

Nonlinear Loop Replacement Applied to Realtime Capable Jet Pump Model

MODPROD Workshop

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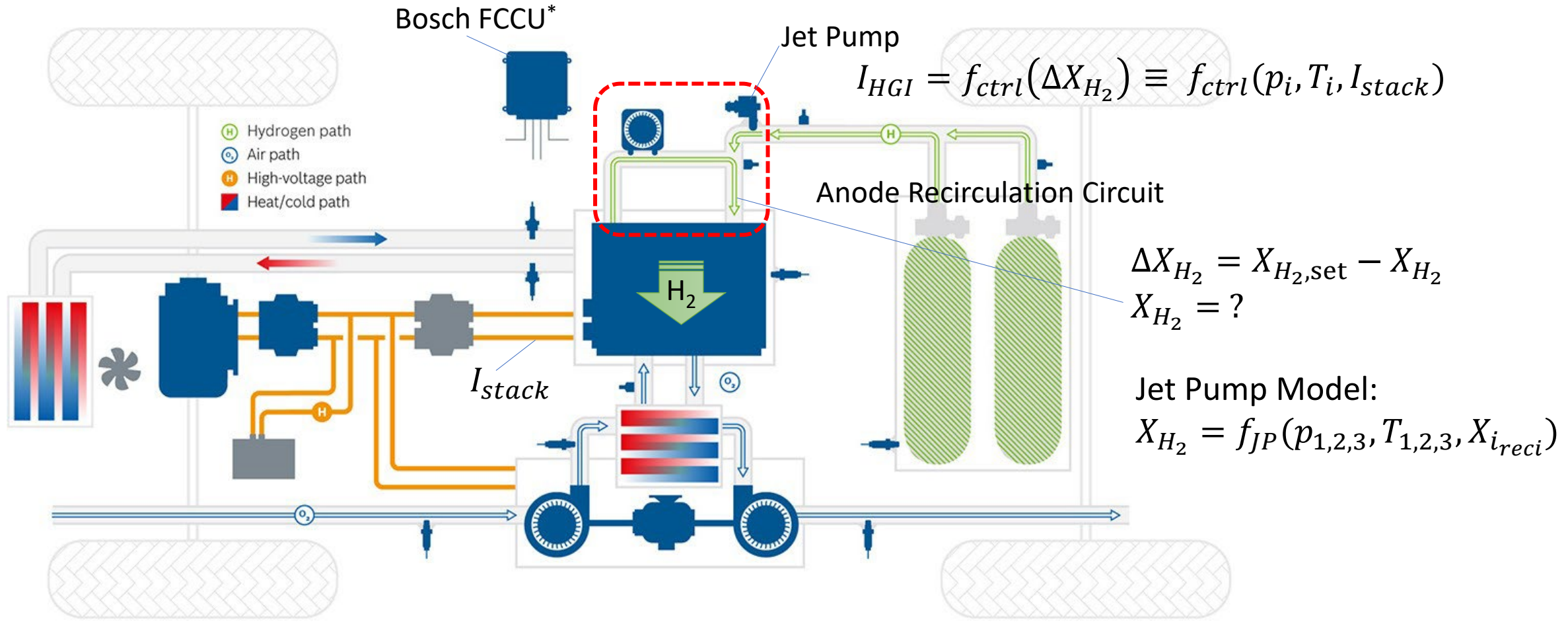
Content



- Application background
- Realtime requirements on the model
- The state-of-the-art model of the jet pump
- The “Loop Replacement” method
- Application to the jet pump model
- Performance of the enhanced jet pump model
- Conclusions and outlook



