

EFFICIENT IMPLEMENTATIONS AND CO-SIMULATION TECHNIQUES IN MULTIBODY SYSTEM DYNAMICS

Francisco Javier González Varela

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University of A Coruña

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LIM



Laboratorio de Ingeniería Mecánica
Universidade da Coruña

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Outline

Introduction

Software Architecture for MBS Simulation

Linear Algebra Implementations

Parallelization

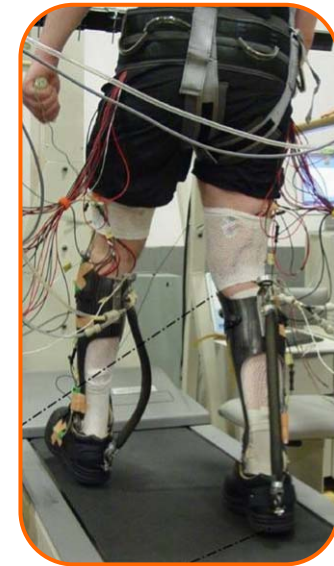
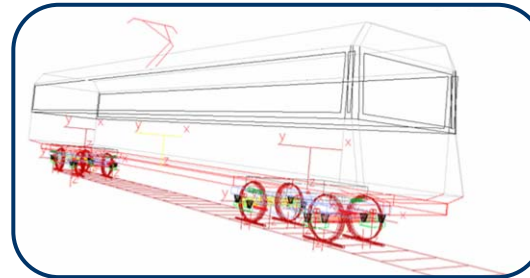
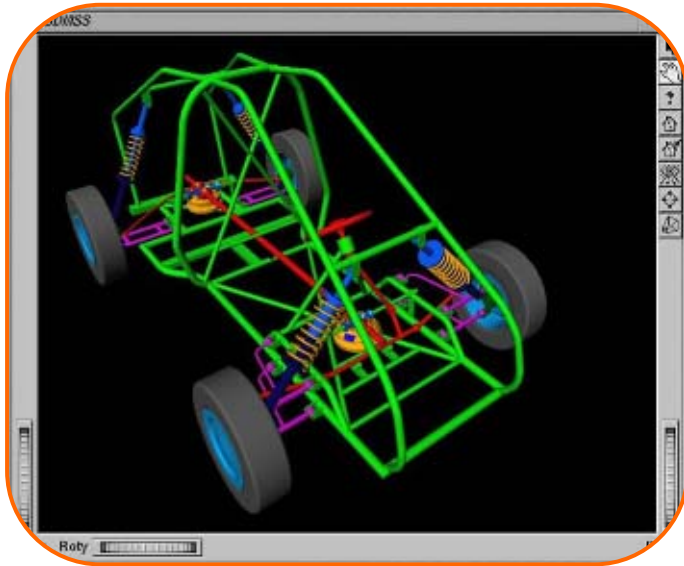
Integration with MATLAB/Simulink

Multirate Co-simulation Methods

Conclusions and Future Research

Motivation

- **Multibody systems (MBS) dynamic simulation is present in a wide range of applications today**



- **MBS simulation is heavily dependent on available software features**
 - Simulated systems are very complex and often multi-disciplinary
 - High efficiency required in real-time applications and what-if analyses

Objectives of this thesis

- **Two main goals in current research in MBS dynamic simulation**
 - Efficiency
 - Addition of new functionality (multiphysics, contact, impacts, etc.)
- **1- Efficient implementations in MBS software**
 - Linear Algebra routines
 - Parallelization
- **2 - Communication with external packages**
 - Comparison of available communication techniques
 - Multirate co-simulation
- **Intermediate goal: MBS software architecture**

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Software requirements

- Research software for MBS simulation

Modular



Collaborative



Object-oriented
paradigm

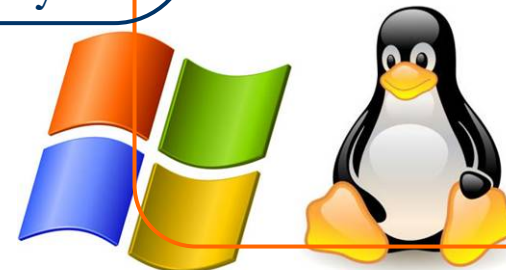
C++

Flexibility - Efficiency

Open

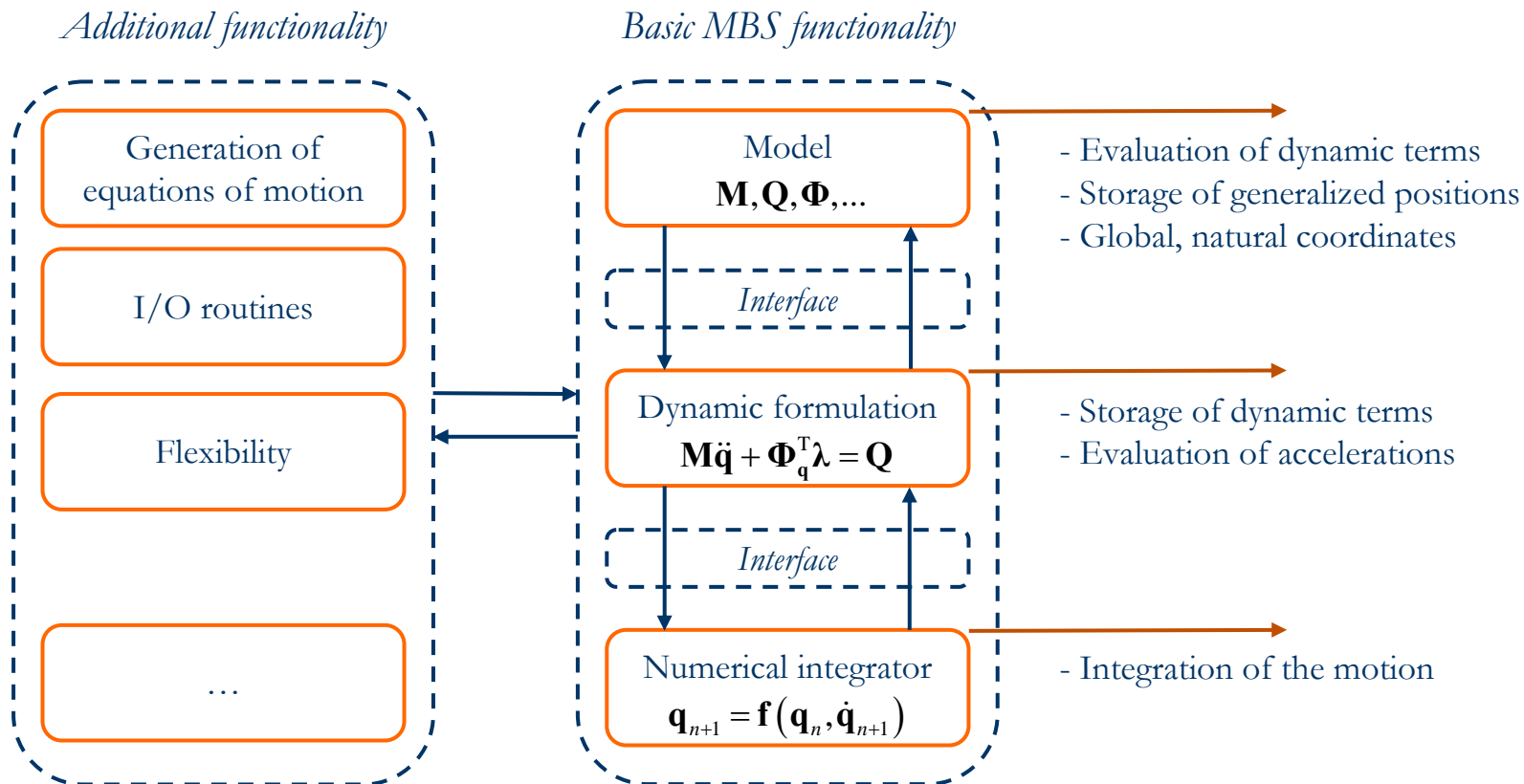


Platform-independent



Structure of the simulation software

■ Modular structure



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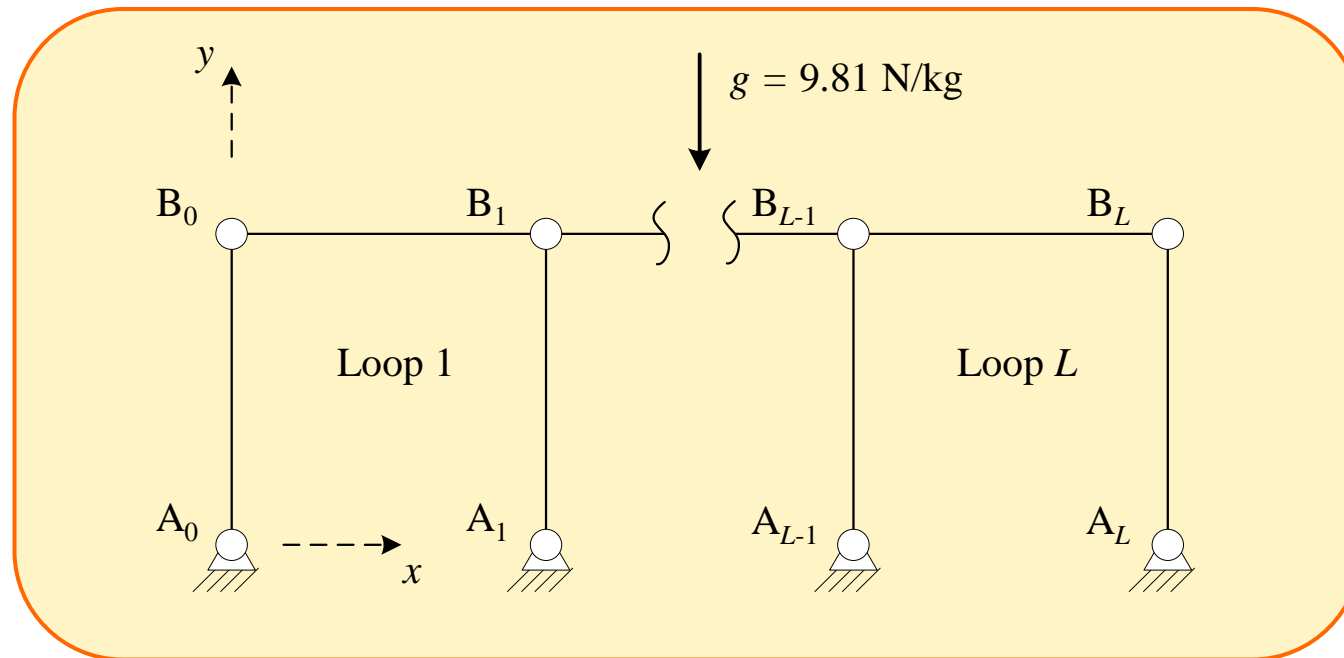
Linear algebra operations in MBS simulation

- **MBS codes make intensive use of linear algebra operations**
 - Low-level scalar-matrix-vector operations $\mathbf{B} = \mathbf{A}^T \mathbf{A}$
 - Solution of linear systems of equations $\mathbf{A}\mathbf{x} = \mathbf{b}$
- **Reference Fortran implementation**
 - Dense: IMSL solver
 - Sparse: MA27 solver

Fraction of elapsed time in computations	Dense	Sparse
Residual and tangent matrix	48%	15%
Factorization and back-substitutions	44%	51%
Velocity and acceleration projections	4%	13%
Other	4%	21%

Benchmark setup: test problem

- 2D assembly of four-bar linkages
- 1 degree of freedom; variable number of loops and size
- Simulation time: 20 s



Benchmark setup: dynamic formulation

- Index-3 augmented Lagrangian (natural coordinates)

$$\mathbf{M}\ddot{\mathbf{q}} + \Phi_{\mathbf{q}}^T \alpha \Phi + \Phi_{\mathbf{q}}^T \lambda^* = \mathbf{Q}$$

$$\lambda_{i+1}^* = \lambda_i^* + \alpha \Phi_{i+1}; \quad i = 0, 1, 2, \dots$$

- Trapezoidal rule as integrator (implicit)
- Newton-Raphson iteration with approximate tangent matrix (SPD)

$$\mathbf{f}(\mathbf{q}) = \mathbf{M}\mathbf{q}_{n+1} + \frac{\Delta t^2}{4} \Phi_{\mathbf{q}(n+1)}^T (\alpha \Phi_{n+1} + \lambda_{n+1}) - \frac{\Delta t^2}{4} \mathbf{Q}_{n+1} + \frac{\Delta t^2}{4} \mathbf{M}\hat{\mathbf{q}}_n$$

$$\left[\frac{\partial \mathbf{f}(\mathbf{q})}{\partial \mathbf{q}} \right] \cong \mathbf{M} + \frac{\Delta t}{2} \mathbf{C} + \frac{\Delta t^2}{4} (\Phi_{\mathbf{q}}^T \alpha \Phi_{\mathbf{q}} + \mathbf{K})$$

- Mass-orthogonal projection of velocities and accelerations

$$\left[\frac{\partial \mathbf{f}(\mathbf{q})}{\partial \mathbf{q}} \right] \dot{\mathbf{q}} = \left[\mathbf{M} + \frac{\Delta t}{2} \mathbf{C} + \frac{\Delta t^2}{4} \mathbf{K} \right] \dot{\mathbf{q}}^* - \frac{\Delta t^2}{4} \Phi_{\mathbf{q}}^T \alpha \Phi_t$$

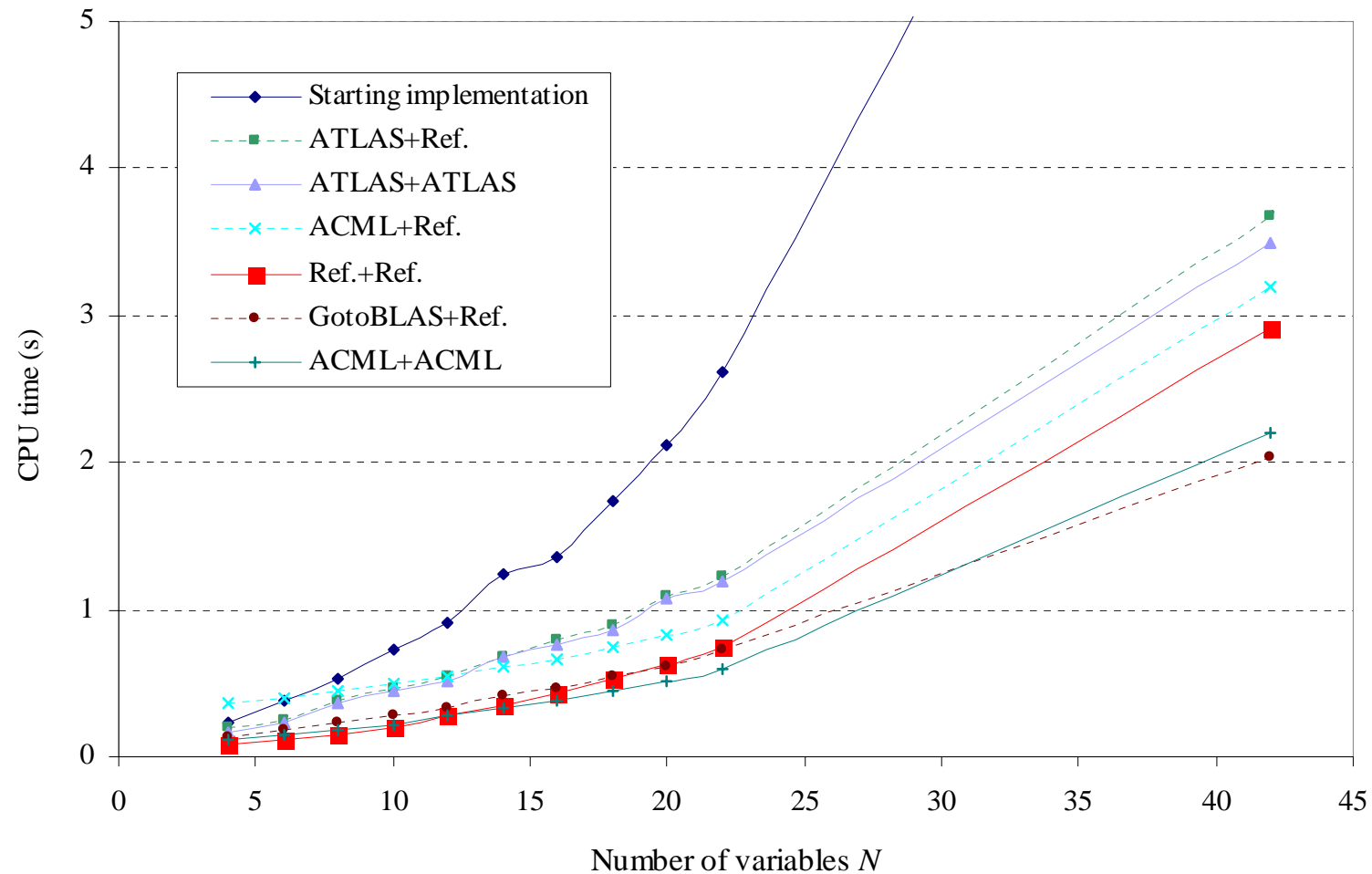
$$\left[\frac{\partial \mathbf{f}(\mathbf{q})}{\partial \mathbf{q}} \right] \ddot{\mathbf{q}} = \left[\mathbf{M} + \frac{\Delta t}{2} \mathbf{C} + \frac{\Delta t^2}{4} \mathbf{K} \right] \ddot{\mathbf{q}}^* - \frac{\Delta t^2}{4} \Phi_{\mathbf{q}}^T \alpha (\dot{\Phi}_{\mathbf{q}} \dot{\mathbf{q}} + \ddot{\Phi}_t)$$

