Automated Verification of Cyber-Physical Systems A.A. 2023/2024

Simulation of Systems

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Simulation vs Model Checking

- In "standard" Model Checking, we are given
 - a non-deterministic Kripke Structure (KS)
 - an LTL or CTL property to be verified
- The output is either PASS or FAIL
 - if PASS, then all evolutions (paths) of the given model fulfill the given property
 - if FAIL, we also have a counterexample
- In probabilistic model checking, we consider probabilities of sets of evolutions
- Simulation of a system only considers one path





Murphi Simulation

```
\mathbf{void} Make_a_run(NFSS \mathcal{N}, invariant \varphi)
 let \mathcal{N} = \langle S, I, \text{Post} \rangle;
 s_curr = pick_a_state(I);
 if (!\varphi(s\_curr))
  return with error message;
 while (1) { /* loop forever */
  if (Post(s_curr) = \emptyset)
    return with deadlock message;
  s_next = pick_a_state(Post(s_curr));
  if (!\varphi(s_next))
    return with error message;
  s_curr = s_next;
```



SPIN Simulation

```
void Make_a_run(NFSS \mathcal{N})
 let \mathcal{N} = \langle S, \{s_0\}, \text{Post} \rangle;
 s_curr = s_0;
 if (some assertion fail in s_curr))
  return with error message;
 while (1) { /* loop forever */
  if (Post(s_curr) = \emptyset)
   return with deadlock message;
  s_next = pick_a_state(Post(s_curr));
  if (some assertion fail in s_curr))
   return with error message;
  s_curr = s_next;
```



Repeating a Simulation

- Simulations may be deterministic or probabilistic
 - both Murphi and SPIN simulations are probabilistic
 - at each step, a transition is chosen among the *n* possible ones with probability $\frac{1}{n}$
 - of course, *n* may be different at each step
- Running multiple probabilistic simulations typically implies obtaining different paths
 - the longest the path, the more likely this is to happen





Repeating a Simulation

- For deterministic simulations, all runs are the same
 - multiple simulations all result in the same path
- Deterministic simulation are however important when *inputs* from the environment are present
 - this is actually true for many systems
 - some inputs must be given an system startup, others must be given during the system evolution
- Running multiple simulation result in different paths if we vary the inputs to be received
 - this is actually true for many systems
- We of course may have inputs from the environment also in probabilistic simulations

Simulation

- Similar to testing
- If an error is found, the system is bugged
 - or the model is not faithful
 - actually, simulation in standard model checking is also used to understand if the model itself contains errors
- If an error is not found, we cannot conclude anything
- The error state may lurk somewhere, out of reach for the random choice in pick_a_state



Simulation vs Modeling

- However, for complex CPSs simulation is needed
- In fact, accurately modeling a complex CPS in a classical model checker is often too difficult or inconvenient
 - plant must be modeled by real variables: inherently infinite state systems
 - can be approximated, but accuracy may be low
- Simulators are often already available for testing, why can't we rely on them?
 - o not "real" model checking, but something close to it
 - far better than "simple" testing
- May be either build from scratch, or implemented with dedicated tools
 - C/Java/Python dedicated programs vs. Simulink/Modelica

Simulation-based Model Checking

- Too many states, we cannot store them in an hash table
 - transition relation defined by a complex simulator, translation in OBDDs cannot be done
- Two main workhorses:
 - System Level Formal Verification chooses system inputs so as to cover as much as possible
 - mainly for safety, but also some sort of LTL may be used
 - Statistical Model Checking uses powerful statistical methods to perform model checking
 - something like Monte-Carlo sampling
 - i.e., we run the simulation several times, and we try to derive some guaranteed answer

Simulation

- A simulation is an experiment on a model
 - we focus on simulations performed by a computer
- Simulation is very easy to implement in the case of classical model checkers
 - no problems with RAM or execution time
- This stems from the fact that classical model checking deals with finite state systems
 - one step at a time, time passing typically not important
 - state space is finite and described by discrete-typed variables