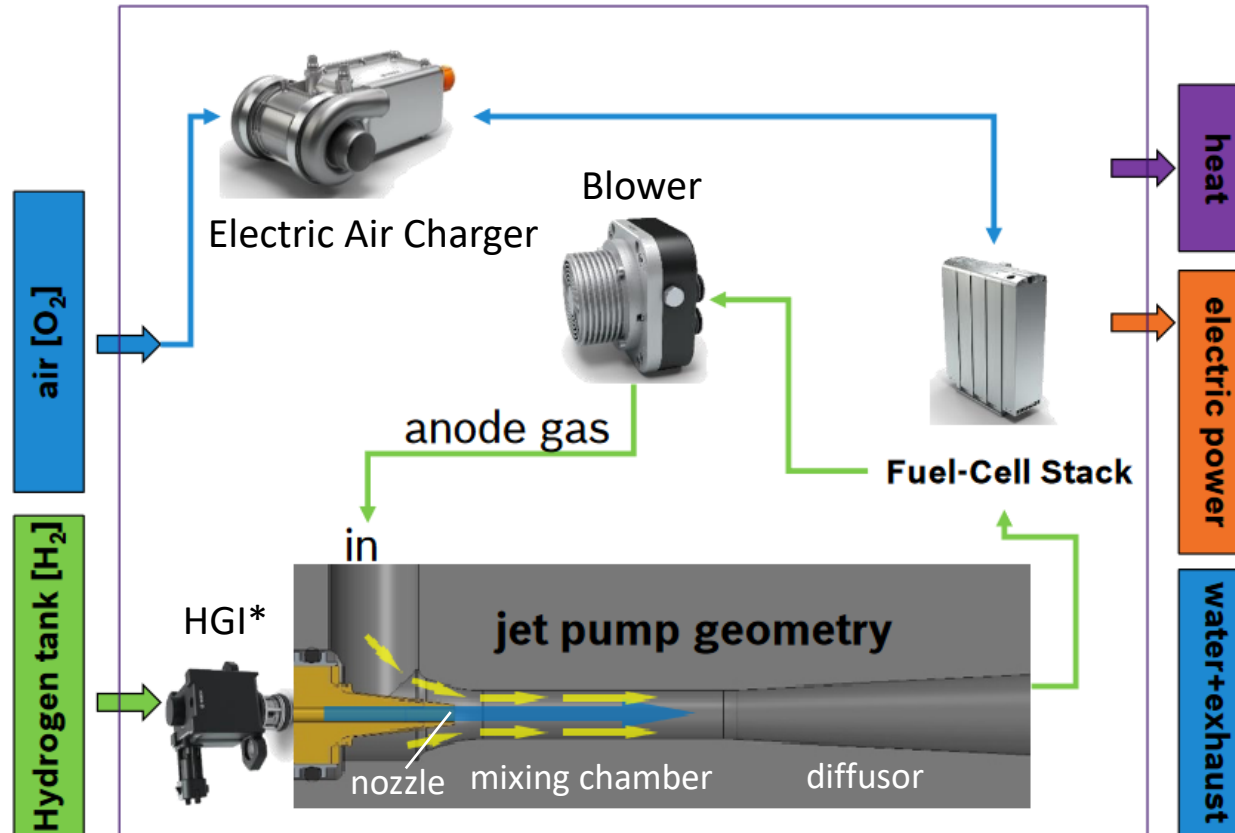
Application background



Fuel cell electric drive system from Bosch Mobility Solutions



Application background



Jet pump in the anode recirculation path of a fuel cell electric drive system

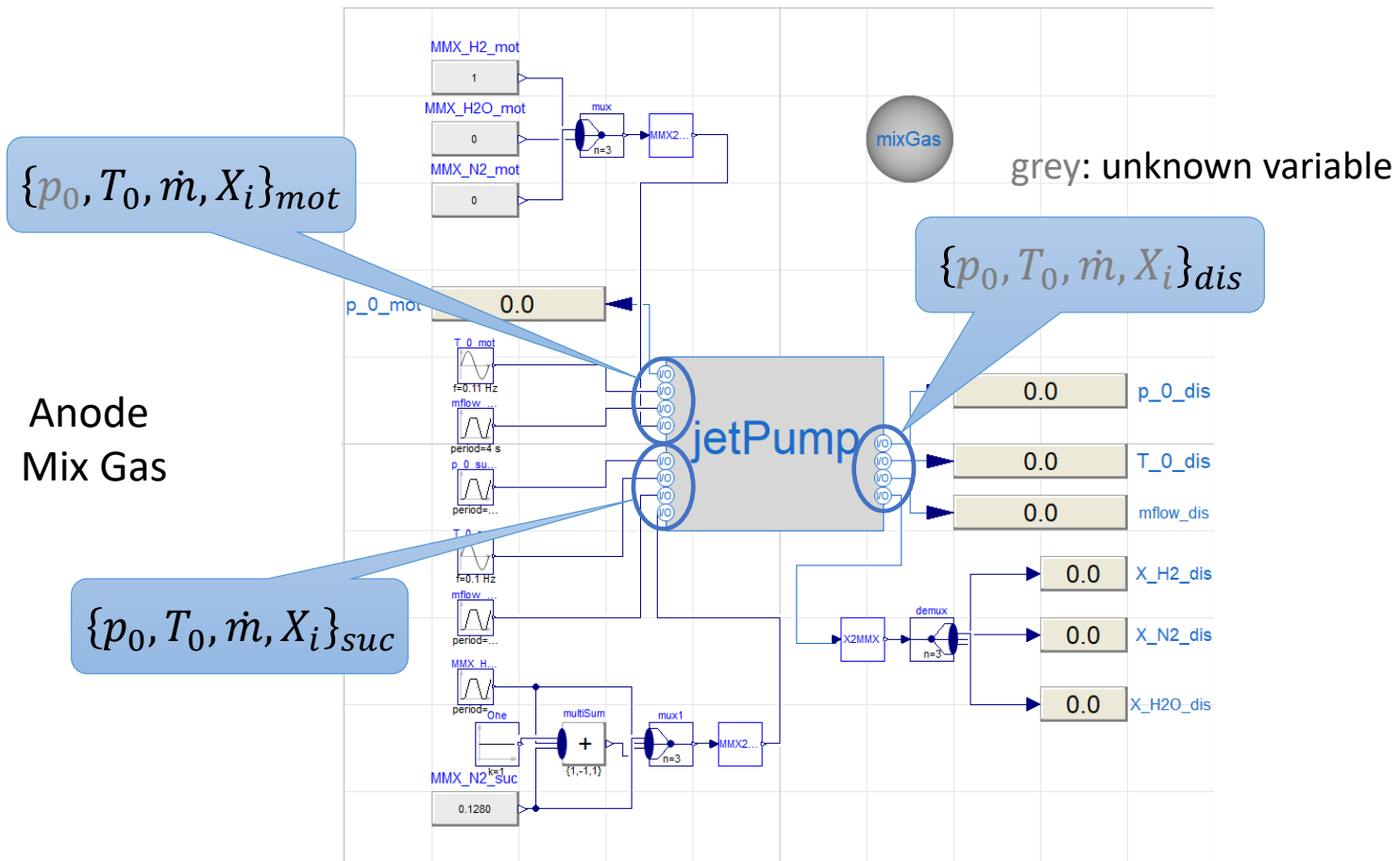
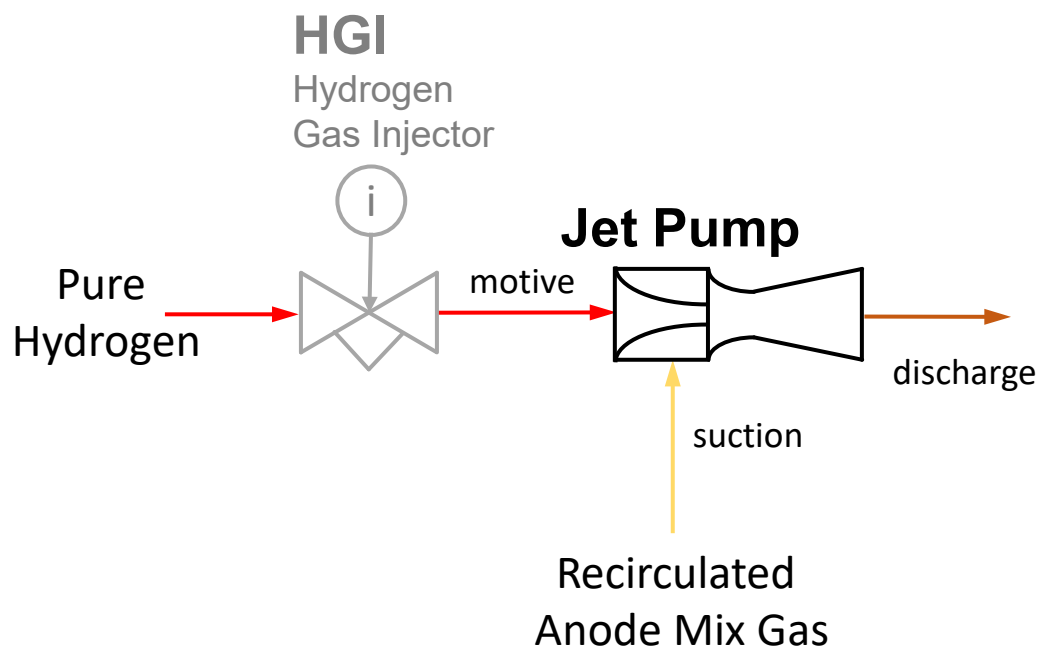


