Matlab Expo 2023

Using Deep Learning and Kalman Filters for Temperature Soft Sensing

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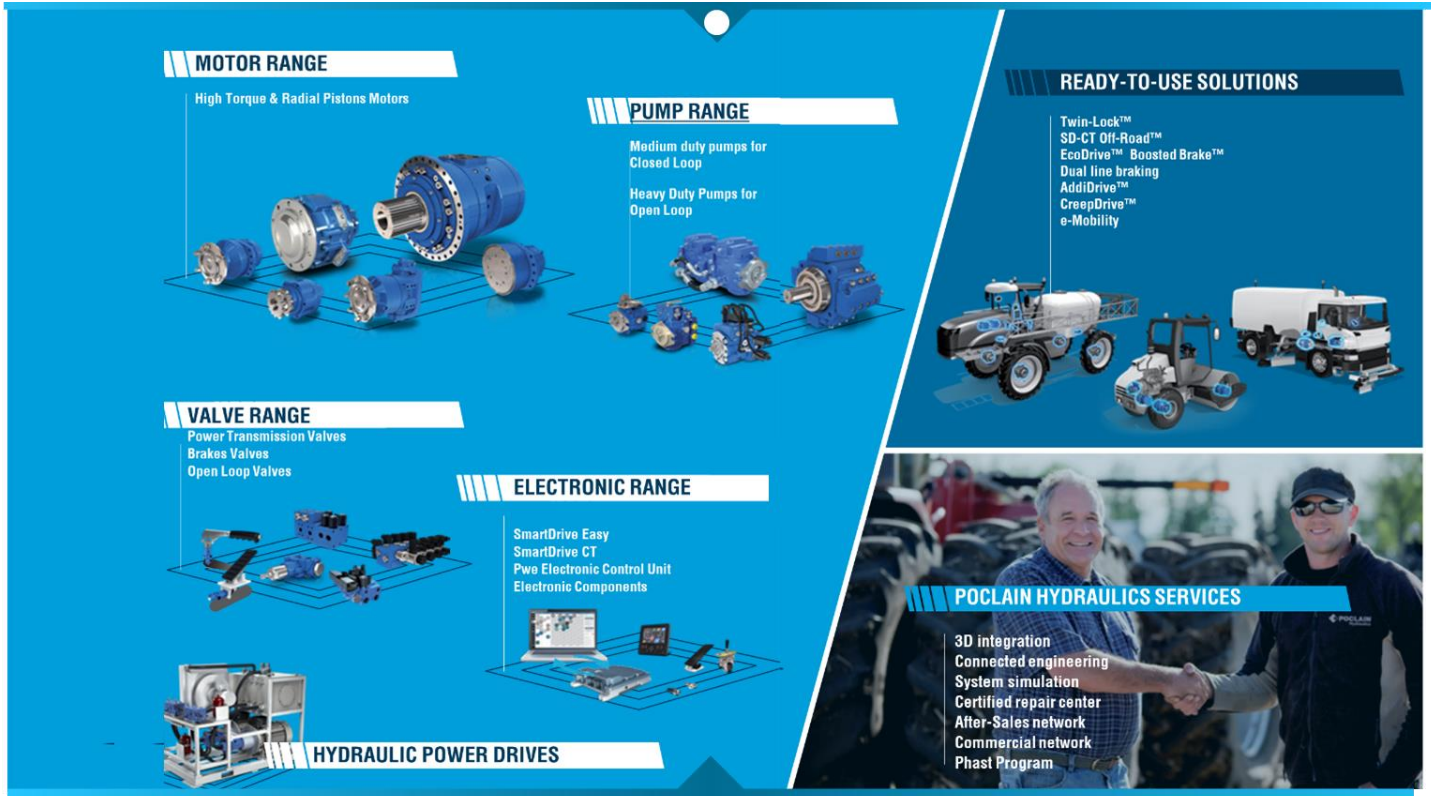
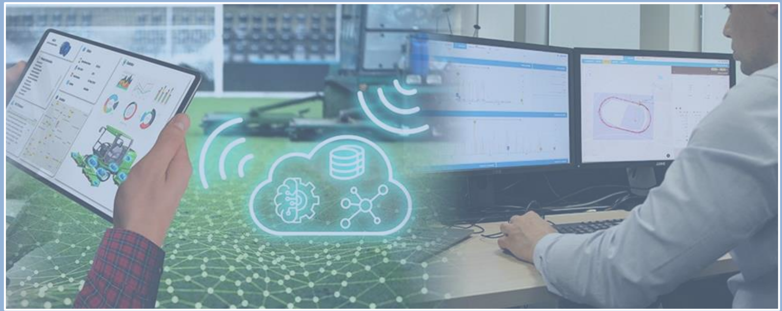
POCLAIN HYDRAULICS