Efficient dense implementations

- Dense storage is *supposed* to be faster for small problems
- Standard libraries for linear algebra operations:
 - Low-level scalar-matrix-vector operations: **BLAS**
 - Linear equation solvers: **LAPACK**
- **BLAS/LAPACK** are available in several implementations:
 - Reference Original Fortran77 implementation (not tuned)
 - ATLAS Tuned for different hardware architectures
 - GotoBLAS Tuned for different CPUs
 - ACML Tuned for AMD CPUs
 - Other

Performance of BLAS/LAPACK implementations

- As a function of problem size



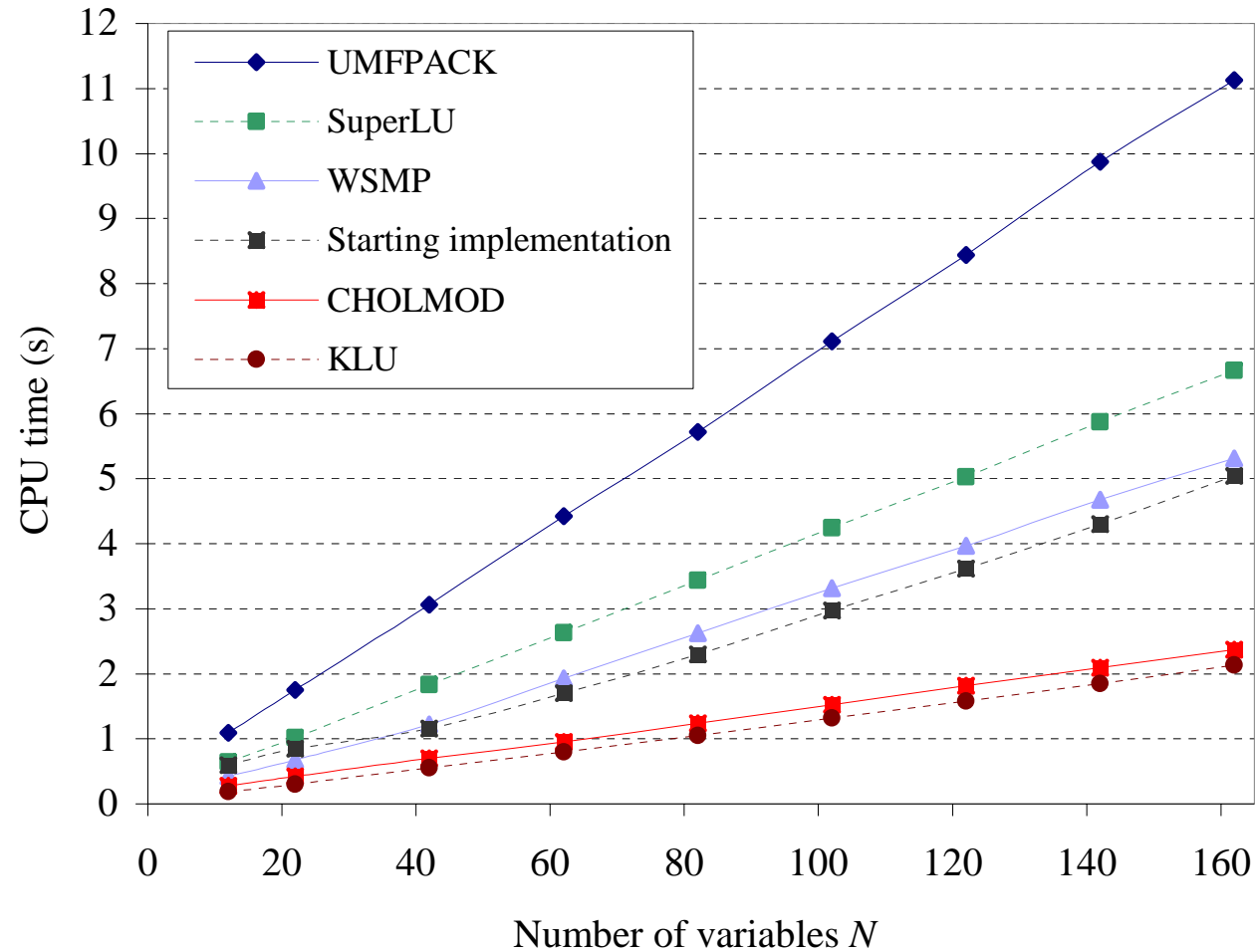
Efficient sparse implementations

- Sparse linear equation solver is critical (50% of CPU)
- Use of optimized matrix handling routines
 - $A + B$
 - $A^T A$
 - Access to Jacobian matrix
- Different solvers have been tested (all CCS)

Sparse linear solver	Matrix type
Cholmod	Symmetric positive definite
KLU	General
SuperLU	General
Umfpack	General
WSMP	Symmetric indefinite

Performance of sparse linear solvers

- As a function of problem size

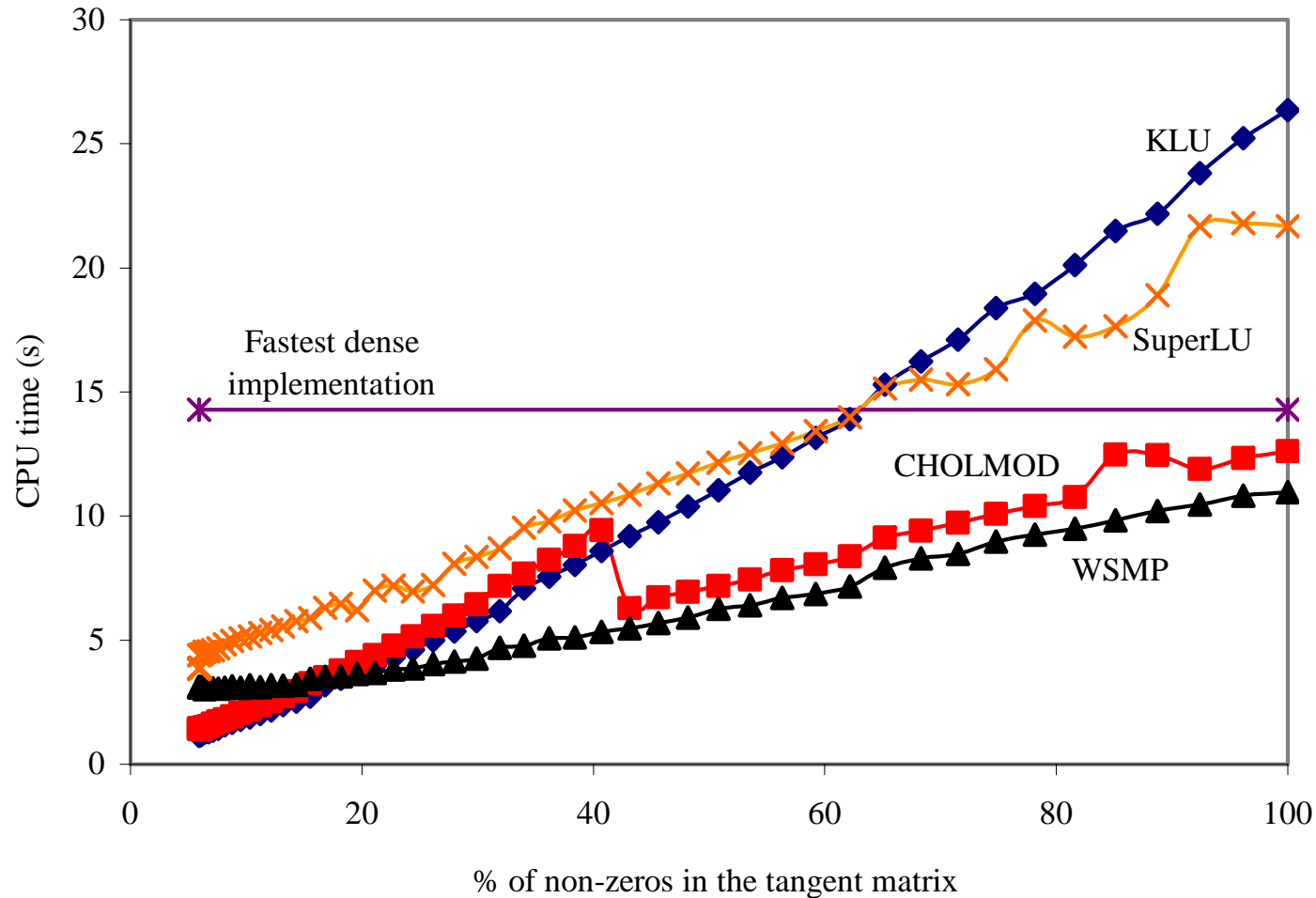


Effect of matrix filling on sparse implementations

- **The percentage of non-zeros in the test problem is small**
 - Global formulation
 - 6% of non-zeros for $N = 100$ variables
- **The % of non-zeros can increase**
 - Recursive and semi-recursive formulations
 - Some methods for flexible bodies
- **Modification of the test problem**
 - Addition of artificial non-zeros to the leading matrix
 - Evaluation of solver performance vs. % of non-zeros

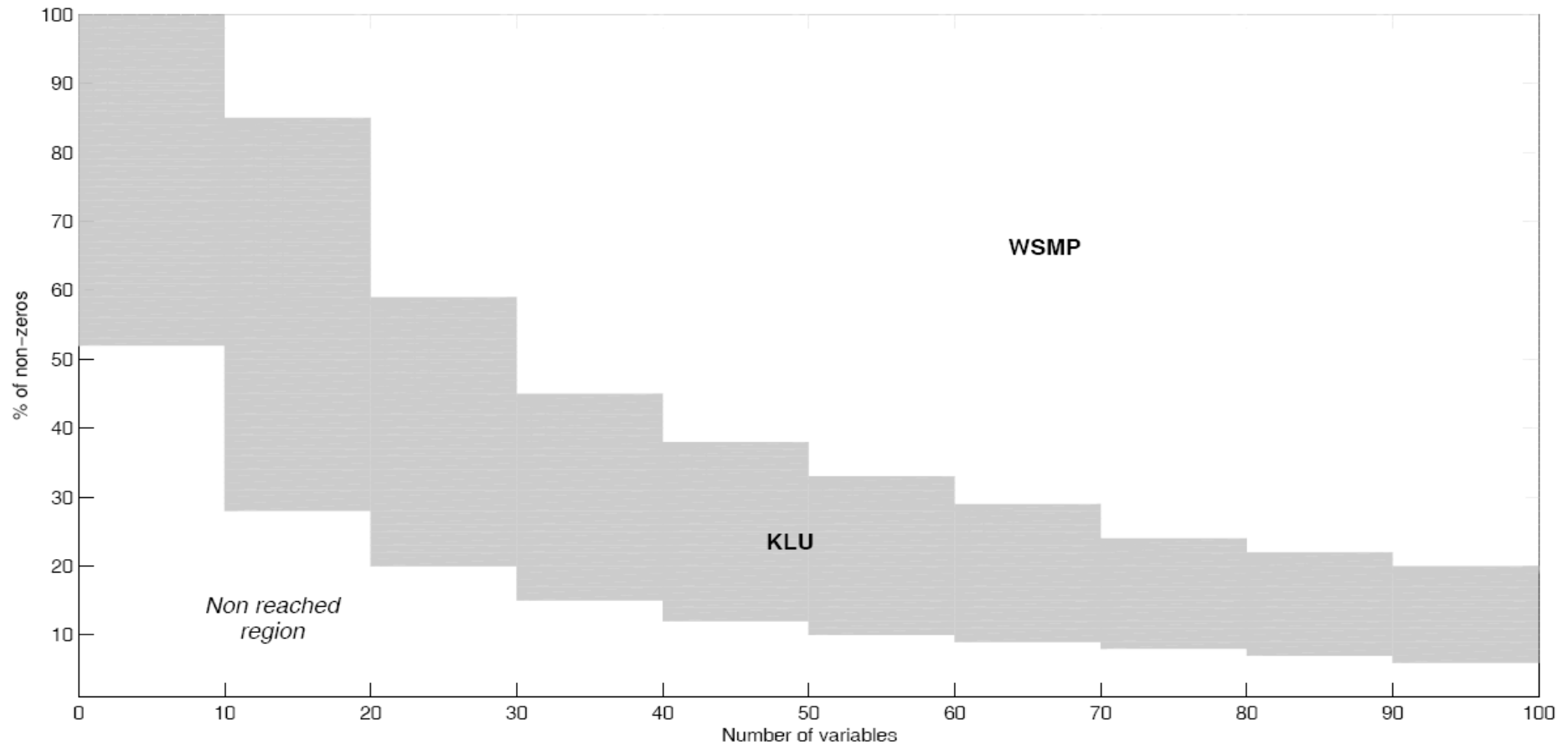
Effect of matrix filling on sparse implementations

- As a function of percentage of non-zeros ($N = 100$)



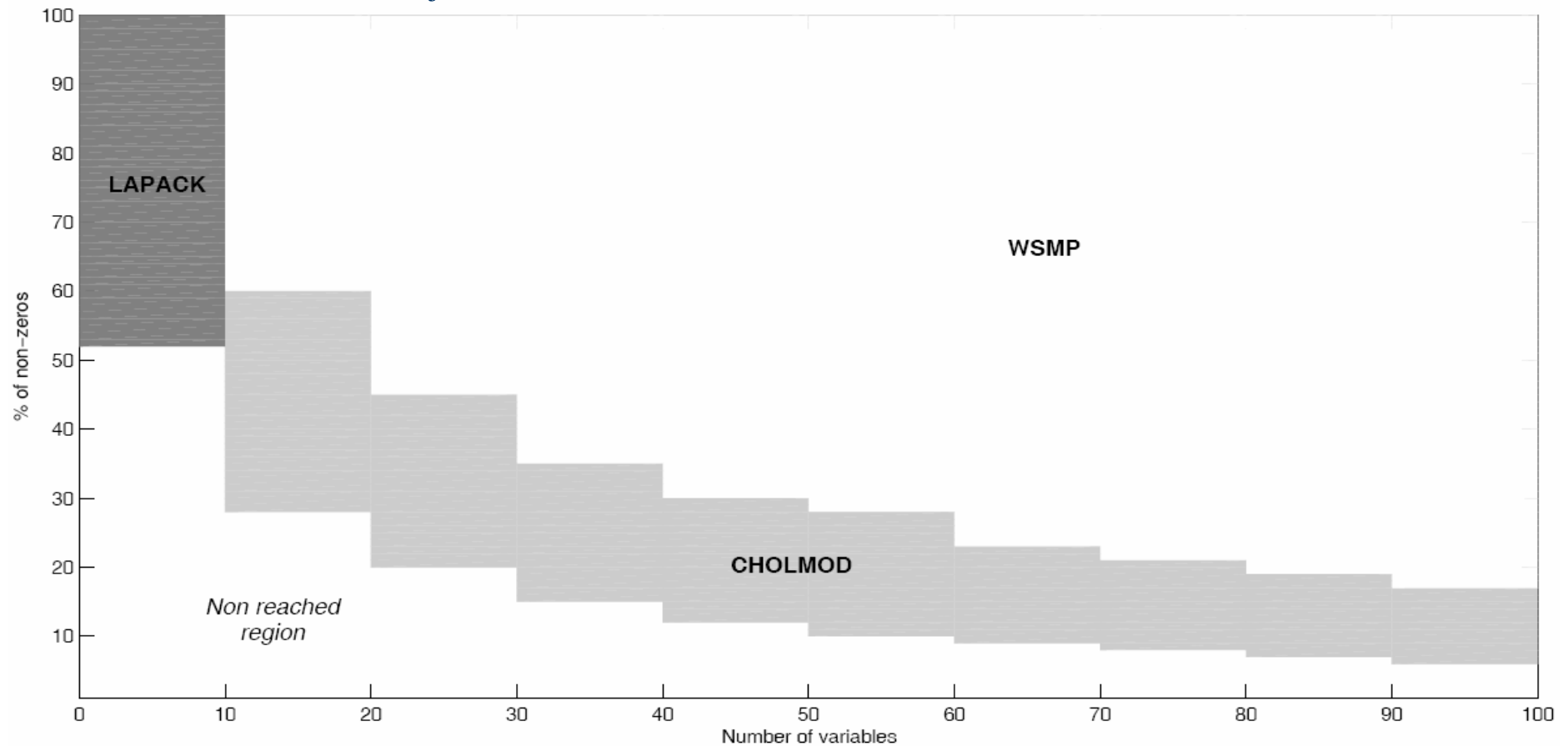
Best linear equation solver

- As a function of problem size and % of non-zeros in leading matrix



Best linear equation solver

- As a function of problem size and % of non-zeros in leading matrix
 - Without KLU *refactor* routine



