



# Symbolic Computation Methods for the Numerical Solution of Dynamic Systems Described by Differential-Algebraic Equations

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Supervisors: *Enrico Bertolazzi & Francesco Biral*

August 1, 2024

# Outline

- 1 Introduction and Motivation**
- 2 Differential-Algebraic Equations**
- 3 Symbolic Computation Essentials**
- 4 Index Reduction Algorithm**
- 5 Application Fields and Performance**
- 6 Conclusions**



# Introduction and Motivation

## The Simulation of Dynamic Systems

### Why do we need simulation?

It is used to

- ⚙️ predict the behavior
- 🌐 design and optimize
- ⌚ accelerate development and testing
- 🚗 risk-free testing environment
- 💲 reduce development costs

### Simulations' complexity is increasing!

Higher fidelity, more complexity, more ...

- ⚙️ components
- ➕ interactions
- 💻 computational resources
- ⌚ computation time



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## Dynamic Systems as a Collection of Subsystems

- Complex systems are divided into **subsystems**
  - ⚙️ mechanical ⚡ electrical 💧 thermal
  - draulic 🔍 control ...
- Subsystems are modeled by **equations**
  - algebraic*
  - ordinary differential*
  - differential-algebraic*
  - other types
- The **challenges** are

Speed      Accuracy      Efficiency



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# Introduction and Motivation

## Solution Approaches

The **solution** of these equations can be

- **Analytical**

- deep understanding of the problem
- rare and difficult to achieve
- low computational resources

- **Numerical**

- well-established and widely used
- parametricity loss
- high computational resources

- **Mixed analytical/numerical**

- ad hoc*, for specific cases
- balance between the two approaches
- reduced computational resources



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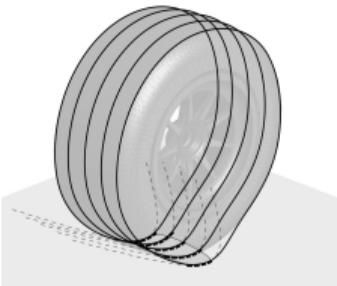
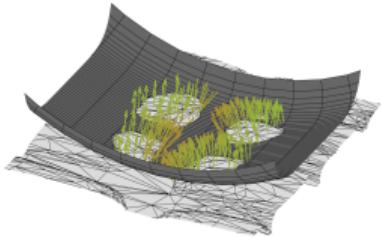
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### Tire-road interaction (A1-2)

$$\mathbf{P} = \frac{1}{V} \int_V \text{proj}(\mathbf{x}, \partial\mathcal{G}) \, d\mathbf{x}$$
$$\hat{\mathbf{n}} = \int_V \mathbf{d}(\mathbf{x}, \mathbf{h}_y) \, d\mathbf{x}$$



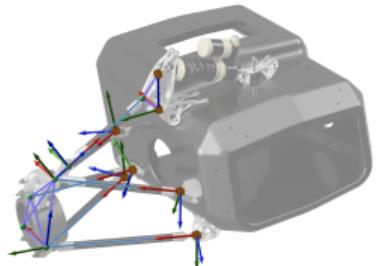
### Tire model (A3)

$$\mathbf{F}(F_z, \sigma_x, \sigma_y, \varphi, \gamma, p, T, t)$$

$$\mathbf{M}(F_z, \sigma_x, \sigma_y, \varphi, \gamma, p, T, t)$$

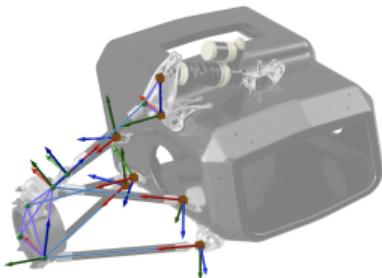
### Suspension System (A4)

- Macro-element FE model
- Modified MB-DAE system



# Introduction and Motivation

A Representative Example: FSAE Double Wishbone Suspension



## Flexibility of components

Macro-element FE model

$$\begin{bmatrix} \mathbf{K}_{ff, 72 \times 72}(\mathbb{R}) & \mathbf{K}_{fs, 72 \times 66}(\mathbb{R}) \\ \mathbf{K}_{sf, 66 \times 72}(\mathbb{R}) & \mathbf{K}_{ss, 66 \times 66}(\mathbb{R}) \end{bmatrix} \begin{bmatrix} \mathbf{d}_{f, 72}(\mathbb{R}) \\ \mathbf{d}_{s, 66}(\mathbb{R}) \end{bmatrix} = \begin{bmatrix} \mathbf{f}_{f, 72}(\mathbb{R}) \\ \mathbf{f}_{s, 66}(\mathbb{R}) \end{bmatrix}$$

symbolic matrix

$$\mathbf{d}_f = \mathbf{K}_{ff}^{-1} (\mathbf{f}_f - \mathbf{K}_{fs} \mathbf{d}_s)$$

factorization of  $\mathbf{K}_{ff}$

$$\mathbf{f}_s = \mathbf{K}_{sf} \mathbf{d}_f + \mathbf{K}_{ss} \mathbf{d}_s$$

## Dynamics of the system

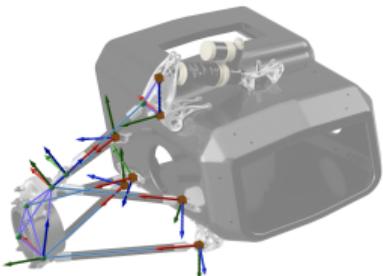
Modified MB-DAE system

$$\begin{cases} \mathbf{y} = \mathbf{x} + \mathbf{d} \\ \mathbf{M}(\mathbf{y})\ddot{\mathbf{y}} + \mathbf{r}(\mathbf{x}, \dot{\mathbf{x}}, \mathbf{d}, \dot{\mathbf{d}}) = \mathbf{f}(t) \\ \Phi_{\mathbf{x}}(\mathbf{x})^{\top} \boldsymbol{\lambda} = \mathbf{K}_c(\mathbf{x})\mathbf{d} + \mathbf{C}_c(\mathbf{x})\dot{\mathbf{d}} + \mathbf{b}(\mathbf{x}, \dot{\mathbf{x}}, t) \\ \Phi(\mathbf{x}) = 0 \end{cases}$$

This problem requires more knowledge and tools!

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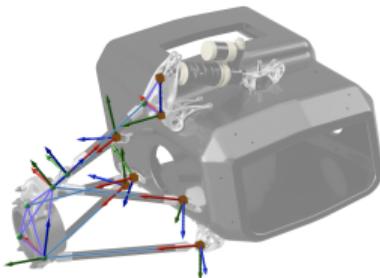
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# Introduction and Motivation

## Dynamic Systems Described by ODEs and DAEs



- Let us take a step back to generic **dynamic systems**

### ODEs

Easy to initialize

Strong theoretical foundation

Efficient numerical methods

Some models do not fit

### DAEs

Hard to initialize

Complex theoretical foundation

Require *ad hoc* numerical methods

State-of-the-art in modeling

- ODEs have **well-established** theoretical foundation, DAEs do not
- Existing tools for DAEs are not as **mature** and **efficient** as ODEs tools
- From an engineering perspective, this is a **problem** (☒ \$ 🚗 😞)

Therefore, the question is

How can we improve the state-of-the-art in the solution of DAEs?

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**1** Introduction and Motivation

**2** Differential-Algebraic Equations

*Solution of Differential-Algebraic Equations*

*Direct Discretization*

*Index Reduction*

*A New Algorithm for Index Reduction*

**3** Symbolic Computation Essentials

**4** Index Reduction Algorithm

**5** Application Fields and Performance

**6** Conclusions

# Differential-Algebraic Equations

## A Brief Introduction



DAEs are

- 1 a generalization of algebraic equations and ODEs

DAEs

$$F(x, x', t) = \mathbf{0} \text{ with } F_{x'} \text{ singular}$$

Algebraic

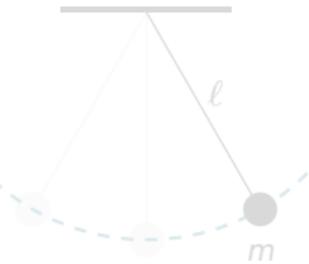
$$F(x, t) = \mathbf{0}$$

ODEs

$$x' = f(x, t)$$

- 2 composed of

- differential equations describe the system's dynamics
- algebraic equations constrain the system to a manifold



ODE model

$$\begin{cases} \theta' = \omega \\ \omega' = -\frac{g}{l} \sin(\theta) \end{cases}$$

DAE model

$$\begin{cases} x' = u \\ y' = v \\ u' = -2x\lambda \\ v' = -2y\lambda - gm \\ 0 = x^2 + y^2 - l^2 \end{cases}$$

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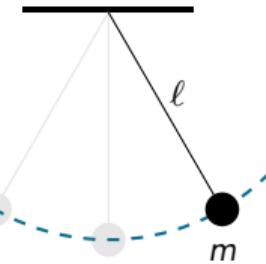
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# Solution of Differential-Algebraic Equations

DAEs are not ODEs

Is the solution of DAEs a straightforward extension of ODEs?

- Specialized **numerical techniques** are required
- Reformulation of the DAE system is typically required

Two main approaches



Index reduction

Direct discretization

L. Petzold. "Differential/Algebraic Equations are not ODE's". In: *SIAM Journal on Scientific and Statistical Computing* 3.3 (Sept. 1982), pp. 367–384. ISSN: 2168-3417



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Index reduction —→ Direct discretization



or a mix between them!

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# Solution of Differential-Algebraic Equations



## Direct Discretization

- Approximate  $\mathbf{x}'$  through a **discretization formula**
  - finite difference scheme
  - polynomial quadrature

Implicit Runge-Kutta

$$\mathbf{F} \left( \mathbf{x}_k + h_k \sum_{j=1}^s a_{ij} \mathbf{K}_j, \mathbf{K}_i, t_k + c_i h_k \right) = 0 \quad \text{for } i = 1, \dots, s$$
$$\mathbf{x}_{k+1} = \mathbf{x}_k + h_k \sum_{i=1}^s b_i \mathbf{K}_i \quad \text{for } k = 0, 1, \dots, m$$

$(a_{ij})$  non-singular +  $h_k$  small enough  $\rightarrow$  we can solve for  $\mathbf{K}_i$  at each  $m$ -th step

⚠ Some order of convergence can be lost on some components depending on the **index**

C. Gear. "Simultaneous Numerical Solution of DAEs". In: *IEEE Transactions on Circuit Theory* 18.1 (1971), pp. 89–95. ISSN: 0018-9324



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# Solution of Differential-Algebraic Equations

## The Index ... Or better Yet, The Indices

The index is a “**measure of difficulty**” in the solution of the DAEs

- Different approaches in classifying such difficulties led to different **index concepts**  
**differential**      structural      tractability  
geometrical      perturbation      strangeness
- Some indices **coincide** under proper regularity conditions

### The Differential Index

It is the minimum number of differentiations required to transform a DAE system into its underlying ODE system.

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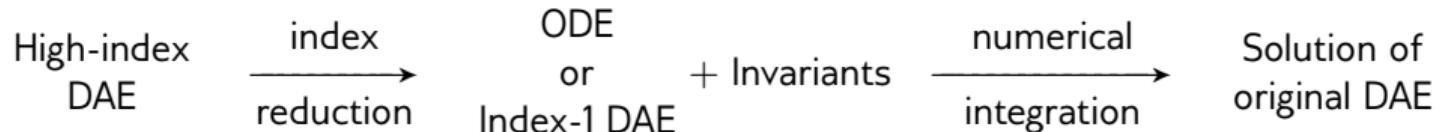
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# Solution of Differential-Algebraic Equations



## Index Reduction

### Index Reduction in the Solution Process



Index reduction is performed

- by expressions **manipulation** and **differentiation**
- through **symbolic computation** or **numerically** (with *automatic differentiation*)

**No simple recipe exists!**

Structural methods    Projector-based analysis

# Solution of Differential-Algebraic Equations

## Differential and Algebraic Equations Separation



### How do we reduce the index?

Exploit an idea common to many index concepts!

- 1 Separate** the differential and algebraic equations
- 2 Differentiate** the algebraic equations
- 3 Repeat 1–2** until necessary (index-1 DAE or ODE is reached)

Easy to say, not so easy to do ...

Numerically

Numerical linear algebra

Automatic differentiation

Track of the separators chain

Symbolically

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Just manipulate the equations

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# Solution of Differential-Algebraic Equations

## A New Algorithm for Index Reduction

### How can we improve the state-of-the-art?

Exploit the **equation separation** concept in a **full-symbolic** framework!

- ? No a priori knowledge of the system structure
- ↗ Basic use of symbolic computation and linear algebra

#### Differentiation

$$\frac{d}{dx}$$

#### Factorization

LU

Fraction-Free LU

### The **software tools**

- 🍁 Maple® for symbolic manipulation
- »» Matlab® for numerical evaluation

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- 1 Introduction and Motivation
- 2 Differential-Algebraic Equations
- 3 Symbolic Computation Essentials
  - Expression Swell*
  - Large Expression Management*
  - Symbolic Matrix Factorization*
- 4 Index Reduction Algorithm
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# Symbolic Computation Essentials

## Expression Swell



### Inside a CAS



CAS are sensitive to expression swell!

