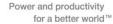
Johan Sjöberg, ABB Corporate Research, Västerås, Sweden

# Equation-based Modeling and Control of Industrial Processes





#### A Global Leader in Power and Automation Technologies Leading Market Positions in Main Businesses



- 135,000 employees in about 100 countries
- \$38 billion in revenue (2011)
- Formed in 1988 merger of Swiss and Swedish engineering companies
- Predecessors founded in 1883 and 1891



 Publicly owned company with head office in Switzerland



#### How ABB is organized Five global divisions



(2011 revenues, consolidated)

#### ABB's portfolio covers:

- Electricals, automation, controls and instrumentation for power generation and industrial processes
- Power transmission
- Distribution solutions
- Low-voltage products

- Motors and drives
- Intelligent building systems
- Robots and robot systems
- Services to improve customers productivity and reliability



#### Power and automation are all around us You will find ABB technology...



orbiting the earth and working beneath it,

#### crossing oceans and on the sea bed,

in the fields that grow our crops and packing the food we eat,

on the trains we ride and in the facilities that process our water,

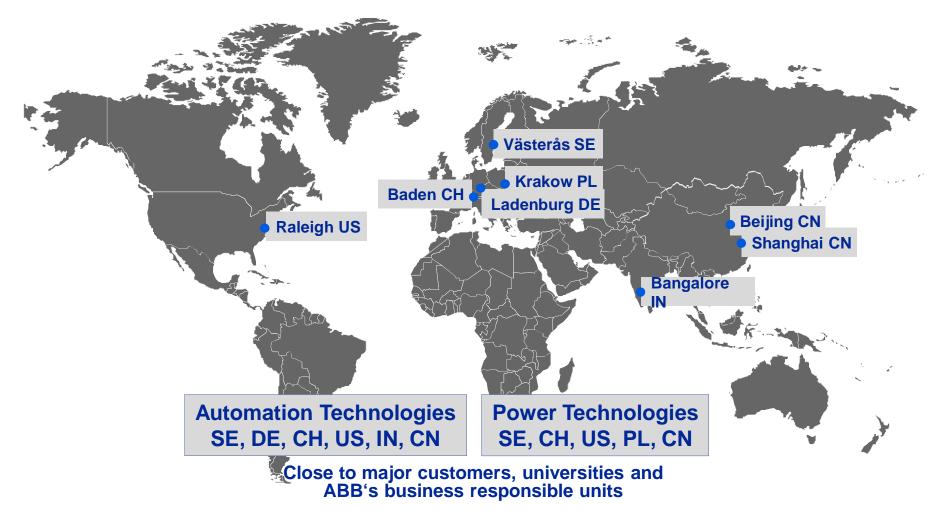




in the plants that generate our power and in our homes, offices and factories

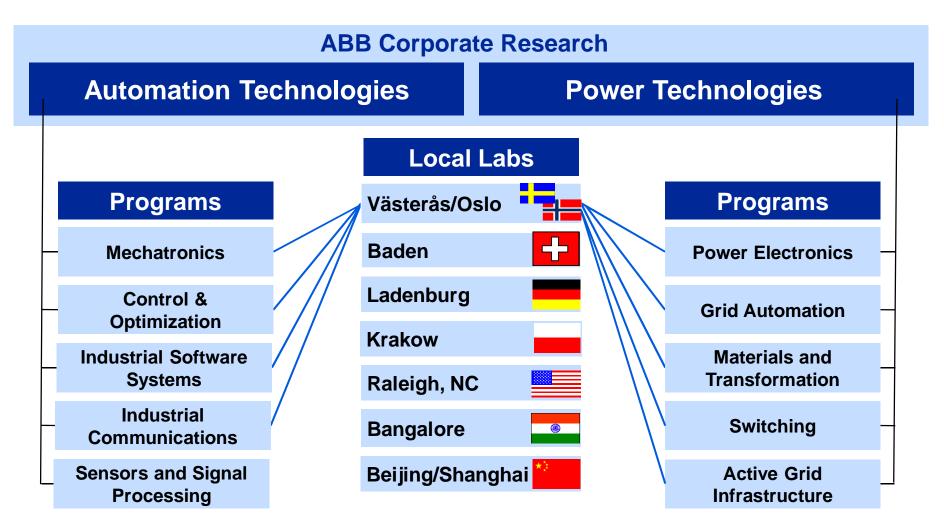


#### Global Labs... ... and Local Lab Locations





#### Global Labs, Corporate Programs and Locations 700 Researchers World-Wide – 250 in Västerås/Oslo





## Examples of Industrial Systems modeled using an Equation-based Approach at ABB

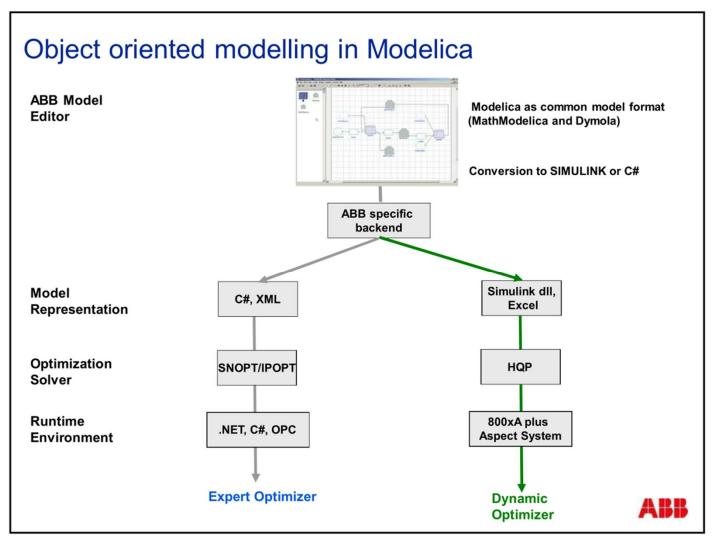




- Pulp & paper
- Metals & minerals
- Mechatronical systems
- Power generation
- Power products
- Power systems

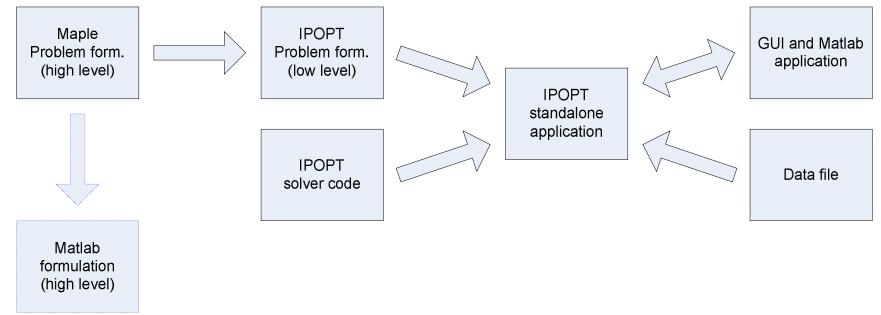
ABB

### Tools for Equation-based Simulation and Control Modelica





## Tools for Equation-based Simulation and Control Maple to IPOPT



Maple (high level description)

```
cact := [];
cact := [op(cact), HeightIn*WidthIn-AreaIn];
# Height out
cact := [op(cact), HeightOut-AGroove/MaxGrooveWidth-Gap];
```

IPOPT (low level description)

```
g[i++] = x[2 + 170 * k] * x[3 + 170 * k] - x[25 + 170 * k];

g[i++] = x[20 + 170 * k] - x[6 + 170 * k] / x[5 + 170 * k] - x[170 * k];
```