Conclusions

- **Efficient linear algebra implementations can speedup simulations**
 - With respect to our starting implementation, in a factor of 2 – 3
- **Sparse solvers have performed better: KLU, Cholmod, WSMP**
 - Selection rule based on matrix type, size (N) and non-zeros (NNZ)

Type of leading matrix	$N \cdot (NNZ - 10)$	
	< 900	> 900
Symmetric positive definite	KLU (smooth problems) Cholmod (rough problems)	WSMP
Symmetric	KLU	WSMP
Unsymmetric	KLU	KLU

- **Future work:**
 - Test the optimization with recursive and/or flexible formulations

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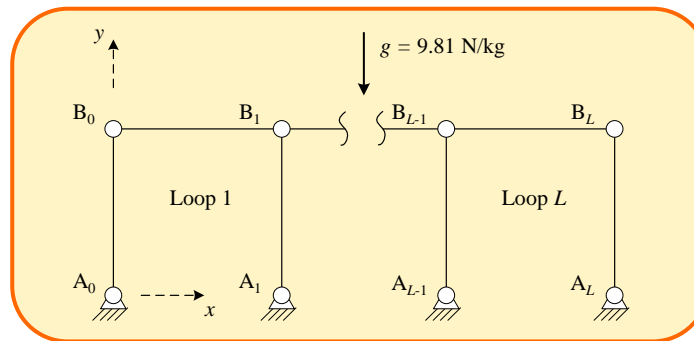
Conclusions and Future Research

Non-intrusive parallelization in MBS simulations

- **In MBS, parallel computing is usually achieved through**
 - Parallel algorithms: recursive formulations, sub-structuring...
 - Implemented with Message Passing Interface (MPI)
- **These are intrusive methods**
 - They require particular code designs and implementations
 - Difficult to apply to existing sequential codes
- **Objective: parallelization of existing sequential codes with minimum effort**
 - Use of non-intrusive techniques (with minor changes in the code)
 - Not as efficient as intrusive methods
 - Easy to apply to existing sequential MBS simulation tools

Benchmark setup

- Same problem and dynamic formulation used in previous chapter
 - L-loop four-bar linkage
 - Index-3 augmented Lagrangian formulation with projection of velocities and accelerations

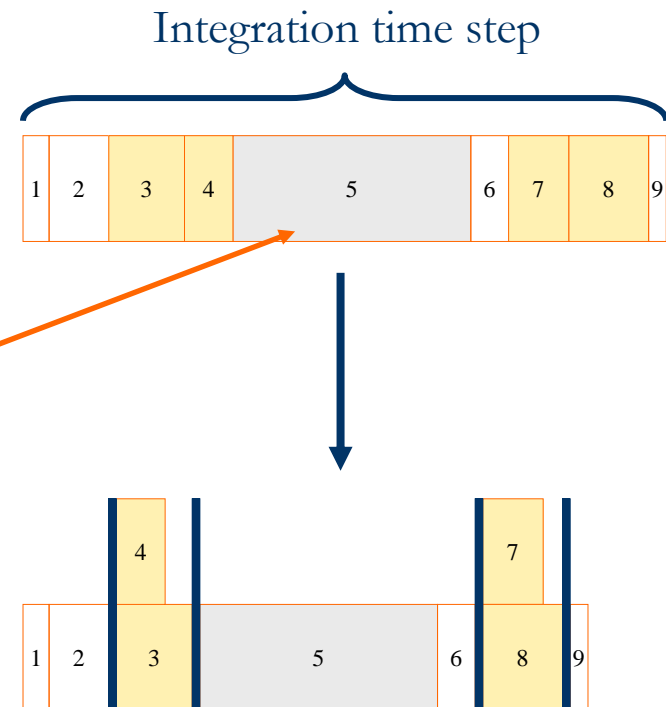


- Heavily optimized for sequential execution
 - Difficult to gain advantage from parallelization
- Tests in 2-core computer
 - Intel Core Duo E6300

Starting sequential implementation

- Profiling of the initial implementation, for N variables

Task	Description	% of elapsed time	
		N = 1000	N = 8000
1	Predictor (Trapezoidal rule)	4.1	4.0
2	Evaluate dynamic terms	9.3	9.8
3	Evaluate tangent matrix	11.8	11.8
4	Evaluate residual vector	7.6	7.6
5	Factorize leading matrix	36.8	36.7
6	Back-substitution	5.9	5.8
7	Project velocities	9.4	9.3
8	Project accelerations	12.3	12.2
9	Other	2.8	2.8
Total elapsed time (s)		10.0	102.4



Parallel linear equation solvers

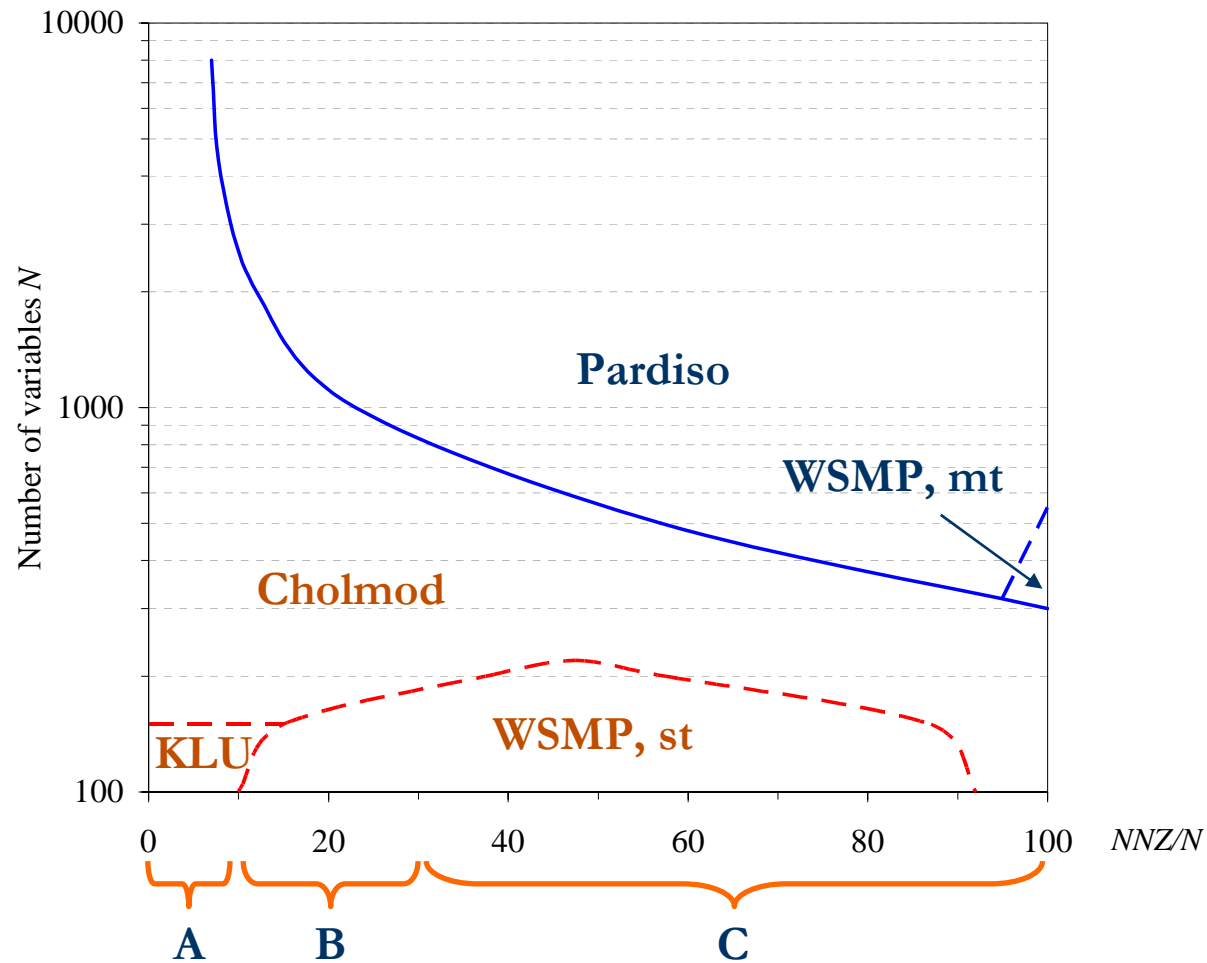
- **Different parallel solvers tested as a function of:**
 - Matrix size (number of variables N from 100 to 8,000)
 - Matrix filling
 - Filling ratio NNZ/N (NNZ = number of non-zeros in the leading matrix)

Type of problem and dynamic formulation		NNZ / N
A)	Rigid bodies – Global formulations	< 10
B)	Rigid bodies – Recursive formulations Flexible bodies – Component mode synthesis	10 – 30
C)	Flexible bodies – Finite element mesh	30 – 100

- **Effect of sparse pattern diminished**
 - Use of reordering strategies: METIS, AMD...

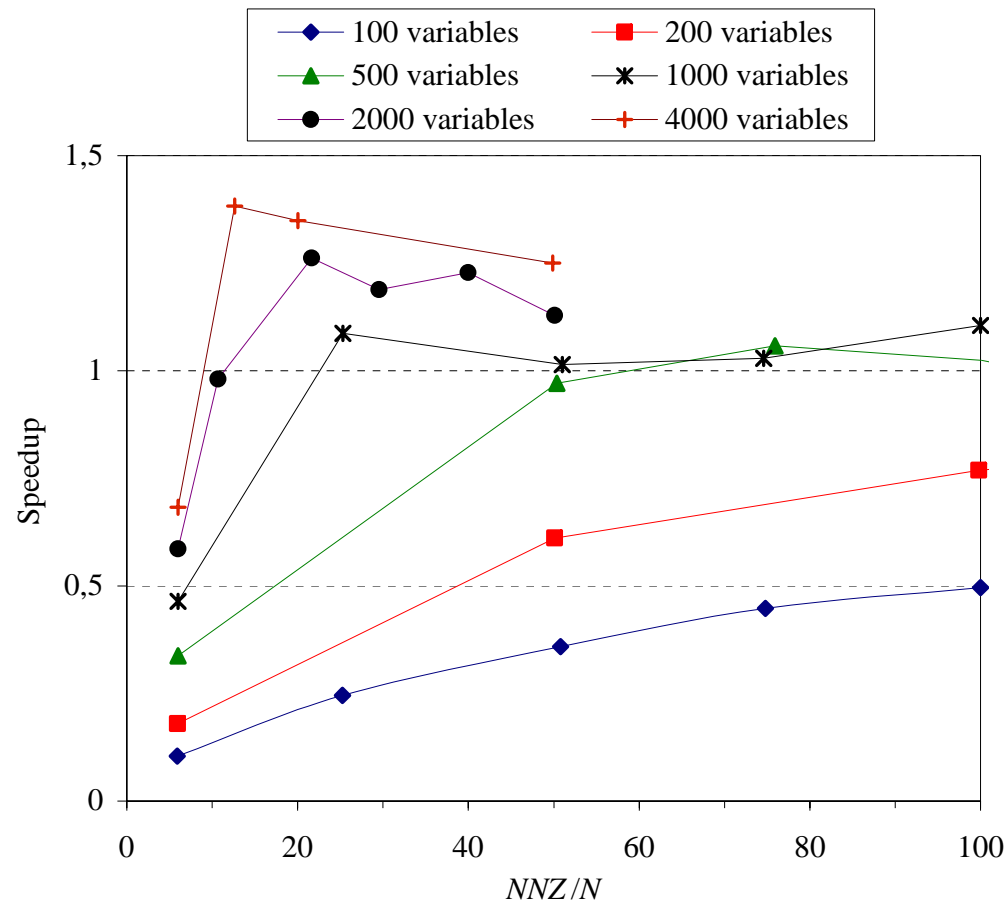
Parallel linear equation solvers: Results

- Best solver as a function of size N and matrix filling NNZ/N



Parallel linear equation solvers: Results

- Speedup of Pardiso (best parallel solver) vs. best sequential solver



$$S = \frac{\textit{elapsed time}_{\textit{sequential}}}{\textit{elapsed time}_{\textit{parallel}}}$$

- Theoretical maximum, for 2 CPUs, is 1.53
- Speedups close to 70% of the theoretical maximum, for $N > 2,000$
- Easy replacement of solvers in code

OpenMP: Description

- Set of compiler directives
 - Guide the compiler to parallelize the code



OpenMP: Description

- Set of compiler directives
 - Guide the compiler to parallelize the code



- Example

Calls 2 functions in parallel

```
void example1()
{
    #pragma omp parallel sections
    #pragma omp section
    function1();
    #pragma omp section
    function2();
}
```

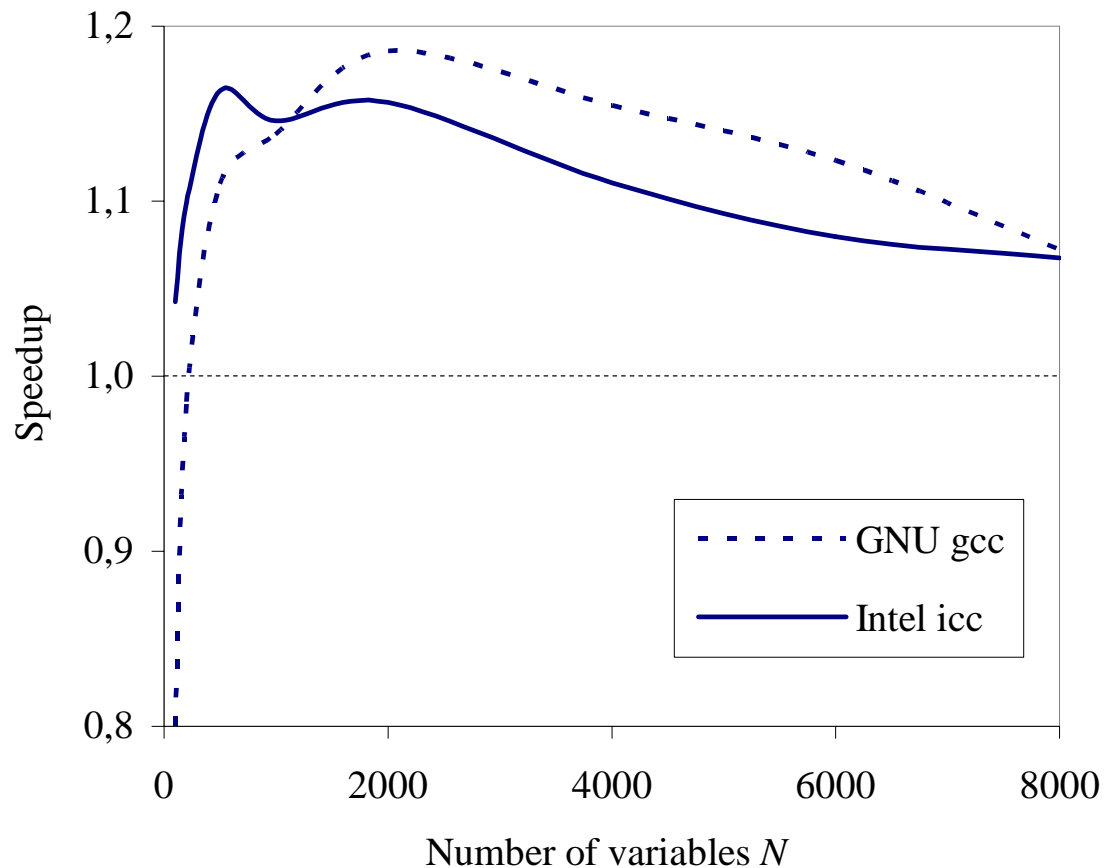
OpenMP: Description

- **Set of compiler directives**
 - Guide the compiler to parallelize the code
- **Advantages (over MPI)**
 - Does not change the design of the code
 - Compiler does the hard work of parallelization in a transparent way
 - Can be applied incrementally
- **Disadvantages (over MPI)**
 - Only supports shared-memory hardware architectures
 - Cannot achieve the same performance as MPI in some cases