⌚ High memory usage    ⚖ Slow computation ✘

Two types of expression swell

Inherent

No applicable simplification rule

Require changes in the problem formulation

Intermediate

Depends on CAS's simplification capabilities

Intermediate growth, en route to a simple result

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# Large Expression Management

## Hierarchical Representation

We progressively **hide** chunks of expressions

$$\frac{2xy(1+y) \cdot f(x,y) + 5z(3a+z) \cdot g(y) + 3c(xy+z) \cdot h(x,z)}{v_1 \cdot f(x,y) + v_2 \cdot g(y) + v_3 \cdot h(x,z)}$$
$$v_4 + v_5$$

to store them in separate variables

$$v_1 = 2x(1+y)$$

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# Large Expression Management

## Hierarchical Representation

Hierarchical representation of expressions is performed through **veiling variables**

$$f(x) \xrightarrow[\text{variables}]{\text{veiling}} f(x, v) \quad \text{where} \quad v(x) = \begin{bmatrix} v_1(x) \\ v_2(v_1, x) \\ \vdots \\ v_n(v_1, \dots, v_{n-1}, x) \end{bmatrix}$$

LEM is made of two actions

- 1 **veiled** large expressions
- 2 **unveil** to recover the original form

Expression complexity remains but the CAS can not see it! 



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## Hierarchical Representation

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$$f(x) \xrightarrow[\text{variables}]{\text{veiling}} f(x, v) \quad \text{where} \quad v(x) = \begin{bmatrix} v_1(x) \\ v_2(v_1, x) \\ \vdots \\ v_n(v_1, \dots, v_{n-1}, x) \end{bmatrix}$$

LEM is made of two actions

- 1 **veiled** large expressions
- 2 **unveil** to recover the original form

Expression complexity remains but the CAS can not see it! 



# Large Expression Management

## Measuring Expression Complexity

Easy to implement, but ...



### How to measure symbolic expression complexity?

- **Length in characters**  
Same expression can have different lengths
- **Directed acyclic graph**  
Measures the number of nodes and edges
- **Computational cost**  
Insensitive to internal representation

### What is the right level of expression complexity?

- Trial and error  
No general rule, depends on the software  
The least to make computations go on



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# Symbolic Matrix Factorization

## Considerations and Challenges



### Maple® factorizations are sensitive to expression swell

- LU and Fraction-Free LU (FFLU) factorizations
  - preserve sparsity and fill-in
  - perform minimal algebraic manipulations
  - allow for custom pivoting strategies
- However ...
  - 1 output's numerical stability is not guaranteed
    - How to ensure numerical stability?
  - 2 expressions grow unpredictably during manipulation
    - How to manage large symbolic expressions?



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# Symbolic Matrix Factorization

## Symbolic Pivoting Strategy

### How to ensure numerical stability?

A good symbolic pivoting strategy

- 1 selects the **minimum-degree** entry

Limit fill-in and expression swell

- 2 if numeric, selects the **bigest** entry

Improve numerical stability

- 3 selects **least complicated** entry

Limit expression swell

- 4 looks for the **best choice**

Full-pivoting strategy

```
procedure SymbolicPivoting(A, k)
    dr, dc ← ComputeDegrees(A)
    for i from k to m do
        for j from k to n do
            Dij ← ∞
            if Aij ≠ 0 then Dij ← dri max(0, dcj - 1) + dcj max(0, dri - 1)
        end for
    end for
    P ← Sort(D)
    q, l ← 0, 0 and p, pc, pn ← ∞, ∞, ∞
    for all (i, j) in P do
        if pc ≠ ∞ and Dij > Dql then break
        t ← Aij
        if Signature(t) = 0 then continue
        t ← Simplify(t) and tc ← ExpressionComplexity(t) and tn ← ∞
        if t is numeric then tn ← max(1, abs(t))
        if tc < pc or (tc = pc and tn > pn) then
            q, l ← i, j and p, pc, pn ← t, tc, tn
        end if
    end for
    return p, q, l
end procedure
```



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# Symbolic Matrix Factorization

## LEM During Factorization

### How to manage large symbolic expressions?

Veils are introduced during ...

- **Factorization step**

Gaussian elimination  
Schur complement

- **Solution step**

forward substitution  
backward substitution

```

procedure BuildLU(A, k)
    M ← A
    rk ← min(m, n)
    for k from 1 to rk do
        p, q, l ← SymbolicPivoting(M, k)
        if p = 0 then
            rk ← k - 1 and break
        end if
        rk, ck ← q, l
        M ← SwapRowsCols(M, k, q, l)
        for i from k + 1 to m do
            Mkk ← Veil(Mkk)
            Mik ← Veil(Normalizer(Mik / Mkk))
            for j from k + 1 to n do
                Mij ← Veil(Normalizer(Mij - MikMkj))
            end for
        end for
    end for
    P, Q ← PermutationMatrices(r, c)
    L, U ← LowerUpperMatrices(M)
    return L, U, P, Q, r, c, rk
end procedure