Realtime requirements on the model



- Realtime capable model of the jet pump:
 - Guaranteed worst case execution time.
 - Robust at a fixed sample rate.
 - Low computational cost and low memory footprint.
 - Mathematical operators available in embedded software service library.
 - Reliable results over the entire operation range.
- Jet pump model requirements:
 - No iterative solvers → No NLS → No non-linear algebraic loops.
 - No high dimensional look-up tables.
 - No overfitting, no outliers.

State-of-the-art jet pump model



Causality applicable for model validation against CFD results

State-of-the-art jet pump model



Translated Model

equations: {5, 4, 1, 1}

nonlinear systems: {2, 1, 0, 0}

ans: 0



→ Not suitable for embedded control function!

Variables appearing in the nonlinear systems of equations

System simulation.nonlinear[1]:

- The equation system depends on the following timevarying variables:
 - jetPump.mflow_suc
 - jetPump.p_0_suc
 - jetPump.T_0_suc
- Iteration variables:
 - jetPump.suctionFlow.p(start = 100000)
 - jetPump.suctionFlow.T(start = 288.15)

System simulation.nonlinear[2]:

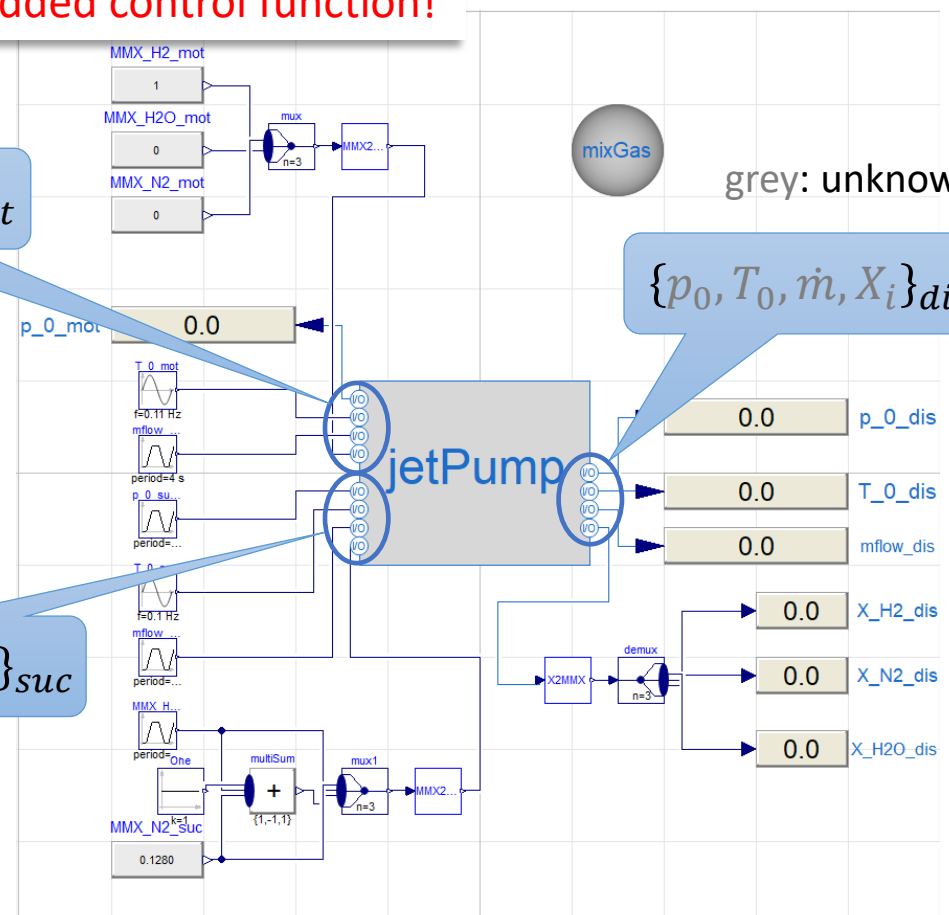
- The equation system depends on the following timevarying variables:
 - jetPump.mflow_dis
 - jetPump.p_0_dis
 - jetPump.T_0_dis
- Iteration variables:
 - jetPump.suctionFlow.p(start = 100000)
 - jetPump.suctionFlow.T(start = 288.15)