Simulation

- What if we need to simulate a cyber-physical system?
 - e.g., simulate the Apollo mission
 - many subsystem interacting with each other via continuous signals
 - some subsystems are described by ODEs (Ordinary Differential Equations)
- In some cases, system developers also builds a simulator from scratch, e.g., in the C language
 - directly experimenting on the physical object may be dangerous, expensive, or simply impossible (e.g., it still does not exist)
- Many tools are available to easily describe complex models to be simulated
 - e.g., able to approximate solutions for ODEs
- Here we will deal with the open-source Modella
 - we will also have a look to Simulink



Some Background: ODEs

With some simplification, an ODE is an equation

$$F(x, y, y', y'', \dots, y^{(n)}) = 0$$

- The unknown y is a function y = f(x)
- In our context, the independent variable is time, denoted by t
 - in simulations, we are interested in the system evolution over time...
 - thus, we have functions x = f(t)
- Moreover, we will consider *explicit* ODEs $\dot{x} = F(t,x)$
 - x usually is in some *n*-dimensional space, e.g., $x \in \mathbb{R}^n$
 - thus, this is a system of equations
 - note that, with explicit ODEs, derivatives higher than 1 are not needed
 - simply put $x_1 = x, x_2 = \dot{x}_1...$



Example ODEs

- $\dot{x} = t + x$
- $(\dot{x}_1,\dot{x}_2)=(t+x_2e^{x_1},x_1\log t)$
- Model of an infectious desease (HIV): $(\dot{x}_1, \dot{x}_2) = (\lambda dx_1 \eta \beta x_1 x_2, -x_2(a+l) + \eta \beta x_1 x_2)$
 - x_1, x_2 are uninfected and infected cells, I is an action by the immune system
 - $a, d, \lambda, \beta, \eta$ are system parameters





ODEs: Euler Approximation

- Given the *time-invariant* ODE $\dot{x} = F(x)$, we may use the Euler approximation
 - for small au, $\dot{x} pprox rac{x(t+ au)-x(t)}{ au}$
 - if we sample time with τ , i.e., we only consider $t \in \{0, \tau, 2\tau, \dots, k\tau, \dots\}\dots$
 - ... we have that $F(x(k\tau)) = \frac{x(k\tau+\tau)-x(k\tau)}{\tau}$
 - thus by setting $x_k = x(k\tau)$, we have a discrete-time difference equation $x_{k+1} = x_k + \tau F(x_k)$
- ullet This only works for small au and small k
 - it can be proved that $||x_k x(k\tau)|| \le \tau \psi(k)$, where ψ is *not* bounded
 - at least, in the general case



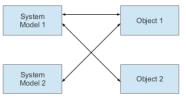




- A system is a mathematical concept used to study properties physical objects
 - sometimes also called abstract system, or system model
- It is typically used to study evolutions as a function of time
- Virtually infinite examples:
 - population of rabbits
 - spread of diseases
 - physical objects: a fridge, an oven, a building, a car, ...
 - part of physical objects: a resistor, a brick, a wheel, ...
 - controllers for physical objects: ABS, autonomous driving, ...
- First distinction is among objects (what we want to model) and system (the mathematical model)
 - a system is defined through functions, sets, et



- Given an object, one may devise different systems
 - as we may have different programs to solve the same problem
 - not only because of different people doing it: different properties on the same object may be investigated
- Given a system, it may be applied to different objects
 - spreading of different diseases may have a common model
 - wheel of a car and of a motorcycle







- We start defining systems by looking at their inputs and outputs
 - keeping in mind that it is all as a function of time
- Deterministic systems: given an input sequence from some "start", the output is the same
 - probabilistic systems also exist, we do not consider them here
- Black-box system: at first, we perform experiments on the system
 - we provide sequences of inputs and observe the sequence of outputs





- We begin experiments at some time $t_0 \in T$, with $T \subseteq \mathbb{R}$
 - ullet for some systems, $\mathcal{T}\subseteq\mathbb{N}$
- We consider all input functions $u: T \to U$ for our object
 - U is some set on which inputs may vary
 - ullet it may be multidimensional, e.g. $U=\mathbb{N} imes\mathbb{Z} imes\mathbb{R}^2$
 - of course, such input functions are uncountably many, this is a conceptual experiment
- For each u, we have an output function $y: T \to Y$ coming out of the object
 - U and Y may be different
 - again, Y may be multidimensional
- We define the system $S = \{(u, y) \mid u \text{ is an input function and } y \text{ the corresponding output function}\}$
 - ullet thus, $\mathcal{S}\subset\mathcal{U}\times\mathcal{Y}$

