Vertical Integration in Tool Chains for Modeling Simulation and Optimization of Large-Scale Systems

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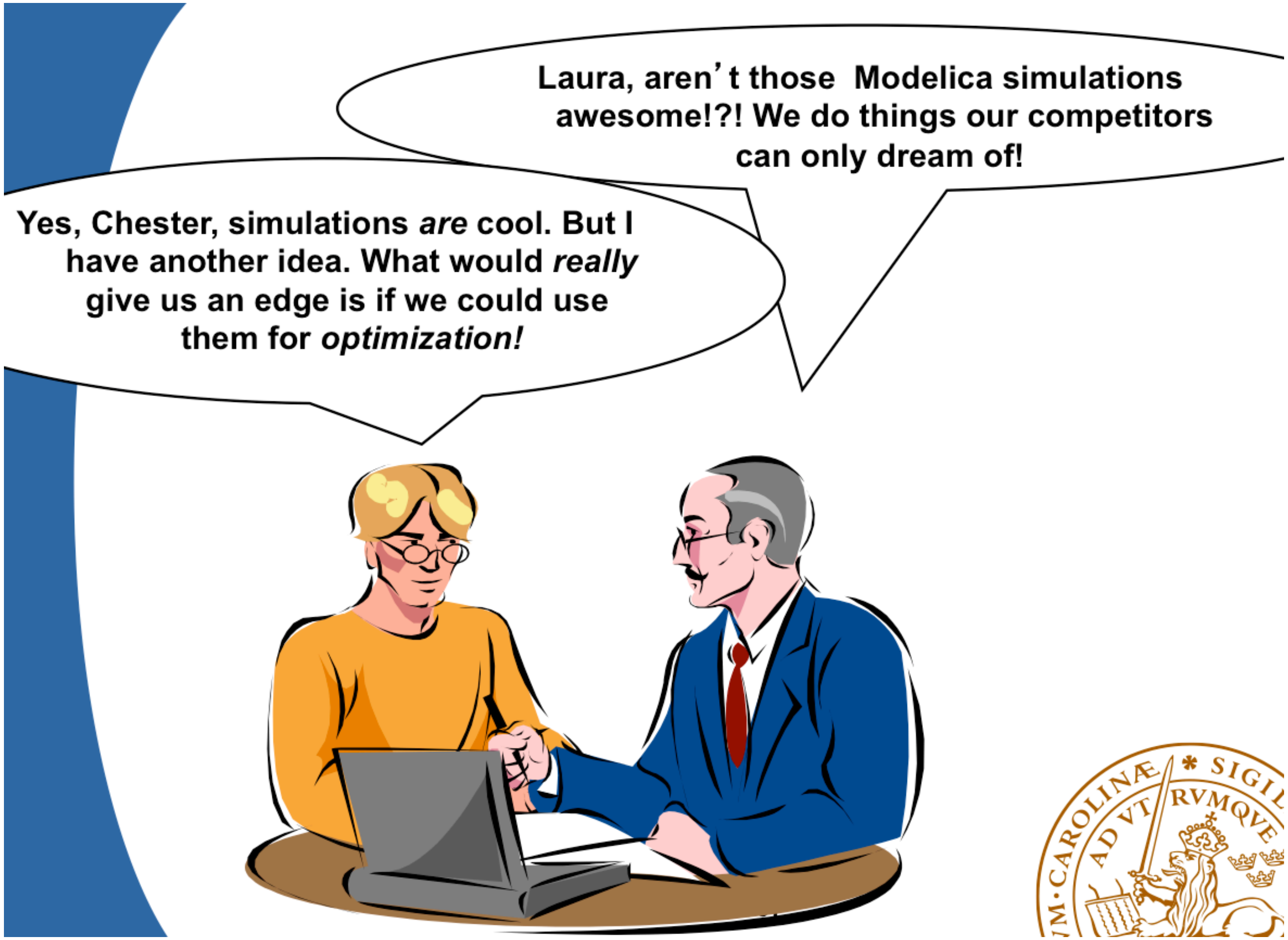
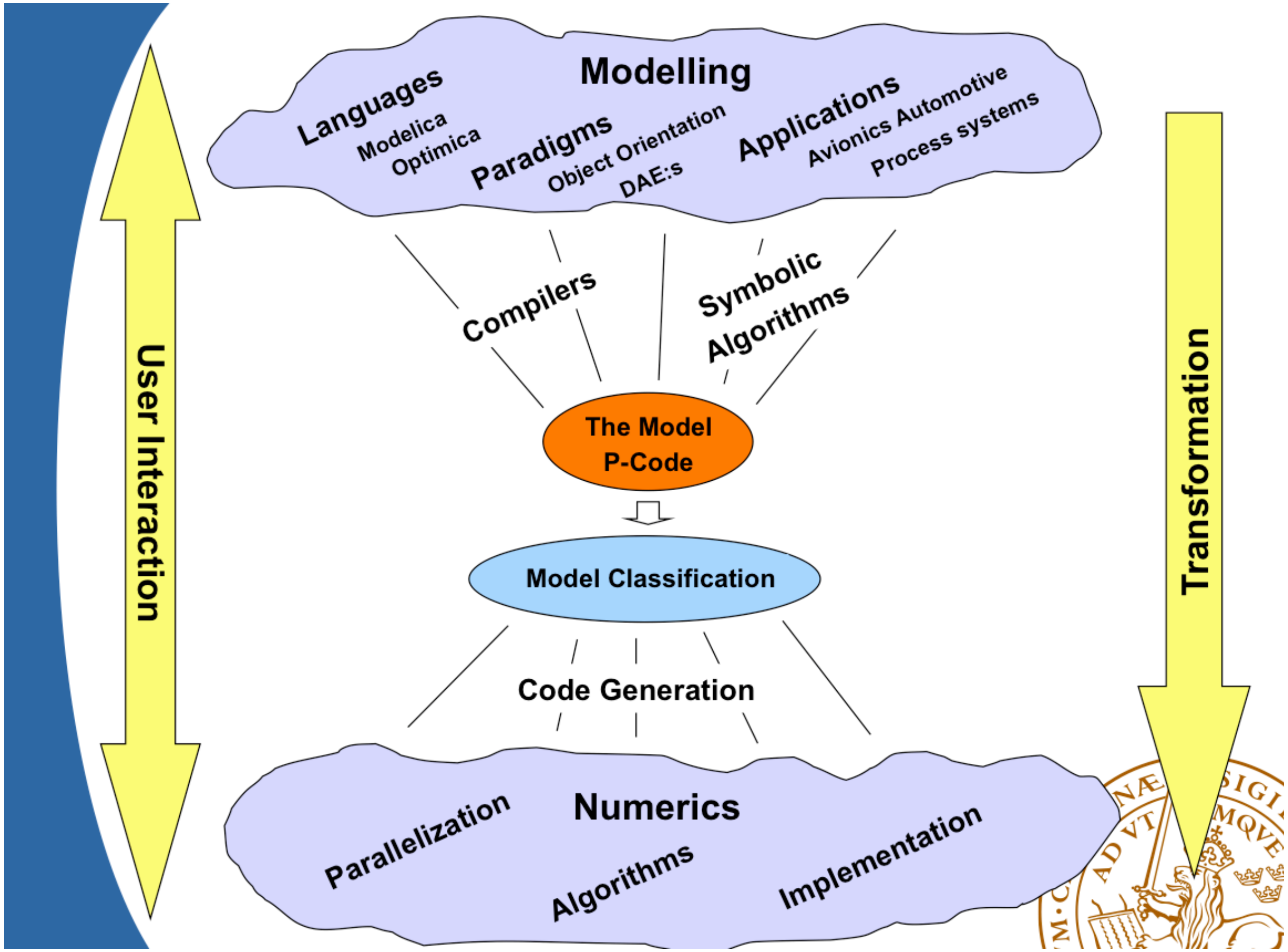
Fredrik Magnusson, Elin Sällberg, Stephane Velut

