



Partial Evaluation of AD for DAE Solvers*

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Differential Algebraic Equations (DAEs)

Differential equations

$$\frac{d^2x(t)}{dt^2} = \lambda(t)x(t)$$

$$\frac{d^2y(t)}{dt^2} = \lambda(t)y(t) - G$$

$$L^2 = x(t)^2 + y(t)^2$$

Algebraic constraint

Model from first principles



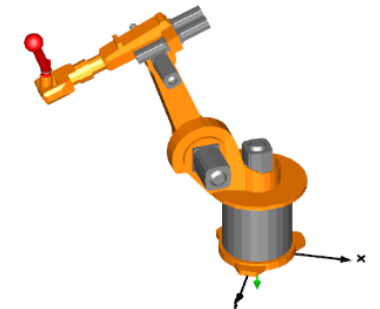
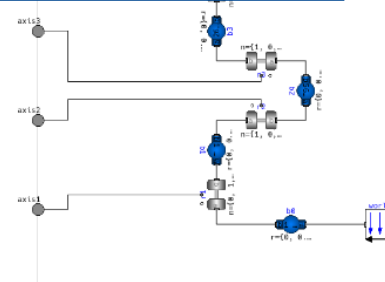
MapleSim™



OpenModelica

Modelica Language

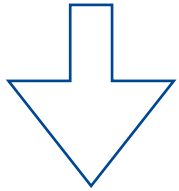
Foundation of
Equation-Based
Object-Oriented (EBO)
modelling languages



*From the Modelica standard library

EOO Language Toolchain Challenges

High-performance
simulation



Numerical integration

Index-reduction

$$\begin{aligned} \frac{d^{c_1}}{dt^{c_1}} f_1(\dot{\mathbf{x}}(t), \mathbf{x}(t)) &= 0 \\ \frac{d^{c_2}}{dt^{c_2}} f_2(\dot{\mathbf{x}}(t), \mathbf{x}(t)) &= 0 \\ &\vdots \\ \frac{d^{c_n}}{dt^{c_n}} f_n(\dot{\mathbf{x}}(t), \mathbf{x}(t)) &= 0 \end{aligned}$$

f_i after index reduction
and
order reduction

$$\mathbf{J}_{ij} = \frac{\partial f_i}{\partial \dot{\mathbf{x}}_j} + \frac{\partial f_i}{\partial \mathbf{x}_j}$$

Jacobian

$$\dot{\mathbf{x}}(t) = \frac{d\mathbf{x}(t)}{dt}$$

Index-reduction and Jacobian evaluation in EOOs

$$\mathcal{D}_x[\sin(x)] = \cos(x)$$

$$\mathcal{D}_{AD}[\lambda x . \sin(x)] = \lambda y . ((\lambda(x, \delta x) . (\sin(x), \delta x \cdot \cos(x))) (y, 1)).1$$

Forward-mode because our problem is square



Symbolic Differentiation (SD)

Automatic Differentiation (AD)

+ Efficient code

+ Natural for general programs

- n^2 symbolic $\frac{\partial f_i}{\partial \dot{x}_j} + \frac{\partial f_i}{\partial x_j}$

+ \mathbf{J}_j size prop to/complexity of f

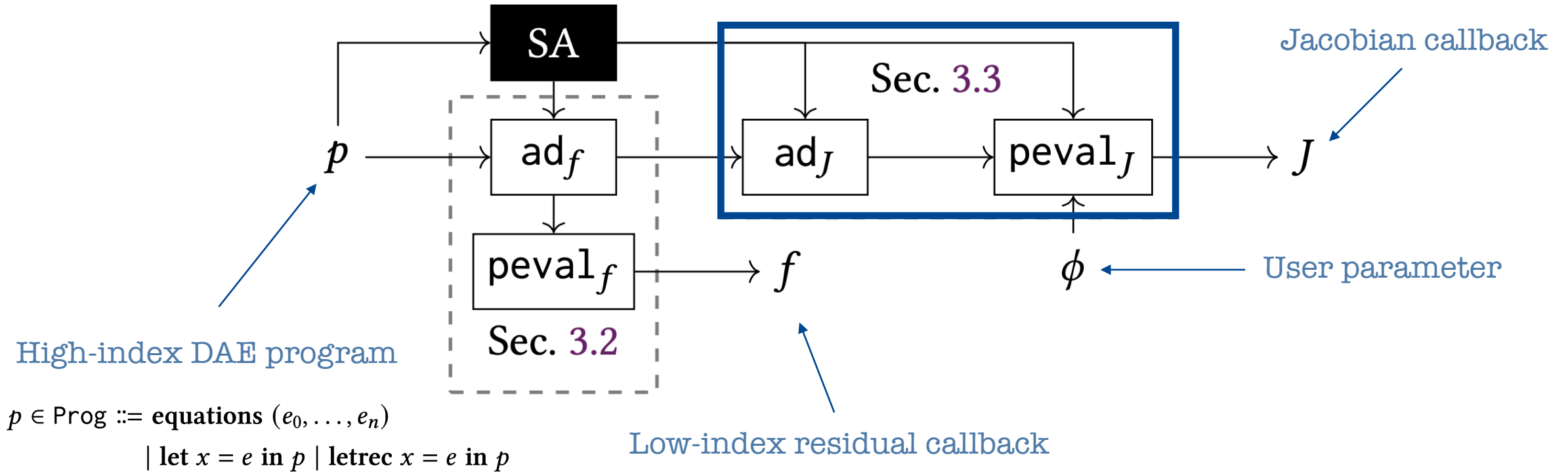
- Not easy for general programs

- Indirection/tupling/projection

Our Approach: Combine AD and SD for DAEs via PE

Forward-mode PEAD for DAEs

$$\text{peval}[\mathcal{D}_{AD}[\lambda x . \sin(x)]] = \lambda y . \cos(y)$$



$p \in \text{Prog} ::= \text{equations } (e_0, \dots, e_n)$
 $| \text{let } x = e \text{ in } p \mid \text{letrec } x = e \text{ in } p$