KEY TAKEAWAYS

<u>**This presentation will emphasize on the following topics:**</u>



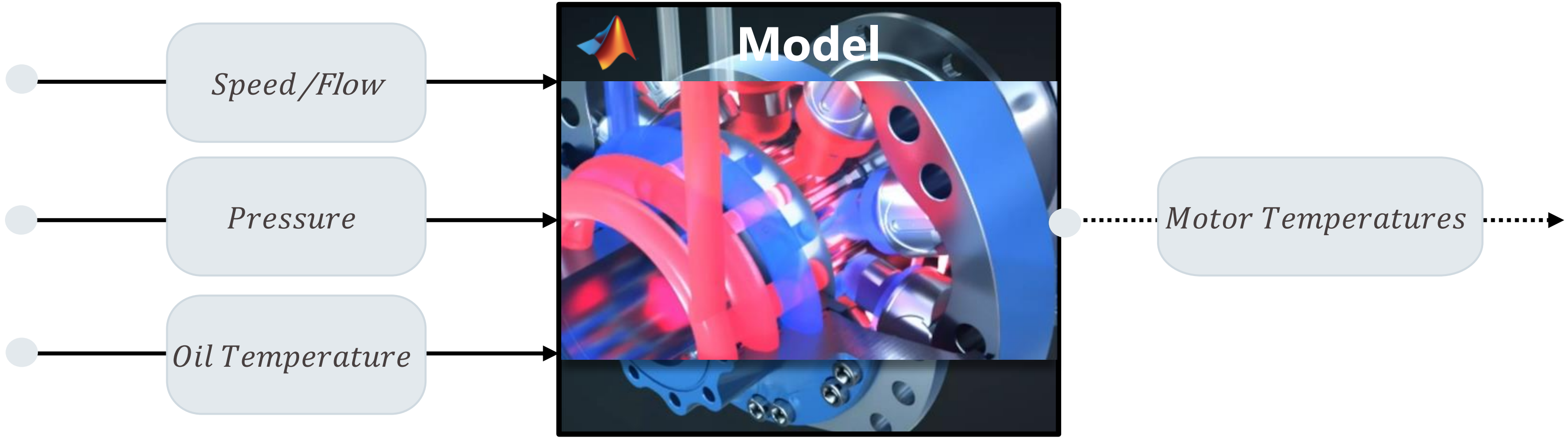
- ❑ Usage of AI in Matlab to solve real time prediction of temperatures :
  - Problem of non linearity
  - Problem of load history dependence
  - Compare the AIs

- ❑ Explore Model Based AI through the Extended Kalman Filters example : Benefits and Drawbacks

- ❑ Explore some Neural Network AI to overcome EKF difficulties : Benefits and Drawbacks

ENERGY CONVERSION & HEAT GENERATION

Temperature variation : a result of heat generation

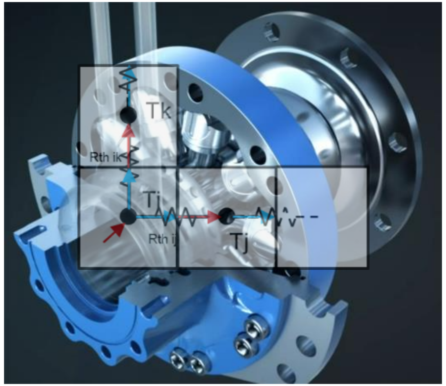


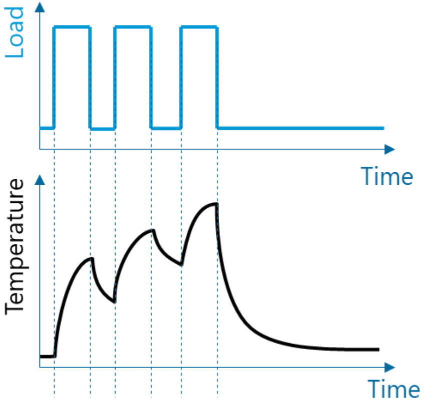
Challenge : Develop an AI to predict temperatures for embedded applications

TEMPERATURE EVOLUTION : A LOAD HISTORY DEPENDENT & NON LINEAR PROBLEM

Nodal Method or Thermal Network

Input Flux = Output Flux
1 mesh → 1 equation
1 mesh → 1 temperature





Method :

- Discretization of the system into nodes
- Solve the heat balance equation for each node

Difficulties :

❑ Find the right level of details

❑ Embed the solver ?

$$\underbrace{(m.Cp).\frac{dTi}{dt}}_{\text{Accumulation potential}} = \underbrace{\frac{(T_j - T_i)}{Rth\ conduction}}_{\text{Conduction transfer}} + \underbrace{\frac{(T_j - T_i)}{Rth\ convection}}_{\text{Convection transfer}} + \underbrace{\frac{(T_j - T_i)}{Rth\ radiation}}_{\text{Radiation transfer}} + \underbrace{(Q.\rho.Cp)(T_j - T_i)}_{\text{Fluid transportation}} + \underbrace{Pi}_{\text{Heat Power}}$$