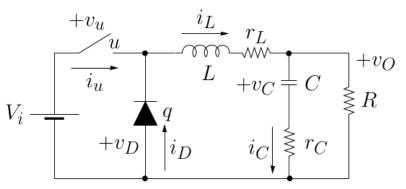


- Example: determine the number of students which graduate in same bachelor course
 - ullet assumption: student enrolls once every year, thus $T\subset \mathbb{N}$
 - $U \subset \mathbb{N}$: number of students enrolling "from outside"
 - $Y \subset \mathbb{N}$: number of graduated students
 - $\mathcal{U} = \{f \mid f : T \to U\}$, analogous for \mathcal{Y}
 - example of input-output:
 - $u_1(2020) = 200$, $u_1(2021) = 221$, $u_1(2022) = 198$, and $u_1(x) = 0$ for $x \notin \{2020, 2021, 2022\}...$
 - ... and we observe $y_1(2020) = 51$, $y_1(2021) = 51$, $y_1(2022) = 60$
 - $u_1(2020) = 136$, $u_2(2021) = 231$, $u_2(2022) = 90$, and $u_2(x) = 0$ for $x \notin \{2020, 2021, 2022\}...$
 - ... and we observe $y_2(2020) = 42, y_2(2021) = 37, y_2(2022) = 98$
 - $u_1, u_2 \in \mathcal{U}, y_1, y_2 \in \mathcal{Y}, (u_1, y_1), (u_2, y_2) \in \mathcal{Y}$





Example: determine the output voltage of a buck DC-DC converter





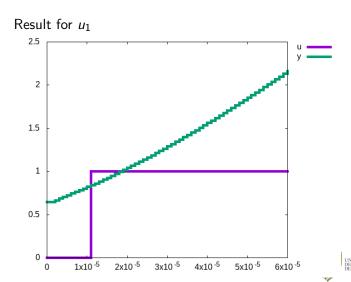


- Example: determine the output voltage of a buck DC-DC converter
 - \bullet $T \subset \mathbb{R}$
 - $U \subset \{0,1\} \times \mathbb{R}$
 - u may be closed (0) or open (1) at any time
 - ullet V_i may be any real number
 - $Y \subset \mathbb{R}$: observed output voltage v_O
 - example of input-output (times are in microseconds):
 - $u_1(t) = (0,5)$ for all $t \in [0,10]$, $u_1(t) = (1,5)$ for all $t \in [10,100]$
 - $u_2(t) = (0,15)$ for all $t \in [0,9]$, $u_2(t) = (1,10)$ for all $t \in (9,15]$, $u_2(t) = (0,7)$ for all t > 15

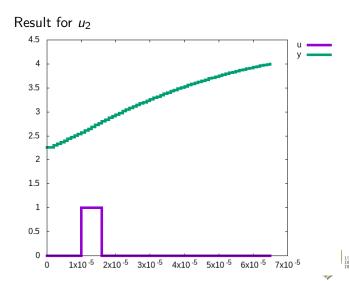








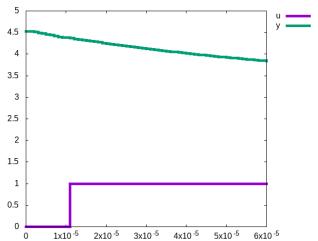






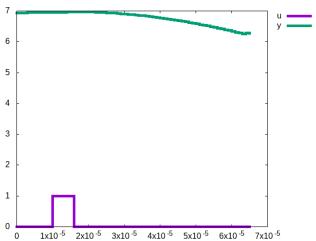


... but this is also a result for u_1





... and this is also a result for u_2





- Is this a non-deterministic system??? NO!
- The point is that output is not determined by input only
 - though for some systems this is the case: number of students above
- The missing element is the state
 - essentially, the input/output function has side effects...
- Thus, the output (for deterministic systems) is a function of both the input and the state
 - in the examples above, we made different choices for the starting state





