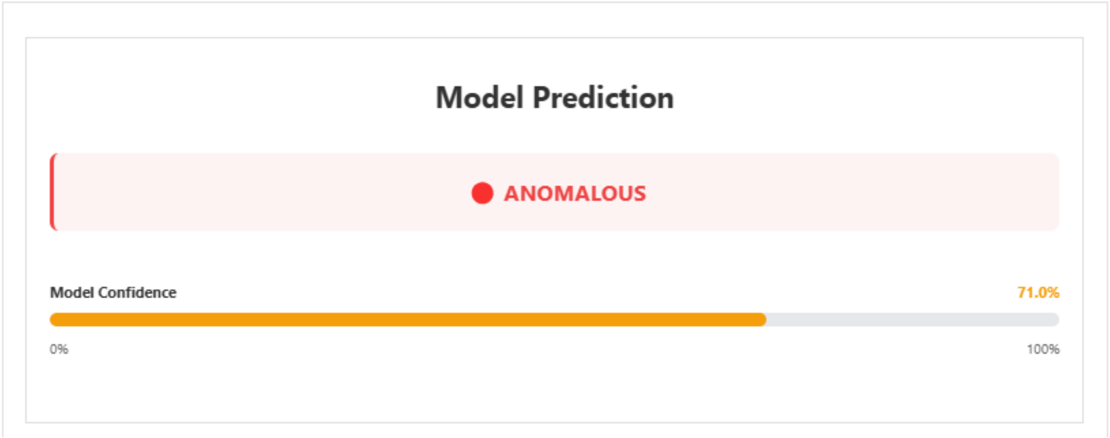
- Train using all samples except one.
- Test on the single left-out sample
- Repeat for every data point
- Each data can represent “unseen data”