OpenMP: Results

- Speedup of the OpenMP parallel implementation



$$S = \frac{\textit{elapsed time}_{\textit{sequential}}}{\textit{elapsed time}_{\textit{parallel}}}$$

- Theoretical maximum, for 2 CPUs, is 1.20
- Speedups close to 90% of the theoretical maximum
- Effect of compiler toolchain

Conclusions

- **OpenMP and parallel linear equation solvers can be used in MBS simulation**
 - Actually non-intrusive and straightforward to implement
 - Can be applied to parallelize existing sequential codes
 - Speedups above 70% of maximum theoretical values
- **Parallel linear equation solvers**
 - Suitable for $N > 2000$ and $NNZ/N > 10$
- **OpenMP**
 - Suitable for $N > 100$

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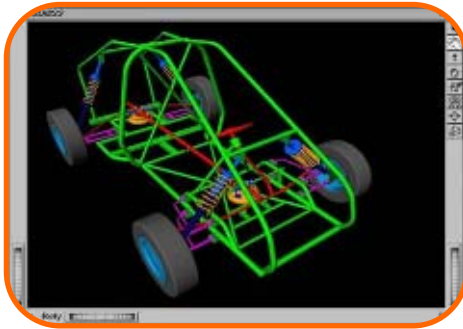
Conclusions and Future Research

Introduction

- Multibody dynamics often needs multiphysics modelling

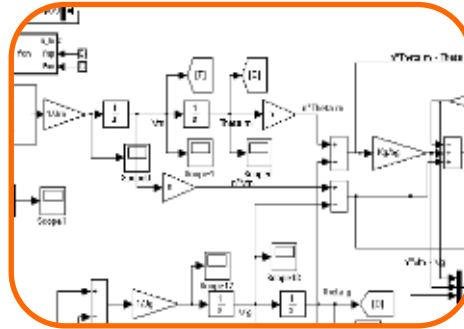


Mechanics

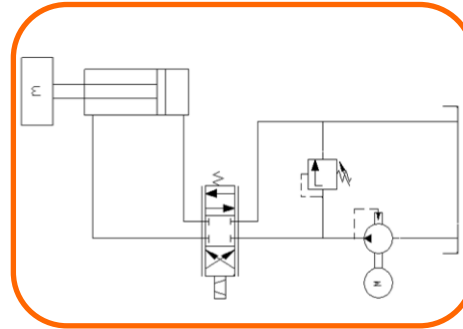


Multibody software

Control



Hydraulics



Other

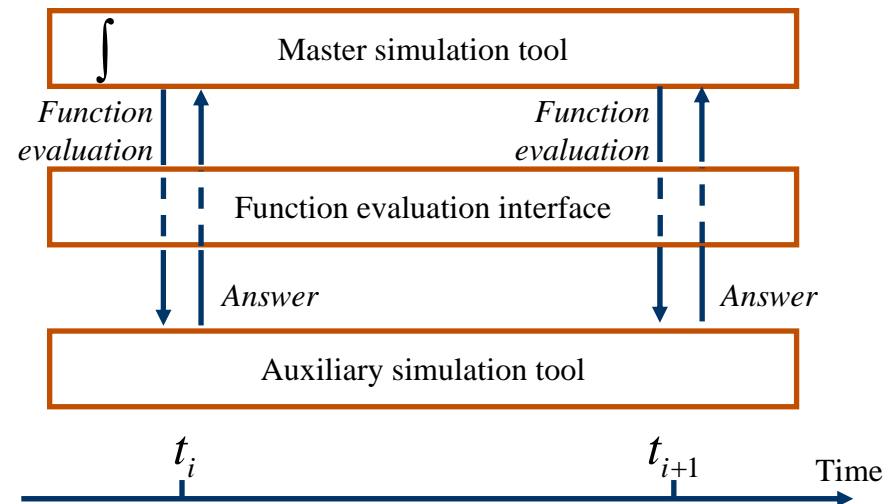


Math tools, block diagram simulators, other software

Communication cases

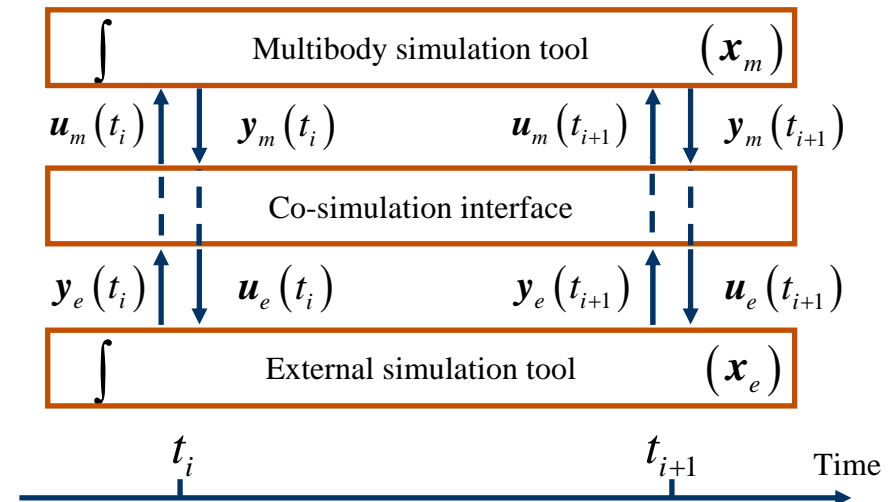
Function evaluation

- MBS software as master
- No numerical integration in auxiliary tool



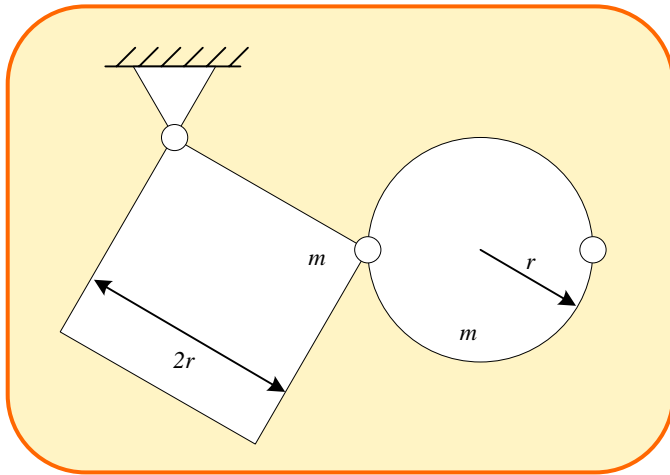
Co-simulation

- Each software package carries out its numerical integration
- Data sharing at defined synchronization points



Function evaluation

- Test problem: dynamic simulation of a double-pendulum (10 s)



- 3 communication techniques:

- MATLAB Engine
- MATLAB Compiler
- MEX functions

Multibody software

Formulation
Integrator

C++ files
- Formulation
- Integrator

MATLAB

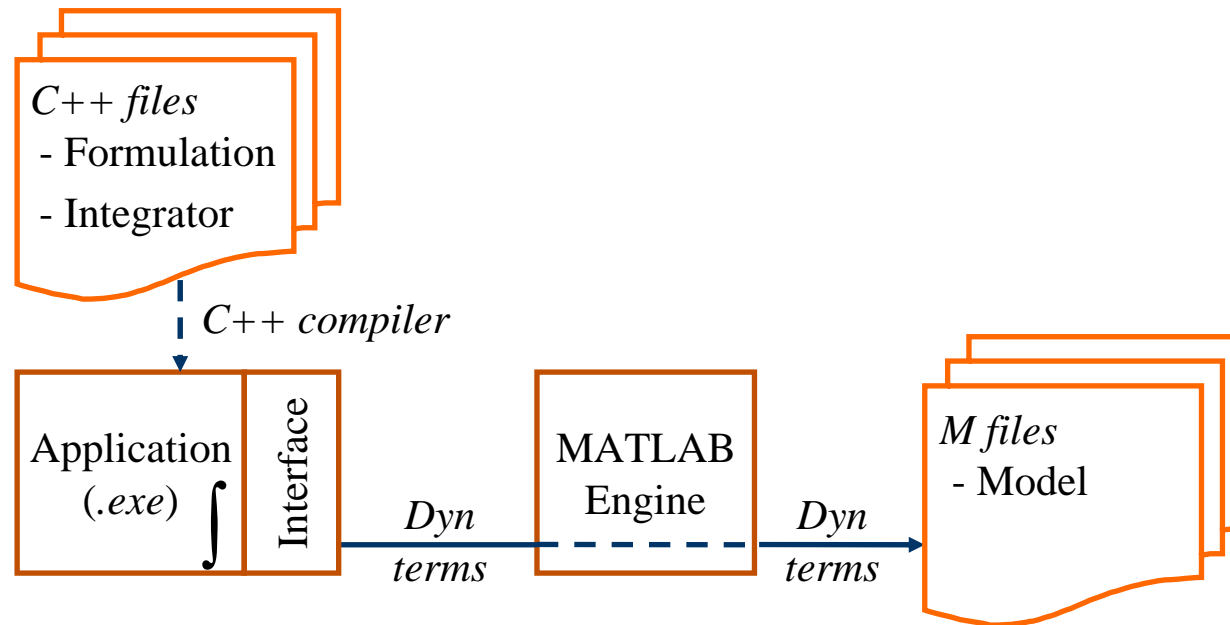
Evaluation
of dynamic
terms

M files
- Model

- Measure CPU times and compare to standalone C++ code

Function evaluation: MATLAB Engine

- **MATLAB Engine**
 - Inter-process communication

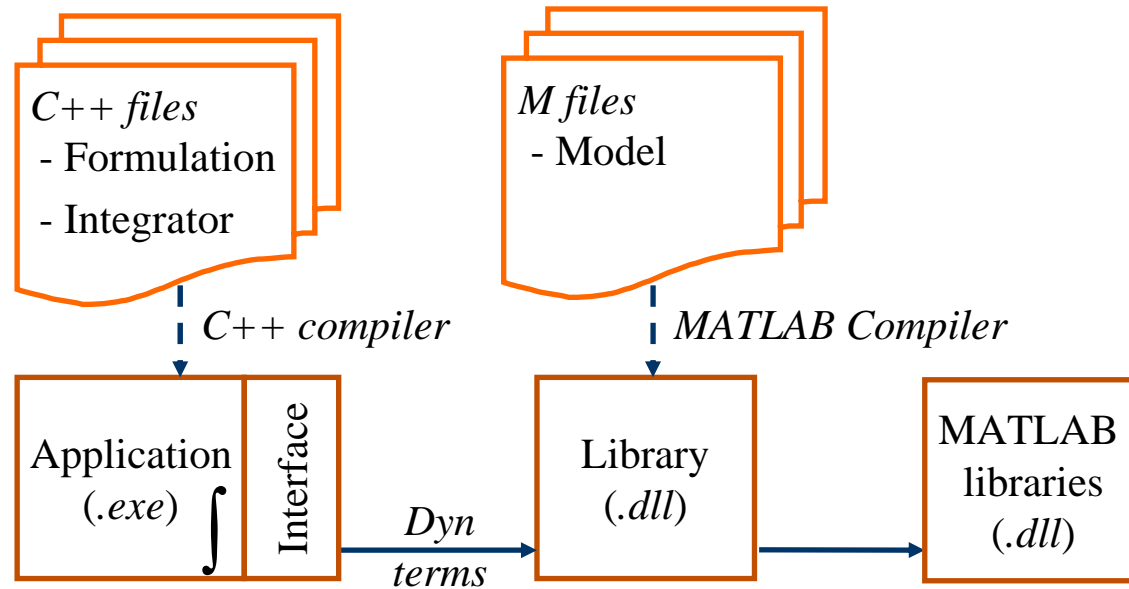


- Easy to implement (direct call to MATLAB)
- Slow: parsing of instructions (overhead about 0.25 ms per call)

Function evaluation: MATLAB Compiler

- **MATLAB Compiler**

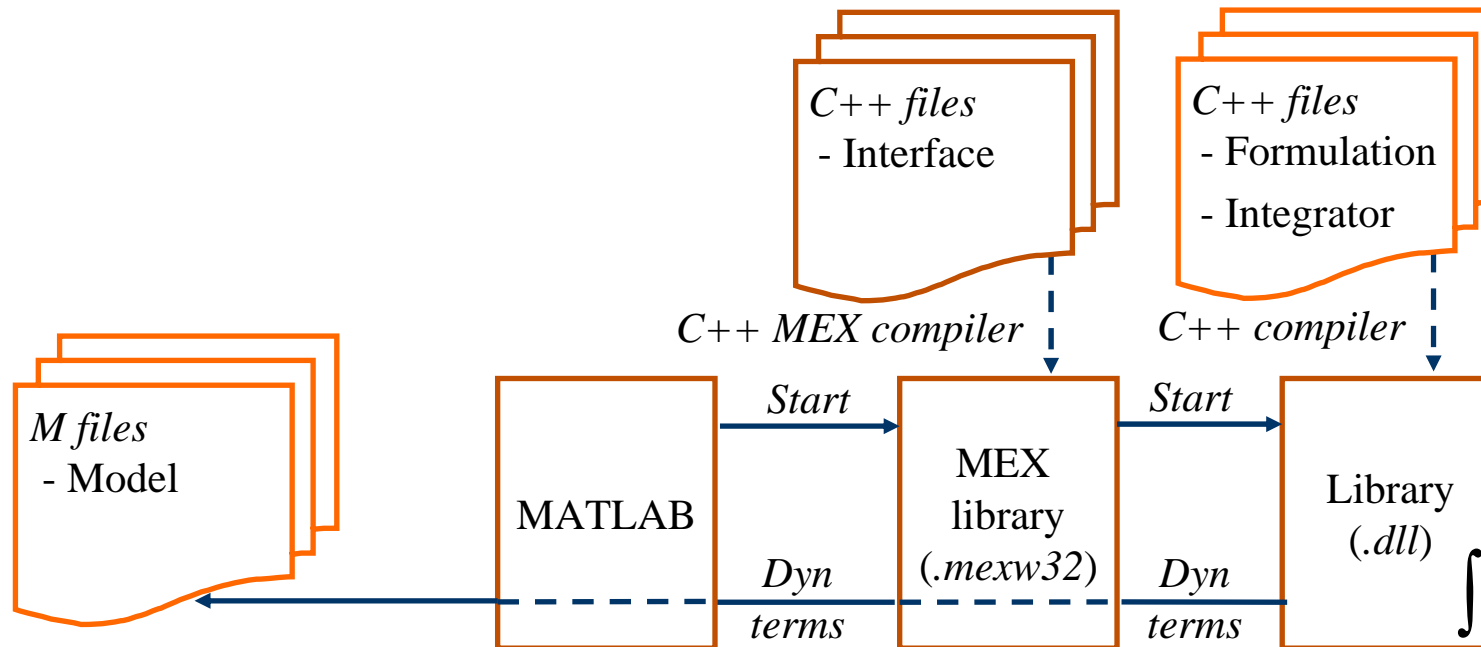
- Invocation of MATLAB code translated to C and compiled into a library



- Claimed to be the fastest method
- Changes in MATLAB code force re-compilation

Function evaluation: MEX functions

- **MEX functions**
 - Originally designed to call C code from MATLAB



- More complex than previous techniques: MEX interface required
- MATLAB code is not compiled