- For our purposes, a system will be defined by a 6-tuple $S = \langle T, U, Y, X, \eta, \phi \rangle$:
 - *U*, *Y* are sets of possible input and output values, resp.
 - T is a set of times
 - ullet if $T\subseteq\mathbb{R}$ then we have a *continuous-time* system
 - if $T \subseteq \mathbb{N}$ then we have a *discrete-time* system
 - X is a set of states
 - may be either finite or infinite
 - if $T\subset \mathbb{N}$ and $|X|<\infty$ then we essentially have a Kripke structure
 - $\eta: T \times X \times U \rightarrow Y$ defines the output function
 - $\phi: T \times T \times X \times \mathcal{U} \to X$ defines the state transition function
 - recall that $\mathcal{U} = \{f \mid f : T \to U\}$







- $\eta: T \times X \times U \rightarrow Y$ is as expected
 - given the current time, the current state, and the current input, we can compute the output
- $\phi: T \times T \times X \times \mathcal{U} \to X$ is somewhat more complicated than expected
 - one would expect $\phi: T \times X \times U \to X$
 - actually, this is enough for most systems
- For some systems, the state transition function depend on some sequence of inputs, not only the last one
 - so we need a function, defined at least on an interval $[t_0, t)$
 - \bullet this is why ϕ also takes two times instead of one
- 3 conditions must hold for η and ϕ : causality, consistency and separation

Some Background: Causal Systems

- $\forall t, t_0 \in T, x_0 \in X. (t \ge t_0 \land u|_{[t_0,t)]} = u'|_{[t_0,t)}) \Rightarrow \phi(t, t_0, x_0, u|_{[t_0,t)]}) = \phi(t, t_0, x_0, u'|_{[t_0,t)})$
- That it is, if we fix the first 3 arguments t, t_0, x_0 of ϕ ...
- ... and we provide, as a fourth argument, two possible different functions u, u'...
- ... which however output the same values in the interval $[t_0, t)$...
- ullet ... then the final value of ϕ does not change
- Thus, what happens in the interval $[t_0, t)$ causes the system to go to one single state





Some Background: Consistent Systems

- $\forall t \in T, x_0 \in X, u \in \mathcal{U}. \ \phi(t, t, x_0, u) = x_0$
- Recall that, for a call $\phi(t, t_0, x, u)$, u is considered in the interval $[t_0, t)$
- Thus, in a call $\phi(t, t, x_0, u)$, we are considering the empty interval [t, t)
- Hence, we have no input at all!
- Of course, without inputs, the system cannot change its current state





Some Background: Separation Property of Systems

- $\forall t, t_0, t_1 \in \mathcal{T}, x_0 \in \mathcal{X}, u \in \mathcal{U}. (t > t_1 > t_0) \Rightarrow \phi(t, t_0, x_0, u|_{[t_0, t_1)}) = \phi(t, t_1, \phi(t_1, t_0, x_0, u|_{[t_0, t_1)}), u|_{[t_1, t)})$
- In few words: the state you obtain if you go straight from t₀ to t, is the same state you would obtain if:
 - ullet you first go from t_0 to some intermediate t_1
 - i.e., $x_1 = \phi(t_1, t_0, x_0, u|_{[t_0, t_1)})$
 - \bullet and then from t_1 to t
 - i.e., $\phi(t, t_1, x_1, u|_{[t_1,t)})$





Some Background: Hybrid Systems

- Note that the set of states X may be multi-dimensional
 - e.g., $X = \mathbb{R}^3$, or $X = \{1, 2, 3\} \times \mathbb{Z}$
- ullet Thus, also ϕ may be multi-dimensional
- Informally, if X has dimension n, then we will have n state variables
 - recall that the same holds for U, Y: we may have multiple input and output variables
- Hybrid systems: those for which some variables are continuous and other are discrete
 - in some texts, a "hybrid system" have some variables depending on $T=\mathbb{N}$ and some other on $T=\mathbb{R}$
- This is exactly the case of cyber-physical systems!
 - plant + controller/monitor
 - plant is continuous, controller/monitor is discrete