$\{p_0, T_0, \dot{m}, X_i\}_{mot}$

$\{p_0, T_0, \dot{m}, X_i\}_{suc}$

grey: unknown variable

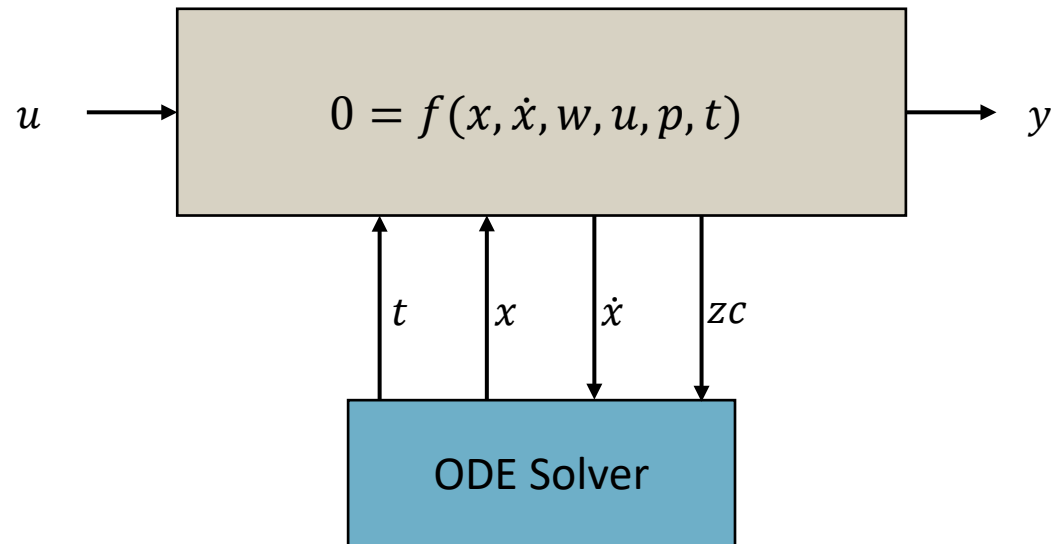
$\{p_0, T_0, \dot{m}, X_i\}_{dis}$



Causality applicable for model validation against CFD results



Replacing Non-Linear Systems



t

Time

p

Parameters

$u(t)$

Inputs

$x(t)$

Continuous states

$\dot{x}(t)$

State derivative

$w(t)$

Local variables

$y(t)$

Outputs

$zc(t)$

Event indicators

Replacing Non-Linear Systems



$$z(t) := \begin{pmatrix} \dot{x}(t) \\ w(t) \end{pmatrix} \text{ system unknowns}$$

$$\begin{aligned} f_1(z_3, z_4) &= 0 \\ f_2(z_2) &= 0 \\ f_3(z_2, z_3, z_5) &= 0 \\ f_4(z_1, z_2) &= 0 \\ f_5(z_1, z_3, z_5) &= 0 \end{aligned}$$

$$\begin{aligned} f_2(z_2) &= 0 \\ f_4(z_1, z_2) &= 0 \\ f_{NLS}(z_1, z_2, z_3, z_5) &= 0 \\ f_1(z_3, z_4) &= 0 \end{aligned} \xrightarrow[\text{surrogate } f_S]{\text{Machine learning}} \begin{aligned} f_2(z_2) &= 0 \\ f_4(z_1, z_2) &= 0 \\ f_S(z_1, z_2) &= z_3, z_5 \\ f_1(z_3, z_4) &= 0 \end{aligned}$$

$$\begin{matrix} & z_1 & z_2 & z_3 & z_4 & z_5 \\ \begin{matrix} f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \end{matrix} & \begin{pmatrix} 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 \end{pmatrix} \end{matrix}$$

before sorting and matching

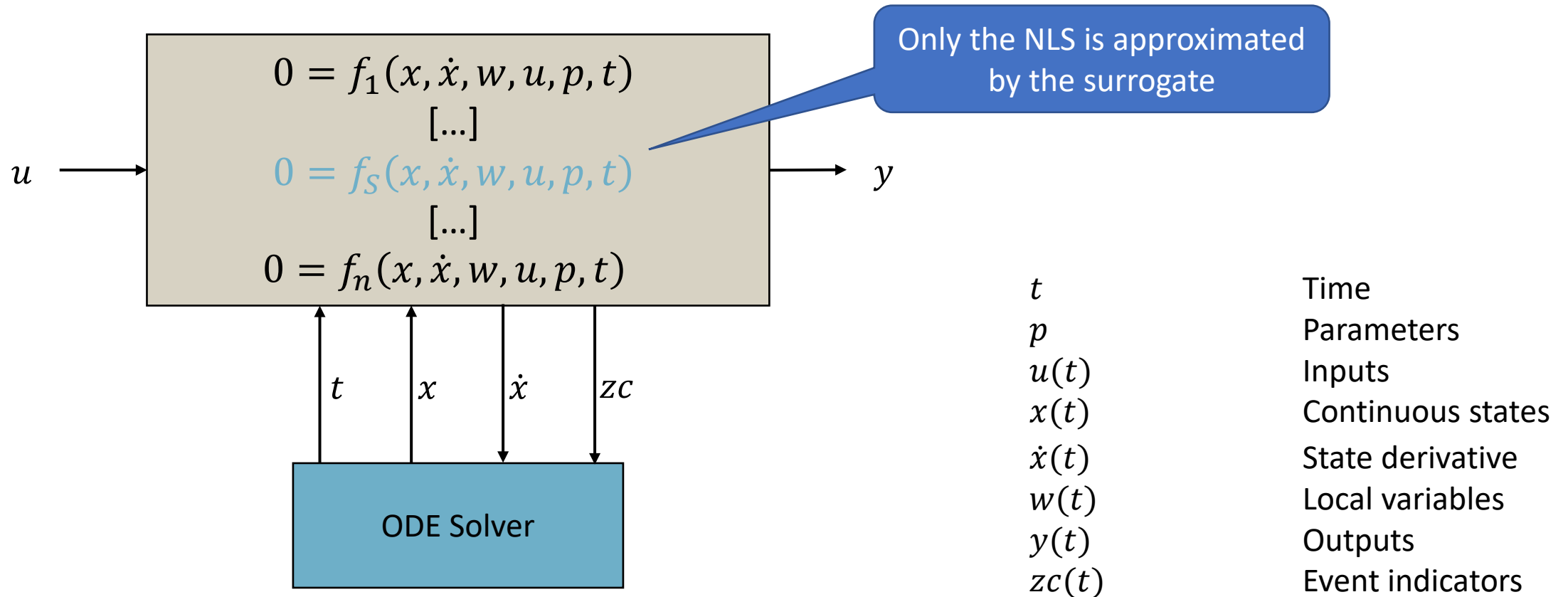
$$\begin{matrix} & z_2 & z_1 & z_3 & z_5 & z_4 \\ \begin{matrix} f_2 \\ f_4 \\ f_3 \\ f_5 \\ f_1 \end{matrix} & \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \end{pmatrix} \end{matrix}$$

implicit

$$\begin{matrix} & z_2 & z_1 & z_3, z_5 & z_4 \\ \begin{matrix} f_2 \\ f_4 \\ f_S \\ f_1 \end{matrix} & \begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix} \end{matrix}$$

explicit

Replacing Non-Linear Systems



The “Loop Replacement” method



Pre-requisite

- Create simulation scenario covering the required operation range.

Workflow

1. Identify and extract NLS
2. Generate training data
3. Train surrogate model
4. Replace NLS with surrogate



Verification

- Compare results of simulation scenario.