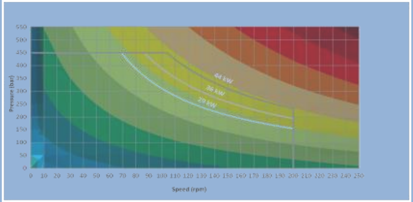
Non linear coefficients

Mostly solved by the Nodal Method

FACTORS OF INFLUENCE

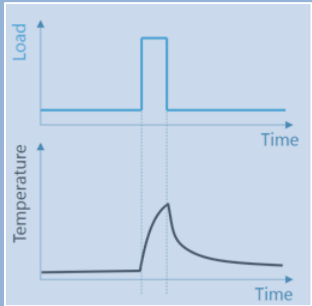
Hydraulic Power / internal losses

- **High Pressure**
- Low Pressure
- **Speed**
- Displacement
- [...]



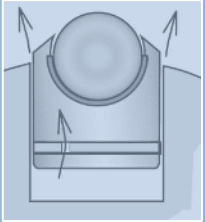
History and time at level

- **Duration** of time at level
- **History** of thermal loads
- [...]



Exogeneous

- **Tank/Inlet Temperature**
- **External Temperature**
- **Flushing flow**
- [...]



Temperature evolution : A load history dependent & non linear Problem

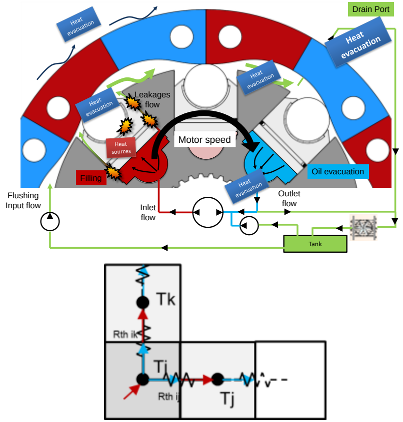
Temperature Soft Sensing with Kalman Filters

SOFT SENSING WITH KALMAN FILTERS

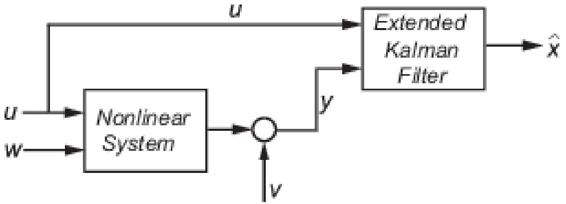
Complete Model
Nodal method + coefficients from test & simulation

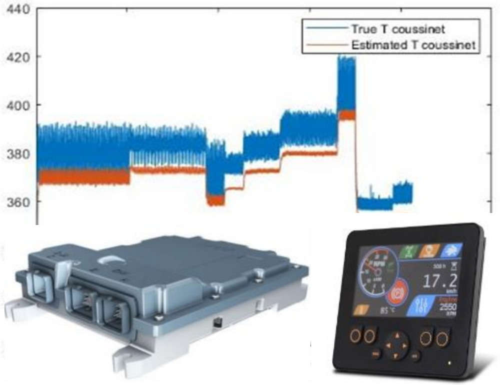
Extended Kalman Filter

Temperature Prediction
Embedded applications



MATLAB&SIMULINK®





Load a Duty Cycle
➔ Pressure, Speed, Tank Tempreature…

Generate Temperatures

AI
Predict Motor Temperatures

Decision
Limit the available power

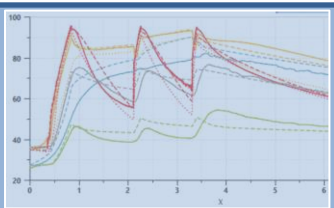
Target : Real-time prediction with Model Based AI

EXTENDED KALMAN FILTERS STEPS

Model Reduction (Embedded Purpose)

FROM

$$X = \begin{pmatrix} T_1 = x_1 \\ T_2 = x_2 \\ \vdots \\ T_i \\ \vdots \\ T_k = x_k \end{pmatrix}$$



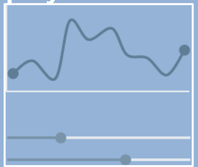
To

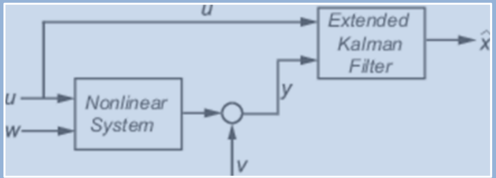
$$X = \begin{pmatrix} T_1 = x_1 \\ T_2 = x_2 \\ \vdots \\ T_7 = x_7 \end{pmatrix}$$

Computation with implicit form to Retrieve the function $f: (X^k; U^k\,; w) \rightarrow X^{k+1}$

$$X^{k+1} = \begin{pmatrix} T_1^{\;k+1} = T_1^{\;k} + Ts[\ldots] + U_1^{\;k} \\ T_2^{\;k+1} = T_2^{\;k} + Ts[\ldots] + U_2^{\;k} \\ \vdots \\ T_7^{\;k+1} = T_7^{\;k} + Ts[\ldots] + U_7^{\;k} \end{pmatrix}$$