Some Background: Special Systems

• With some semplification, a system is *time-invariant* iff $\forall t, t_0, t_1 \in T, x \in X, u \in \mathcal{U}. \ \phi(t, t_0, x, u) = \phi(t - t_0, 0, x, u) \land \eta(t, x, u(t)) = \eta(t_1, x, u(t_1))$

- that is, the absolute time is not important
- the relative time is
 - given a state x, system evolution from 1 to 3 seconds and from 10 to 12 seconds is the same
- For time-invariant systems, we can always set $t_0 = 0$
- For time-invariant systems, we can also write $x(t) = \phi(x(t), u(t)), y(t) = \eta(x(t), u(t))$





Some Background: Special Systems

- With some semplification, a system is linear iff
 - U, Y, X are linear spaces
 - that is, any linear combination $\sum_{i=1}^{n} a_i x_i$ is in X etc
 - \mathcal{U} is a linear subspace of $U^T = \{f \mid f : T \to U\}$
 - again, any linear combination $\sum_{i=1}^n a_i u_i(t)$ is in $\mathcal U$
 - fixed any 2 times $t, t_0 \in T$ as first 2 arguments, ϕ is linear in the remaining 2 arguments
 - $\phi(t, t_0, x, u) = A \cdot [x, u] + b$ for some A and b
 - A, b may depend on t, t_0 , but not on x, u
 - fixed any time $t \in T$ as first argument, η is linear in the remaining 2 arguments
- Linear systems are easy to model, simulate and verify
- With some semplification, a system is:
 - a finite-state system if U, X, Y are finite sets (Kripke structure)
 - a finite-dimensional system if U, X, Y are linear photostation spaces



Some Background: Generating Functions

- For discrete-time systems, we have that $x(t+1) = \phi(t+1,t,x(t),u|_{[t,t+1)}) = \phi(t+1,t,x(t),u(t)) = f(t,x(t),u(t))$
 - \bullet first and second argument of ϕ are not independent...
 - f has the same domain of η
- For continuous-time systems, we focus on *regular* systems, i.e., those systems for which ϕ is differentiable and there exists a function f s.t.
 - $\frac{d\phi(t,t_0,x,u)}{dt} = f(t,\phi(t,t_0,x,u),u(t))$
 - with the initial condition that exists an $x_0 \in X$ s.t.
 - $x_0 = \phi(t_0, t_0, x_0, u)$
 - ullet often, it is easier to provide f than ϕ
- Using Newtonian notation, we have $\dot{x}(t) = f(t, x(t), u(t))$
- For time-invariant systems, we have $\dot{x}(t) = f(x(t), u(t)), y(t) = \eta(x(t))$







Some Background: System For Students' Example

- $X \subseteq \mathbb{N}^3$, $U, Y \subseteq \mathbb{N}$, $T = \mathbb{N}$
- Parameters $\alpha_i(t) \in [0,1]$ is ratio of students passing an year t
- $x_1(t+1) = (1 \alpha_1(t))x_1(t) + u(t)$
- $x_i(t+1) = (1 \alpha_i(t))x_i(t) + \alpha_{i-1}(t)x_{i-1}(t)$ for i = 2, 3
- $y(t) = \alpha_3(t)x_3(t)$
- Note that, if $a_i(t) = 1$ for all t, then states are not needed, as we have y(t) = u(t-3)
- Summing up:

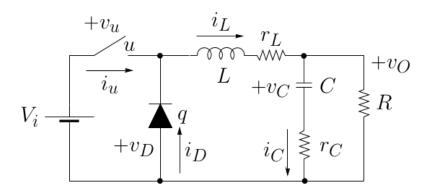
•
$$f(t) = \begin{pmatrix} (1 - \alpha_1(t))x_1(t) + u(t) \\ (1 - \alpha_2(t))x_2(t) + \alpha_1(t)x_1(t) \\ (1 - \alpha_3(t))x_3(t) + \alpha_2(t)x_2(t) \end{pmatrix}$$