* <https://github.com/AnHeuermann/NonLinearSystemNeuralNetworkFMU.jl>



Application to the Jet Pump Model

1. Identify and extract NLS



NLS occurs in the SuctionFlow model

Iteration variables:

```
jetPump.suctionFlow.p(start = 100000)
jetPump.suctionFlow.T(start = 288.15)
```

```
partial model EQS_SuctionFlow "Suction flow equation 85 to 90"

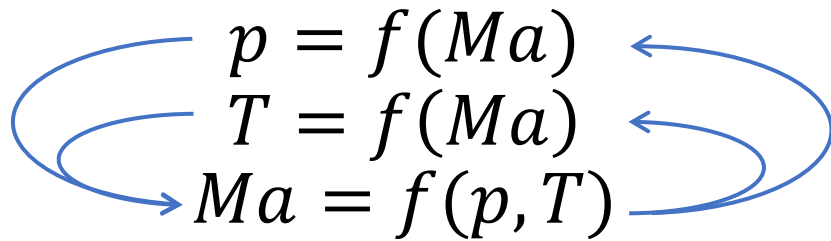
input Modelica.Units.SI.AbsolutePressure p_0 "total pressure at inlet";
input Modelica.Units.SI.Temperature T_0 "total temperature at inlet";

input Modelica.Units.SI.AbsolutePressure p "static pressure at outlet";
output Modelica.Units.SI.Temperature T = 338 "static temperature at outlet";
output Modelica.Units.SI.MassFlowRate mflow = 0 "mass flow rate";
Modelica.Units.SI.MachNumber Ma "Mach number at outlet";
Modelica.Units.SI.VelocityOfSound c "velocity of sound at outlet";
Modelica.Units.SI.Velocity v "fluid velocity at outlet";
output Modelica.Units.SI.ImpulseFlowRate I = 0 "impulse at outlet";

parameter Modelica.Units.SI.Area A=7.5775215E-05 "area of outlet";
parameter Real k=1.4 "specific isentropic exponent";
parameter Modelica.Units.SI.SpecificHeatCapacity R_s=716.41 "specific gas constant";

equation
p_0/p = (1+(k-1)/2 * Ma^2)^(k/(k-1)) "eq. 85";
T_0/T = (1+(k-1)/2 * Ma^2) "eq. 86";
v = R_s * mflow/A * T/p "eq. 87";
c = sqrt(k*R_s*T) "eq. 88";
Ma = v/c "eq. 89";
I = v * mflow "eq. 91";

end EQS_SuctionFlow;
```





Application to the Jet Pump Model

2. Generate training data



- Derive value ranges of the loop inputs from scenario



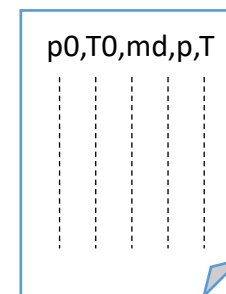
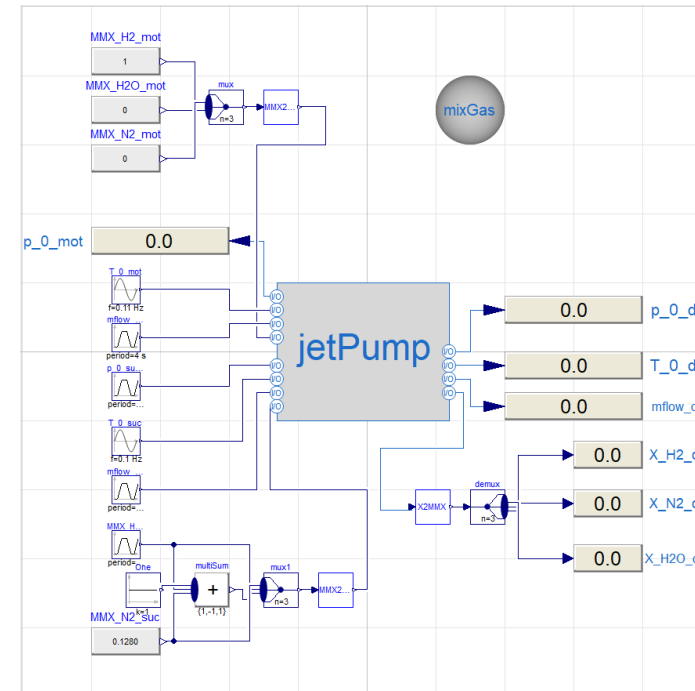
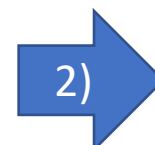
- Evaluate FMU to solve:

$$p = f(Ma)$$

$$T = f(Ma)$$

$$Ma = f(p, T)$$

- Sample the input ranges
- Record as training data set



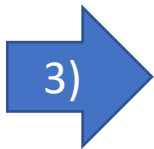
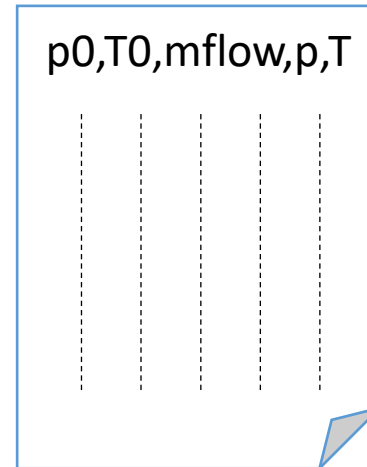
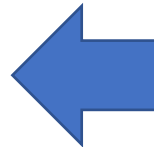


Application to the Jet Pump Model

3. Train surrogate model



- Define accepted operators:
 - +, -, *, /, sqrt, ...
- Run symbolic regression on subset of training data
- Determine RMSE on validation data
- Output the found symbolic expressions



```
Surrogate.mo

p = ((p_0 - (sqrt(T_0)))
     * (0.5483443 + (1.7069604 * sqrt(sqrt(mflow)))))
- (1 * (-0.004339092 + mflow) * (5.246307e6 + T_0))
"eq. 85 surrogate";

T = T_0 * (1.0472907 - (mflow * (15.949435
- (0.20818402 * sqrt(mflow * (p_0 - (2.307301 * T_0)))))))
"eq. 86 surrogate";
```

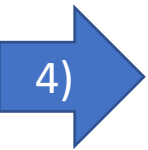
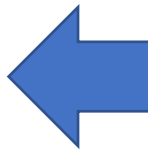