In 2006…


Laura, aren't those Modelica simulations awesome!?! We do things our competitors can only dream of!
Yes, Chester, simulations *are* cool. But I have another idea. What would *really* give us an edge is if we could use them for *optimization!*

The Landscape



Outline

- Modelica
- Application examples
- Extension example
- Interface example
- Towards a vertically integrated tool chain
- Challenges

What is Modelica?

- A language for modeling of complex heterogeneous physical systems
  - Open language
    - Modelica Association (www.modelica.org)
  - Several tools supporting Modelica
    - Dymola
    - OpenModelica (free)
    - MosiLab
    - Scilab/Scicos (free)
  - Extensive (free) standard library
    - Mechanical, electrical, thermal etc.

Key Features of Modelica

- Declarative equation-based modeling
  - Text book style equations
- Multi-domain modeling
  - Heterogeneous modeling
- Object oriented modeling
  - Inheritance and generics
- Software component model
  - Instances and (acausal) connections
- Graphical and textual modeling

A Simple Modelica model

Differential equation

$$\dot{x}(t) = ax(t) + bu(t)$$

Class definition

Parameter declaration

Variable declaration

Initialization

Derivative operator

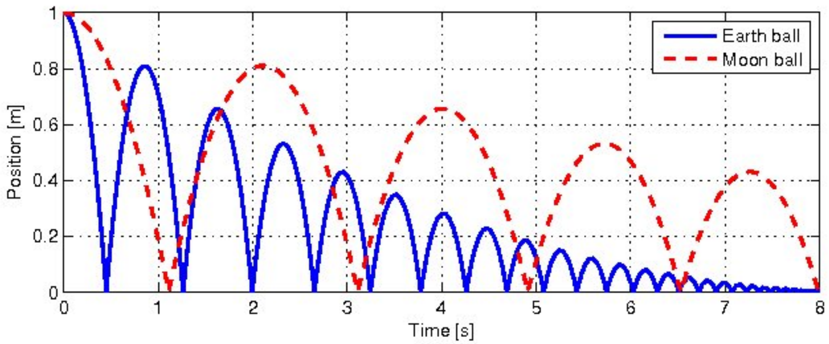
Equation

```
model FirstOrder
  input Real u;
  parameter Real b = 1;
  parameter Real a = -1;
  Real x(start=1);
equation
  der(x) = a*x + b*u;
end FirstOrder;
```