Some Background: System For Buck DC/DC Converter







Some Background: System For Buck DC/DC Converter

- $X \subseteq \mathbb{R}^2$, $U \in \{0,1\} \times \mathbb{R}$, $Y \subseteq \mathbb{R}$, $T = \mathbb{R}$
- $L, C, R, r_L, r_C \in \mathbb{R}$ are system parameters
 - we will also use 6 real numbers $a_{i,j}$ for $i \in \{1,2\}, j \in \{1,2,3\}$ which are functions of such parameters
 - e.g., $a_{2,3} = -\frac{1}{L} \frac{r_C R}{r_C + R}$
- Variables for state are $i_L, v_O, v_D, i_D, v_u, i_u$ (real) and q (boolean)
- Variables for input are u (boolean) and V_i (real)
- $y(t) = v_O(t)$, thus η is easy
- \bullet ϕ is defined by cases in the following slide
 - for the definition of ϕ , some other (auxiliary) variables are useful: v_D , i_D , v_u , i_u (real) and q (boolean)
 - $R_{on} \approx 0, R_{off} >> R_{on}$ are fixed parameters



Some $\mathsf{Background}\colon\mathsf{System}$ For Buck DC/DC Converter

We omit (t) for better readability There must exist a value for $v_D, i_D, v_u, i_u \in \mathbb{R}, q \in \{0,1\}$ s.t.

$$i_L = a_{1,1}i_L + a_{1,2}v_O + a_{1,3}v_D$$
 (1)

$$\dot{v_O} = a_{2,1}i_L + a_{2,2}v_O + a_{2,3}v_D$$
 (2)

$$q \rightarrow v_D = R_{\rm on} i_D$$
 (3) $\bar{q} \rightarrow v_D = R_{\rm off} i_D$ (7)

$$q \rightarrow i_D \geq 0$$
 (4) $\bar{q} \rightarrow v_D \leq 0$ (8)

$$u \rightarrow v_u = R_{\rm on}i_u$$
 (5) $\bar{u} \rightarrow v_u = R_{\rm off}i_u$ (9)

$$v_D = v_u - V_{in}$$
 (6) $i_D = i_L - i_u$ (10)

Both ODEs and algebraic equations







Modeling in Modelica

- Modelica is an open-source language for specifying (complex) systems
 - developed by experts starting in late 1990s
- Many implementations exist
 - OpenModelica+simForge, Dymola, Simulation X, MapleSim, MathModelica
 - here we will stick to OpenModelica+simForge
- Also see Modelica slides





Modeling in Modelica

- Object-oriented language: classes and objects (i.e., class instances)
 - strongly typed
- Compositional modeling:
 - break up the system in subsystems (components)
 - connect the components
- Very useful for complex systems, with many components
 - some standard components already defined, e.g., resistors, flows etc
- May use equations, also with derivatives
- Generates a C program, thus it is very efficient





Modeling in Modelica

- Synchronous data flow principle: time is the same for all components
 - such as clocks for digital systems, but in Modelica it may be continuous
- May specify "algorithms" using assignments, ifs, whiles, etc
 - all variables must be instances of some class
 - this also includes integers and reals
- Acausal modeling: simply first provide the equations for each object, then connect the objects between them
 - other modeling languages, e.g., Simulink, requires to first design the full chain of connections...
 - ...and to make computation in sequence
 - Modelica allows both causal and acausal modeling
 - physical "reality" is lost
- Modelica easier for modelers, Simulink easier for computers



Acausal Modeling

The order of computations is not decided at modeling time

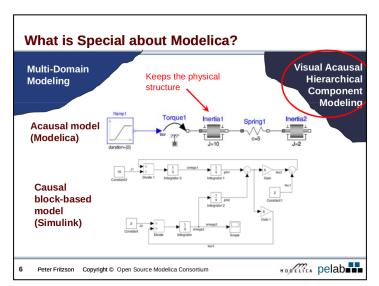
	Acausal	Causal
Visual Component Level	Toget bots Syrigt	
Equation Level	A resistor <i>equation</i> : R*i = v;	Causal possibilities: i := v/R; v := R*i; R := v/i;