Application to the Jet Pump Model

4. Replace NLS with surrogate



- Duplicate SuctionFlow class
 - Replace equations with symbolic expressions
- Integration into validation scenario
 - Make suctionFlow component replaceable within validation scenario
 - Redeclare suctionFlow component as SuctionFlow_surr within validation scenario



Surrogate.mo

```
p = ((p_0 - (sqrt(T_0)))
      * (0.5483443 + (1.7069604 * sqrt(sqrt(mflow)))))
  - (1 * (-0.004339092 + mflow) * (5.246307e6 + T_0))
  "eq. 85 surrogate";

T = T_0 * (1.0472907 - (mflow * (15.949435
  - (0.20818402 * sqrt(mflow * (p_0 - (2.307301 * T_0)))))))
  "eq. 86 surrogate";
```

SuctionFlow_surr.mo

```
partial model EQS_SuctionFlow_surr
  "Suction flow equation 85 to 90 replaced with surrogate eqs"
  :
  equation
    p = ((p_0 - (sqrt(T_0))) * (0.5483443 + (1.7069604 * sqrt(sqrt(mflow)))))
          - (1 * (-0.004339092 + mflow) * (5.246307e6 + T_0)) "eq. 85 surrogate";
    T = T_0 * (1.0472907 - (mflow * (15.949435
          - (0.20818402 * sqrt(mflow * (p_0 - (2.307301 * T_0))))))) "eq. 86 surrog";
    v = R_s * mflow/A * T/p "eq. 87";
    c = sqrt(k*R_s*T) "eq. 88";
    Ma = v/c "eq. 89";
    I = v * mflow "eq. 91";

  a
end EQS_SuctionFlow_surr;
```

Application to the Jet Pump Model

Verification against original model

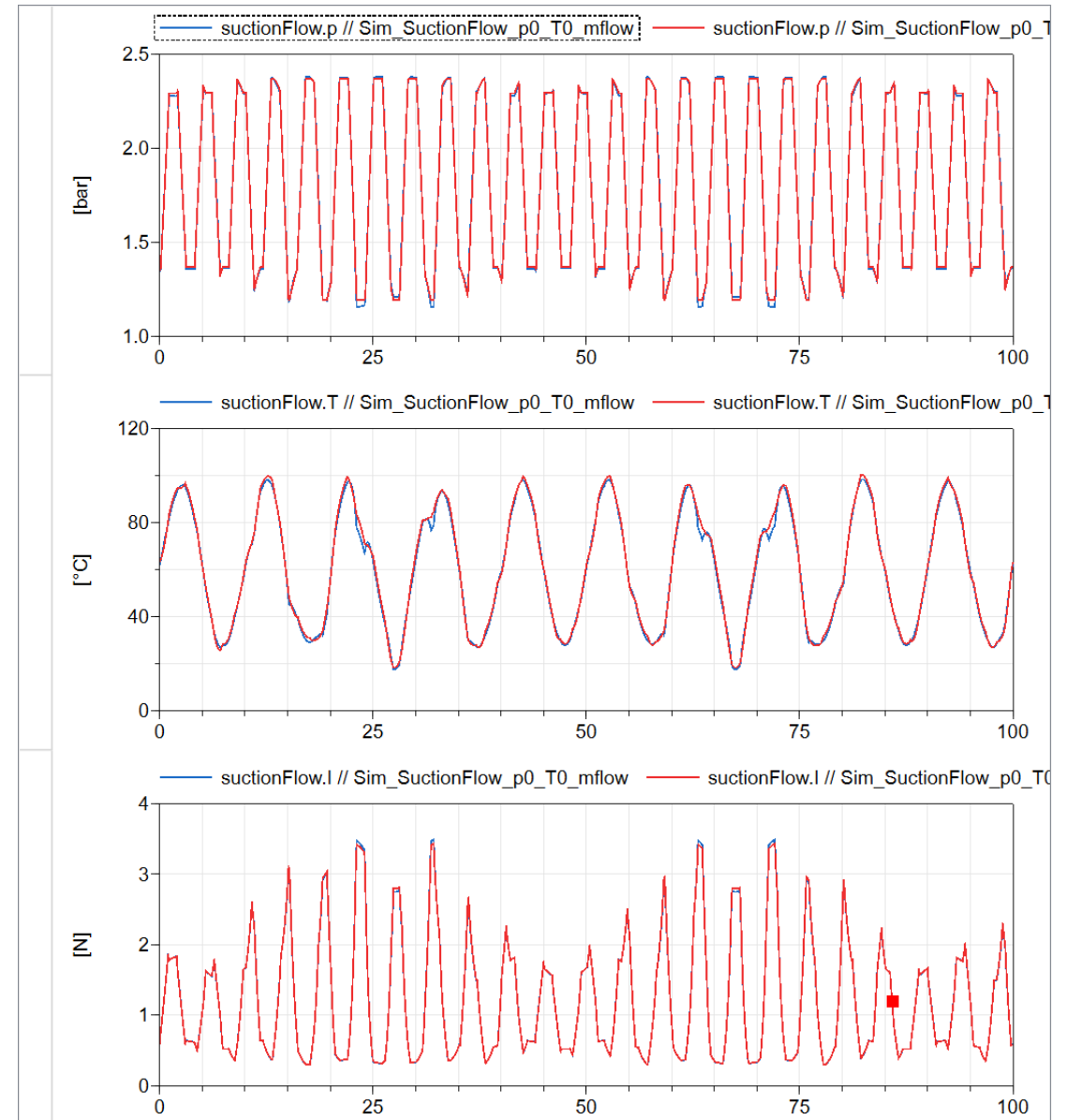


suctionFlow vs. suctionFlow_surr

- Max abs. error:
 - $p = 0.04\text{bar}$ (3.3%)
 - $T = 5\text{K}$ (6.3%)
 - $I = 0.06\text{N}$ (1.8%)
- Mean abs. error
 - $p = 0.008\text{bar}$ (0.66%)
 - $T = 1.1\text{K}$ (1.4%)
 - $I = 0.007\text{N}$ (0.22%)