```

```

procedure SolveLU(L, U, P, Q, b)
    y ← Pb
    m, n ← Size(L)
    for i from 2 to m do
        yi ← Veil(yi - ∑j=1i-1 Lijyj)
    end for
    xn ← Veil(yn / Unn)
    for i from n - 1 to 1 do
        xi ← Veil(yi - ∑j=i+1n Uijxj)
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    x ← QTx
end procedure

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# Outline

- 1** Introduction and Motivation
- 2** Differential-Algebraic Equations
- 3** Symbolic Computation Essentials
- 4** Index Reduction Algorithm
  - Separation of Differential and Algebraic Equations*
  - Differentiation of Algebraic Equations*
  - Projection on Invariants*
- 5** Application Fields and Performance
- 6** Conclusions



# Index Reduction Algorithm

## Separation of Differential and Algebraic Equations

- 1 Consider the **generic** DAEs system

$$\mathbf{F}(\mathbf{x}, \mathbf{x}', t) = \mathbf{A}(\mathbf{x}, t)\mathbf{x}' - \mathbf{b}(\mathbf{x}, t) = \mathbf{0}$$

- 2 Separate the equations with the cokernel  $\mathbf{K}(\mathbf{x}, t)$  and its orthogonal complement  $\mathbf{N}(\mathbf{x}, t)$  of  $\mathbf{A}(\mathbf{x}, t)$

$$\begin{bmatrix} \mathbf{E}(\mathbf{x}, t) \\ \mathbf{0} \end{bmatrix} \mathbf{x}' = \begin{bmatrix} \mathbf{g}(\mathbf{x}, t) \\ \mathbf{a}(\mathbf{x}, t) \end{bmatrix} \quad \text{with} \quad \begin{aligned} \mathbf{E}(\mathbf{x}, t) &= \mathbf{N}(\mathbf{x}, t)\mathbf{A}(\mathbf{x}, t) \\ \mathbf{g}(\mathbf{x}, t) &= \mathbf{N}(\mathbf{x}, t)\mathbf{b}(\mathbf{x}, t) \\ \mathbf{a}(\mathbf{x}, t) &= \mathbf{K}(\mathbf{x}, t)\mathbf{b}(\mathbf{x}, t) \end{aligned}$$

### Cokernel Computation

The cokernel  $\mathbf{K}(\mathbf{x}, t)$  and its orthogonal complement  $\mathbf{N}(\mathbf{x}, t)$  of  $\mathbf{A}(\mathbf{x}, t)$  are calculated using matrix factorization



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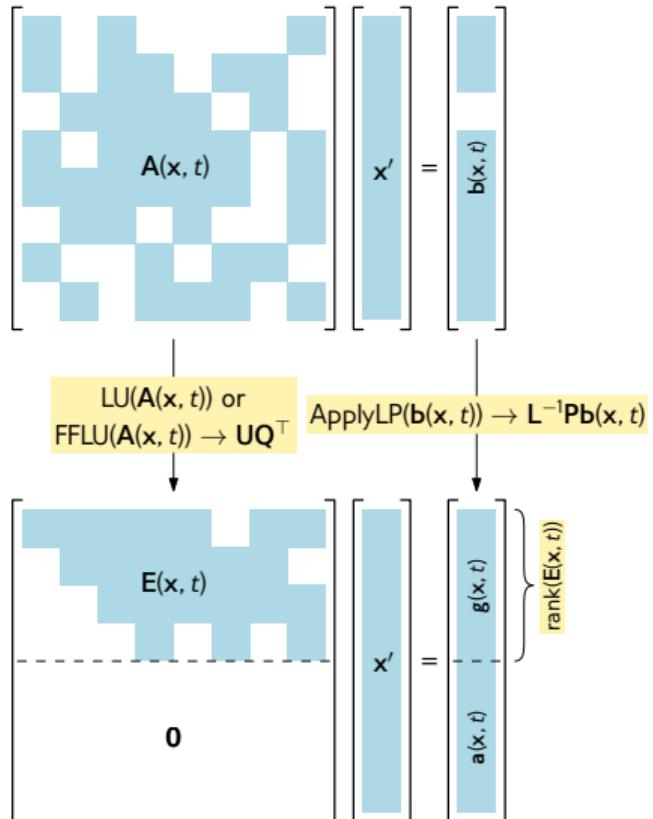
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# Index Reduction Algorithm

## Differentiation of Algebraic Equations

3 Update the **invariants** as  $\mathbf{h}(\mathbf{x}, t) = \mathbf{h}(\mathbf{x}, t) \cup \mathbf{a}(\mathbf{x}, t)$

4 Differentiate the algebraic equations  $\mathbf{a}(\mathbf{x}, t)$

$$\frac{d}{dt} \mathbf{a}(\mathbf{x}, t) = \mathbf{E}_a(\mathbf{x}, t) \mathbf{x}' - \mathbf{g}_a(\mathbf{x}, t)$$

5 The index reduced system of DAEs takes the form

$$\begin{bmatrix} \mathbf{E}(\mathbf{x}, t) \\ \mathbf{E}_a(\mathbf{x}, t) \end{bmatrix} \mathbf{x}' = \begin{bmatrix} \mathbf{g}(\mathbf{x}, t) \\ \mathbf{g}_a(\mathbf{x}, t) \end{bmatrix}$$
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Apply 1–6 repeatedly until  $\mathbf{A}(\mathbf{x}, t)$  is non-singular

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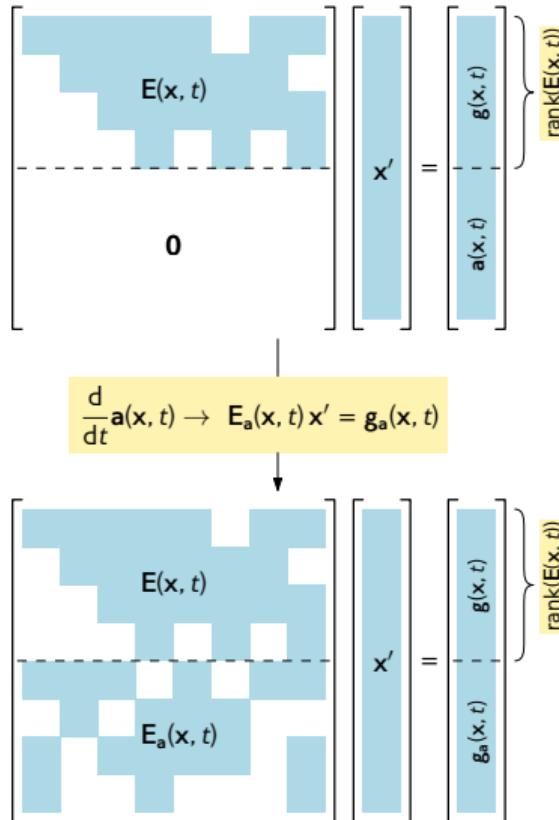
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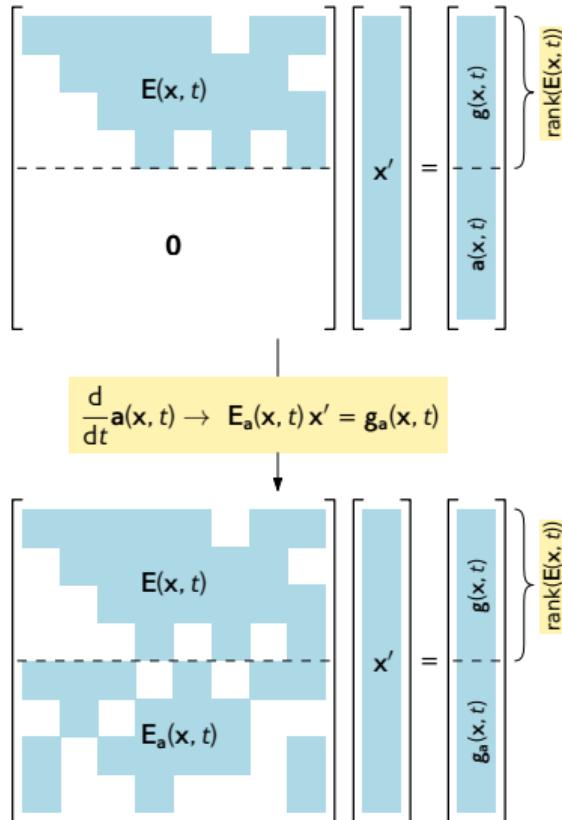
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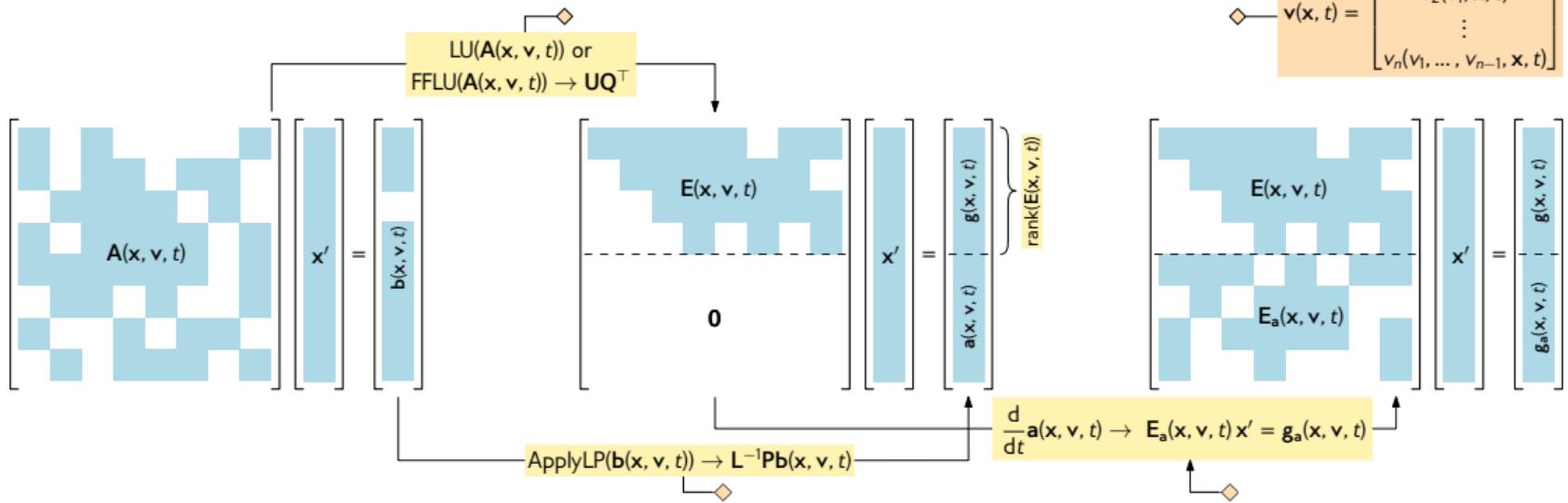


# Index Reduction Algorithm

## Including Veiling Variables

The algorithm can be extended to include LEM

- veiling variables are stored in the list  $v(x, t)$
- equations are also function of  $v(x, t)$
- veiling variables add an evaluation layer to the algorithm





# Index Reduction Algorithm

## The Reduced DAE System



Now we can code-generate the reduced DAE system!

- Differential part

$$\begin{array}{ll} \mathbf{F}(\mathbf{x}, \mathbf{x}', \mathbf{v}, t) = \mathbf{0} & \text{implicit system class} \\ \mathbf{A}(\mathbf{x}, \mathbf{v}, t)\mathbf{x}' = \mathbf{b}(\mathbf{x}, \mathbf{v}, t) & \text{semi-explicit system class} \\ \mathbf{x}' = \mathbf{f}(\mathbf{x}, \mathbf{v}, t) & \text{explicit system class} \end{array}$$

- Invariants

$$\mathbf{h}(\mathbf{x}, \mathbf{v}, t) = \begin{bmatrix} \mathbf{h}_i(\mathbf{x}, \mathbf{v}, t) \\ \mathbf{h}_u(\mathbf{x}, \mathbf{v}, t) \end{bmatrix} = \mathbf{0}$$

hidden constraints  
*optional* user-defined invariants

- Veiling variables

$$\mathbf{v}(\mathbf{x}, t) = \begin{bmatrix} v_1(\mathbf{x}, t) \\ v_2(v_1, \mathbf{x}, t) \\ \vdots \\ v_n(v_1, \dots, v_{n-1}, \mathbf{x}, t) \end{bmatrix}$$



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# Projection on Invariants

## Theoretical Background and Implementation

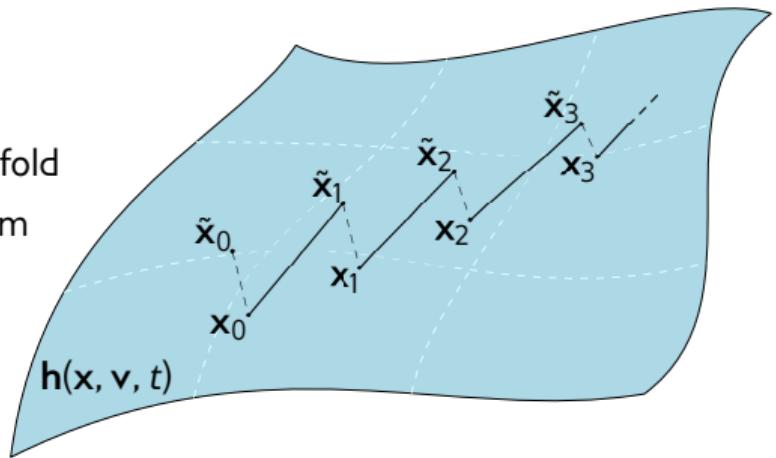
»» Now we can integrate the system in Matlab®!

Projection is performed

- during the **numerical integration**
- to **enforce** the solution  $\mathbf{x}$  onto the  $\mathbf{h}(\mathbf{x}, \mathbf{v}, t)$  manifold
- by solving the **constrained minimization** problem

$$\underset{\mathbf{x}}{\text{minimize}} \quad \frac{1}{2} (\mathbf{x} - \tilde{\mathbf{x}})^2$$

$$\text{subject to} \quad \mathbf{h}(\mathbf{x}, \mathbf{v}, t) = 0$$



Find  $\mathbf{x}$  with minimal distance from  $\tilde{\mathbf{x}}$  that satisfies the invariants  $\mathbf{h}(\mathbf{x}, \mathbf{v}, t)$

# Symbolic-Numerical Validation

## The Problem

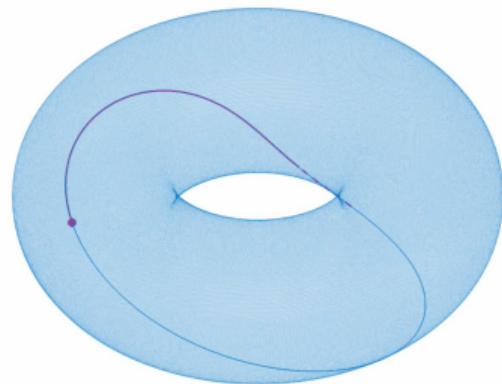