Hybrid modeling

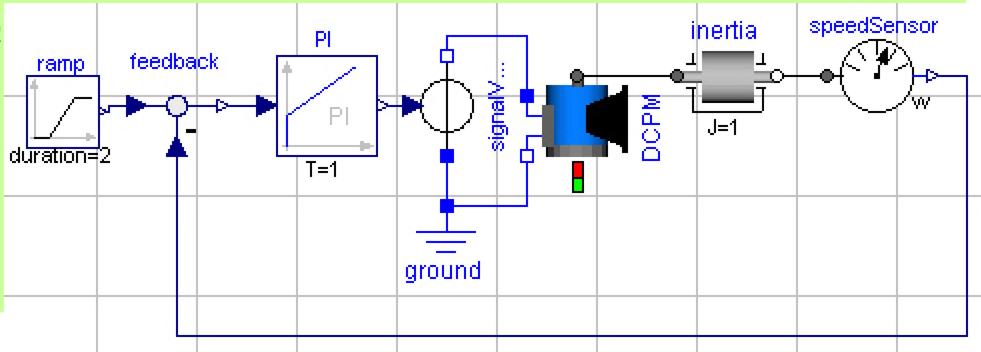
```
class BouncingBall //A model of a bouncing ball
  parameter Real g = 9.81; //Acceleration due to gravity
  parameter Real e = 0.9; //Elasticity coefficient
  Real pos(start=1); //Position of the ball
  Real vel(start=0); //Velocity of the ball
equation
  der(pos) = vel;   // Newtons second law
  der(vel) = -g;
  when pos <=0 then
    reinit(vel,-e*pre(vel));
  end when;
end BouncingBall;
```

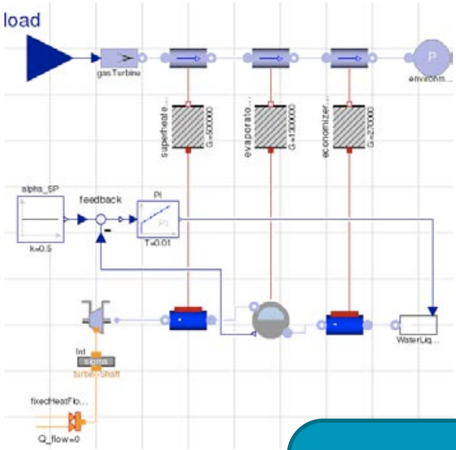
```
class BBex
  BouncingBall eBall;
  BouncingBall mBall(g=1.62);
end BBex;
```



Graphical Modeling

```
model MotorControl
  Modelica.Mechanics.Rotational.Inertia inertia;
  Modelica.Mechanics.Rotational.Sensors.SpeedSensor speedSensor;
  Modelica.Electrical.Machines.BasicMachines.DCMachines.DC_PermanentMagnet DCPM;
  Modelica.Electrical.Analog.Basic.Ground ground;
  Modelica.Electrical.Analog.Sources.SignalVoltage signalVoltage;
  Modelica.Blocks.Math.Feedback feedback;
  Modelica.Blocks.Sources.Ramp ramp(height=100, startTime=1);
  Modelica.Blocks.Continuous.PI PI(k=-2);
equation
  connect(inertia.flange_b, speedSensor.flange_a);
  connect(DCPM.flange_a, inertia.flange_a);
  connect(speedSensor.w, feedback.u2);
  connect(ramp.y, feedback.u1);
  connect(signalVoltage.n, DCPM.pin_ap);
  connect(signalVoltage.p, ground.p);
  connect(ground.p, DCPM.pin_an);
  connect(feedback.y, PI.u);
  connect(PI.y, signalVoltage.v);
end MotorControl;
```





A Modelica-based Tool Chain

Flattening of Modelica source code
Compiler front-end

→ Unstructured Flat DAE

→ Symbolic maniulation
Index reduction
Analytic solution of simple equations

→ Transformed flat DAE

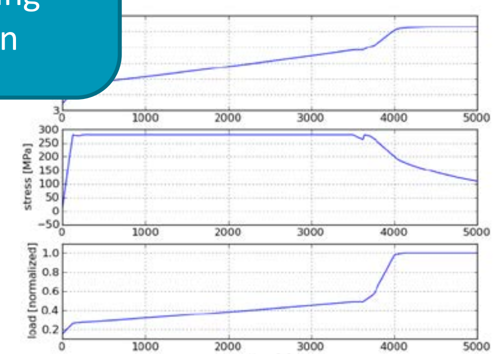
→ Code generation
Residual equations
Analytic Jacobians