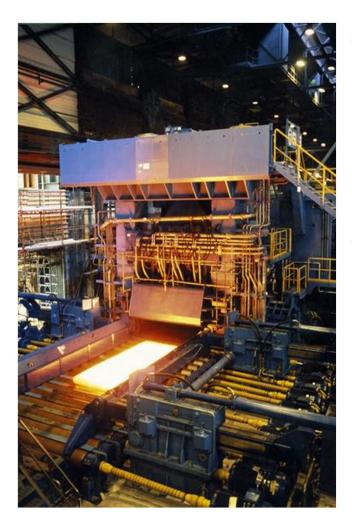


#### **Optimization of Hot Rolling**





#### (Energy) Optimization in Hot Rolling Mills Huge Potential

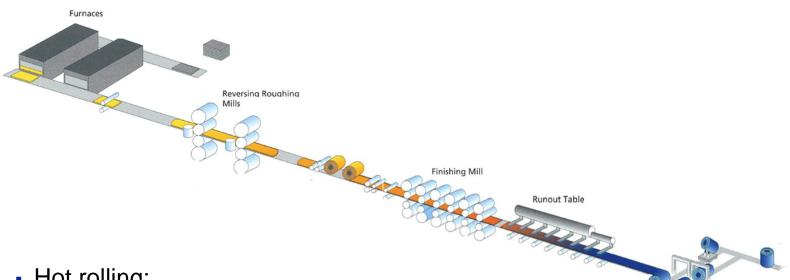


- Profile mills:
  - 7% reduction =>

     1.2 GWh/yr
     (>1000 profile mills globally)
- Flat mills:
  - 0,5% reduction => 1.6 GWh/yr (~400 flat mills globally)



### Introduction to Hot Rolling



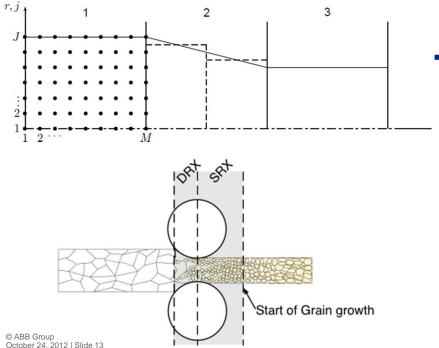
- Hot rolling:
  - Temperature above the recrystallization temperature. (otherwise cold rolling).
- Profile rolling
  - To produce rods, bars, wires, etc.





#### **Process Model**

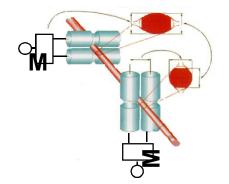




- Covers room temperature to room temperature
- The model includes for instance
  - Mass balance, rolling geometries, power, groove utilization, temperature field, microstructure of material
- Model properties:
  - Large but sparse
  - Discontinuities due to switching behavior
  - Bad numerical scaling of certain equations



#### **Optimization Formulation**



 $\min f(v, g, htc, T_0, \mathcal{X})$ s.t.  $\begin{aligned} c_i(v, g, htc, T_0, \mathcal{X}) &= 0, \ i \in \mathcal{E} \\ c_i(v, g, htc, T_0, \mathcal{X}) &\geq 0, \ i \in \mathcal{I} \end{aligned} \approx 700 + 45 \\ A(htc, \mathcal{X})T^{m+1} &= b(T^m, htc, \mathcal{X}) \end{aligned} \approx 10000 - 100000 \end{aligned}$ 

v =roll speed

 $g = \operatorname{gap}$ 

 $T_0 =$ furnace temperatures

htc = heat transfer coefficients

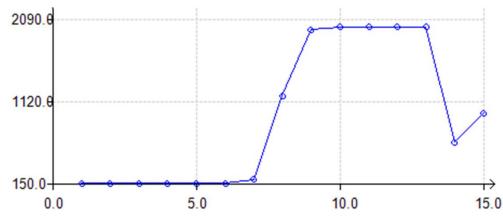
 $\mathcal{X} =$ intermediate variables and

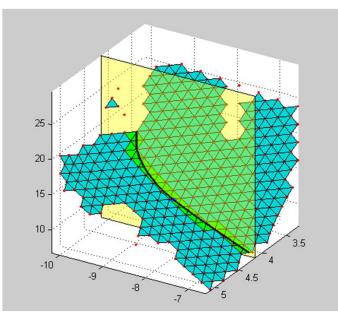
parameters such as  $T_j, \sigma, \ldots$ 



### **Multiobjective Optimization**

- Real life: Compromise between different objectives:
  - Total power
  - Austenite grain size (related to strength of material)
  - Production speed
- Pareto front analysis yields many insights, for instance, for the cooling.
  - Grain size reduction requires cooling. For low energy consumption, start from behind.