A **particle** moving over a **torus** surface

$$\begin{cases} x'_1 = u_1 \\ x'_2 = u_2 \\ x'_3 = u_3 \\ u'_1 = u_3 \cos(t) - x_3 \sin(t) - u_2 + 2cx_1\lambda \\ u'_2 = u_3 \sin(t) + x_3 \cos(t) + u_1 + 2cx_2\lambda \\ u'_3 = x_3 + 2x_3\lambda \\ \rho^2 = x_1^2 + x_2^2 + x_3^2 - 2r(x_1^2 + x_2^2)^{\frac{1}{2}} + r^2 \end{cases}$$

with  $c = 1 - r/(x_1^2 + x_2^2)^{\frac{1}{2}}$ ,  $\rho = 5$ ,  $r = 10$ ,  
and ICs  $\mathbf{x}_0 = [15, 0, 0, 0, 15, -5, \lambda]^T$

## Exact Solution

$$\mathbf{x}_{\text{exact}} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} (\rho \cos(2\pi - t) + r) \cos(t) \\ (\rho \cos(2\pi - t) + r) \sin(t) \\ \rho \sin(2\pi - t) \end{bmatrix}$$



S. L. Campbell and E. Moore. "Constraint preserving integrators for general nonlinear higher index DAEs". In: *Numerische Mathematik* 69.4 (Feb. 1995), pp. 383–399. ISSN: 0945-3245

# Symbolic-Numerical Validation

## Index Reduction

### LU Factorization

Original DAEs	$F(x, x', t) = 47f + 30m + 23a \quad h(x, t) = 0$		
Reduction step	$E(x, t)$	$g(x, t)$	$a(x, t)$
Index-3 DAEs	0	$39f + 36m + 13a$	$7f + 10m + 6a$
Index-2 DAEs	0	$39f + 36m + 13a$	$22f + 20m + 8a$
Index-1 DAEs	0	$39f + 36m + 13a$	$68f + 72m + 33a$
Index-0 DAEs	$388f + 424m + 180a$	$79f + 77m + 26a$	0
Reduced DAEs	$F(x, x', t) = 258f + 239m + 109a \quad h(x, t) = 97f + 102m + 47a$		

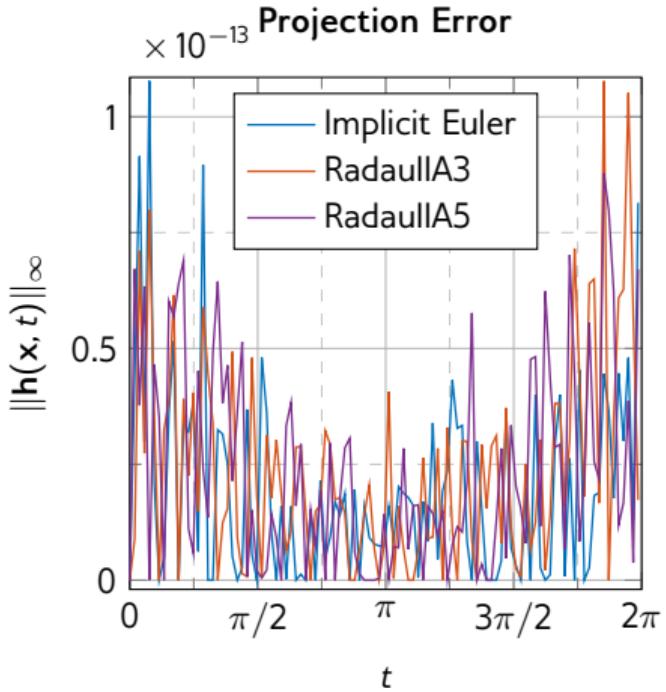
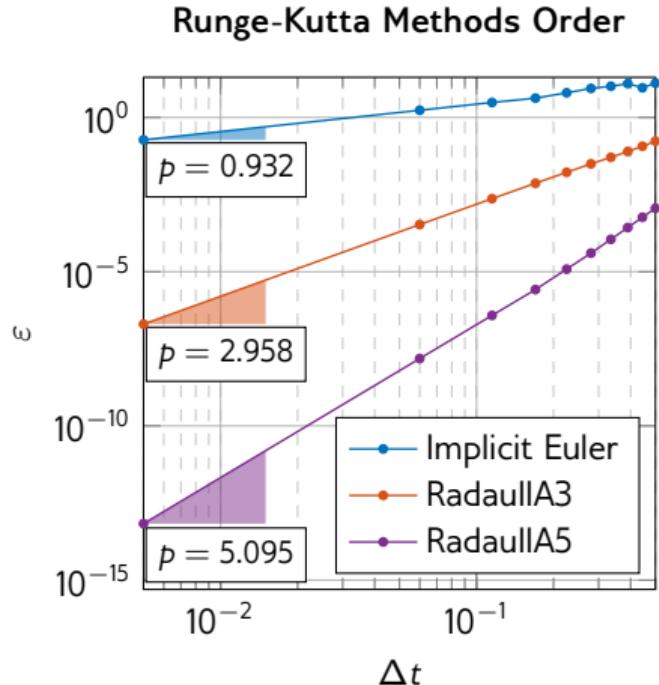
### FFLU Factorization

Original DAEs	$F(x, x', t) = 47f + 30m + 23a \quad h(x, t) = 0$		
Reduction step	$E(x, t)$	$g(x, t)$	$a(x, t)$
Index-3 DAEs	0	$39f + 36m + 13a$	$7f + 10m + 6a$
Index-2 DAEs	0	$39f + 36m + 13a$	$26f + 23m + 8a$
Index-1 DAEs	0	$39f + 36m + 13a$	$68f + 72m + 33a$
Index-0 DAEs	$388f + 424m + 180a$	$79f + 77m + 26a$	0
Reduced DAEs	$F(x, x', t) = 258f + 239m + 109a \quad h(x, t) = 101f + 105m + 47a$		

Legend: f = functions, a = additions, m = multiplications, and d = divisions.

# Symbolic-Numerical Validation

## Order and Error Analysis

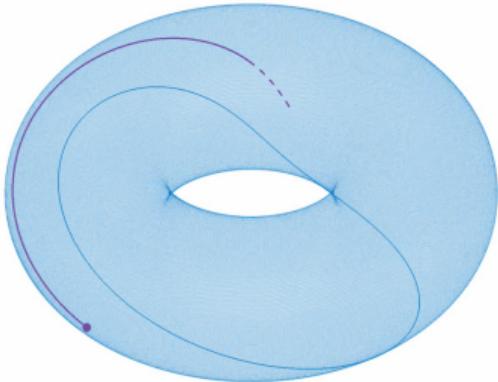


# Symbolic-Numerical Validation

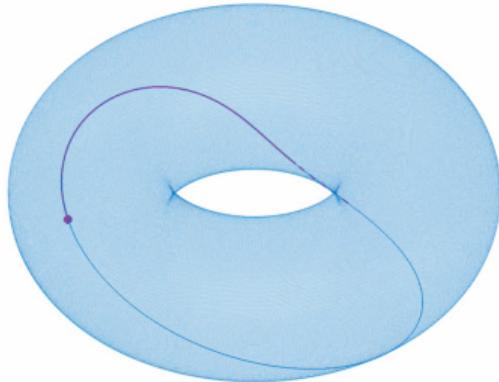
## Solution Visualization

RadauIIA5     $\Delta t = 0.05 \text{ s}$      $t \in [0, 200\pi] \text{ s}$

No projection



With projection



# Outline

- 1 Introduction and Motivation**
- 2 Differential-Algebraic Equations**
- 3 Symbolic Computation Essentials**
- 4 Index Reduction Algorithm**
- 5 Application Fields and Performance**
- 6 Conclusions**

# Application Fields and Performance



## Benchmark Problems

### Multi-body dynamics

- 1 Car-axis (index-3)
- 2 Flexible slider-crank (index-3)
- 3 Double-wishbone suspension (index-3)

### Trajectory prescribed path control problems

- 4 Space shuttle initial stage reentry (index-3)
- 5 Space shuttle final stage reentry (index-2)
- 6 Robotic arm control (index-5)

### Electric circuits

- 7 Eight-nodes transistor-amplifier (index-3)
- 8 Electric ring modulator (index-1)
- 9 Cascaded differential amplifiers (up to index-100)

### Generic DAE systems

- 10 Particle motion (index-3);
- 11 2-pendula (index-3)
- 12 3-pendula (index-5)
- 13 4-pendula (index-9)
- 14 5-pendula (index-11)

Most of the problems are taken from:

F. Mazzia and C. Magherini. *Test set for initial value problem solvers*. Tech. rep. Department of Mathematics, University of Bari, 2008  
K. E. Brenan, S. L. Campbell, and L. R. Petzold. *Numerical Solution of Initial-Value Problems in DAEs*. SIAM, Jan. 1995. isbn: 978-1611971224

# Application Fields and Performance

## Benchmarking the Index Reduction Algorithm

### The rules

- ☒ 100 s time limit for symbolic simplification
- ♾️ unlimited time for numerical integration
- ✓ if you can integrate the problem, you win

### The competitors

- Maple® dsolve (undisclosed)
- Matlab® reduceDAEIndex (Pantelides)
- Matlab® reduceDAEToODE (Gaussian elim.)
- Mathematica® NDSolve (Pantelides)
- **Maple® + Matlab® Proposed**

Solver	Problems													
	MBD			TPPC			El. Circuits			Generic DAEs				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Maple® dsolve	✓	✓	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗
Matlab® NDSolve	✓	✓	-	-	-	-	-	-	-	-	✗	✓	-	-
Matlab® reduceDAEIndex	✓	✓	-	-	-	-	-	-	-	-	✗	✓	-	-
Mathematica® reduceDAEToODE	✓	✓	-	-	-	-	-	-	-	-	✗	✓	-	-
<b>Maple® + Matlab® Proposed</b>	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓

\* Incomplete testing results.

D. Schwarz Estévez, R. Lamour, and R. März. "Singularities of the Robotic Arm DAE". In: *DAEs Forum*. Springer, 2020, pp. 433–480. isbn: 978-3030539054

# Application Fields and Performance

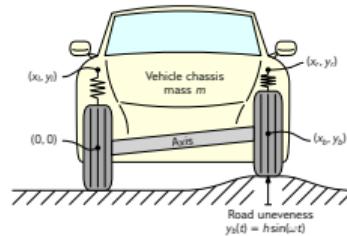
## Factorizations Performance



**LU performs better than FFLU**

Car-Axis (Index-3) – LU Factorization

Original DAEs	$F(x, x', t) = 108f + 131m + 56a \quad h(x, t) = 0$		
Reduction step	$E(x, t)$	$g(x, t)$	$a(x, t)$
Index-3 DAEs	12 m	94 f + 145 m + 54 a	14 f + 16 m + 10 a
Index-2 DAEs	12 m	94 f + 145 m + 54 a	26 f + 45 m + 15 a