→ C code

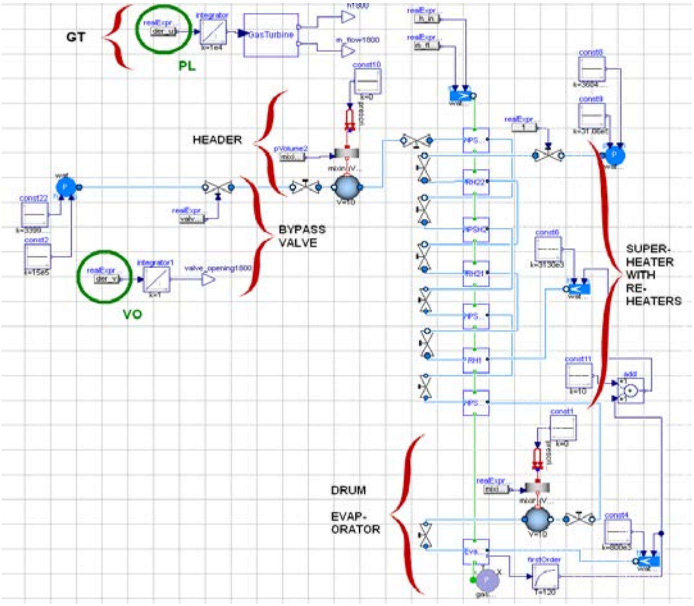
→ Numerical solvers
NLP algorithms
Integrators

→ Solution profiles

→ Result
Post processing
Visualization



Industrial Application I
Power Plant Start-up Optimization



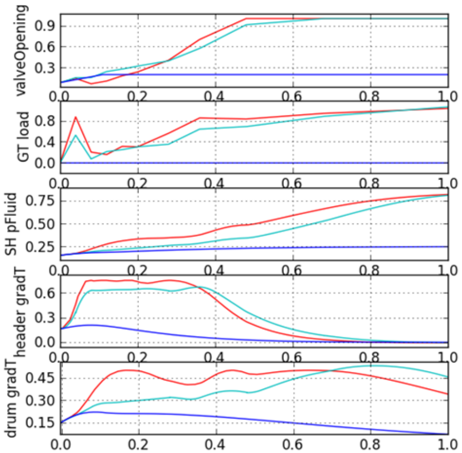
- Start-up optimization of combined cycle power plants
- Reduce start-up time
- Model-based optimization
- Siemens AG, LU, Modelon collaboration

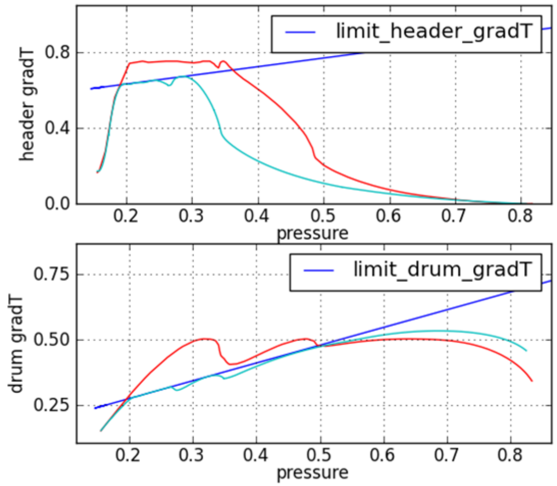
Continuous time states: **39**

Scalar equations: **569**

Algebraic variables: **530**

NLP equations: **26824**





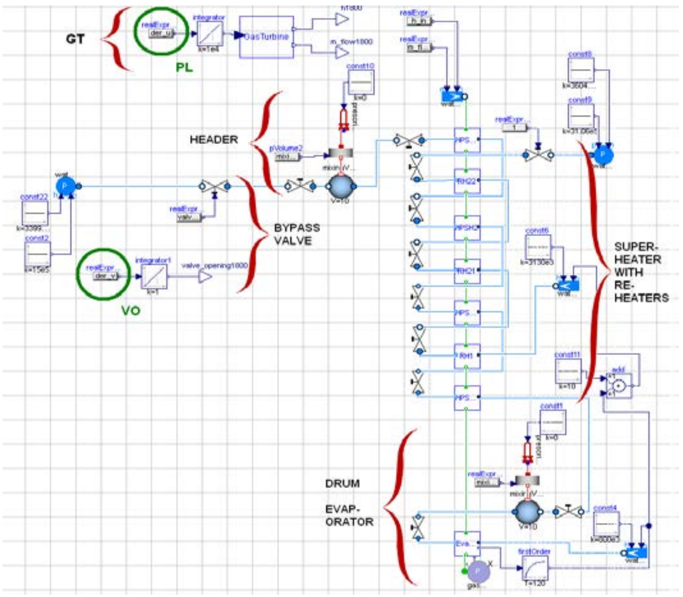
Industrial Application I
Power Plant Start-up Optimization

- ☺ Design-patterns from Modelica media model libraries applied to optimization-friendly models
- ☺ Intuitive high-level descriptions of dynamic optimization problem appreciated by users – a vehicle for communicating ideas

- ☹ Large effort to develop models suitable for optimization
- ☹ Scaling of problem significantly more challenging than in simulation
- ☹ Convergence and robustness of numerical algorithms