Deploy Kalman Filter





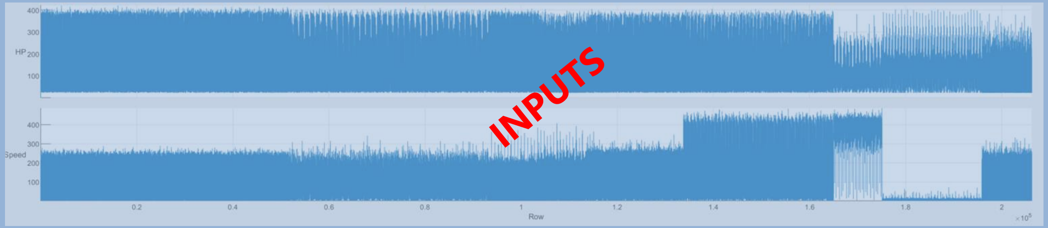
MATLAB®

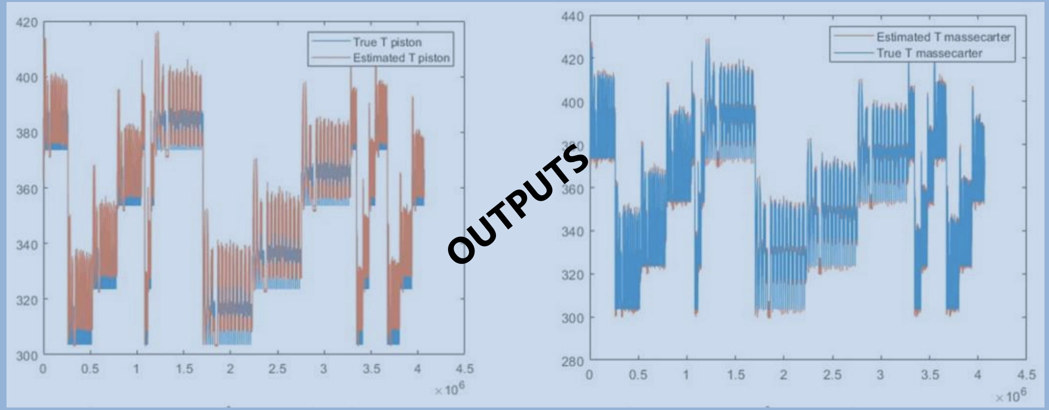
Process simplification, linearisation and deployment

EKF RESULTS

Evaluate the EKF
(RMSE and size compatibility with the embedded hardware):

RMSE [°C]	Size [KB]
10	30





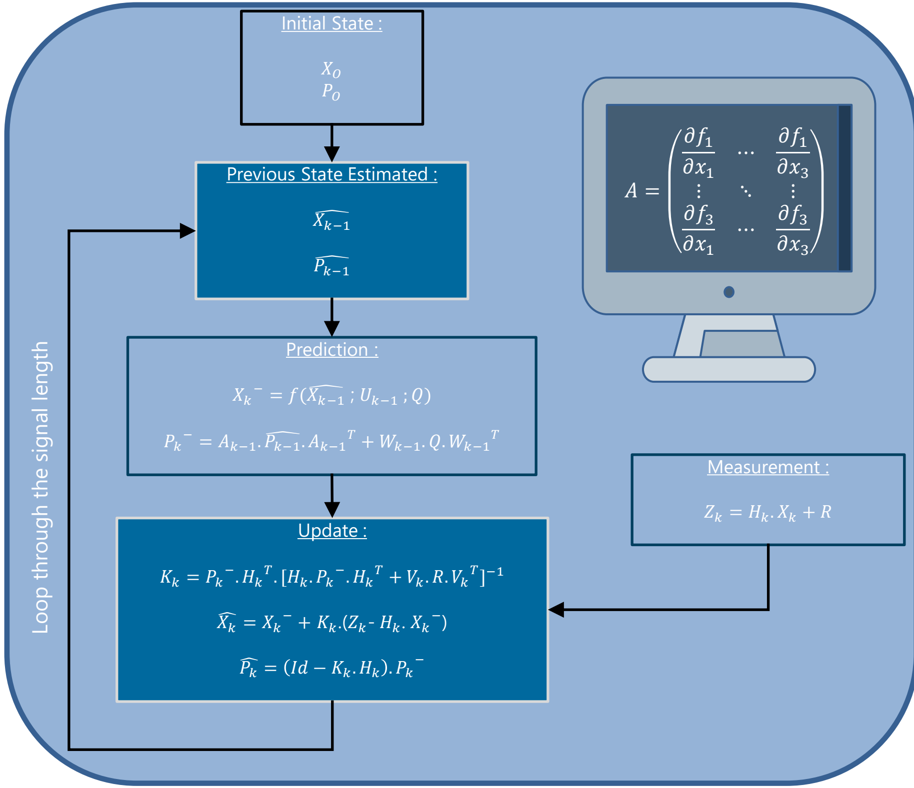
**over 100 hrs of concatenated validation data*