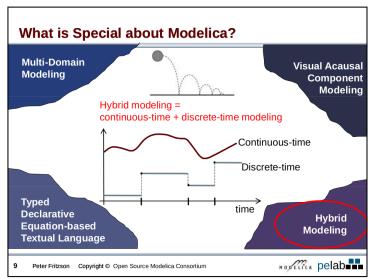
HODELICA pelab

Modelica: Acausal Modeling





Modelica: Hybrid Modeling







Modelica: Toy Example

end Example;

 Text file with .mo extension, let us say model.mo class Example output Real x, y, z; algorithm when initial() then //at 0, both this... x := 0; // Pascal-like assignments elsewhen sample (0, 1) then $// \dots$ and this x := 1;y := pre(x); //0 till 1, then always 2elsewhen sample(0, 0.5) then x := 2;z := pre(x); //0 till 0.5, then always 1if $(z \iff 2)$ then z := 2; end if; end when;

Modelica: Toy Example

Text file with .mos extension, let us say run.mos





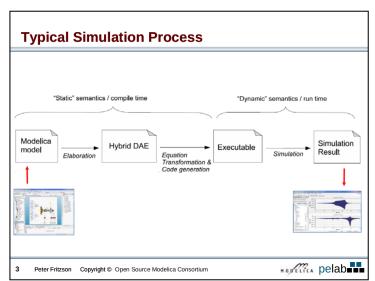
Modelica: Toy Example

- Run the command omc run.mos
 - of course, you must have installed omc for your OS
- This has the following effect:
 - generates a C program model.c
 - Occupiles model.c to obtain the executable file model
 - executes model
 - outputs both a file Example_res.mat and a graphical window with the graph of variables x, y, z as function of time





Modelica: Commands Chair





Modelica: Toy Example Examined

```
class Example
  output Real x, y, z;
  algorithm
    when initial() then //at 0, both this...
      x := 0:
    elsewhen sample (0, 1) then // \dots and this
      x := 1:
      y := pre(x); //0 till 1, then always 2
    elsewhen sample(0, 0.5) then
      x := 2:
      z := pre(x); //0 till 0.5, then always 1
      if (z \iff 2) then z := 2; end if;
    end when;
end Example;
```



Modelica: Toy Example Examined

- Example is a class defined by the modeler: Modelica is OO
- It has 3 real-valued variables, which may become the input for other blocks
- The dynamics is an algorithm based on the sample construct
 - when initial() C executes code in C at time 0
 - when sample (A, B) C executes code in C every A + Bx seconds, for $x \in \mathbb{N}$
 - elsewhen sample(A, B) C applies if no other preceding (else) when was triggered but...
 - ... if the preceding when had initial, then they are both triggered
- In expressions, pre(var) holds the value of var before the current event



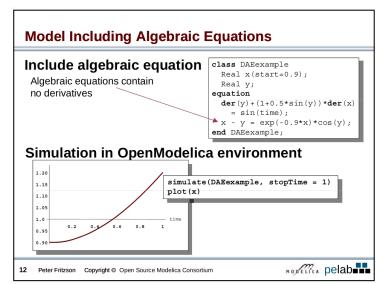
Modelica: Derivatives

Simplest Model – Hello World! A Modelica "Hello World" model Equation: x' = -xclass HelloWorld "A simple equation" Real x(start=1): Initial condition: x(0) = 1equation der(x) = -x: end HelloWorld; Simulation in OpenModelica environment simulate(HelloWorld, stopTime = 2) 0.8 plot(x) 0.6 0.4 0.2 0.5 1.5 HODELICA pelab Copyright @ Open Source Modelica Consortium 11





Modelica: Derivatives and Algebraic Equations





Modelica: Derivatives and Algebraic Equations

- time is a special variable, holding current simulation time
- System dynamics of previous example is defined as

$$\dot{y} + \left(1 + \frac{\sin y}{2}\right)\dot{x} = \sin t$$
$$x - y = e^{-0.9x}\cos y$$