Index-1 DAEs	12 m	94 f + 145 m + 54 a	136 f + 4 d + 261 m + 95 a
Index-0 DAEs	1060 f + 38 d + 1901 m + 717 a	431 f + 8 d + 842 m + 268 a	0
Reduced DAEs	$F(x, x', t) = 896f + 4d + 1202m + 546a \quad h(x, t) = 176f + 4d + 322m + 120a$		



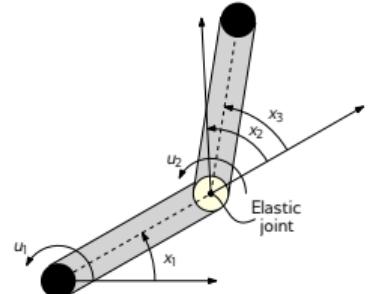
Car-Axis (Index-3) – FFLU Factorization

Original DAEs	$F(x, x', t) = 108f + 131m + 56a \quad h(x, t) = 0$		
Reduction step	$E(x, t)$	$g(x, t)$	$a(x, t)$
Index-3 DAEs	0	94 f + 8 d + 150 m + 54 a	14 f + 21 m + 10 a
Index-2 DAEs	0	94 f + 8 d + 154 m + 54 a	26 f + 1 d + 44 m + 15 a
Index-1 DAEs	0	94 f + 8 d + 155 m + 54 a	136 f + 6 d + 4 d + 261 m + 95 a
Index-0 DAEs	1066 f + 55 d + 1888 m + 717 a	431 f + 18 d + 851 m + 268 a	0
Reduced DAEs	$F(x, x', t) = 1549f + 73d + 2765m + 1011a \quad h(x, t) = 176f + 7d + 326m + 120a$		

# Application Fields and Performance

## Expression Swell

And when strong expression swell arise ...



Robotic Arm (Index-5)

Original DAEs	$F(x, x', t) = 125f + 19d + 56m + 64a$	$h(x, t) = 0$	
Reduction step	$E(x, t)$	$g(x, t)$	$a(x, t)$
Index-5 DAEs	0	$66f + 3d + 50m + 35a$	$16f + 12a$
Index-4 DAEs	0	$66f + 3d + 50m + 35a$	$24f + 6m + 14a$
Index-3 DAEs	0	$66f + 3d + 50m + 35a$	$162f + 2d + 138m + 114a$
Index-2 DAEs	$14f + 2d + 6m + 6a$	$372f + 4d + 375m + 253a$	$972f + 1d + 1062m + 770a$
Index-1 DAEs	$14f + 2d + 6m + 6a$	$372f + 4d + 375m + 253a$	$\star(6.5f + 5.6m + 1.8a) \cdot 10^6 + 4d$
Index-0 DAEs	$\star(8.3f + 7.1m + 2.3a) \cdot 10^7 + 58d$	$(2.4f + 2.0m + 0.9a) \cdot 10^6 + 8d$	0
Reduced DAEs	$\star F(x, x', t) = (8.6f + 7.3m + 2.4a) \cdot 10^7 + 66d$		$\star h(x, t) = (6.5f + 5.6m + 1.8a) \cdot 10^6 + 7d$

# Application Fields and Performance

## Expression Swell Mitigation

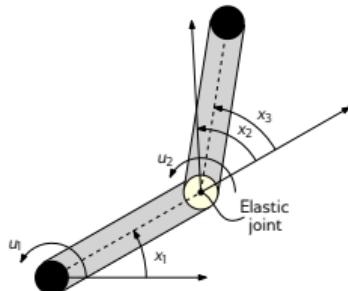
... hierarchical representation does the job

Robotic Arm (Index-5)

Original DAEs	$F(x, x', v, t) = 125f + 19d + 56m + 64a$	$h(x, v, t) = 0$	$v(x, t) = 0$
Reduction step	$E(x, v, t)$	$g(x, v, t)$	$a(x, v, t)$
Index-5 DAEs	0	$66f + 3d + 50m + 35a$	$16f + 12a$
Index-4 DAEs	0	$66f + 3d + 50m + 35a$	$24f + 6m + 14a$
Index-3 DAEs	0	$66f + 3d + 50m + 35a$	$162f + 2d + 138m + 114a$
Index-2 DAEs	$14f + 2d + 6m + 6a$	$66f + 1v + 3d + 51m + 35a$	$1m + 1v$
Index-1 DAEs	$2v + 1a$	$66f + 1v + 3d + 51m + 35a$	$9f + 4v + 2d + 8m + 5a$
Index-0 DAEs	$7v + 1d + 2m + 2a$	$66f + 2v + 3d + 52m + 35a$	0
<b>Reduced DAEs</b>		$F(x, x', v, t) = 90f + 9v + 4d + 63m + 48a$	$h(x, v, t) = 202f + 5v + 4d + 141m + 130a$

Hierarchical representation details (29 veils)

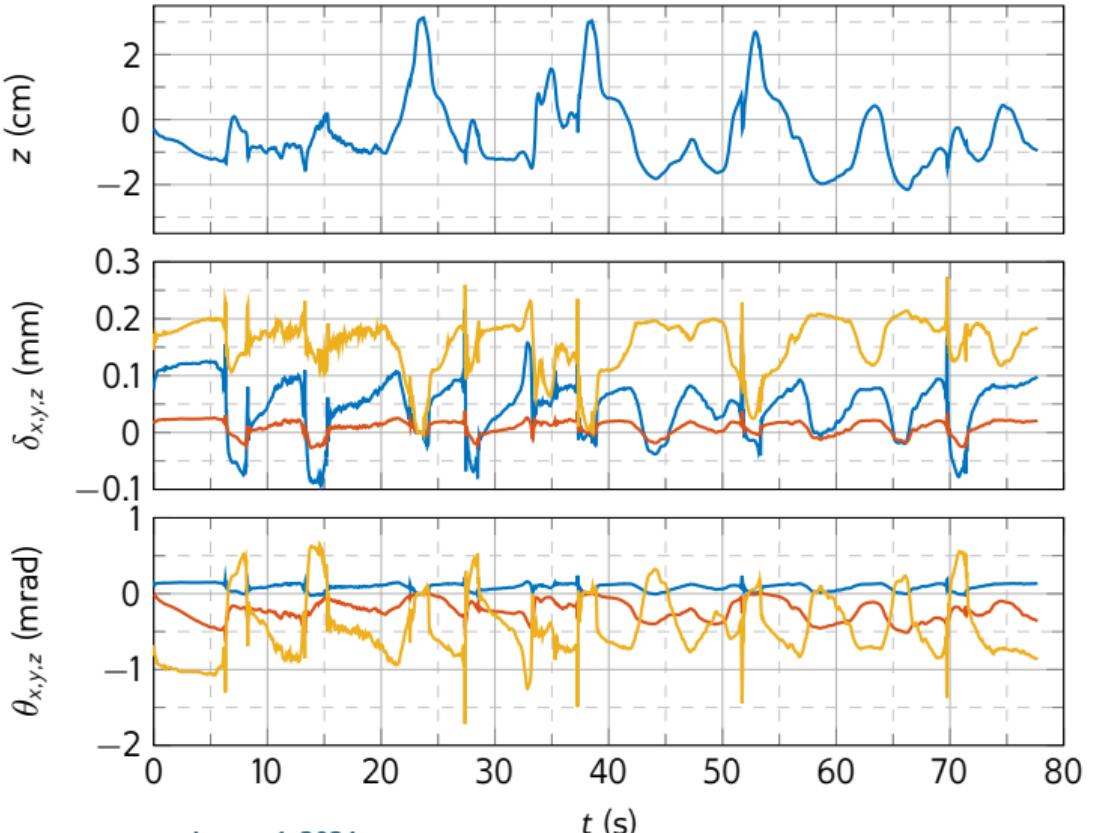
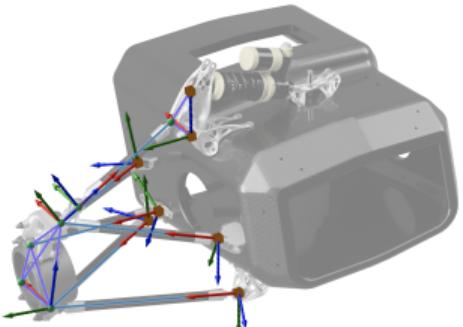
Reduction step	$v(x, t)$
Index-5 DAEs	0
Index-4 DAEs	0
Index-3 DAEs	0
Index-2 DAEs	$1278f + 3v + 6d + 1319m + 918a$
Index-1 DAEs	$8401f + 20v + 24d + 9451m + 6095a$
Index-0 DAEs	$37010f + 558v + 56d + 45087m + 28665a$
<b>Reduced DAEs</b>	$v(x, t) = 37010f + 558v + 56d + 45087m + 28665a$



# Application Fields and Performance

## Numerical Stability

Numerical stability is preserved but not guaranteed



# Outline

- 1** Introduction and Motivation
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# Conclusions

PhD Period

## What are the main takeaways?

- Index reduction of DAEs
  - basic linear algebra operations
  - heavy use of symbolic computation
  - capabilities and limitations
- Side and related work
  - geometry library
  - tire-road interaction
  - tire model
  - symbolic analysis of structures (DSM) → *The reason that lead to the birth of LAST!*
- Software tools





# Possible Improvements

## Index Reduction Algorithm

### Technical Aspects

- 1 Detection of **linear index-1 variables**, similar to the MBD case

$$\begin{cases} \dot{\mathbf{q}}' = \mathbf{p} \\ \dot{\mathbf{p}}' = \dot{\mathbf{p}} \end{cases} \quad \text{where} \quad \begin{bmatrix} \mathbf{M}(\mathbf{q}, \mathbf{p}, t) & -\boldsymbol{\Phi}_{\mathbf{q}}(\mathbf{q}, t)^T \\ -\boldsymbol{\Phi}_{\mathbf{q}}(\mathbf{q}, t) & 0 \end{bmatrix} \begin{bmatrix} \dot{\mathbf{p}} \\ \lambda \end{bmatrix} = \begin{bmatrix} \mathbf{f}(\mathbf{q}, \mathbf{p}, t) \\ \dot{\boldsymbol{\Phi}}_{\mathbf{q}}(\mathbf{q}, t)\mathbf{p} + \boldsymbol{\Phi}_{tt}(\mathbf{q}, t) \end{bmatrix}$$

- 2 System augmentation with “veil” equations  
complicated pivots become “veil” equations  
1s in the diagonal, complicated terms on the RHS

### Implementation Aspects

- 1 Open-source CAS  
what is happening inside?  
why is it not working on this example?
- 2 Development of a C++ library for enhanced integration speed and precision

# Possible Improvements

## Index Reduction Algorithm

### Technical Aspects

- 1 Detection of **linear index-1 variables**, similar to the MBD case

$$\begin{cases} \dot{\mathbf{q}}' = \mathbf{p} \\ \dot{\mathbf{p}}' = \dot{\mathbf{p}} \end{cases} \quad \text{where} \quad \begin{bmatrix} \mathbf{M}(\mathbf{q}, \mathbf{p}, t) & -\boldsymbol{\Phi}_{\mathbf{q}}(\mathbf{q}, t)^T \\ -\boldsymbol{\Phi}_{\mathbf{q}}(\mathbf{q}, t) & 0 \end{bmatrix} \begin{bmatrix} \dot{\mathbf{p}} \\ \lambda \end{bmatrix} = \begin{bmatrix} \mathbf{f}(\mathbf{q}, \mathbf{p}, t) \\ \dot{\boldsymbol{\Phi}}_{\mathbf{q}}(\mathbf{q}, t)\mathbf{p} + \boldsymbol{\Phi}_{tt}(\mathbf{q}, t) \end{bmatrix}$$