RMSE ~10°C

EXTENDED KALMAN FILTERS

- ❑ Widely available publications
- ❑ System Engineering State of the Art
- ❑ Bayesian Filter : mixes a model based prediction with measurements. Benefits from both worlds :
  - model simplification
  - prediction of data not measurable
  - increased accuracy
  - […]

- ❑ Can be Computationally Intensive
- ❑ Precision dependent on the model complexity
- ❑ Requires deep understanding of Process & Noise Covariance matrix
- ❑ Industrialization hard if thermal resistance are not properly calculated

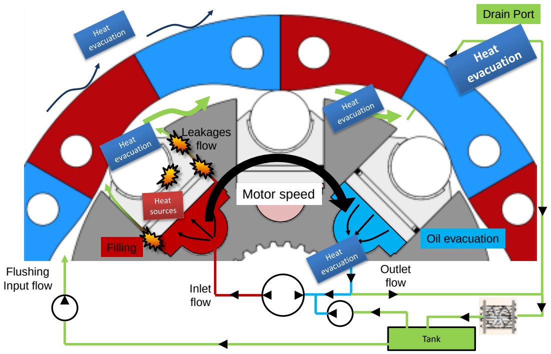


A Model Based primitive AI

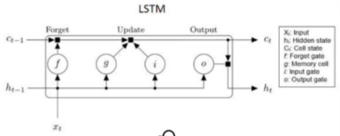
Temperature Soft Sensing with Deep Learning

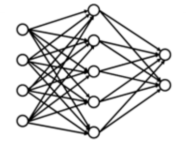
SOFT SENSING WITH DEEP LEARNING

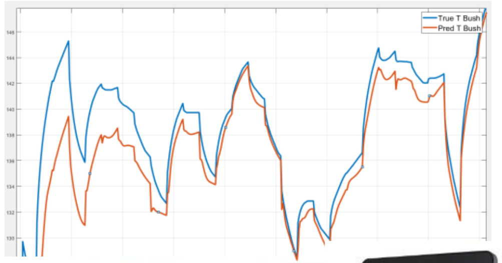
Complete Model	***AI***	***Temperature Prediction***
Nodal method + coefficients from test & simulation	*Long short-term memory (LSTM)* *Feed Forward Neural Network (FFNN)*	***Embedded applications***