 Can be transformed in "normal" form by adding state variables:

$$\dot{x} = \frac{\sin t - y_1}{1 + \frac{\sin y}{2}}$$

$$\dot{y} = y_1$$

$$z_1 = e^{-0.9x}$$

$$z_2 = \cos y$$

$$x = z_1 z_2 + y$$

$$y = x - z_1 z_2$$







Modelica: Subsystems and Connections

- Till now, stand-alone systems with just one component
- Modelica allows compositional modeling of many components
- Each component is modeled autonomously, by simply looking at the interaction with the environment (input/output)
- Complex systems are made of *connected* components
- Connectors can be explicitly defined
 - causal: input/output relation is explicitly stated
 - acausal: input/output relation is left unspecified
 - Modelica will understand which is input and which is output





```
Mind the difference between = and :=
model ContinuousBehav

Boolean x;
Real i (start = 1);

equation
   (if x then 0.5*time else -0.1*time)*der(i) = time;
end ContinuousBehav;
```





```
model GenerateBoolInputs
  Boolean x;
  parameter Real sampling = 1.0;
  algorithm
    when initial() then
      x := false;
    elsewhen sample(sampling, sampling) then
      x := not(x);
    end when;
end GenerateBoolInputs;
```

```
model BoolCont

GenerateBoolInputs gbi;
ContinuousBehav cb;

equation
   gbi.x = cb.x;
end BoolCont;
```









Modelica: Passing of Time

- For all objects defined, the time passes in the same way
 - it is a kind of common clock, as in digital circuits
- This is of course consistent with physical reality
 - components are close enough...
- It is always continuous time, but using sample we can also have discrete time



Modelica: Algorithms and Equations

- Both may be used, the modeler has to choose
 - of course, x := x + 1 inside an algorithm is ok, x = x + 1 in an equation is not
 - using imperative vs. declarative style is left to the modeler
 - in some cases, algorithm is more natural, in some other equation has to be preferred
 - note that loops and ifs are available in both formats
 - e.g., a = (if b then 1 else 2); vs if (b) then a:=1; else a:=2; end if;
 - or simply a := (if b then 1 else 2);
- Algorithms, as well as equations solving, does not cause time to pass
 - number of computation steps required is not important



Modelica: Algorithms

- Generally speaking, when A B clauses triggers the corresponding block B when condition A is true
- A can be any boolean expression, not only sample
- Functions may also be defined and used
 - time does not pass during function calls
 - again, number of computation steps is not important
 - must have input and output
- External C or Fortran functions may be called
 external "C" result = myfun();
 annotation(Include = "#include \"myfile.c\"");





Modelica: Events

- Discrete events happens in a discrete number of time points
 - given that the simulation terminates somewhere, it is actually a finite number of points
- We saw initial and sample, there is also terminal
 - triggered at the end of the simulation
- Simulation ends either because of:
 - the stopTime attribute inside simulate command
 - a terminate statement





- Simulink is a graphical extension to MATLAB
 - MATLAB itself is proprietary, but UnivAQ provides it to students
- Main goal: modeling and simulation of systems
 - also non-linear ones
- Also see https://ctms.engin.umich.edu/CTMS/index. php?aux=Basics_Simulink
- No way of simply writing a text file: you have to use the GUI and manipulate graphical objects
 - model files are saved in a binary proprietary SLX format



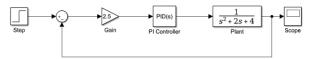


- Two major classes of objects: blocks and lines
 - blocks used to generate, modify, combine, output, and display signals
 - lines used to connect blocks, i.e., transfer signals from one block to another
 - again, a common clock for all objects in a model
- Suppose you create a new or open an existing Simulink model file
- How to add a new block:
 - click "Library Browser"
 - select the type of block you need
 - hundreds of types available, could also be searched by name
 - drag it to the model window
 - by double clicking, you can edit the properties





- How to add a new connecting line:
 - simply drag the mouse from the first object to the second object
- If you are connecting an object with a line:
 - first make a dangling line from the destination
 - connect the end of such line with the "source" line
 - this will make the source line bifurcated







Most notable types of blocks:

- Sources: used to generate various signals
- Sinks: used to output or display signals
- Continuous: continuous-time system elements
 - transfer functions, state-space models, PID controllers, etc.
- Discrete: linear, discrete-time system elements
 - discrete transfer functions, discrete state-space models, etc.
- Math Operations: contains many common math operations
 - gain, sum, product, absolute value, etc.
- Ports & Subsystems: contains useful blocks to build a system