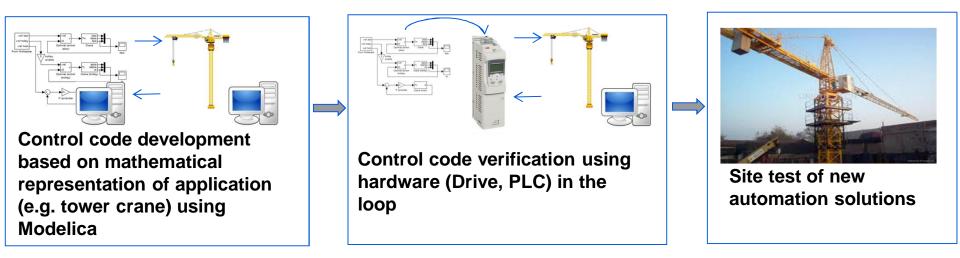




#### Optimization & Optimal control are important but... Hardware-in-the-loop

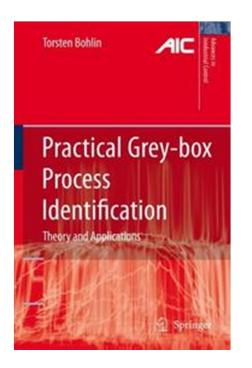


Winch Deck crane Indoor crane Tower crane Harbor crane





#### Optimization & Optimal control are important but... System Identification - Grey-box identification



Book by Torsten Bohlin Springer, 2006

- In an optimization project, modelling is by far the most time-consuming part
- Physical model should be gradually extended while testing statistical significance against experimental data
- Estimation of parameters using horizon estimation (HE) gives biased parameters without the right regularization in many cases.

$$\min_{x_k,\theta} \frac{1}{2} \sum_{k=0}^{N} w_k^T Q^{-1} w_k + v_k^T R^{-1} v_k + \log(\det(S_k(\theta)))$$
  
s.t.  $x_{k+1} = f(x_k, u_k) + w_k$   
 $y_k = h(x_k, u_k) + v_k$   
 $x(0) = x_0$ 



## Equation-based Modeling and Control for Industry Conclusions





Modeling

- More and more use of first principle modeling
- Requires considerable knowledge to succeed process as well as theoretical
- Optimization
  - Optimization and decision support are slowly gaining ground
  - Increased competition will force more and more optimization solutions
  - More plant-wide & wider scope (production scheduling etc)
  - Optimal solution often used for comparison, not for the actual control



## Equation-based Modeling and Control for Industry Conclusions, cont'd.





- Identification
  - Parameter identification is not supported enough yet.
- Virtualization
  - Hardware-In-the-Loop / training simulators gain popularity
- Generally
  - Ease of use (incl. look-and-feel)
  - Model management
  - Integration (process, data, tool etc)



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#### Proposed grey-box scheme for nonlinear systems

- 1. Model process in Modelica
- 2. Discretize symbolically and export equations
- 3. Linearize model symbolically
- 4. Import and prepare data
- 5. Carefully introduce noise variables at equations motivated by physical insight
- 6. Solve by nonlinear programming (e.g. using IPOPT)

$$\min_{x_k,\theta} V = \frac{1}{2} \sum_{k=0}^{N} (w_k^T Q^{-1} w_k + v_k^T R^{-1} v_k + \log(\det(S_k(\theta))))$$

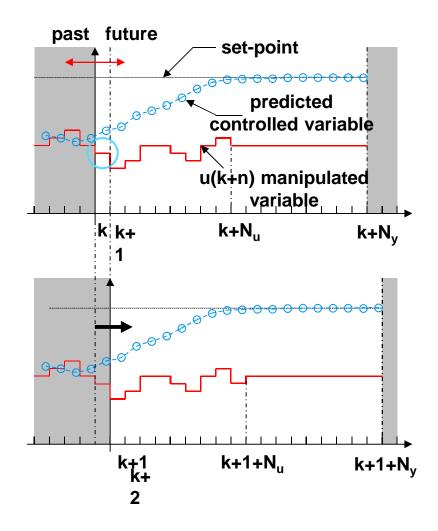
#### subject to

$$x_{k+1} = g(x_k, u_k) + w_k$$
$$y_k = h(x_k, u_k) + v_k$$

- 7. For every evaluation of V calculate the (time varying) linearized system along the trajectory to compute  $S_k$
- 8. Test which parameters to make free (including noise parameters) by hypothesis testing using the chi-squared risk calculation
- 9. Repeat 5-8 until no further improvement



#### Model Predictive Control (MPC) Algorithm



Use model to

- Estimate where you are state estimation
- Optimize future control signals over a time horizon
- Repeat at next sampling instant
- Shift horizon one step receding horizon control