MATLAB & SIMULINK







Load a Duty Cycle
→ Pressure, Speed, Tank Tempreature…

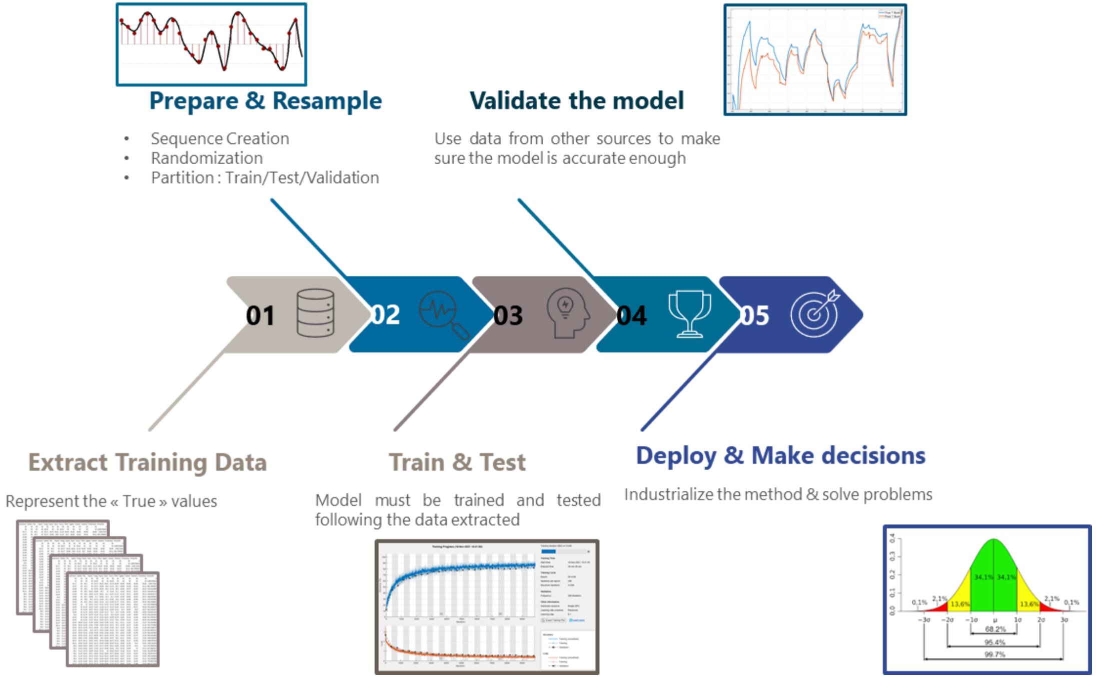
Generate Temperatures

AI
Predict Motor Temperatures

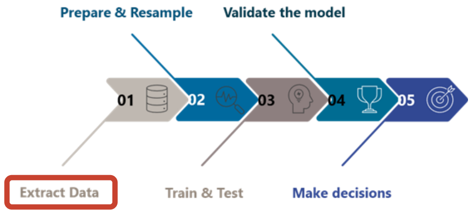
Decision
Limit the available power

Target : Real-time prediction with NN

AI INDUSTRIALISATION GENERAL PROCESS

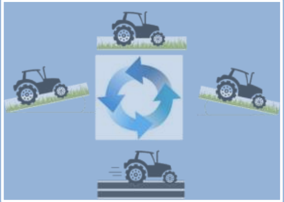


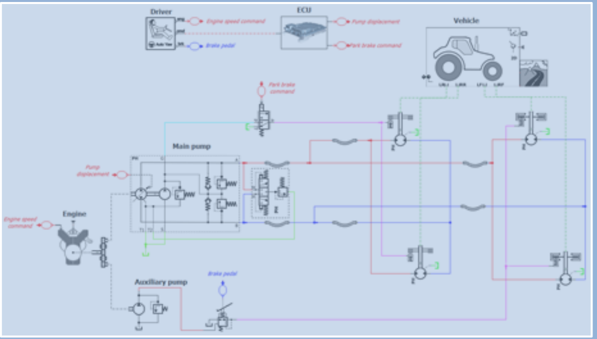
Key Steps for AI Industrialisation



TRAINING THE AI : DATA GENERATION

DOE
Parameters of Influence

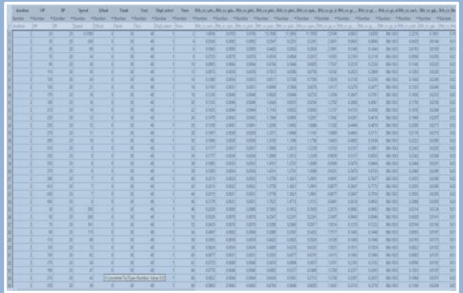




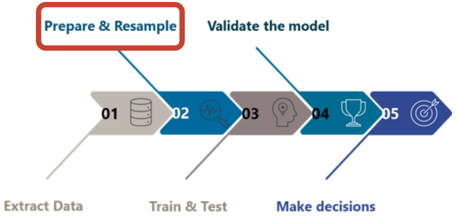
Simulate Usage Profiles
Program a Data Generator

	Duration	HP	BP	Nmot	Qflushing	Ttank	Text	Disp
1	600	150	20	70	0	80	20	1
2	600	250	20	30	0	80	20	1
3	100	450	20	100	0	80	20	1
4	600	100	20	200	0	80	20	2
5	600	250	20	150	0	80	20	1
6	600	150	20	100	0	80	20	1

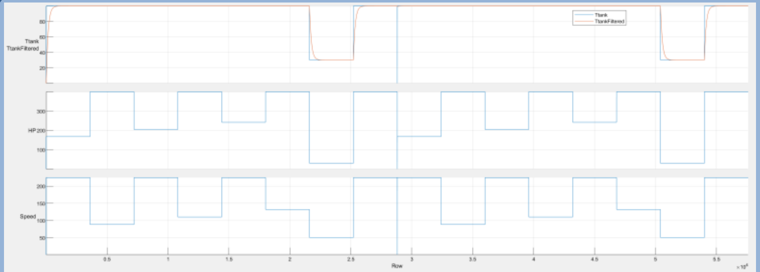
Retrieve Inputs and Outputs
Assess the temperatures and thermal Resistances

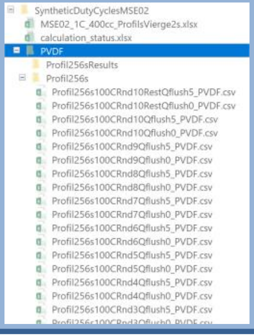


Key Steps for Data Generation with few Data available



PREPARATION & RESAMPLING





Select a new set of parameters

Creation of N Randomized set of Data :

- HP : min to max Pressure
- Speed : min to max Speed
- Tank : min to max Tank temperature

Save all files

Repeat For each Parameter

Organise, Randomize and Resample the Data

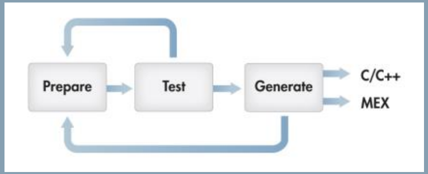
AI CHOICES

REQUIREMENTS

- **Solve Non Linearities**
- **Memory for Inputs Data**
- Inputs through buffers
- Physics of failure knowledge
- Predict temperatures based on different machine dynamics : low / medium / high .