Decision Support System for Manufacturing

Step 3 – Prediction results



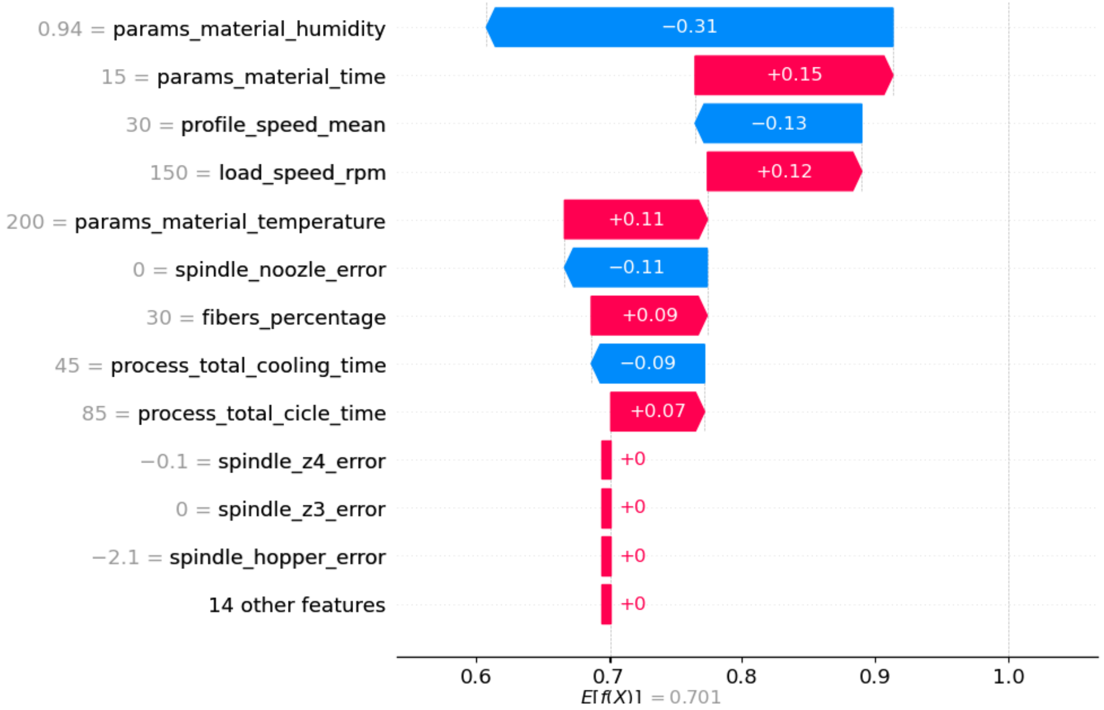


Decision Support System for Manufacturing

Step 4.1 - Confidence-driven decision making

Which parameters drive the defect

- Not black-box model
- Measure how much the prediction changes when a variable changes
- Quantifies which variables are the most important in the model decision
- E.g.
    - Humidity has strong influence on defect probability.
    - Less humidity → lower predicted defect risk

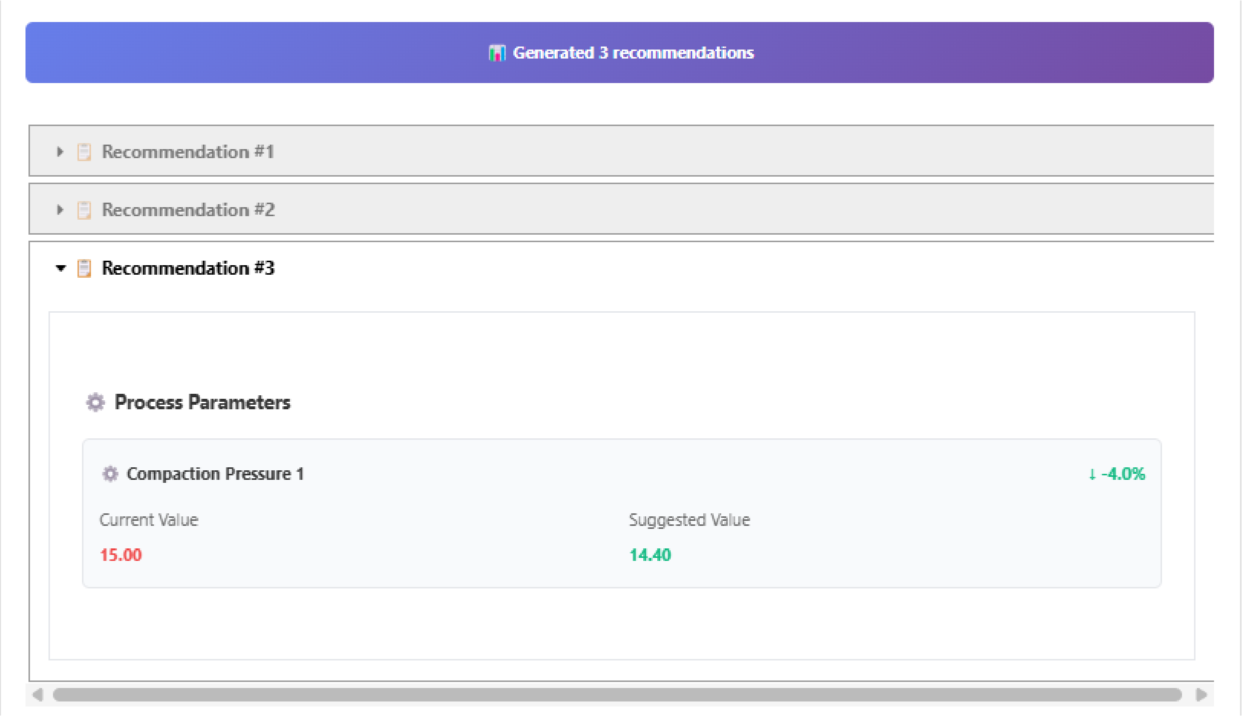


Decision Support System for Manufacturing

Step 4.2 - Confidence-driven decision making

Recalibration Recommendations

- Some variables are important for prediction but cannot be adjusted in the plant (e.g. humidity → predictive but not recalibrable)
- Recalibration model is limited to what we can control.
- The model proposes 3 safe recalibration scenarios. Each one shows a parameter change that shift prediction from defective to acceptable.
- The AI assists, but final decision always stays with the expert!



Digital Thread

DEMO

Digital Tools for Efficient Biomaterials Design & Manufacturing - FAQ

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