- 2 **System augmentation** with “veil” equations  
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# Possible Improvements

## Index Reduction Algorithm

### Technical Aspects

- 1 Detection of linear index-1 variables, similar to the MBD case

$$\begin{cases} \dot{\mathbf{q}}' = \mathbf{p} \\ \dot{\mathbf{p}}' = \dot{\mathbf{p}} \end{cases} \quad \text{where} \quad \begin{bmatrix} \mathbf{M}(\mathbf{q}, \mathbf{p}, t) & -\Phi_{\mathbf{q}}(\mathbf{q}, t)^T \\ -\Phi_{\mathbf{q}}(\mathbf{q}, t) & 0 \end{bmatrix} \begin{bmatrix} \dot{\mathbf{p}} \\ \lambda \end{bmatrix} = \begin{bmatrix} \mathbf{f}(\mathbf{q}, \mathbf{p}, t) \\ \dot{\Phi}_{\mathbf{q}}(\mathbf{q}, t)\mathbf{p} + \Phi_{tt}(\mathbf{q}, t) \end{bmatrix}$$

- 2 System augmentation with “veil” equations  
complicated pivots become “veil” equations  
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### Implementation Aspects

- 1 Open-source CAS  
what is happening inside?  
why is it not working on this example?
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# Possible Improvements

## Index Reduction Algorithm

### Technical Aspects

- 1 Detection of linear index-1 variables, similar to the MBD case

$$\begin{cases} q' = p \\ p' = \dot{p} \end{cases} \text{ where } \begin{bmatrix} M(q, p, t) & -\Phi_q(q, t)^T \\ -\Phi_q(q, t) & 0 \end{bmatrix} \begin{bmatrix} \dot{p} \\ \lambda \end{bmatrix} = \begin{bmatrix} f(q, p, t) \\ \dot{\Phi}_q(q, t)p + \Phi_{tt}(q, t) \end{bmatrix}$$

- 2 System augmentation with “veil” equations
  - complicated pivots become “veil” equations
  - 1s in the diagonal, complicated terms on the RHS

### Implementation Aspects

- 1 Open-source CAS
  - what is happening inside?
  - why is it not working on this example?
- 2 Development of a C++ library for enhanced integration speed and precision



# Symbolic Computation Methods for the Numerical Solution of Dynamic Systems Described by Differential-Algebraic Equations

Davide Stocco

**Thank you for your attention!**

**Questions?**

# Projector-based Analysis

## Tractability Index

- Projector-based analysis deals with properly stated leading term DAEs of the form

$$F(d(x, t)', x, t) = 0$$

- If we define the matrix sequence

$$G_0 = AD \quad \text{and} \quad B_0 = B$$

$$G_{i+1} = G_i + B_i Q_i$$

$$B_{i+1} = \left( B_i - G_{i+1} D^{-\frac{d}{dt}} (D P_i \dots P_{i+1} D^{-}) D P_i \dots P_{i-1} \right) P_i$$

with

$$\begin{aligned} D &:= D(x, t) = d_x(x, t) \\ A &:= A(y, x, t) = F_y(y, x, t) \\ B &:= B(y, x, t) = F_x(y, x, t) \end{aligned}$$

and where  $P_i = I - Q_i$ ,  $Q_i Q_j = 0$ ,  $D^{-\frac{d}{dt}} D = P_0$

- The tractability index first integer  $\mu$  where the matrix  $G_\mu$  becomes non-singular

**The difficult part is to compute the projectors  $Q_i$**



# Projector-based Analysis

## Nullspace Projectors

- The **nullspace projector**  $\mathbf{Q}_i$  is found such that

$$\text{im}(\mathbf{Q}_i) = \ker(\mathbf{G}_i) \quad (\mathbf{G}_i \mathbf{Q}_i = \mathbf{0})$$

- In R. Lamour, R. März, and C. Tischendorf. *DAEs: A Projector Based Analysis*. Springer, 2013. isbn: 978-3642275555, ch.7, p.400 is claimed that:

*For problems of limited dimension a formula manipulation system like Mathematica® or Maple® can be used to compute a basis [of  $\ker(\mathbf{Q})$ ]. The command in Mathematica® is NullSpace[G] and in Maple® nullspace(G).*

However, to provide a basis of the nullspace of a given matrix one usually has to carry out a factorization, for instance a singular value decomposition (SVD).

# Projection and Consistent Initialization

## Projection Scheme

- Same the **constrained minimization** problem

$$\underset{\mathbf{x}}{\text{minimize}} \quad \frac{1}{2} (\mathbf{x} - \tilde{\mathbf{x}})^2 \quad \text{subject to} \quad \mathbf{h}(\mathbf{x}, \mathbf{v}, t) = \mathbf{0}$$

- The **Lagrangian** of the minimization problem is

$$\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}) = \frac{1}{2} (\mathbf{x} - \tilde{\mathbf{x}})^2 + \boldsymbol{\lambda} \cdot \mathbf{h}(\mathbf{x}, \mathbf{v}, t) \quad \rightarrow \quad \begin{cases} \mathbf{x} + \mathbf{Jh}_x^\top \boldsymbol{\lambda} = \tilde{\mathbf{x}} \\ \mathbf{h}(\mathbf{x}, \mathbf{v}, t) = \mathbf{0} \end{cases}$$

- The **iterative method** is ...

$$\begin{bmatrix} \mathbf{I} & \mathbf{Jh}_x^\top \\ \mathbf{Jh}_x & \mathbf{0} \end{bmatrix} \begin{bmatrix} \delta\mathbf{x} \\ \boldsymbol{\lambda} \end{bmatrix} = \begin{bmatrix} \tilde{\mathbf{x}} - \mathbf{x} \\ -\mathbf{h}(\mathbf{x}, \mathbf{v}, t) \end{bmatrix} \quad \text{where the step is} \quad \mathbf{x} = \tilde{\mathbf{x}} + \delta\mathbf{x}$$

... derived from the Taylor expansion