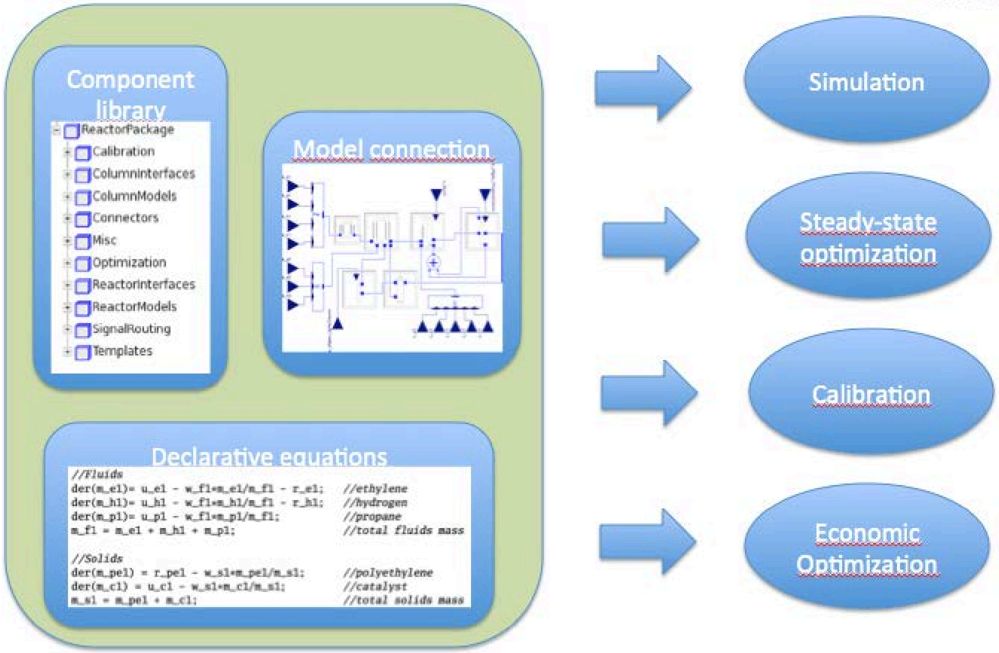
Lessons learnt

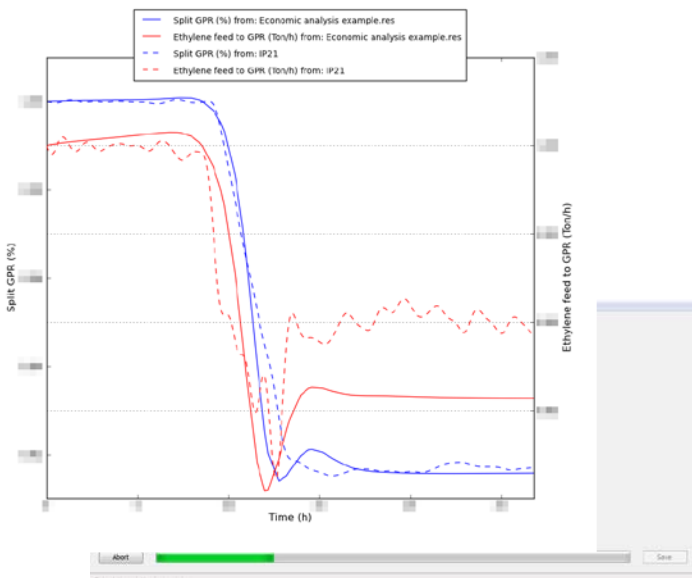
- Modeling for optimization is significantly different from modeling for simulation
- Numerical optimization algortihm is significantly less robust than simulation algorithm
- Scaling of problem and initial guesses have major impact



Industrial Application II
Grade Changes in Polyethylene Production

- Optimization of economics of polyethylene grade changes
- Model calibration to data
- Modeling with Modelica and Optimica
- Development of end-user GUI
- PIC-LU – Lund University and Borealis





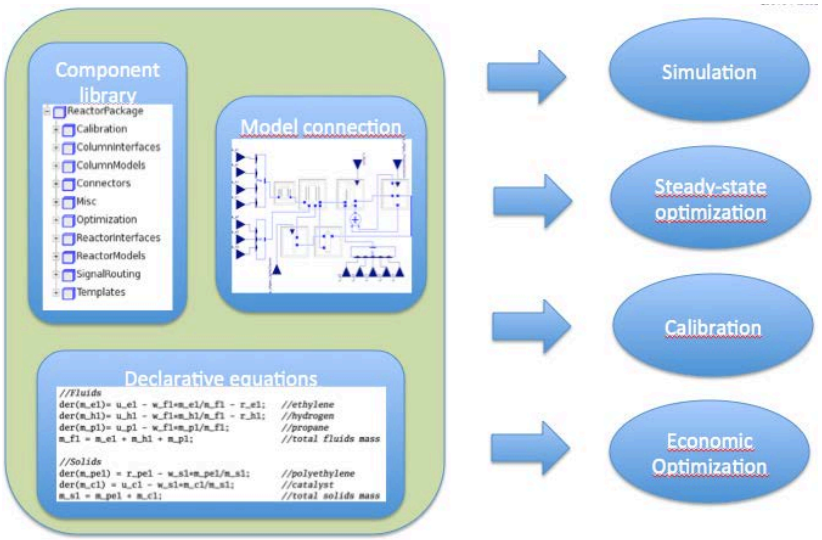
Industrial Application II
Grade Changes in Polyethylene Production