Function evaluation: computational efficiency

- **Comparison of CPU-times**

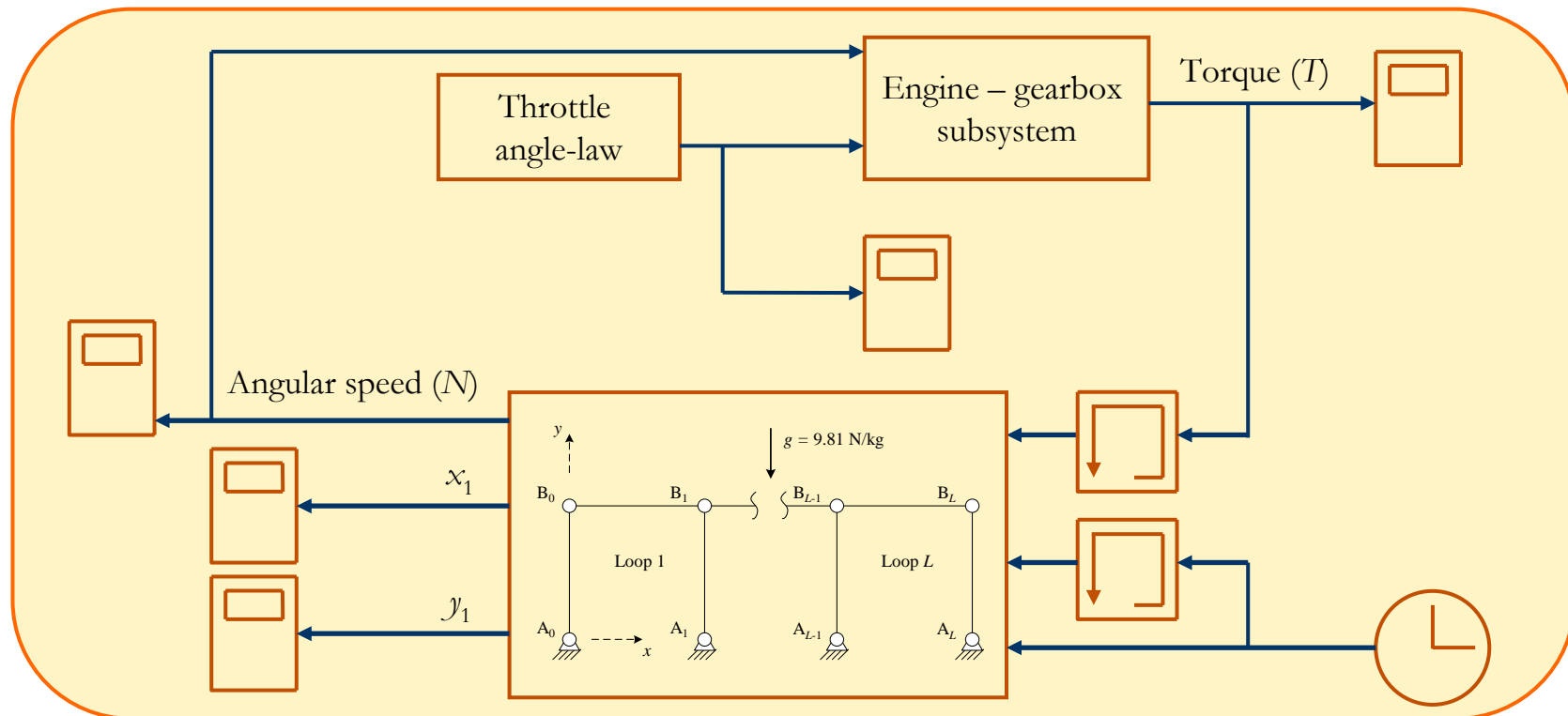
- For two different time-steps ($\Delta t = 10^{-3}$ s and $\Delta t = 10^{-2}$ s)

Method	CPU-time ($\Delta t = 10^{-3}$ s)	Ratio	CPU-time ($\Delta t = 10^{-2}$ s)	Ratio
Standalone MBS code (reference)	$5.02 \cdot 10^{-2}$ s	1	$8.40 \cdot 10^{-3}$ s	1
MATLAB Engine	18.12 s	361.0	3.32 s	395.2
MATLAB Compiler	5.56 s	110.8	1.07 s	127.4
MEX functions	0.64 s	12.7	0.12 s	14.3

- MEX functions are 7 times faster than MATLAB Compiler and 25 than MATLAB Engine

Co-simulation

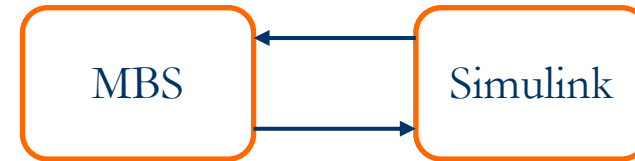
- **Test problem: dynamic simulation**
 - L -loop four-bar linkage (MBS software)
 - Powered by an internal combustion engine (Simulink)



Co-simulation: implementation techniques

- **Network connection**

- Inter-process communication
- Use of TCP/IP sockets



- **Simulink as master**

- MBS code compiled as a .dll
- Embedded in an S-function block



- **MBS as master**

- Simulink model compiled as a .dll
- Use of Real-Time Workshop

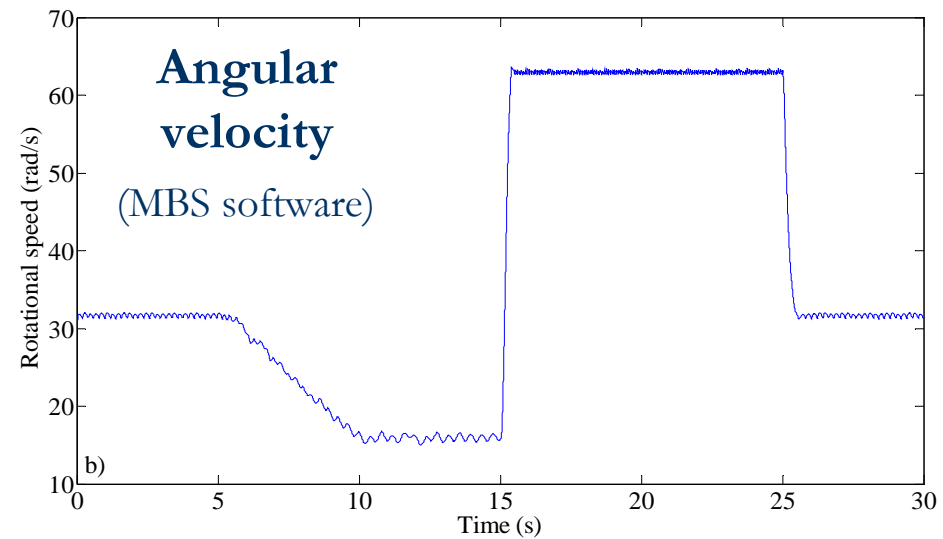
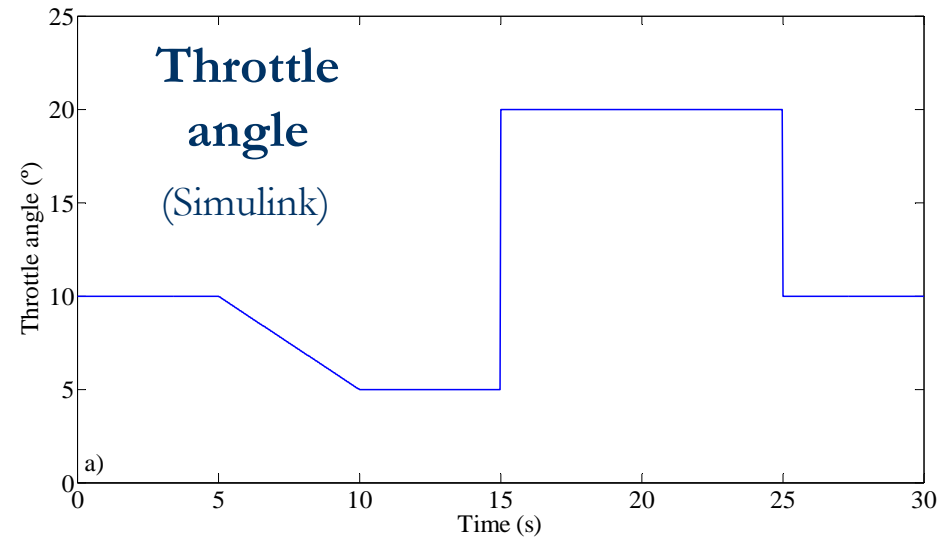


- **Compared to monolithic counterparts**

- Simulink model with SimMechanics elements
- C equivalent compiled with Real-Time Workshop

Co-simulation

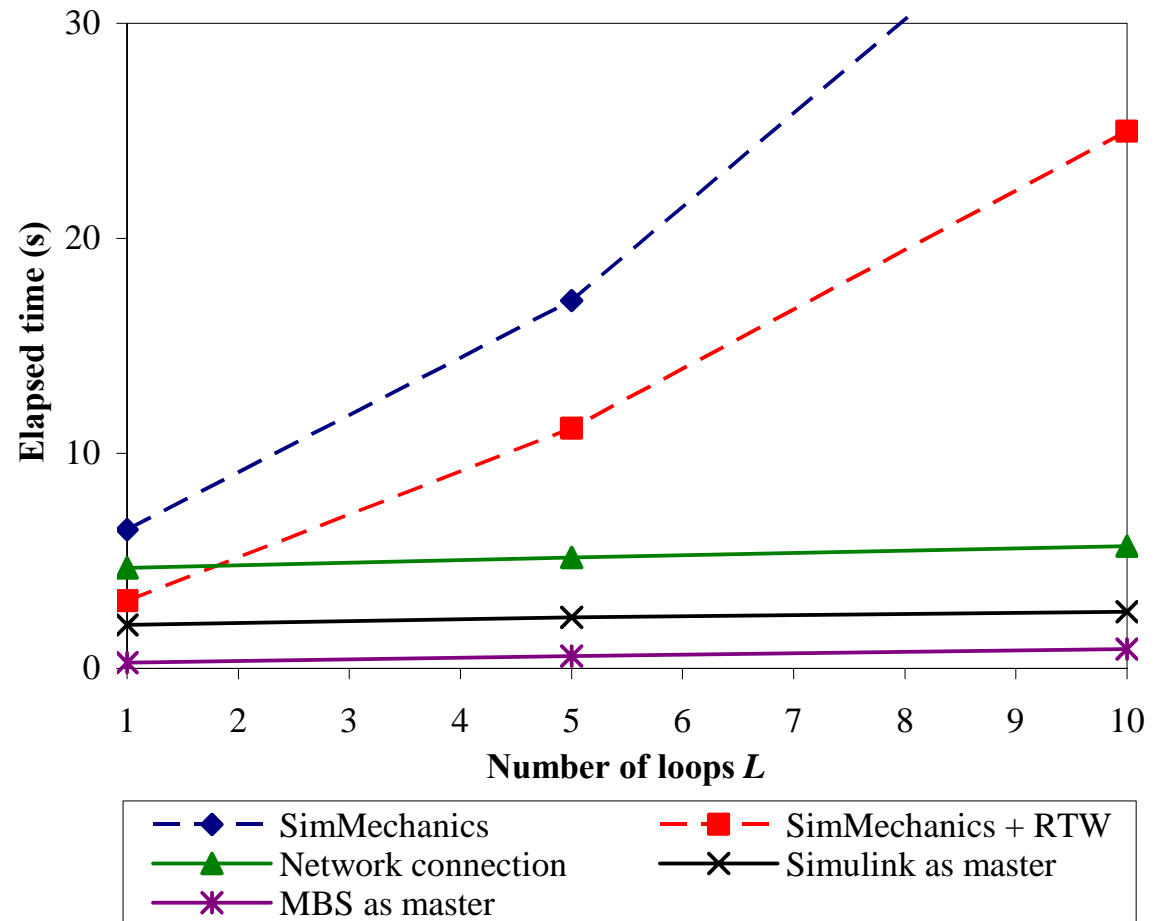
- Dynamic response for a 1-loop mechanism



Co-simulation: computational efficiency

Comparison of CPU-times

- For $\Delta t = 1$ ms
- 30 s simulation



Conclusions

- Different coupling techniques with MATLAB/Simulink have been explored
- **Function evaluation**
 - Recommended use of MEX functions
- **Co-simulation**
 - Able to efficiently simulate models up to 300 global variables
 - *Simulink as master* recommended in development stages (easy to modify)
 - *MBS as master* recommended for real-time applications (efficient)

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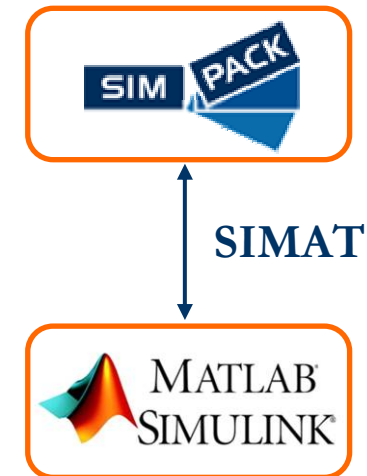
- **Weakly coupled co-simulation**

- Each solver integrates a subsystem
- Commercial packages only allow exchange of data at fixed rates

- **Multirate integration**

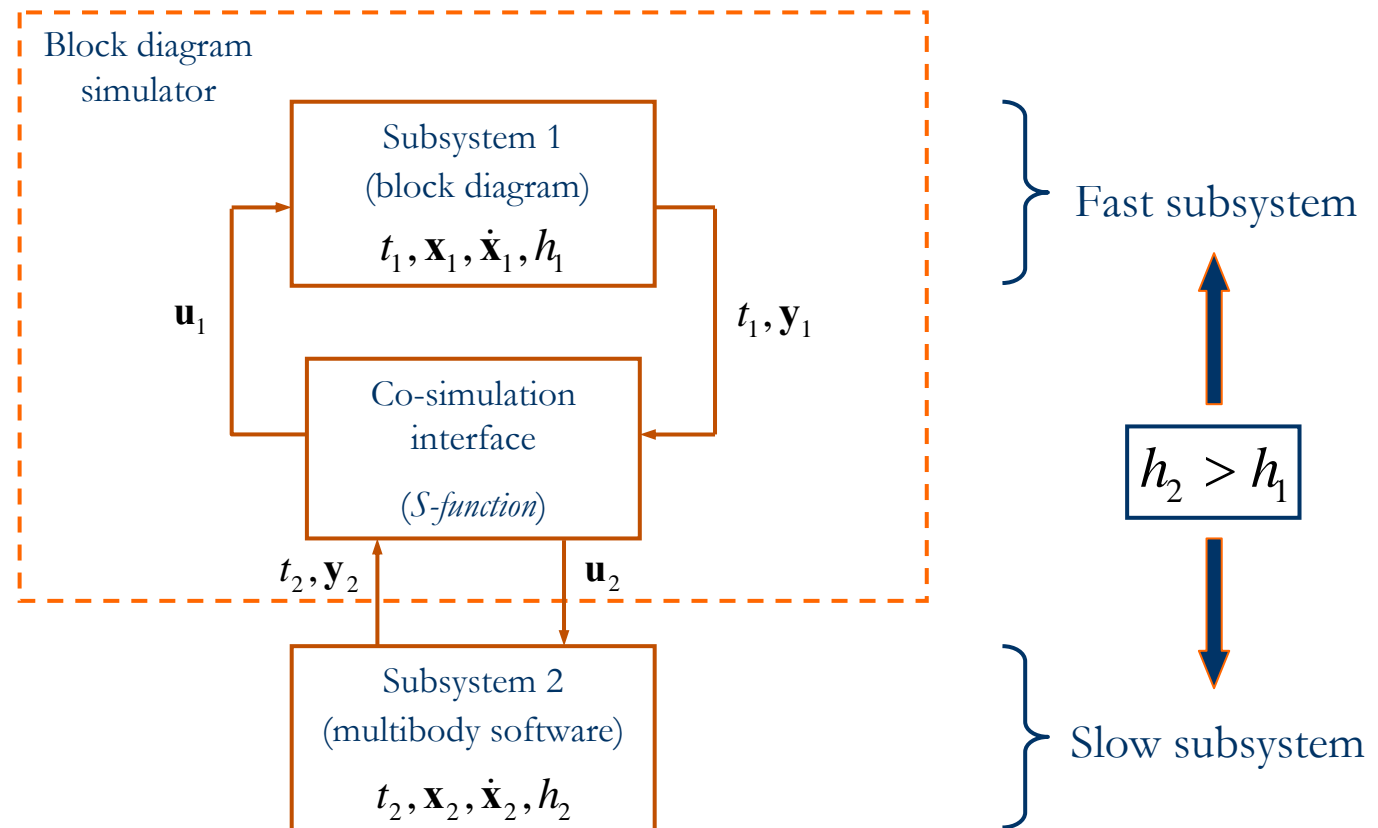
- Different time-steps in each subsystem
- Reduces the elapsed time in simulations
- Difficult to implement with commercial block diagram simulators
 - Non-modifiable integration schemes
 - Iterative coupling schemes cannot be used
 - Variable-step integrators not supported by interfaces