$$\begin{cases} \mathbf{x} + \delta\mathbf{x} + \mathbf{Jh}_x^\top (\mathbf{x} + \delta\mathbf{x}, \mathbf{v}, t) \boldsymbol{\lambda} = \tilde{\mathbf{x}} \\ \mathbf{h}(\mathbf{x}, \mathbf{v}, t) + \mathbf{Jh}_x(\mathbf{x}, \mathbf{v}, t) \delta\mathbf{x} + \mathcal{O}(\|\delta\mathbf{x}\|^2) = \mathbf{0} \end{cases}$$

# Projection and Consistent Initialization

Two Problems, One Solution

If part of ICs are not available:

- We can use the **projection scheme** to calculate consistent ICs
- The **iterative method** is reduced as selecting only the unknown ICs and the invariants we want to be maintained

$$\begin{bmatrix} \text{red blocks} \\ \text{blue blocks} \end{bmatrix} = \begin{bmatrix} \text{red blocks} & \text{blue blocks} \\ \text{red blocks} & \text{blue blocks} \end{bmatrix} \begin{bmatrix} \delta x \\ \lambda \end{bmatrix} - \begin{bmatrix} h(x, v, t) \\ 0 \end{bmatrix}$$

# Outline

**7 The Implemented Symbolic Matrix Factorization**

**8 A Symbolic Approach to Structure Compliance**

**9 Tire-Road Interaction Modelling**



### Full-Pivoting LU Factorization

Given a matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ , with  $m \geq n$ , the full-pivoting LU decomposition is defined as the process of decomposing  $\mathbf{A}$  into the product of

- a  $\mathbf{L} \in \mathbb{R}^{m \times m}$  lower-triangular matrix with all diagonal entries equal to 1
- a  $\mathbf{U} \in \mathbb{R}^{m \times n}$  upper-triangular matrix
- a  $\mathbf{P} \in \mathbb{R}^{m \times m}$  and a  $\mathbf{Q} \in \mathbb{R}^{n \times n}$  matrices for rows and columns permutation

such that  $\mathbf{PAQ} = \mathbf{LU}$



# Symbolic Matrix Factorization

## Fraction-Free Lower-Upper (FFLU)

### Full-Pivoting FFLU Factorization

Given a matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ , with  $m \geq n$ , the full-pivoting FFLU decomposition is defined as the process of decomposing  $\mathbf{A}$  into the product of

- a lower-triangular matrix  $\mathbf{L} \in \mathbb{R}^{m \times m}$  with all diagonal entries equal to 1;
- a diagonal matrix  $\mathbf{D} \in \mathbb{R}^{m \times m}$
- an upper-triangular matrix  $\mathbf{U} \in \mathbb{R}^{m \times n}$
- a  $\mathbf{P} \in \mathbb{R}^{m \times m}$  and a  $\mathbf{Q} \in \mathbb{R}^{n \times n}$  matrices for rows and columns permutation

such that  $\mathbf{PDAQ} = \mathbf{LU}$

# Outline

**7** The Implemented Symbolic Matrix Factorization

**8** A Symbolic Approach to Structure Compliance

**9** Tire-Road Interaction Modelling

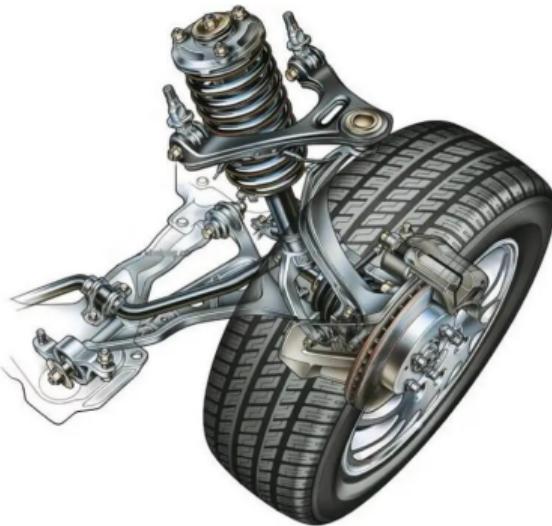
# A Symbolic Approach to Structure Compliance

## Practical Application on Vehicle Suspension Compliance Analysis

- The suspension system has to **guarantee** ...
  - 1 **comfort** to the passengers minimize vertical accelerations of the chassis
  - 2 **road holding and stability** of the vehicle
  - 3 control the **wheel attitude** with respect to the road surface



Flexibility affects the vehicle dynamics



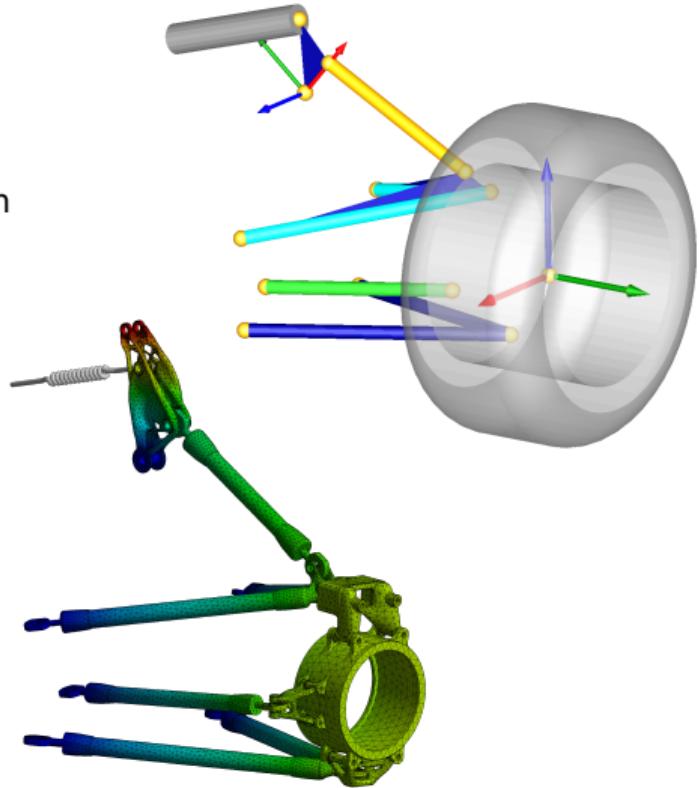
# K&C analysis

## Introduction

The **kinematics** and **compliance** of the suspension system are ...

- 1 the **motion** and **deformation** of the system
- 2 key aspects of the **design** of the system

**Kinematics and compliance are what is needed to describe the suspension in a vehicle model**





Methods	Real-Time	Accuracy	Parametric	Easy to Setup
FE methods	✗	✓	✗	✗
Map-based methods	✓	●	✗	✓
Flexible multibody	●	✓	●	✗
What we aim to ...	✓	●	✓	✓

Legend: ✓ satisfied, ● satisfied with limitations, and ✗ not satisfied.

# Symbolic computation

## Finite element method problem

- Symbolic computation can be applied to the **finite element (FE) method**.
- **Stiffness matrix, load vector, and boundary conditions** are defined symbolically.

$$\begin{bmatrix} \mathbf{K}_{ff} & \mathbf{K}_{fs} \\ \mathbf{K}_{sf} & \mathbf{K}_{ss} \end{bmatrix} \begin{bmatrix} c\mathbf{d}_f \\ \mathbf{d}_s \end{bmatrix} = \begin{bmatrix} c\mathbf{f}_f \\ \mathbf{f}_s \end{bmatrix} \xrightarrow[\text{method}]{\text{direct stiffness}} \begin{aligned} \mathbf{d}_f &= \mathbf{K}_{ff}^{-1} (\mathbf{f}_f - \mathbf{K}_{fs} \mathbf{d}_s) \\ \mathbf{f}_s &= \mathbf{K}_{sf} \mathbf{d}_f + \mathbf{K}_{ss} \mathbf{d}_s \end{aligned}$$

- 1 Possibility to **evaluate** the system **without** the need to “**reassemble**” the system
- 2 Parametric formulation
- 3 Symbolic solution of the structure deformations and reaction forces

FE method  $\xrightarrow[\text{computation}]{\text{symbolic}}$  Symbolic FE model + **A lot of flexibility!**

- We combined all these features in the Maple® TrussMe-Fem library (open-source)

# Symbolic computation

## Linear algebra

- Symbolic matrix factorization is used for the computation of the linear system **solutions**

$$\mathbf{d}_f = \mathbf{K}_{ff}^{-1} (\mathbf{f}_f - \mathbf{K}_{fs} \mathbf{d}_s)$$

### Problem

Maple® matrix factorizations have **limited capabilities**.

- We developed the LAST symbolic matrix factorization toolbox capable of ...
  - extending Maple® factorization capabilities
  - introducing **veiling variables** not to increase the expressions size (through LEM toolbox)