- ☺ Model reuse across different computations
- ☺ High-level model and optimization problem formulation enabled promoted focus on problem formulation
- ☺ Custom GUI in Python appreciated by end-users

- ☹ Careful manual scaling of problem required for convergence
- ☹ Difficult to tailor collocation optimization formulation to problem description
- ☹ Non-standard economic cost difficult to handle

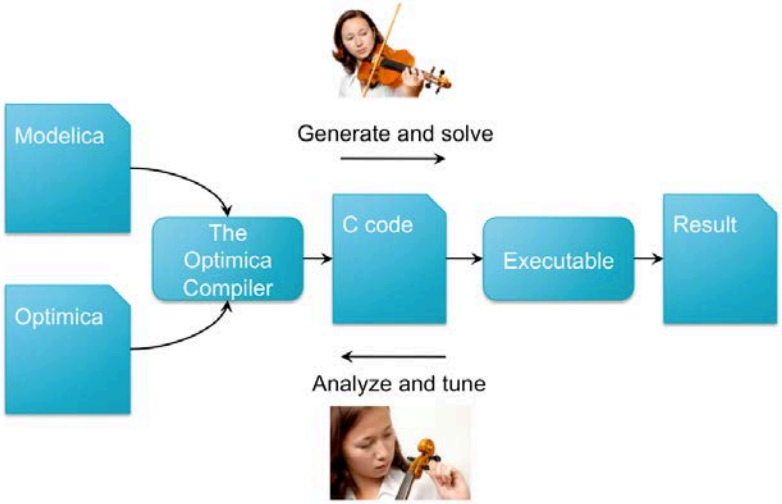
Lessons learnt

- Significant advantages from Modelica technology – same model used for steady-state, dynamic simulation, calibration and optimization
- Increased interaction with discretization sometimes important



Extension Example – Optimica

- High-level description of optimization problems
  - Steady-state
  - Dynamic
- Extension to Modelica
  - Optimization of physical models




```
optimization VDP_Opt(objective=cost(finalTime),
     startTime=0,
     finalTime(free=true, initialGuess=1))
  VDP vdp(u(free=true,initialGuess=0.0));
   Real cost (start=0);
equation
   der(cost) = 1;
constraint
   vdp.x1(finalTime) = 0;
   vdp.x2(finalTime) = 0;
   vdp.u >= -1; vdp.u <= 1;
end VDP_Opt;
```

$$\min_{u(t),\,p} \Psi(\bar{z}, p)$$

subject to the dynamic system

$$F(\dot{x}(t), x(t), y(t), u(t), p, t) = 0, \quad t \in [t_0, t_f]$$

and the constraints

$$c_{ineq}(x(t), y(t), u(t), p) \leq 0, \quad t \in [t_0, t_f]$$
$$c_{eq}(x(t), y(t), u(t), p) = 0, \quad t \in [t_0, t_f]$$
$$c^p_{ineq}(\bar{z}, p) \leq 0$$
$$c^p_{eq}(\bar{z}, p) = 0$$

where

$$\bar{z} = [x(t_1), \ldots, x(t_{N_p}), y(t_1), \ldots, y(t_{N_p}), u(t_1), \ldots, u(t_{N_p})]^T, \quad t_i \in [t_0, t_f]$$

Extension Example – Optimica

- ☺ High-level problem descriptions promote focus on formulation rather than encoding
- ☺ New users without optimization experience quickly gets up to speed
- ☺ Model reuse for different usages
- ☺ Automatic model transformation reduce user effort