Part of DAE DSL in Miking Framework

Illustration of Parametrised Jacobian Specialisation

$n = 6$

$$\begin{pmatrix}
 \bullet & 0 & \bullet & 0 & 0 & 0 \\
 0 & \bullet & \bullet & 0 & 0 & 0 \\
 \bullet & \bullet & 0 & 0 & \bullet & \bullet \\
 0 & 0 & 0 & \bullet & \bullet & \bullet \\
 0 & 0 & 0 & 0 & \bullet & 0 \\
 0 & 0 & 0 & 0 & 0 & \bullet
 \end{pmatrix}$$

$\phi n = 0$

Specialised columns

Pure AD columns

0 structurally zero • structurally non-zero

Illustration of Parametrised Jacobian Specialisation

$n = 6$

•	0	•	0	0	0
0	•	•	0	0	0
•	•	0	0	•	•
0	0	0	•	•	•
0	0	0	0	•	0
0	0	0	0	0	•

$\phi n = 1$

Specialised columns

Pure AD columns

0 structurally zero • structurally non-zero

Illustration of Parametrised Jacobian Specialisation

•	0	•	0	0	0
0	•	•	0	0	0
•	•	0	0	•	•
0	0	0	•	•	•
0	0	0	0	•	0
0	0	0	0	0	•

$n = 6$

$\phi n = 2$

Specialised columns

Pure AD columns

0 structurally zero • structurally non-zero

Illustration of Parametrised Jacobian Specialisation

$n = 6$

•	0	•	0	0	0
0	•	•	0	0	0
•	•	0	0	•	•
0	0	0	•	•	•
0	0	0	0	•	0
0	0	0	0	0	•

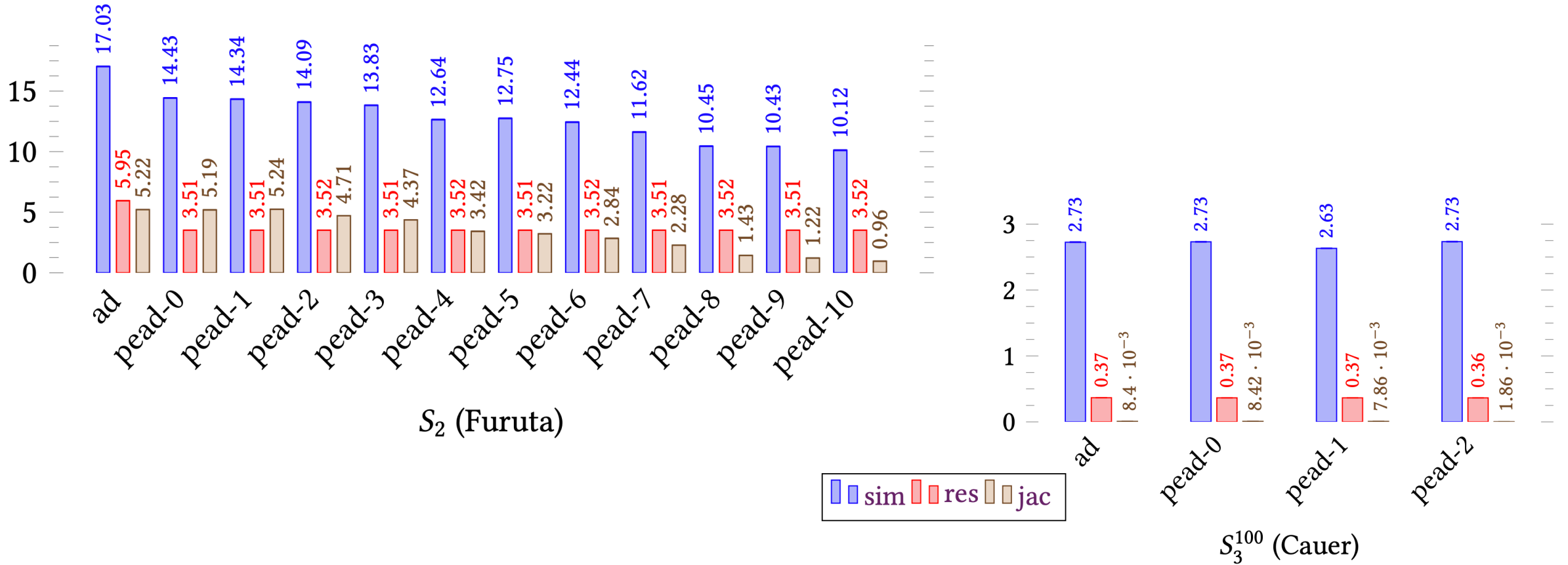
$\phi n = 3$

Specialised columns

Pure AD columns

0 structurally zero • structurally non-zero

Experimental Results (median execution time [s], 25 runs)





Conclusion

We design a technique for PE of AD in a DAE context

It applies to both index-reduction and Jacobian evaluation

The evaluation shows that improves performance of non-linear models compared to a pure AD approach