BENEFITS AND DRAWBACKS

- Code Industrialization : C code, ECU, compressed models…
- Train on large datasets for robustness



- Model and results Interpretability? Not necessarily an issue

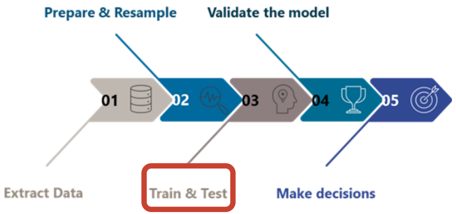
AI CHOICE : Preliminary tests lead to :

- **LSTM Neural Network**
- **Feed Forward Neural Network**

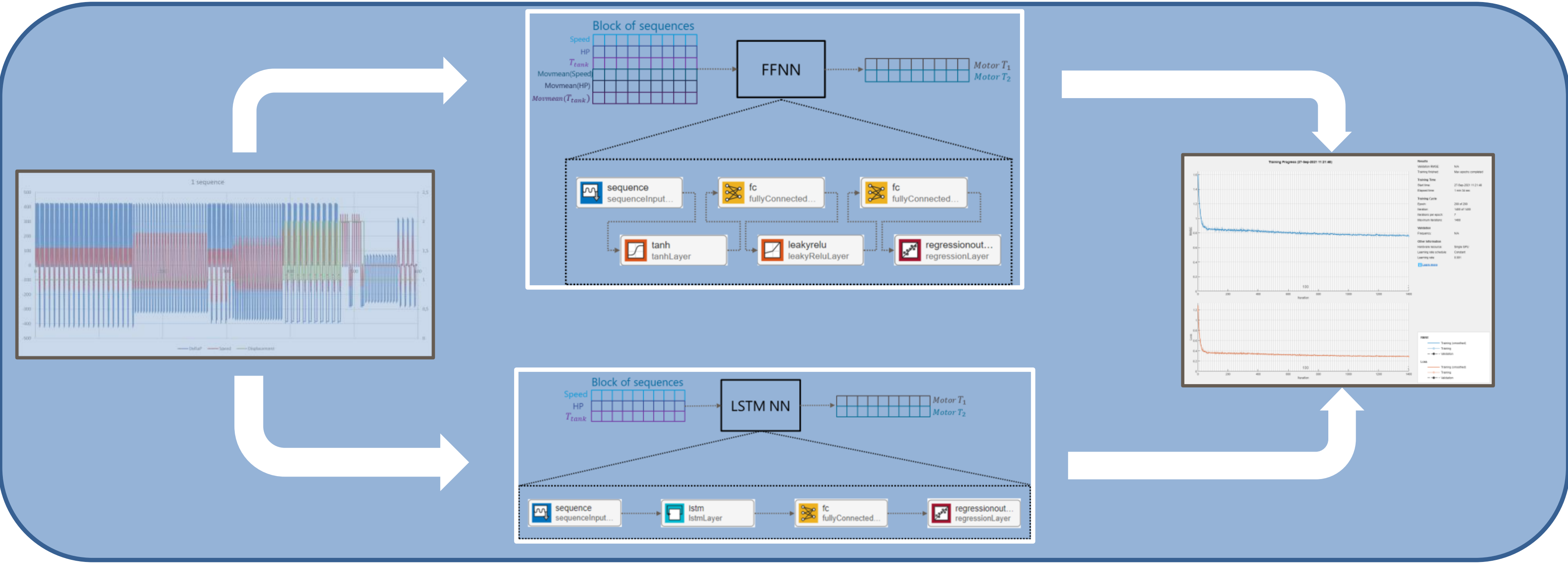
Other AIs :

- NAR(X)Neural Network
- Machine Learning + Feature Engineering + Buffer
- […]

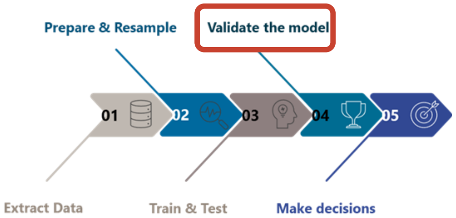
Selecting AIs for solving the thermal prediction