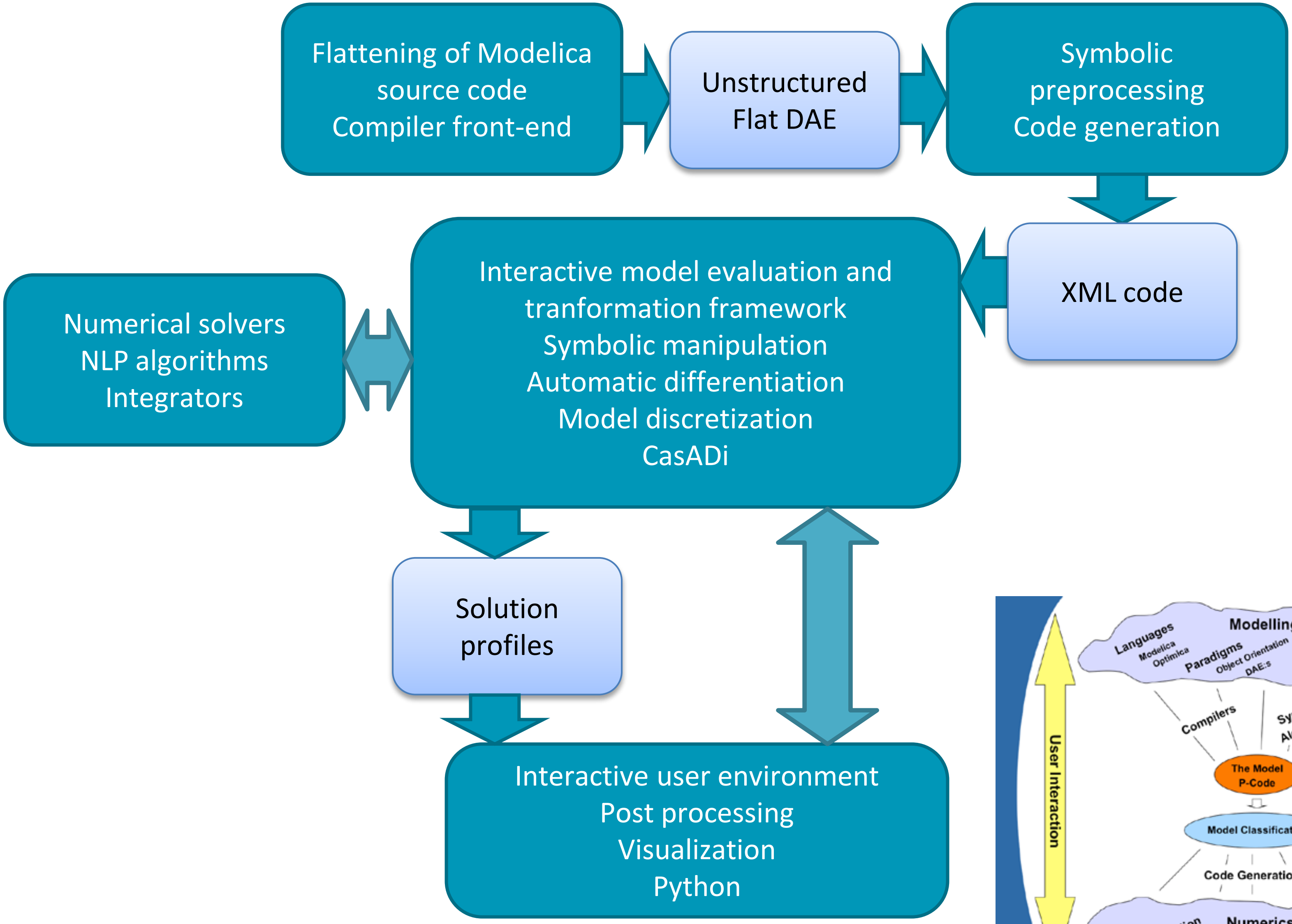
- ☹ Tailoring of problem discretization difficult, but sometimes needed
- ☹ Power-users of dynamic optimization tools feel constrained

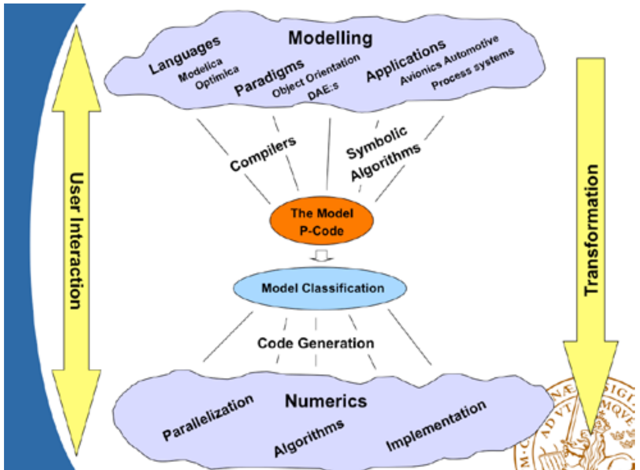
Lessons learnt

- High-level descriptions make optimization technology available to non-experts
- Automatic model transformation reduces design cycle times
- Modern compiler construction technology is accessible to non-experts (e.g., JastAdd)

```
optimization VDP_Opt(objective=cost(finalTime),
     startTime=0,
     finalTime(free=true, initialGuess=1))
  VDP vdp(u(free=true,initialGuess=0.0));
   Real cost (start=0);
equation
   der(cost) = 1;
constraint
   vdp.x1(finalTime) = 0;
   vdp.x2(finalTime) = 0;
   vdp.u >= -1; vdp.u <= 1;
end VDP_Opt;
```