1) with respect to size of value range

2) Euler solver, PC

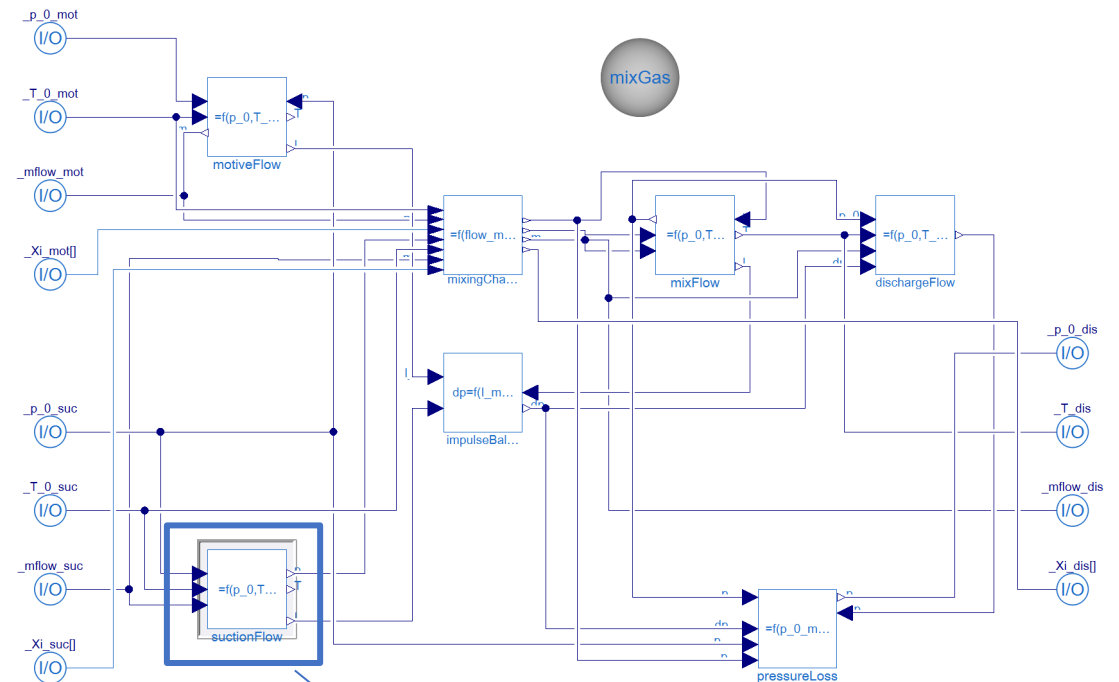




Application to the Jet Pump Model



- Integration of the surrogate into Jet Pump Model:
 - Make suctionFlow component replaceable in JetPump class.



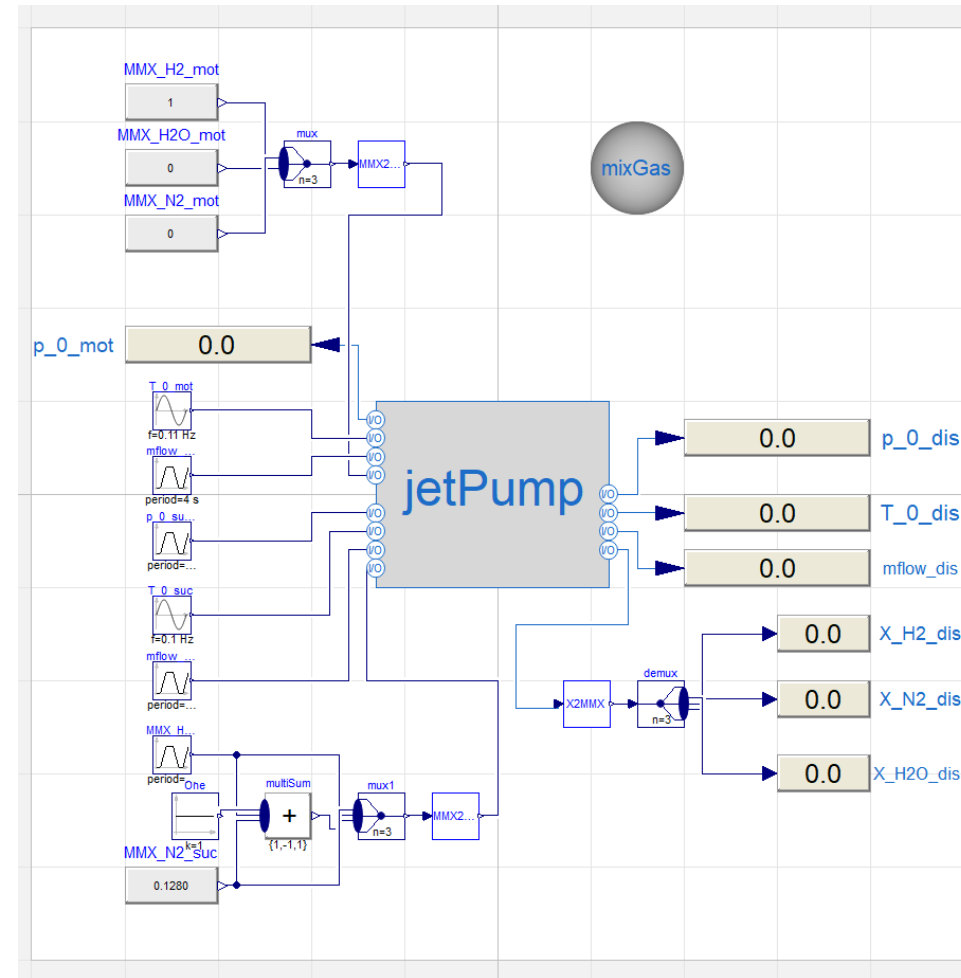
replaceable suctionFlow
component



Application to the Jet Pump Model



- Integration of the surrogate into Jet Pump Model:
 - Make suctionFlow component replaceable in JetPump class.
 - Redecclare suctionFlow component as SuctionFlow_surr within jetPump.