- **Development and test of a multirate co-simulation interface between MBS software and block diagram simulators**



Multirate co-simulation interface

- Weakly coupled co-simulation scheme

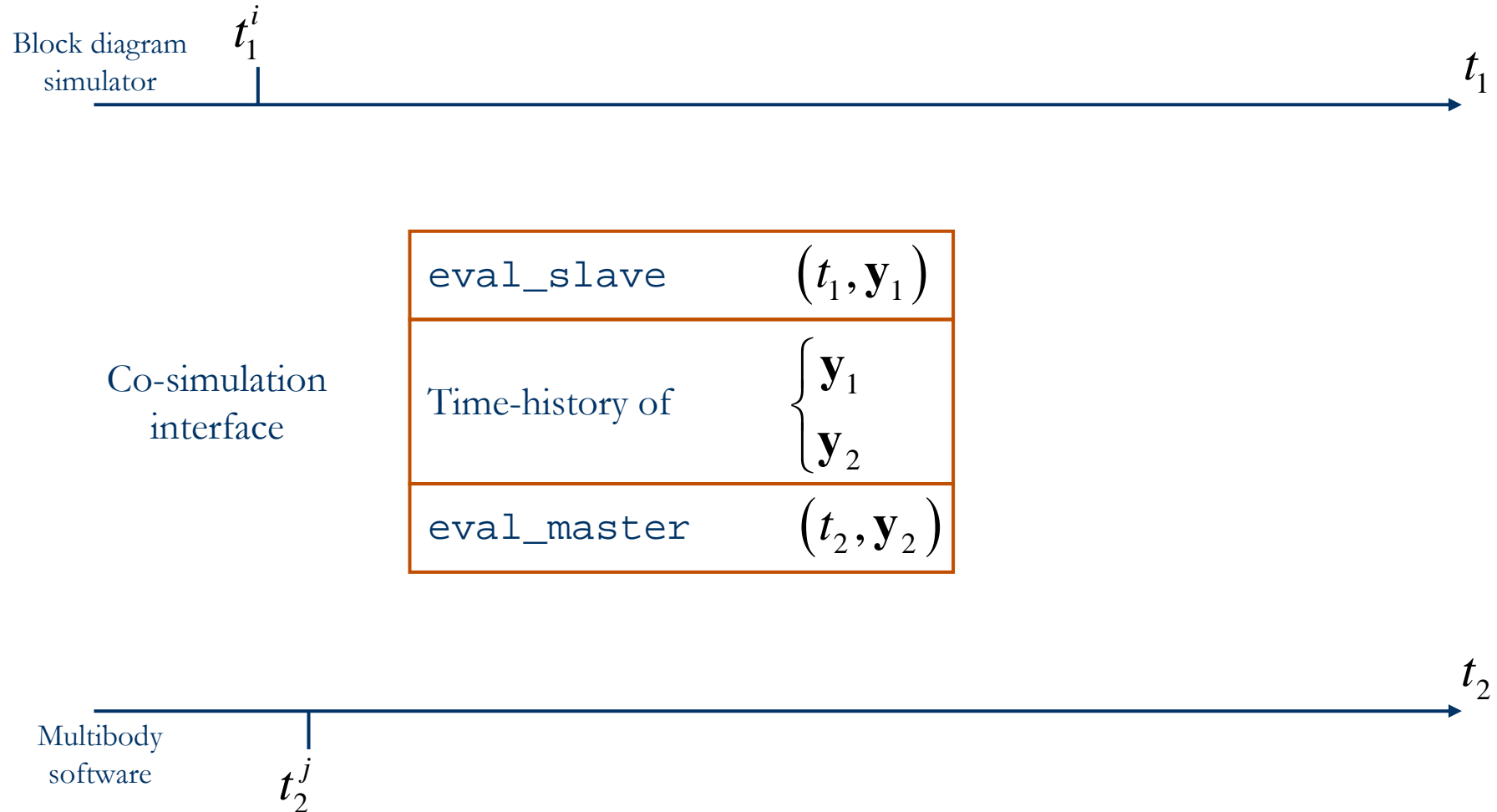


Coupling strategy

- **Two methods:**
 - Slowest-first (*SF*): slow subsystem is ahead in the integration
 - Fastest-first (*FF*): fast subsystem is ahead in the integration
- **Interpolation / Extrapolation polynomials used for approximating the values of the inputs between time-steps**
- **Smoothing:**
 - Averaging of the outputs of the fast subsystem during a time-step of the slow one

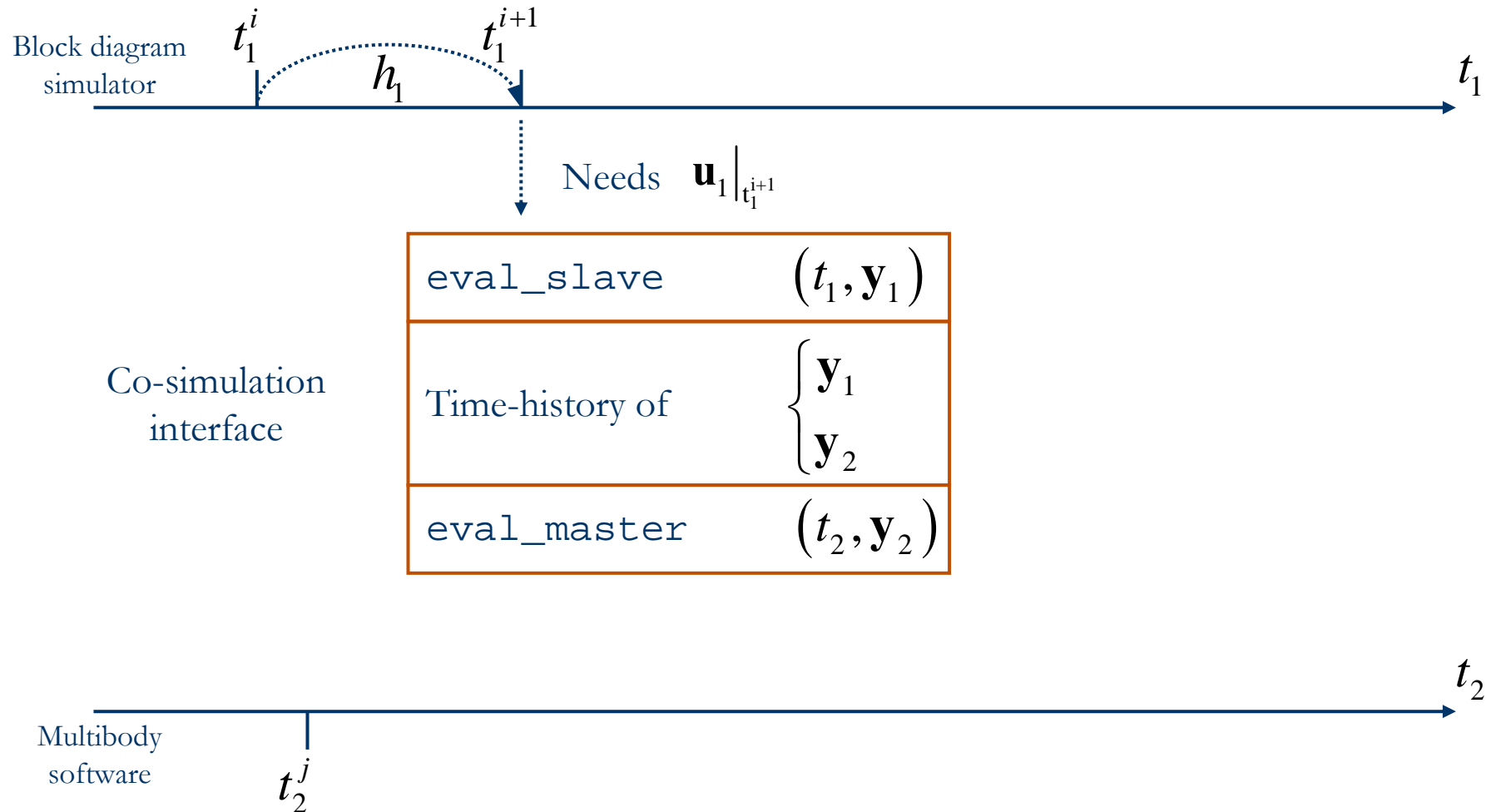
Coupling strategy

- Initial situation (*slowest-first* configuration)



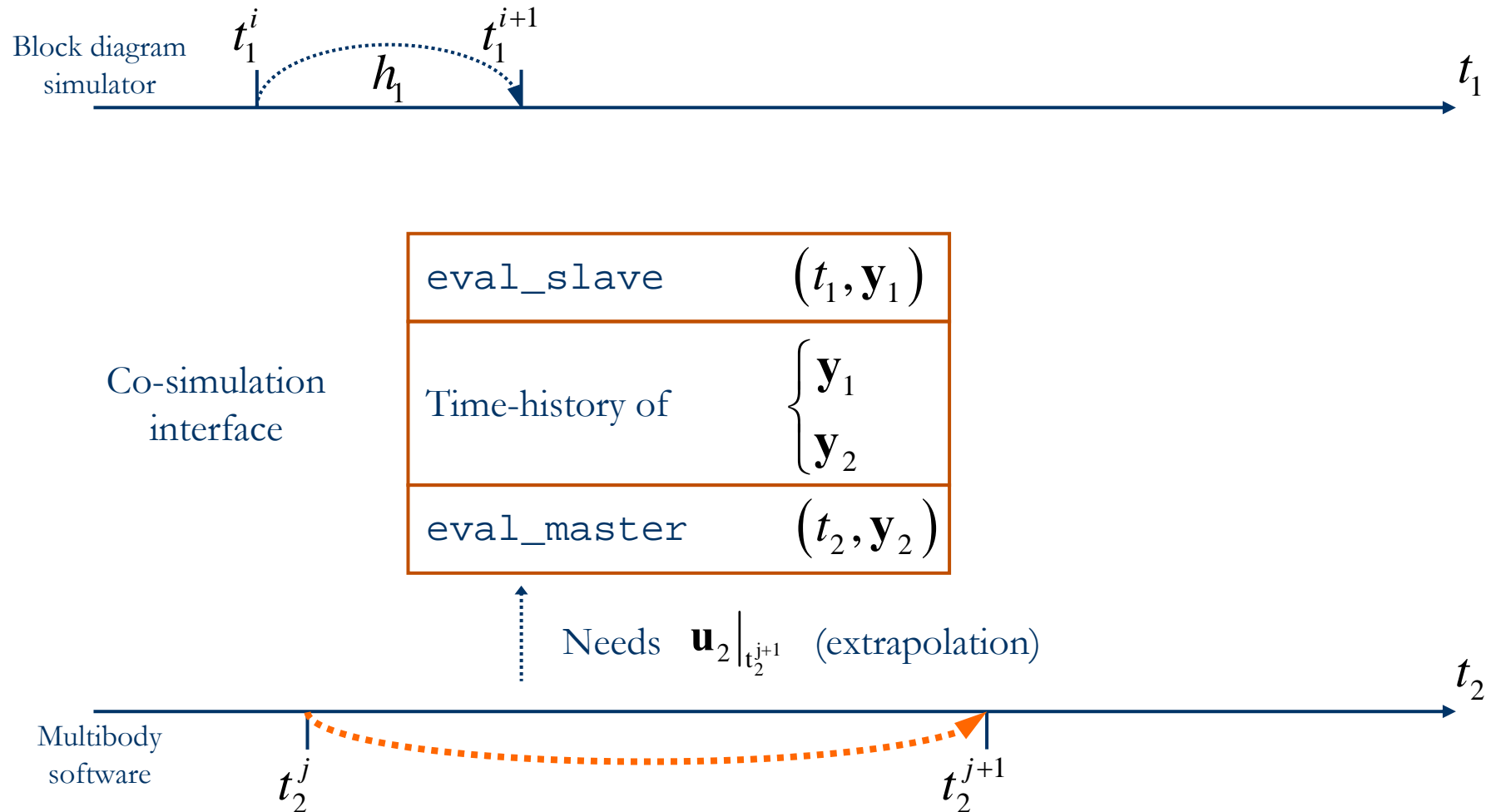
Coupling strategy

- Block diagram simulator starts a time-step (h_1)



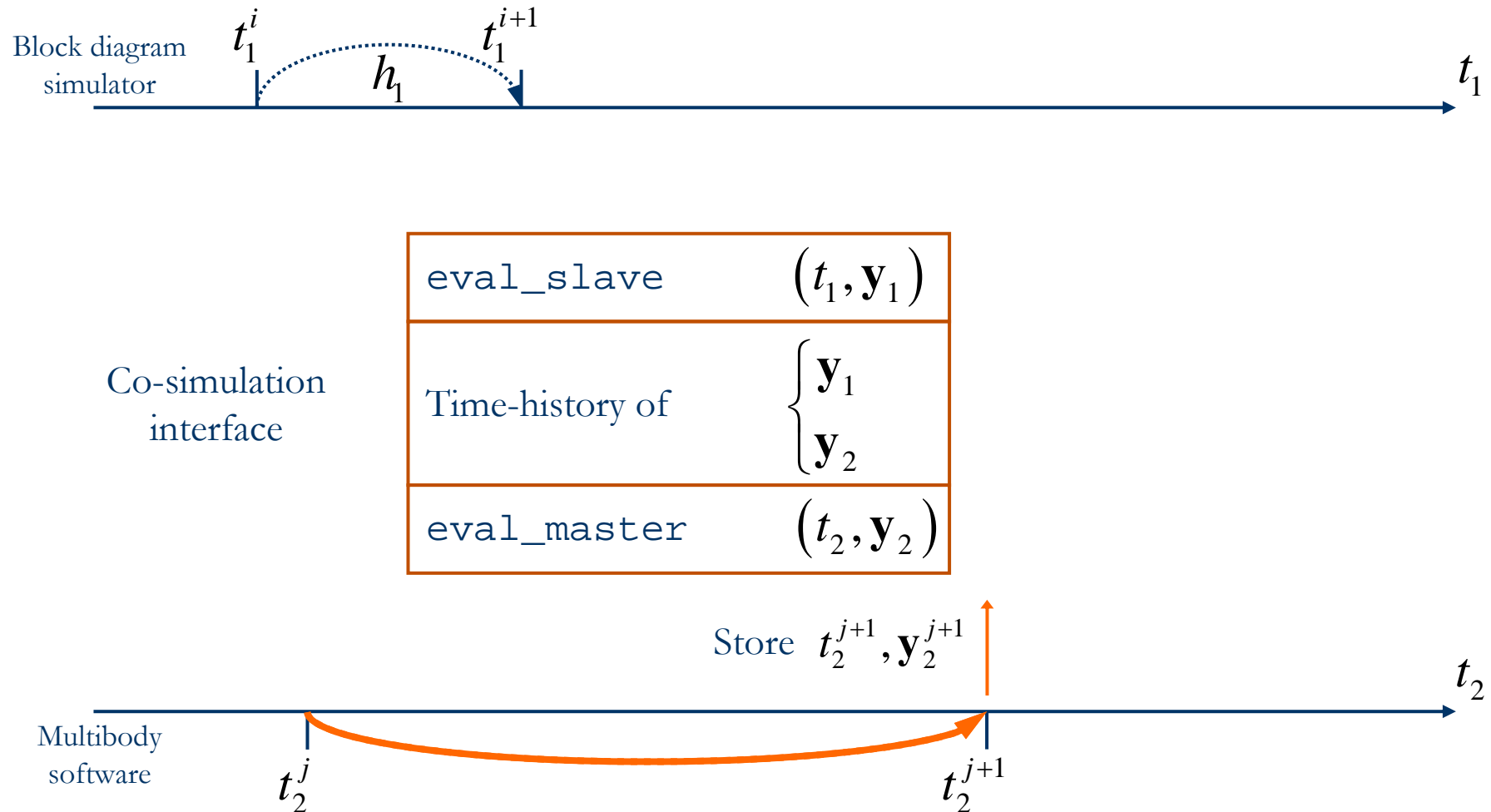
Coupling strategy

- MBS software advances a time-step (h_2)