TRAIN & TEST THE AI

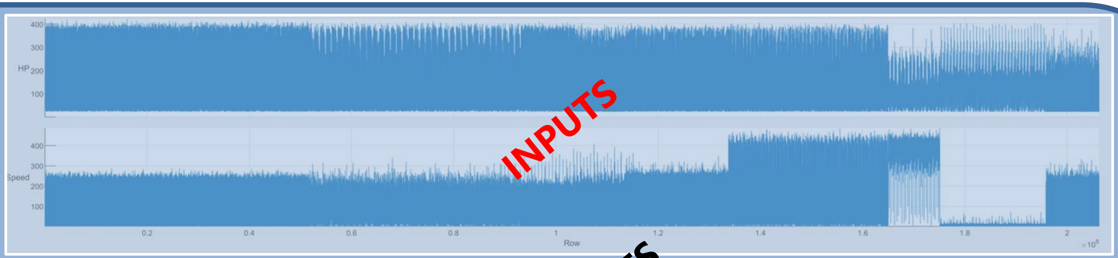


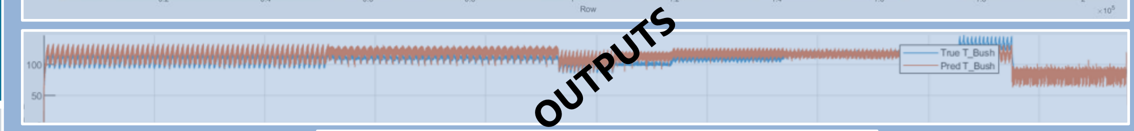
Adjust training parameters and NN structure to achieve efficient convergence

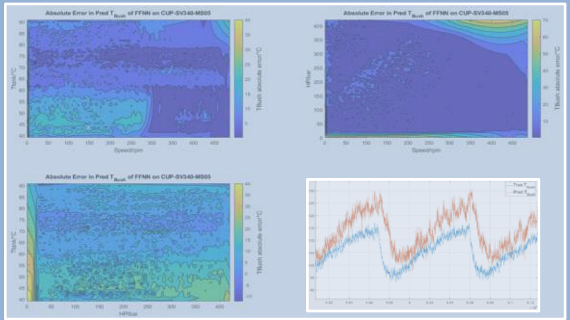


VALIDATE THE MODEL

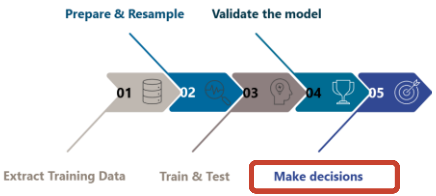
	RMSE [°C]	Size [KB]	Data Generation + Training Duration [Days]
LSTM	7 - 11	110 - 130	8
FFNN	9 - 11	80 - 120	8





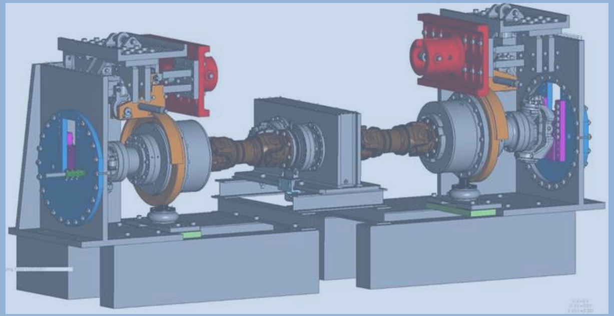


7°C<RMSE<11°C

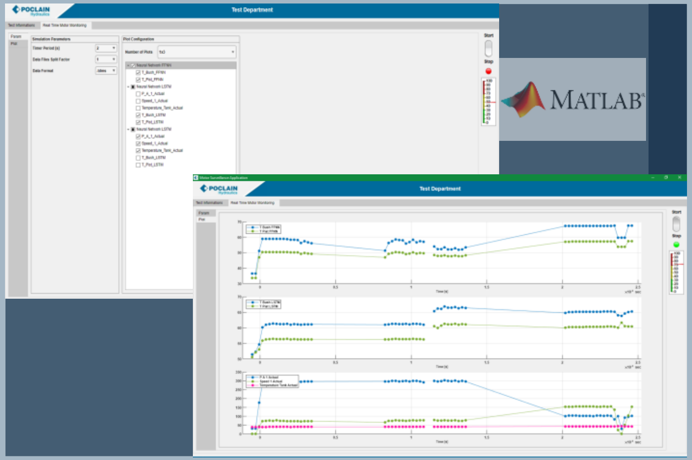


APPLICATION ON TEST MONITORING

Creation of an App in Matlab for Test Temperature Monitoring:



- ❑ Real time predictions on sequences of data
- ❑ Multiple AI available
- ❑ Available for different motors



AI Industrialisation

CONCLUSIONS

Parameter \ AI	EKF	FFNN 2 hidden layers Artificial memory through Moving Mean LSTM 1 hidden layer
Training Complexity & Duration	N/A	🟡
Prediction Risk Evaluation	🟡	🔴
Size	🟢	🟢
Accuracy (RMSE)	🟢	🟢
Interpretability	🟢	🔴
Industrialisation	🟡	🟢

Pros & Cons of AI for thermal predictions

PROJECT NEXT STEPS

- ❑ Improve the time to generate data
- ❑ Implement the AI on testing machines for additionnal feedback. Test the algorithms with dedicated softwares/hardwares.
- ❑ Work with system & application engineers to deploy connected packages of real time thermal predictions. Allow or limit power.

Continuing with the study

THANK YOU FOR YOUR SUPPORT MATHWORKS TEAM !

Application engineering

Training

Consulting

Thank You !

Questions

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