  - performing efficient LU, Fraction-Free LU, QR, and Gauss-Jordan factorizations with limited **expression swell**

# Symbolic computation

Mixed symbolic/numerical solution

- Symbolic solution is not always possible due to
  - 1 capability of the symbolic kernel to handle **complicated** expressions
  - 2 **non-linear** or mathematically **unsolvable** problems
- Symbolic computation should be exploited as much as possible!

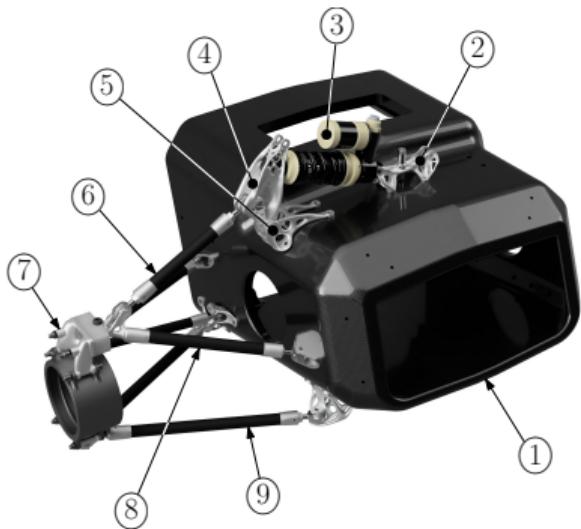


- K&C of suspensions are computed through a **mixed** symbolic/numerical approach

# Suspensions symbolic modeling

## Case study

The modeled suspension is a **double wishbone** suspension system of the **Formula SAE** vehicle of *E-Agle Trento Racing Team* (University of Trento)



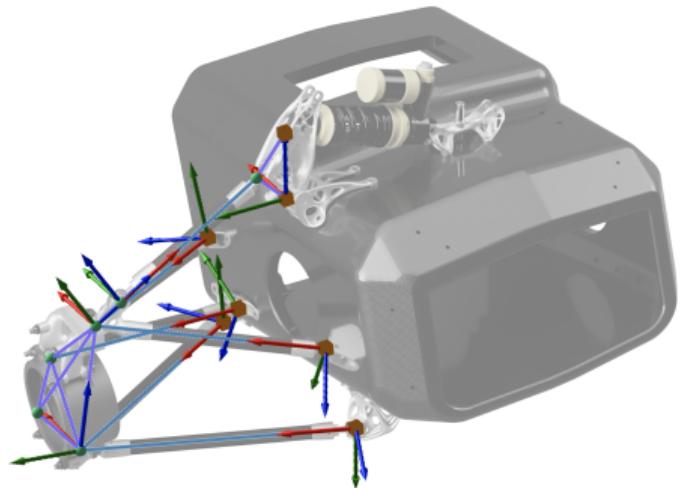
### Components:

- ① Carbon fiber cell
- ② Shock absorber support
- ③ Shock absorber
- ④ Rocker
- ⑤ Rocker support
- ⑥ Push rod
- ⑦ Wheel carrier
- ⑧ Upper wishbone arm
- ⑨ Lower wishbone arm

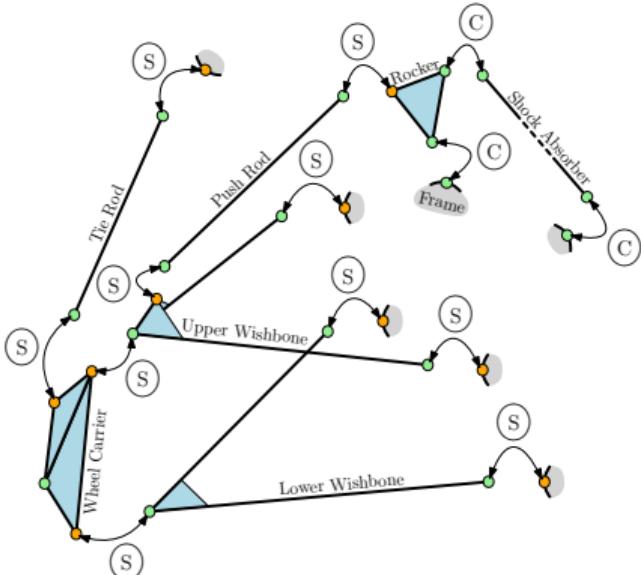


# Suspensions symbolic modeling

Rigid multibody & FE models



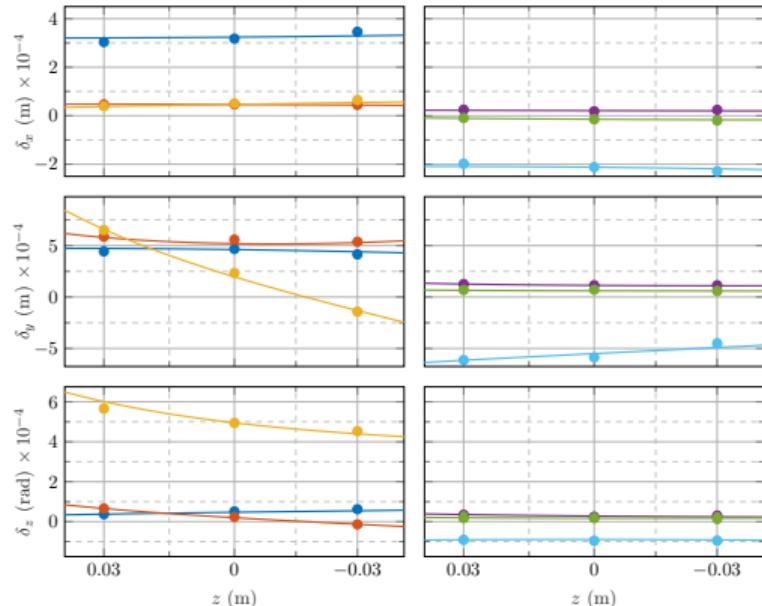
138 DoFs symbolic FE model



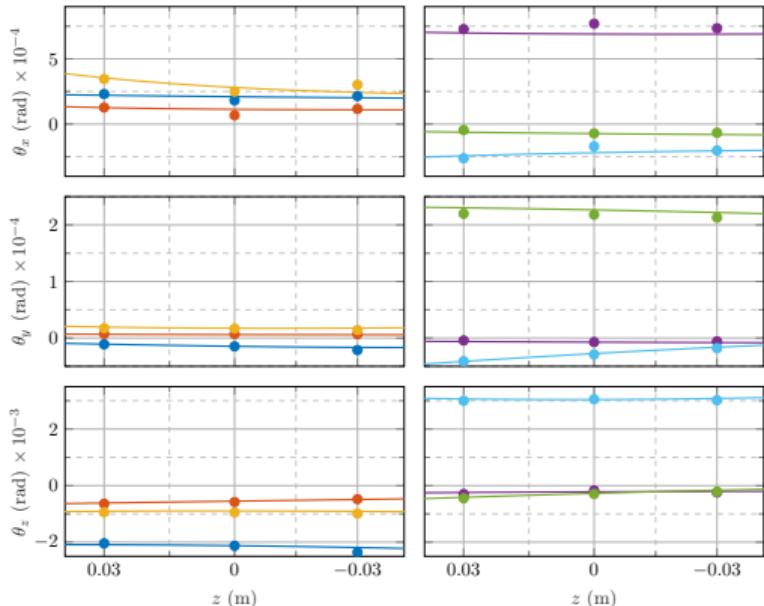
# Simulation results

## Static analysis

### Static translations



### Static rotations



Legend: TrussMe-Fem solution (solid lines), Ansys® data (bullets).

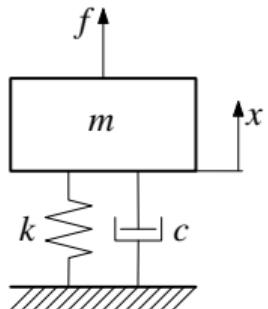
■  $F_x = 4000 \text{ N}$ , ■  $F_y = 4000 \text{ N}$ , ■  $F_z = 4000 \text{ N}$ , with  $M_x = M_y = M_z = 0 \text{ N m}$ .

■  $M_x = 400 \text{ N m}$ , ■  $M_y = 400 \text{ N m}$ , ■  $M_z = 400 \text{ N m}$ , with  $F_x = F_y = F_z = 0 \text{ N}$

# Suspensions symbolic modeling

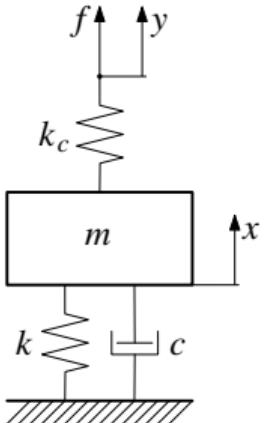
## Modeling assumptions

### No compliance



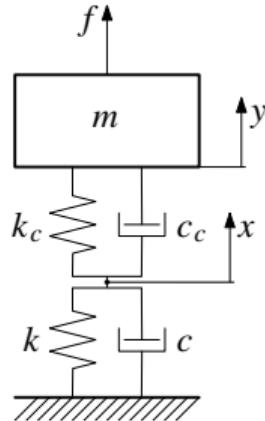
$$m\ddot{x} + c\dot{x} + kx = f$$

### Quasi-static compliance



$$\begin{cases} y = x + d \\ k_c d = f \\ m\ddot{x} + c\dot{x} + kx = f \end{cases}$$

### Dynamic compliance



$$\begin{cases} y = x + d \\ kx + c\dot{x} = k_c d + c_c \dot{d} \\ m\ddot{y} = k_c d + c_c \dot{d} + f \end{cases}$$

# Suspensions symbolic modeling

## Frequency response

The **frequency response** of the system is influenced by the **decoupling strategy**.

- no compliance

$$\frac{\ddot{Y}(s)}{F(s)} = \frac{s^2}{ms^2 + cs + k}$$

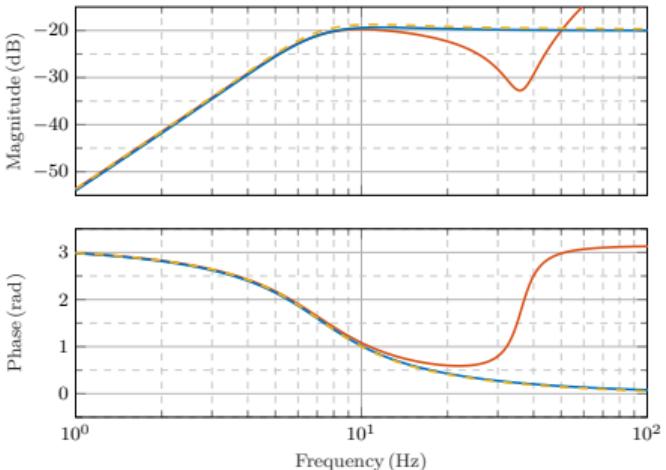
- quasi-static compliance

$$\frac{\ddot{Y}(s)}{F(s)} = \frac{s^2}{ms^2 + cs + k} + \frac{s^2}{k_c} \quad \omega_n = \sqrt{\frac{k}{m}}$$

$$\omega_z = \sqrt{\frac{k+k_c}{m}}$$

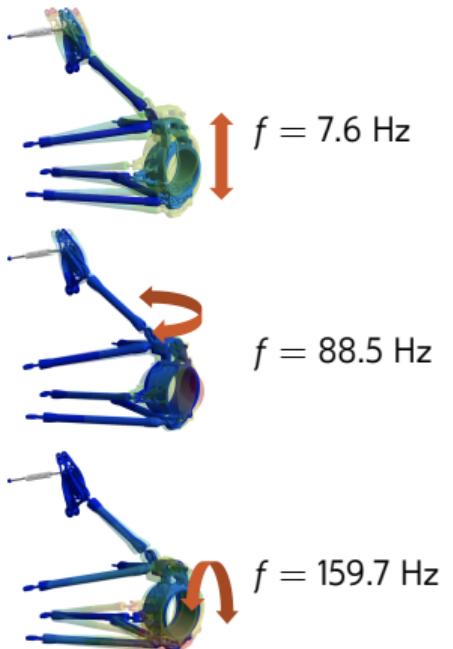
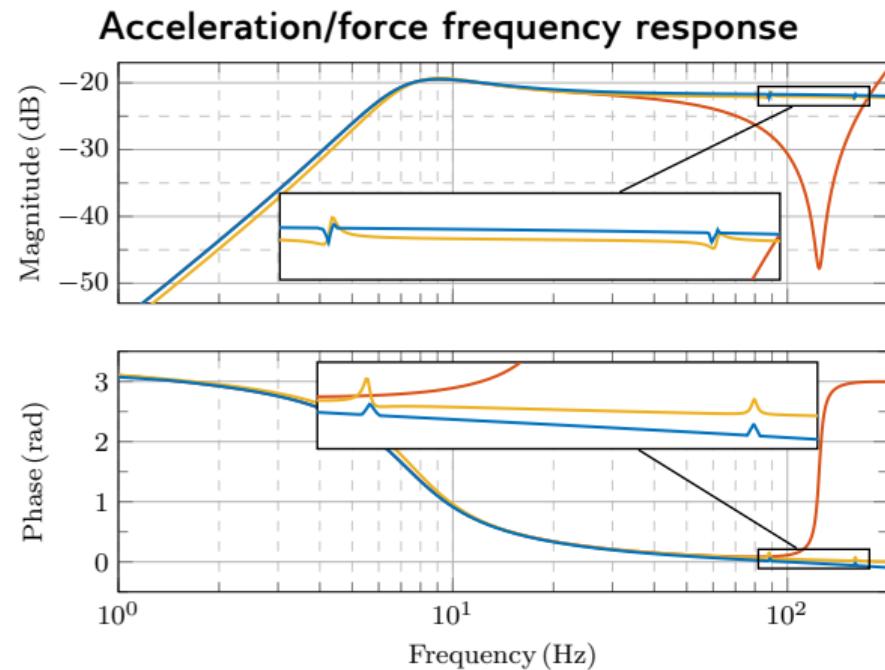
- dynamic compliance

$$\frac{\ddot{Y}(s)}{F(s)} = \frac{(c+c_c)s^3 + (k+k_c)s^2}{m(c+c_c)s^3 + (c c_c + m(k+k_c))s^2 + (k_c c + k c_c)s + k k_c}$$



# Simulation results

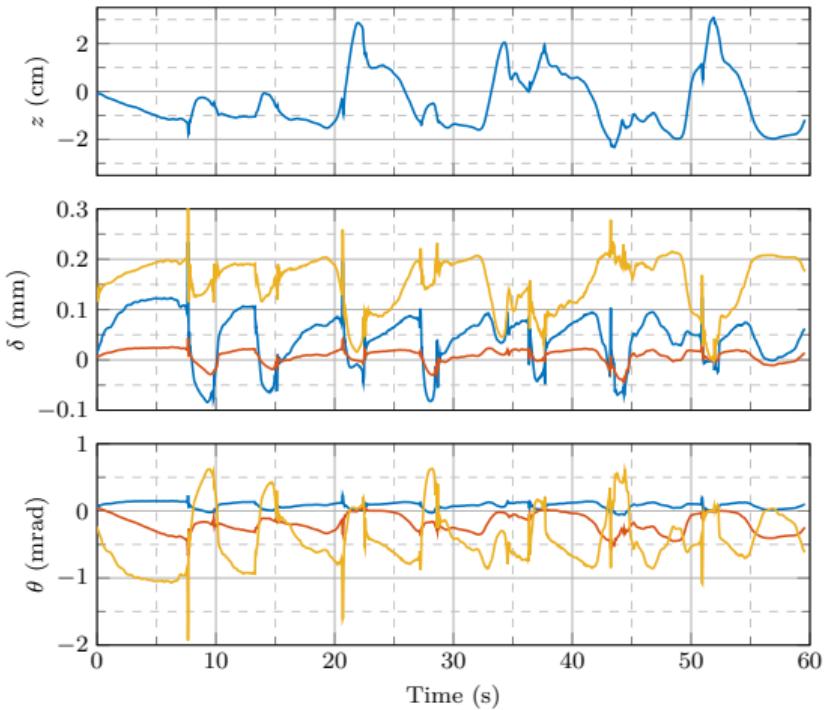
## Frequency response



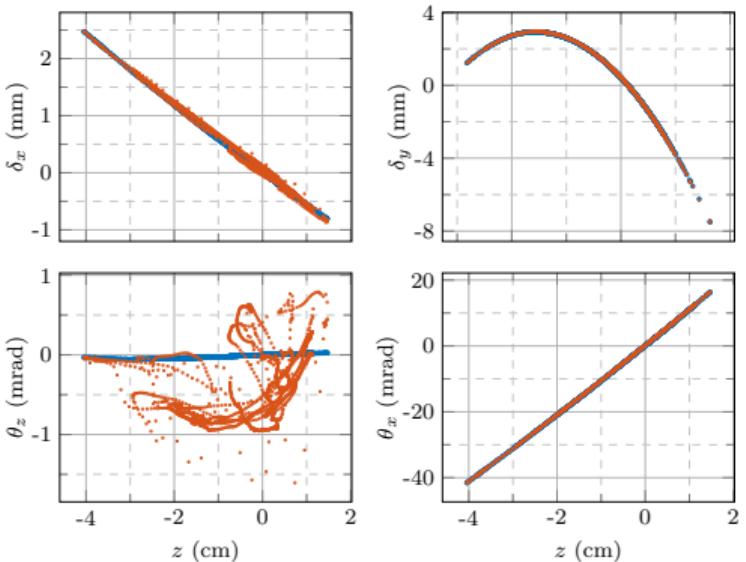
Legend: ■ MB with compliance dynamic, ■ MB and steady-state compliance, ■ Ansys® Finite Element (FE) modal analysis.

# Simulation results

## Full Vehicle Simulation



Legend: ■  $x$ - , ■  $y$ - , ■  $z$ -component.



Legend: ■ kinematic, ■ total.

# Simulation results

## Timing

model	Computation time			
	$\mu$ ( $\mu$ s)	min ( $\mu$ s)	max ( $\mu$ s)	$\sigma^2$ ( $\mu$ s $^2$ )
Compliance maps (linear)	40	4	48	1.2
Compliance maps (cubic)	193	84	880	42.9
Symbolic FEM	181	42	417	45.2

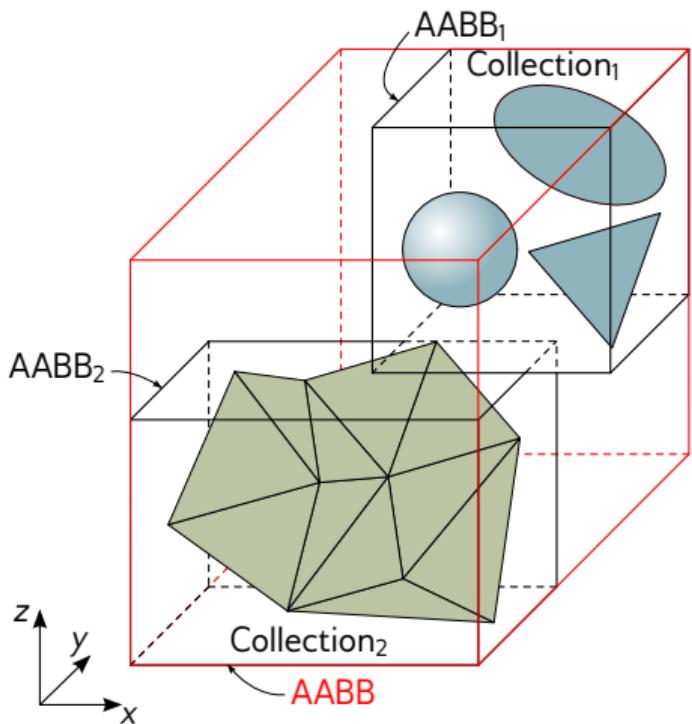
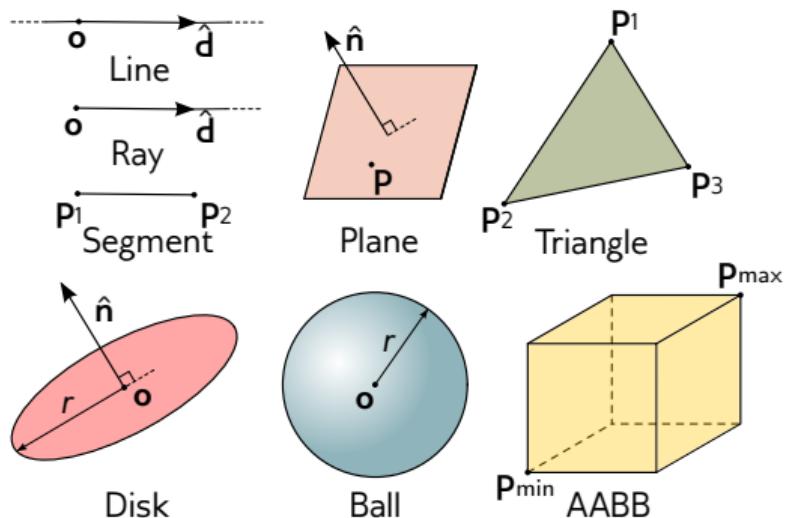
# Outline

**7** The Implemented Symbolic Matrix Factorization

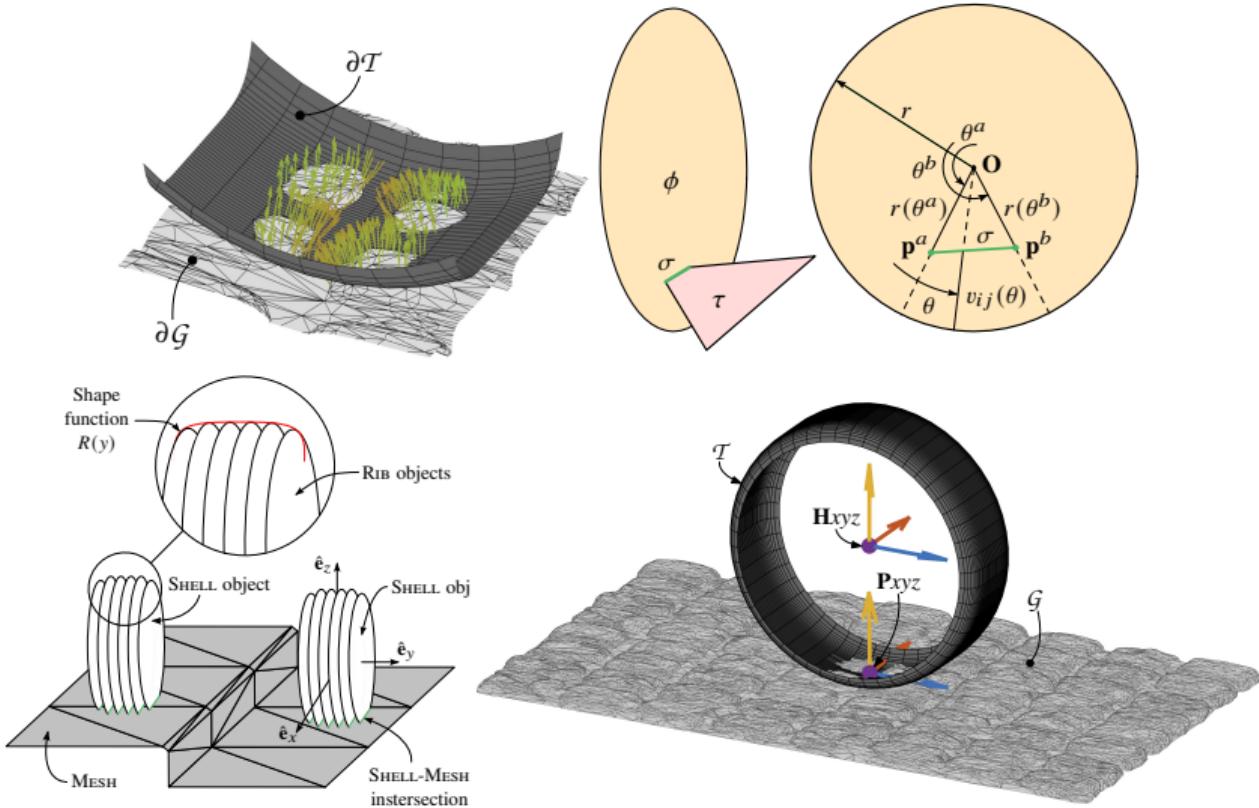
**8** A Symbolic Approach to Structure Compliance

**9** Tire-Road Interaction Modelling

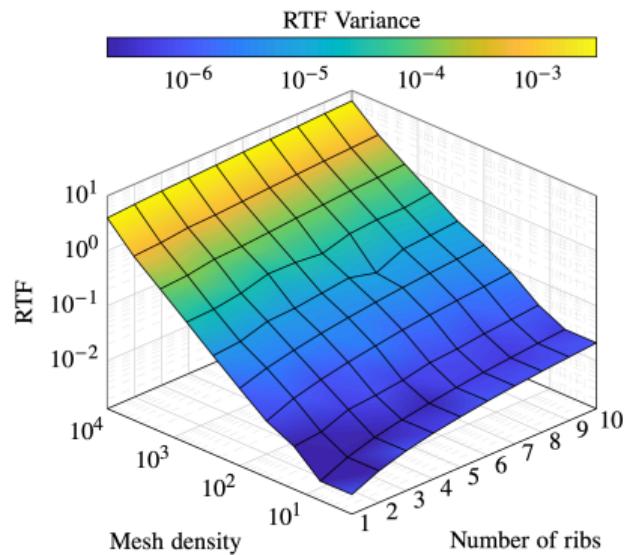
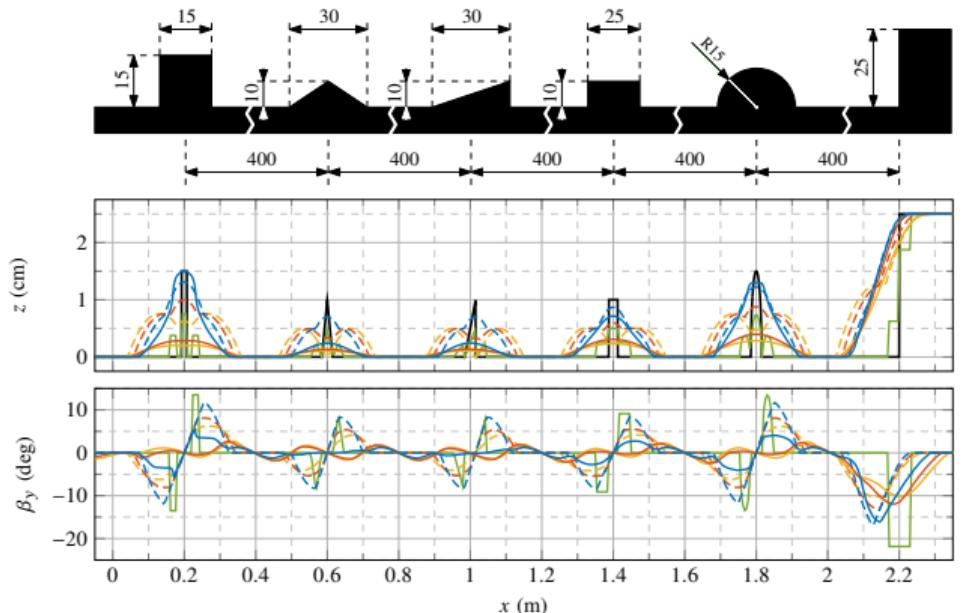
# Geometry Library



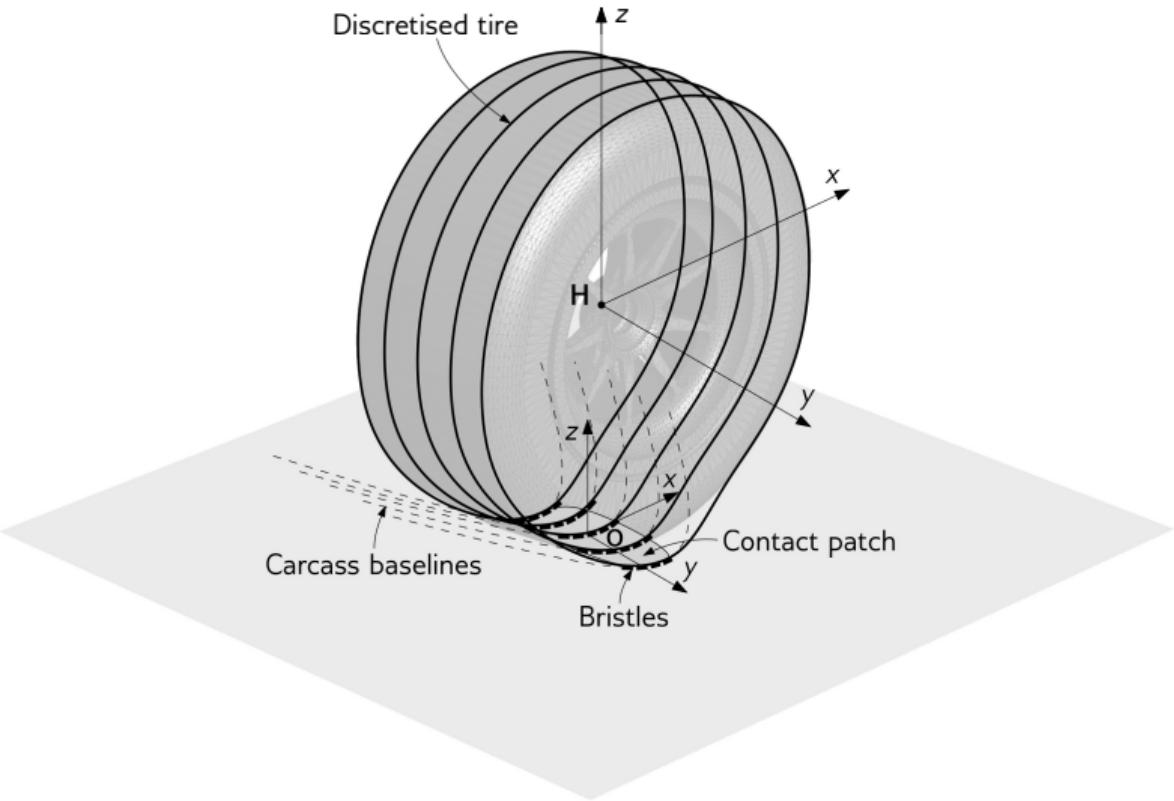
# Tire-Road Interaction Model



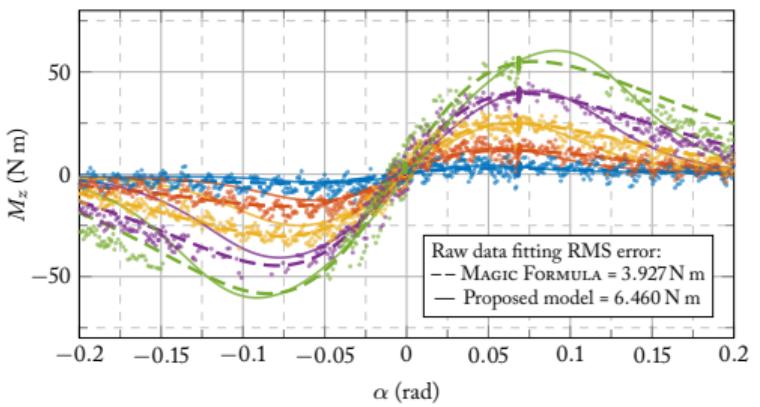
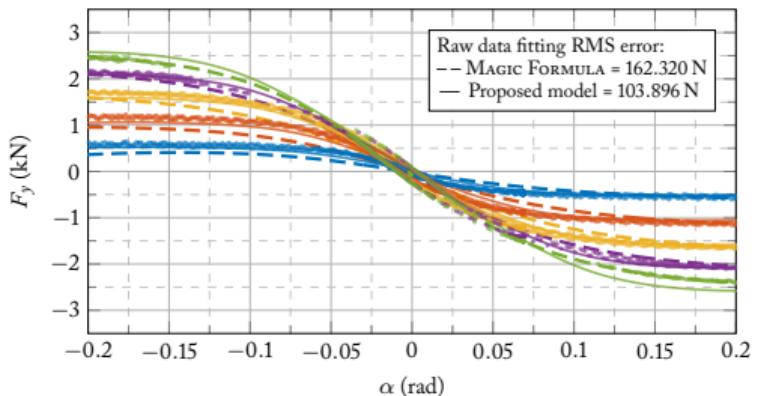
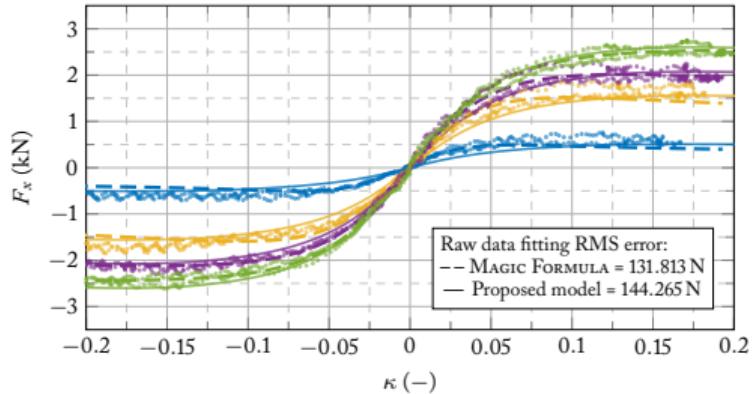
# Tire-Road Interaction Model



# Brush Tire Model



# Brush Tire Model



# Brush Tire Model



Quasi-Newton Methods Performance with 5 Ribs

Method	Time (μs)				Success
	min	max	$\mu$	$\sigma^2$	
PIM	518.0	7949.0	617.2	13953.2	0.0%
G1M	—	—	—	—	Overflow
G2M	23.5	1089.4	69.0	5252.0	99.5%
ENM	25.0	2025.0	81.5	11002.8	99.4%
BBM	—	—	—	—	0.0%
BGM	22.6	948.1	62.5	1973.0	99.9%
BCM	22.9	264.4	55.7	885.9	100.0%
D-PIM	507.0	5383.0	1151.9	568491	0.0%
D-G1M	—	—	—	—	Overflow
D-G2M	21.5	3195.5	80.4	40321.9	99.5%
D-ENM	27.0	5207.7	97.5	52752.6	99.5%
D-BBM	22.3	1284.0	76.9	5126.3	100.0%
D-BGM	21.3	3238.9	67.0	8142.9	99.9%
D-BCM	22.5	316.8	62.1	1615.1	100.0%

# Brush Tire Model



Broyden Combined Method Performance

Ribs	Time (μs)				Success
	min	max	$\mu$	$\sigma^2$	
1	12.1	89.0	19.4	20.6	100.0%
5	22.9	264.4	55.7	885.9	100.0%
10	106.9	361.8	167.3	1746.22	100.0%
15	158.0	523.5	249.4	3878.2	100.0%
20	210.1	693.3	332.9	7028.7	100.0%
25	262.7	858.4	414.0	10708.3	100.0%