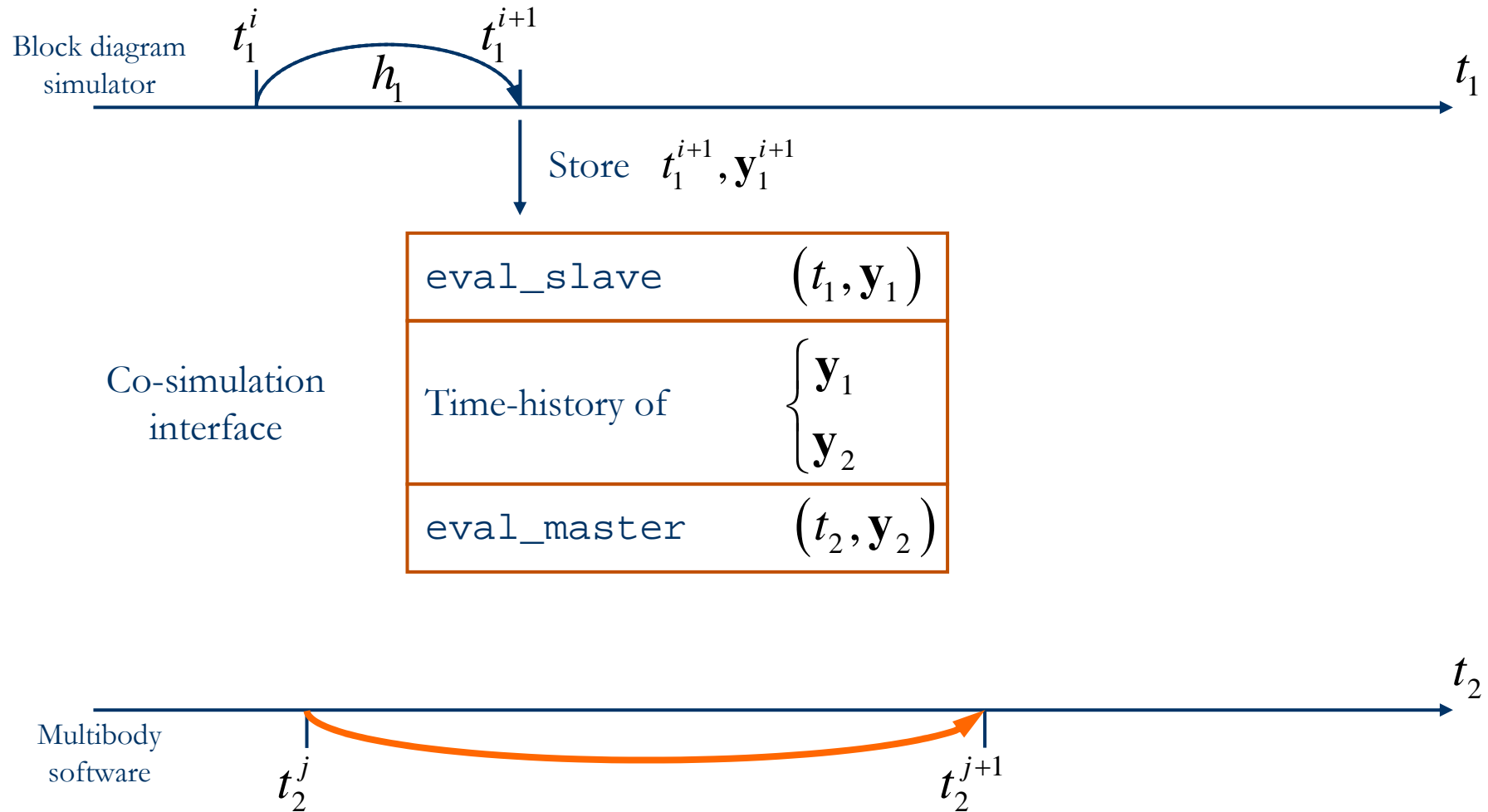
Coupling strategy

- MBS software advances a time-step (h_2)



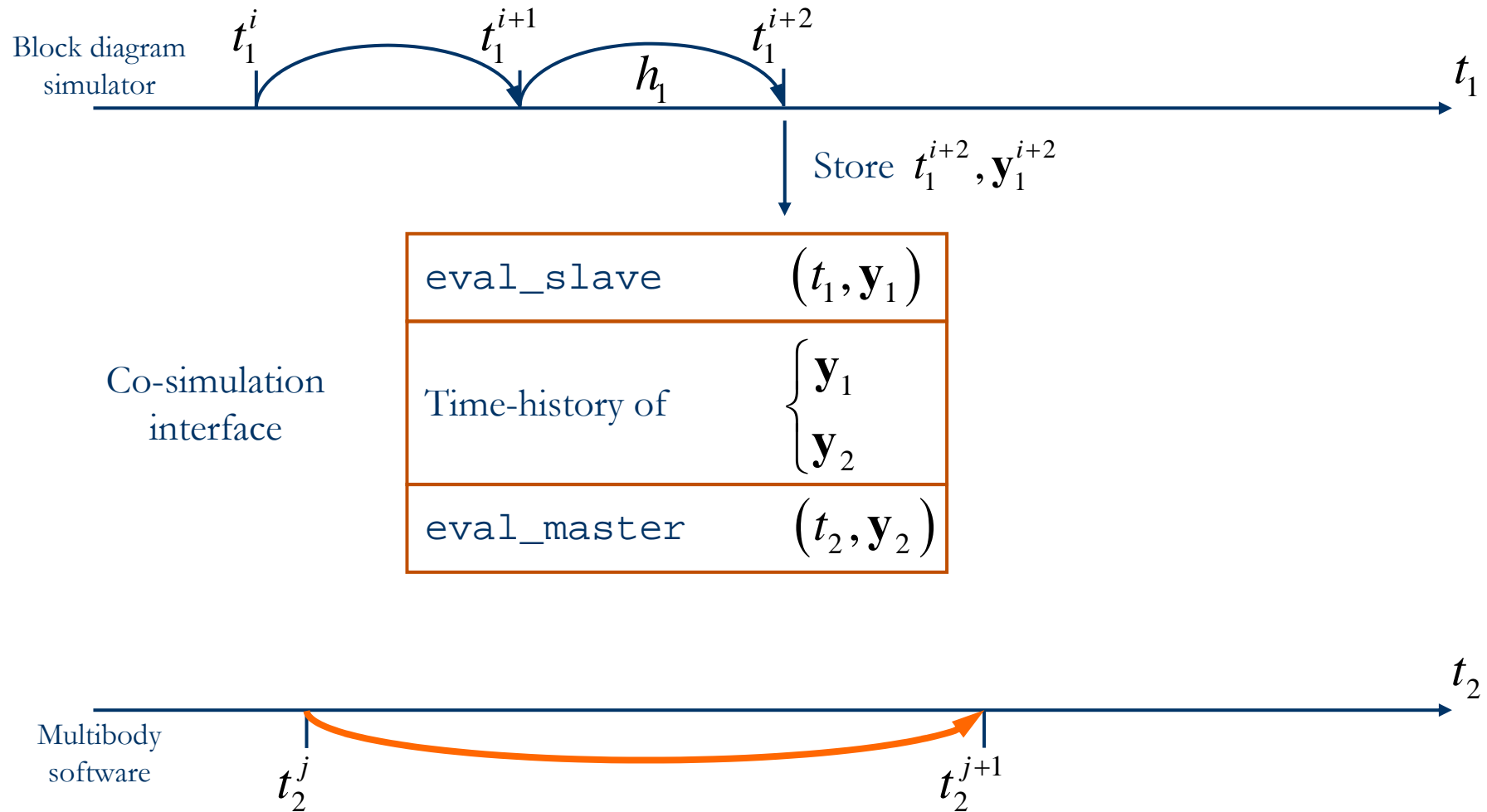
Coupling strategy

- The block diagram simulator can resume its time-step



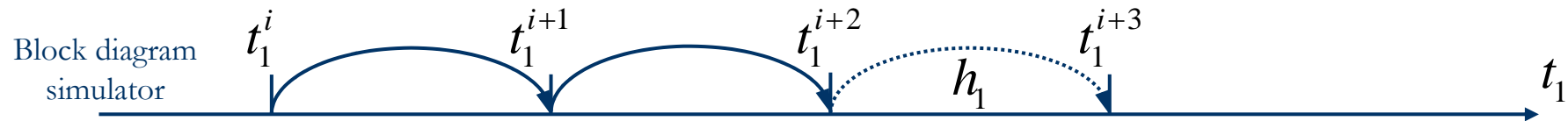
Coupling strategy

- And more time-steps can be taken



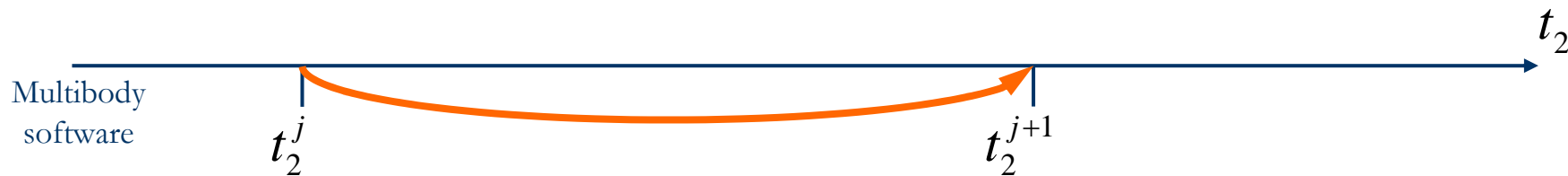
Coupling strategy

- And the process starts again...



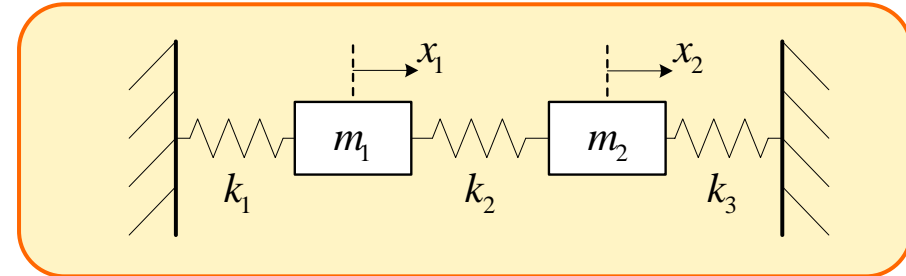
Co-simulation interface

eval_slave	(t_1, \mathbf{y}_1)
Time-history of	$\begin{cases} \mathbf{y}_1 \\ \mathbf{y}_2 \end{cases}$
eval_master	(t_2, \mathbf{y}_2)



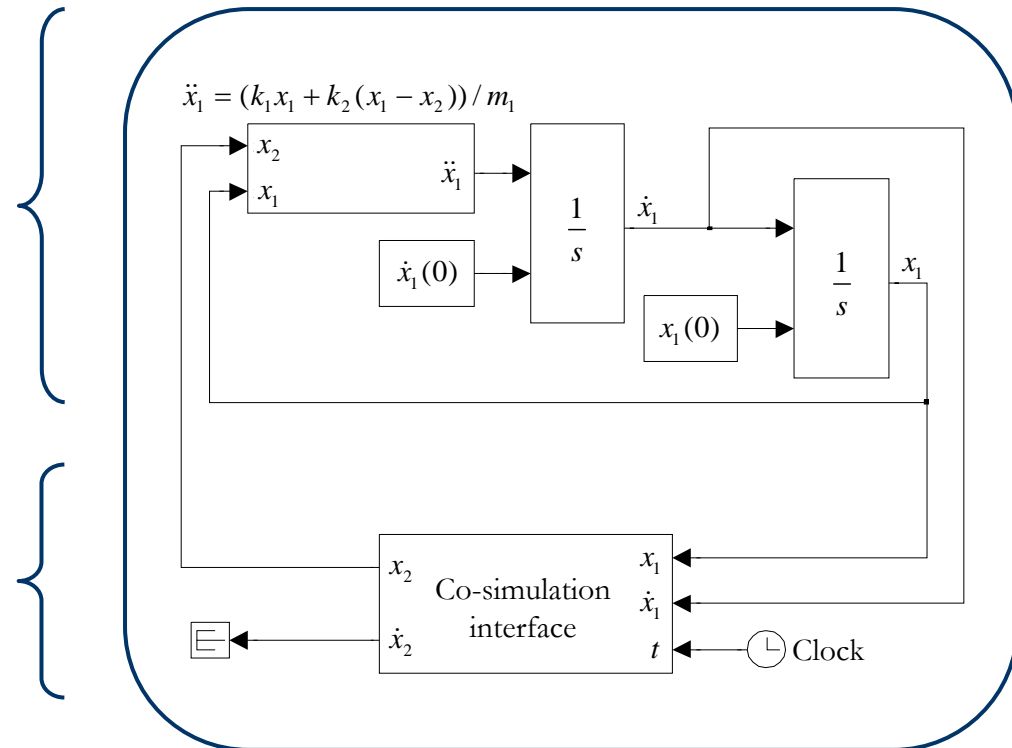
Test problem: modelling approach

- Double-mass, triple-spring assembly (linear system)
- Purely mechanical



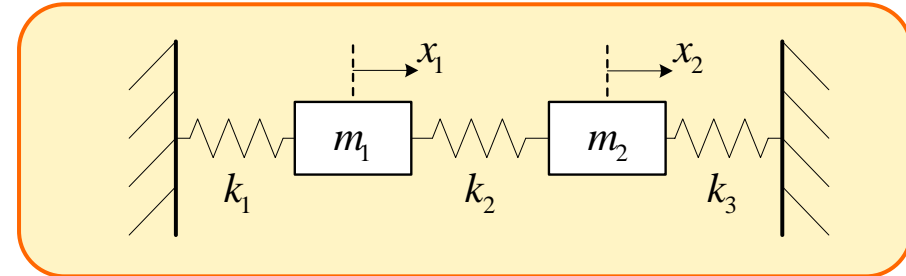
m_1 : Simulink

m_2 : MBS software embedded in *S-function* block



Test problem

- **Known analytical solution**
(reference to measure error in position and energy)



- **Simulation: 100 cycles of the fast subsystem**

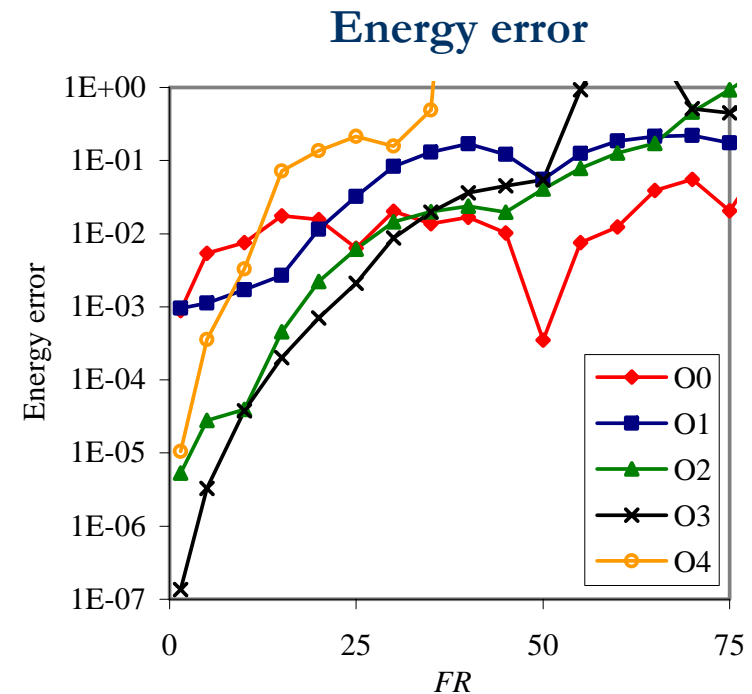
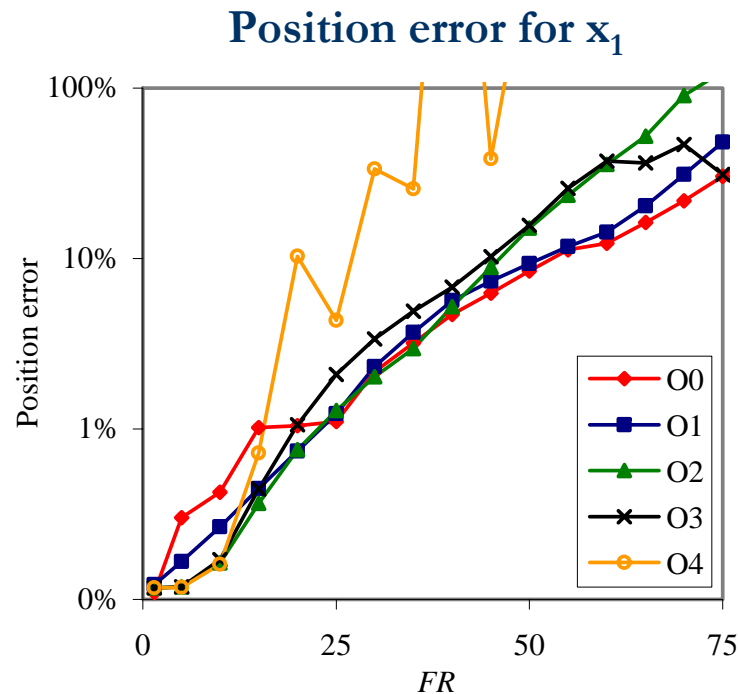
$$\begin{cases} x_1(t) = C_{11} \cdot \cos(\omega_1 t) + C_{13} \cdot \cos(\omega_2 t) \\ x_2(t) = C_{21} \cdot \cos(\omega_1 t) + C_{23} \cdot \cos(\omega_2 t) \end{cases}$$