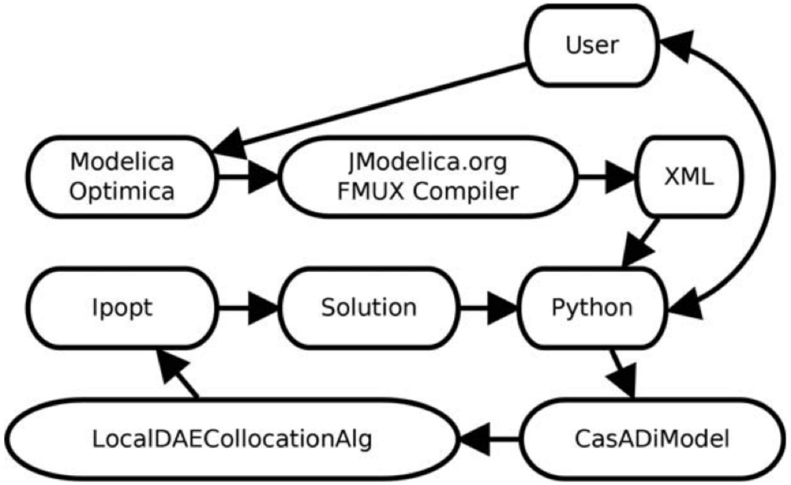
Towards a vertically integrated toolchain

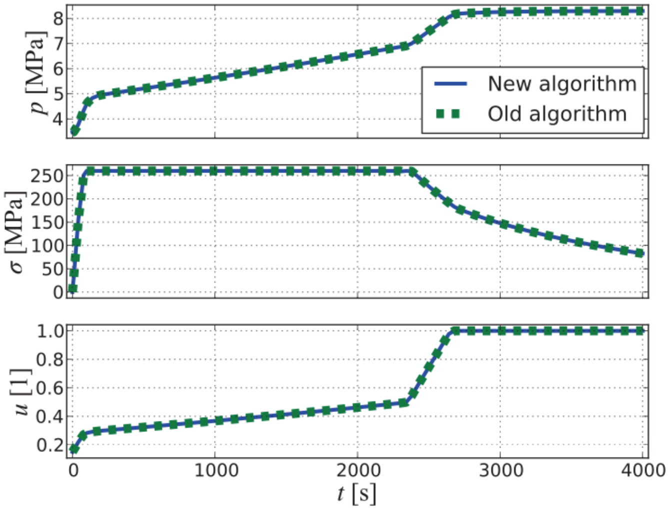




Interfacing Example – Modelica, XML Models and CasADi

- Replace C implementation of a collocation algorithm
- Intermediate symbolic model format in XML
- Decreased solution times by an order of magnitude
- Decreased implementation time by an order of magnitude
- Significantly increased flexibilty
- Tailoring to specific problems





	Off-line	On-line	Total	Iterations
New alg.	4.9	3.0	7.9	79
Old alg.	13.2	23.9	37.2	75

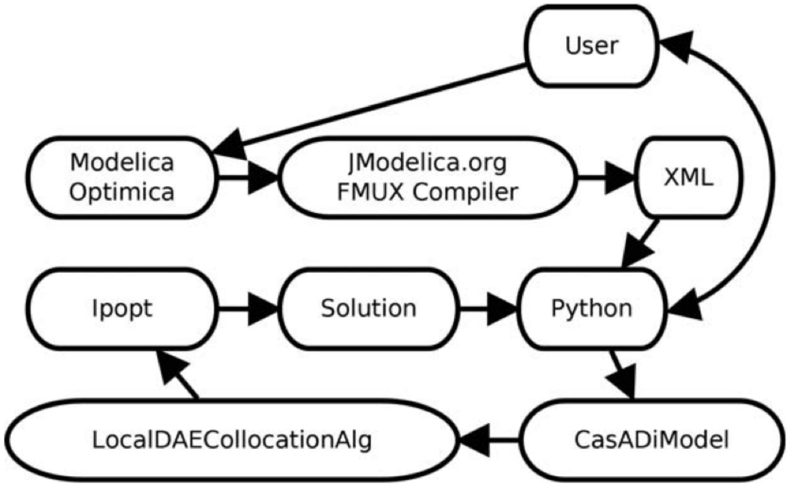
Interfacing Example – Modelica, XML Models and CasADi

- ☺ Rapid prototyping with interactive model evaluation and transformation frameworks
- ☺ Flexibility to tailor model descretization to problem formulation
- ☺ Inspiration for future versions of Optimica

- ☹ Partial problem formulation in high-level format
- ☹ Some of the overview lost when parts of the problem is formulated in Modelica/Optimica some part is in scripting language

Lessons learnt

- Interactive model transformation powerful
- Symbolic model exchange format needed (standardization on-going)
- High performance and flexibility can be combined



Challenges

- *How do we make advanced algorithms in systems design in general and in optimization in particular PhD-free?*
- *How do we combine declarative modeling languages with ideas from interactive model transformation/evaluation frameworks?*
- *How do we propagate consistent error/diagnostics through the tool chain?*
- *Open interfaces and interoperability, FMI and extensions*
- *Classify models applicable to different solution algorithms*

Conclusions

- In users' perception, current optimization algorithms for large-scale non-linear dynamic systems requires high level of expertise
- Very different cultures and best practices in simulation and optimization communities – expectation management
- Users sometimes need to/desire to to interact with both mathematical model and solution algorithm implementation
- Challenges in usability and robustness of numerical algorithms
- Challenges in vertically integrated tool chains – languages and open interfaces and tool decoupling

Thank you!

Questions, comments?