Application to the Jet Pump Model

Validation against original model



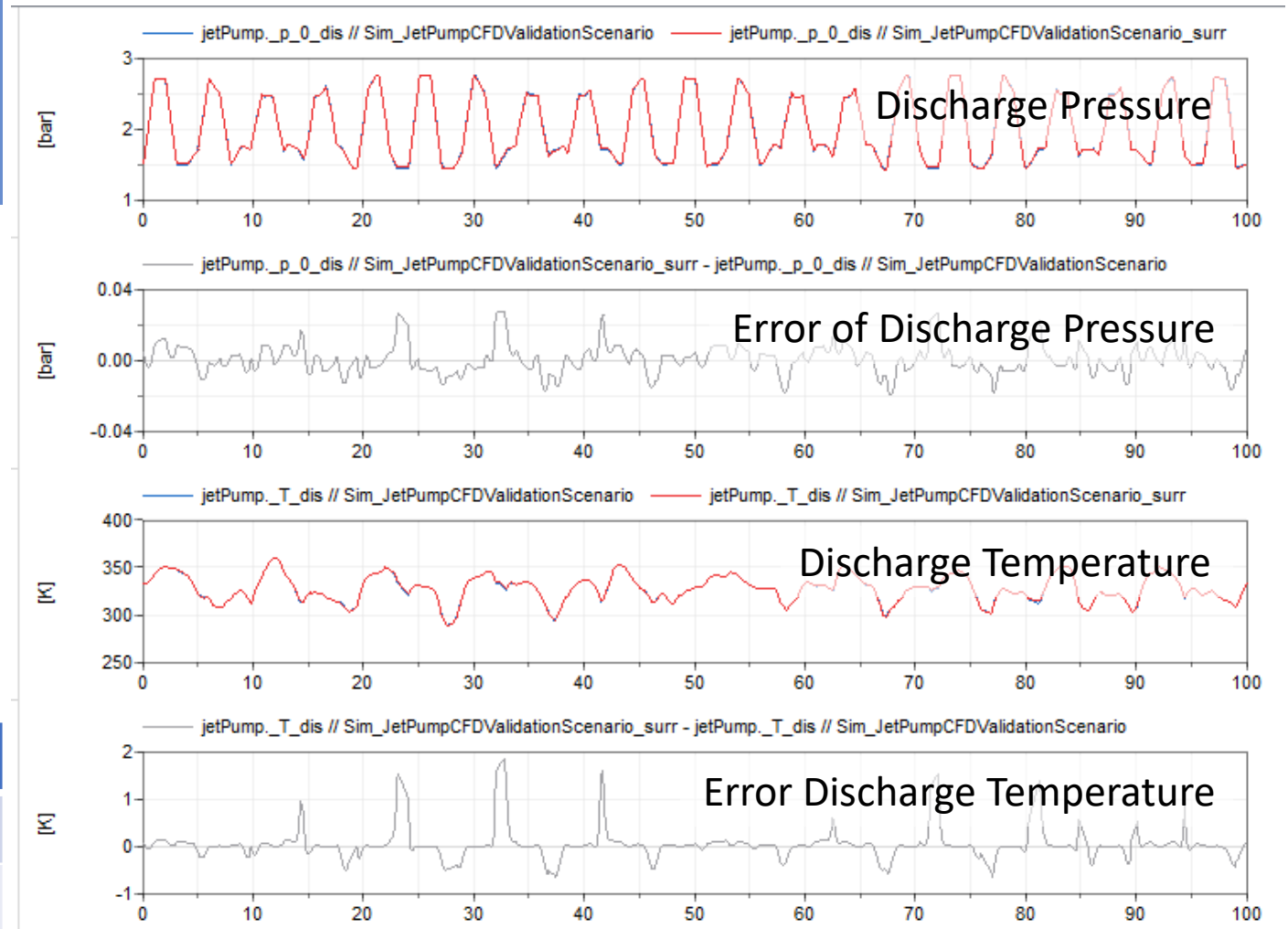
jetPump vs. jetPump_surr

- Max error abs. (rel.):
 - $p_{0_dis} = 0.028\text{bar}$ (2.1%)¹⁾
 - $T_{0_dis} = 1.8\text{K}$ (2.6%)¹⁾
- Mean error abs. (rel.)
 - $p_{0_dis} = 0.006\text{bar}$ (0.46%)¹⁾
 - $T_{0_dis} = 0.97\text{K}$ (1.4%)¹⁾

	size NLS	CPU time ²⁾	speed-up
jetPump	{2,1}	12ms	-
jetPump_surr	{0,1}	6ms	2x

¹⁾ with respect to size of value range

²⁾ Euler solver, PC





Realtime requirements on the model



- Realtime capable model of the jet pump.

- Guaranteed worst case execution time. ✓

Executable with Euler

- Robust at a fixed sample rate. ✓

Results not dependent on step size

- Low computational cost and low memory footprint. ✓

2x speed-up, only few constants added

- Mathematical operators available in embedded software service library. ✓

Basic math only

- Reliable results over the entire operation range. ✓

Training data from dense sampling

- Jet pump model requirements

- No iterative solvers → No NLS → No non-linear algebraic loops. ✓

replaced with surrogate

- No high dimensional look-up tables. ✓

Not needed

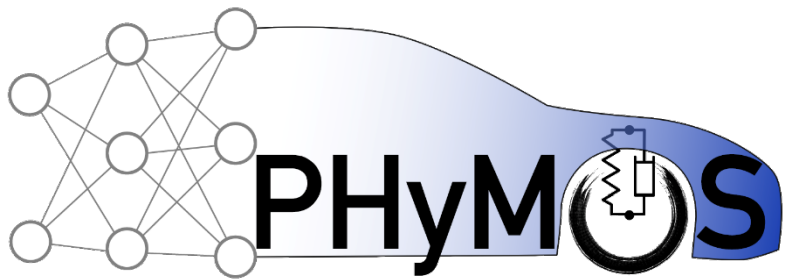
- No overfitting, no outliers. ✓

No higher order polynomials, successful validation

- Loop Replacement with Symbolic Surrogate:
 - Applicable to jet pump model (good performance).
 - Satisfaction of realtime requirements.
 - Applicable to embedded software.
 - Tunable Trade-off between complexity and accuracy.
 - Straight forward integration of symbolic surrogate into model.
 - No special treatment in the further processing (embedded code generation).
 - Training data generated from exact solution at low computation cost.



- Validation of the jet pump behavior in system context.
- Evaluate performance on embedded target.
- Application to higher dimensional problems (inverse jet pump {8}).
- Evaluate other symbolic regression packages:
 - E.g., preserve physical dimensions.
 - Try out other base operations.
- Export surrogate as Base Modelica:
 - Automated integration of symbolic surrogate.
 - Convert to other languages, e.g. SYQ.



Thanks for your attention.

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