- **Different co-simulation strategies evaluated in a sweep of FR**
 - FR varies from 1.5 to 100

$$FR = \omega_1 / \omega_2 \approx h_2 / h_1$$

Test problem: results

- There is not a 'general purpose' technique valid for every FR
- SF is suitable for $FR < 50$
 - With cubic interpolation (O3) for $FR < 25$
 - Without interpolation (O0) for $25 < FR < 50$



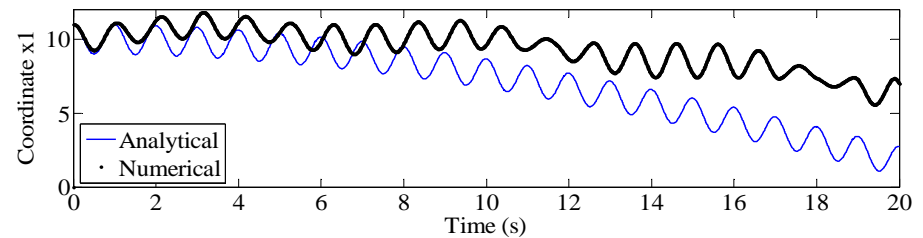
Test problem: results

- For $FR > 50$
 - SF scheme increases position error (phase error)
 - FF scheme increases energy error (amplification/attenuation)

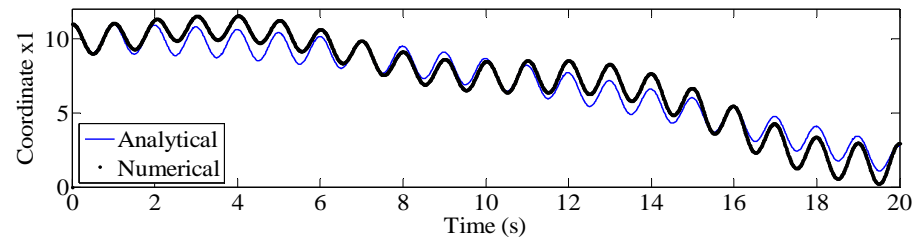
- Smoothing techniques can reduce error for certain combinations of FR and interpolation order

$FR = 90$

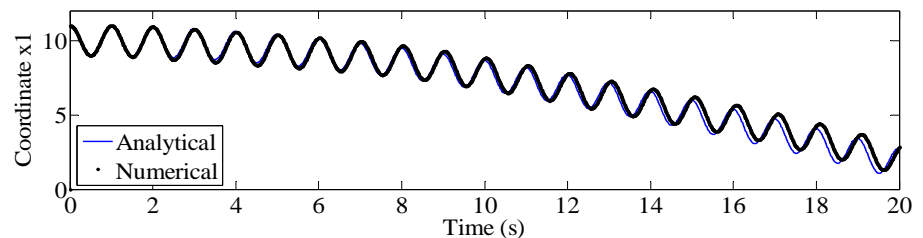
SF
+
 $O0$



FF
+
 $O3$

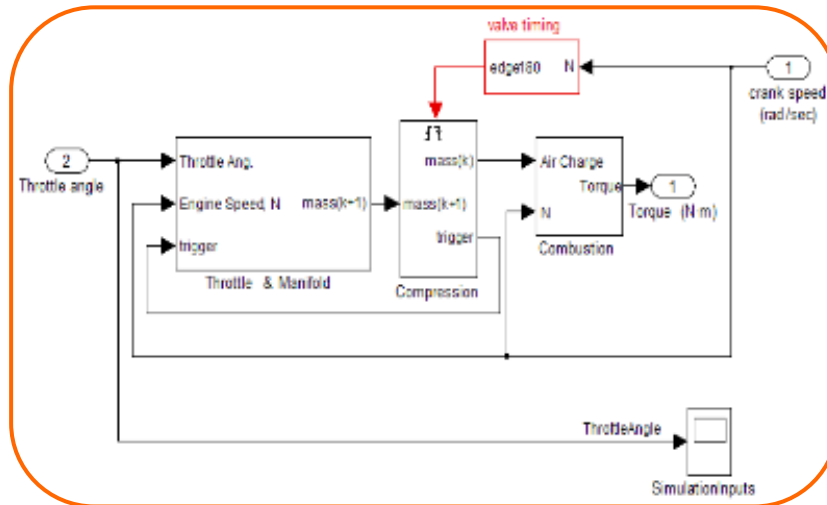


Smoothing
+
 $O3$

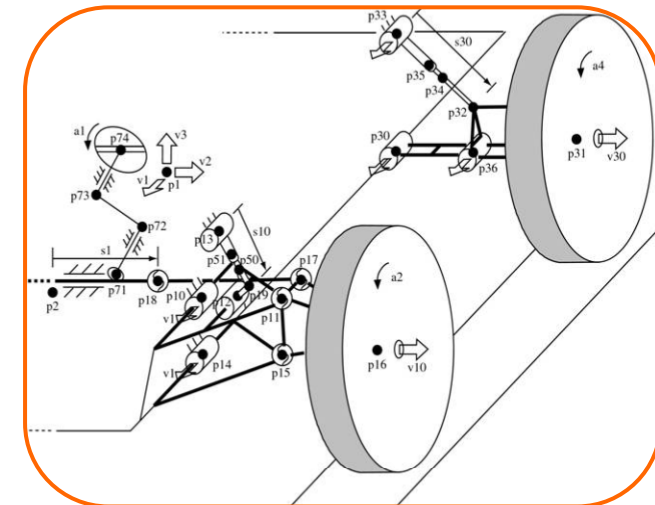


Application to a multiphysics problem

- Simulink model of a thermal engine + MBS model of a kart



$$h_1 = 0.1 \text{ ms}$$



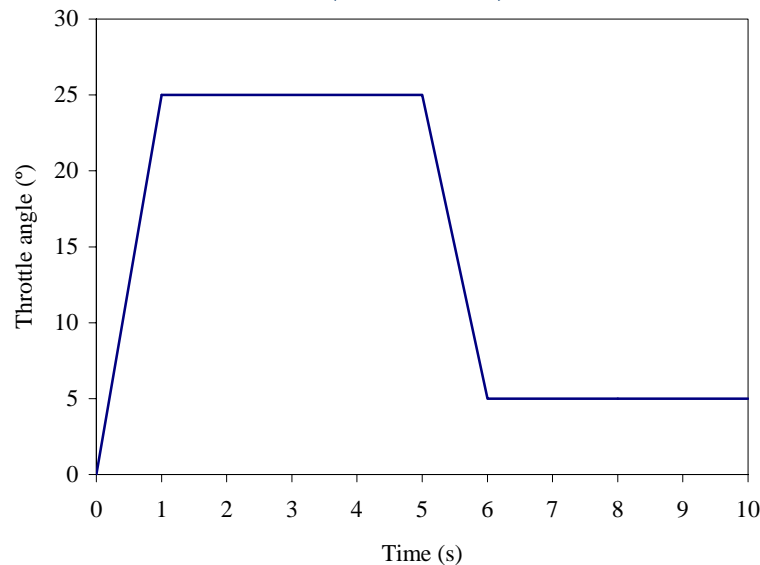
$$h_2 = 10 \text{ ms}$$



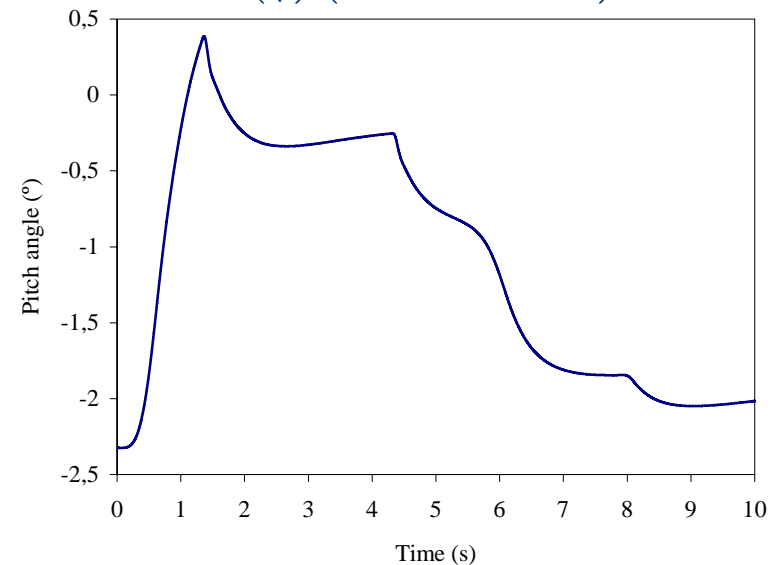
Application to a multiphysics problem

- 10 s simulation

Input: angle law of throttle pedal
(Simulink)



Output: pitch angle of vehicle
(ψ) (MBS software)



- Reference simulation: $h_1 = h_2 = 0.1$ ms ($FR = 1$; ∞)

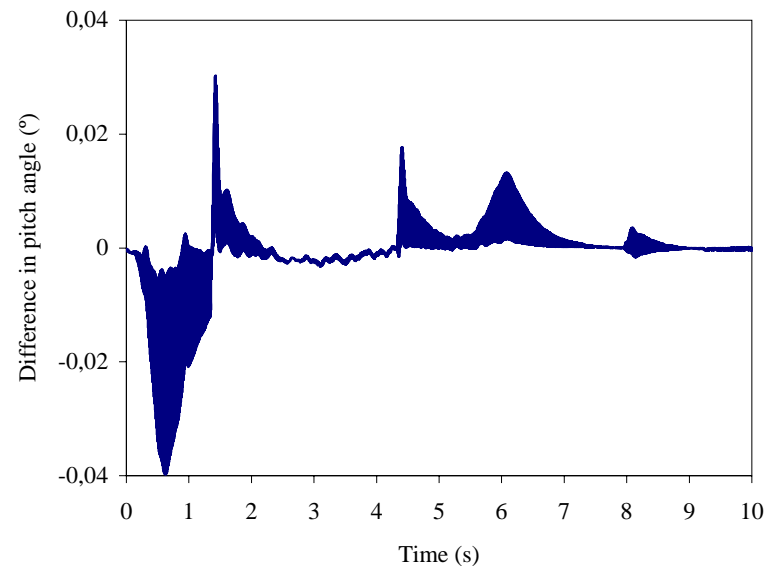
- Elapsed time: 158.4 s

Application to a multiphysics problem

- Simulation with multirate techniques (increase of h_2 up to 10 ms)
- Measurement of deviations with respect to reference pitch ($\Delta\psi$)

	FR = 1	FR = 5	FR = 10	FR = 50	FR = 100
Elapsed time (s)	158.4	44.8	30.4	19.0	17.1
$\Delta\psi$ (°)	0	0.0031	0.0055	0.0252	0.0398

FR = 100



SF

OO (Simulink)

OO (MBS)

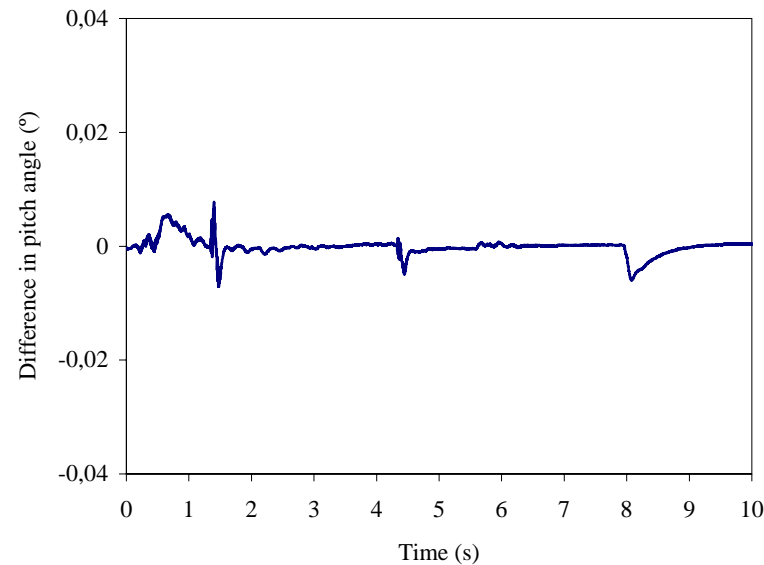
$\Delta\psi_{\max} = 0.0398$

Application to a multiphysics problem

- Simulation with multirate techniques (increase of h_2 up to 10 ms)
- Measurement of deviations with respect to reference pitch ($\Delta\psi$)

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FR = 100



FF

O0 (Simulink)

O1 (MBS)

$\Delta\psi_{\max} = 0.0078$

Conclusions

- **A multirate co-simulation interface has been implemented and tested, which allows the use of**
 - Different interpolation/extrapolation polynomial orders
 - Fastest-first and slowest-first integration schemes
 - Smoothing
- **Use of the interface demonstrated**
 - In a simple example with analytical solution
 - In a complex multiphysics model
- **Multirate techniques enable reductions in simulation time (up to a factor of 9, in the shown example) with acceptable derived errors**
- **A way of finding the best co-simulation strategy beforehand is desirable**

Outline

Introduction

Software Architecture for MBS Simulation

Linear Algebra Implementations

Parallelization

Integration with MATLAB/Simulink

Multirate Co-simulation Methods

Conclusions and Future Research

Conclusions and future research

- **A modular software tool for MBS dynamic simulation has been built**
 - Open-source, object-oriented, implemented in C++
 - Extensible, through the addition of new modules
- **Optimization of MBS simulation codes explored through**
 - Streamlining of linear algebra routines
 - Non-intrusive parallelization
 - Communication with math software and block diagram simulators
 - Multirate integration

Conclusions and future research

- **Future research lines will focus on**
 - Assessment of the validity of the tested optimization techniques in recursive and semi-recursive formulations
 - Co-simulation of complex multiphysics systems
 - Research on a way to determinate beforehand the optimal co-simulation scheme when multirate techniques are introduced
 - Definition of general purpose indicators of the quality of the results of the co-simulation

Publications

- The research conducted in this thesis has yielded the following papers
 - M. González, F. González, D. Dopico and A. Luaces. On the effect of linear algebra implementations in real-time multibody system dynamics. *Computational Mechanics*, 41(4):607-615. 2008.
 - F. González, A. Luaces, U. Lugrís and M. González. Non-intrusive parallelization of multibody system dynamic simulations. *Computational Mechanics*, 44(4):493-504. 2009.
 - F. González, M. González and A. Mikkola. Efficient coupling of multibody software with numerical computing environments and block diagram simulators. *Multibody System Dynamics*, online first. 2010.
 - F. González, M.A. Naya, A. Luaces and M. González. On the effect of multirate co-simulation techniques in the efficiency and accuracy of multibody system dynamics. Submitted to *Multibody System Dynamics* in March, 2010 (undergoing revision process).

EFFICIENT IMPLEMENTATIONS AND CO-SIMULATION TECHNIQUES IN MULTIBODY SYSTEM DYNAMICS

Francisco Javier González Varela

Doctoral thesis

University of A Coruña

Ferrol, May 3rd, 2010

LIM



Laboratorio de Ingeniería Mecánica
Universidade da Coruña

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