

# Modelling & Simulation

## Mathematical Models of Systems

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# [ Contents ]

- Input-output modelling
- State space modelling
- Taxonomy of models (and systems)



# [ Input-output modelling I ]

$t$  - time (variable)  $t_0 \leq t \leq t_f$



$u$  - input variables  $\{u_1(t), \dots, u_p(t)\}$

- $\vec{u}(t) = [u_1(t), \dots, u_p(t)]^T$  (vector form)

$y$  - output variables  $\{y_1(t), \dots, y_m(t)\}$

- $\vec{y}(t) = [y_1(t), \dots, y_m(t)]^T$
- suppressed output variables
  - not associated with either the input or the output

# [ Input-output modelling II ]

- $t_0 \leq t \leq t_f$
- $\vec{u}(t) = [u_1(t), \dots, u_p(t)]^T$
- $\vec{y}(t) = [y_1(t), \dots, y_m(t)]^T$



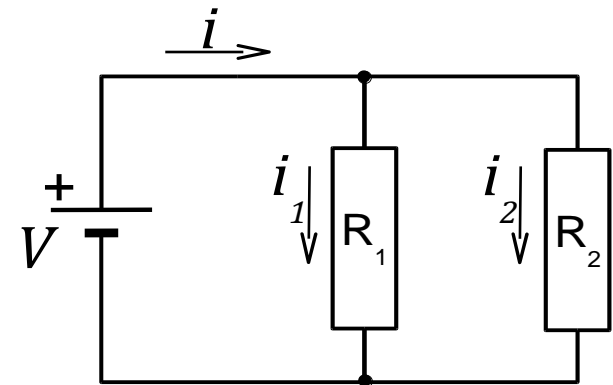
$g$  - function, defining mathematical relationship between the input and output

$$\vec{y}(t) = \vec{g}(\vec{u}(t)) = [g_1(u_1(t), \dots, u_p(t)) \dots g_m(u_1(t), \dots, u_p(t))]^T$$
$$y_i(t) = g_i(u_1(t), \dots, u_p(t))$$

- in general,  $g$  can explicitly depend on  $t$  :  $\vec{y}(t) = \vec{g}(\vec{u}(t), t)$

# Input-output model example

- Current divider circuit
- From Kirchhoff's current law:
  - $i = i_1 + i_2$
- From Ohm's law:
  - $i_1 = \frac{V}{R_1}, \quad i_2 = \frac{V}{R_2}$
- Input-output model:
  - $u_1(t) = R_1, \quad y_1(t) = i = V \frac{R_1 + R_2}{R_1 R_2}$



# State space modelling I

- State of a system at time  $t_0$ 
  - the information required at  $t_0$  such that  $\vec{y}(t)$ , for all  $t \geq t_0$ , is uniquely determined from this information and from the input  $\vec{u}(t), t \geq t_0$ .
  - $\vec{x}$  - vector of state variables
$$\vec{x}(t) = [x_1(t), \dots, x_n(t)]^T$$
- $X$  – State space of a system
  - the set of all possible values that the state may take.

# State space modelling II

## ■ State equations

- the set of equations required to specify the state  $\vec{x}(t)$  for all  $t \geq t_0$  given  $\vec{x}(t_0)$  and the function  $\vec{u}(t)$ ,  $t \geq t_0$ .

- usually differential equations of the form

$$\dot{\vec{x}}(t) = \vec{f}(\vec{x}(t), \vec{u}(t), t)$$

# State space modelling III

- State space model

$$\dot{\vec{x}}(t) = \vec{f}(\vec{x}(t), \vec{u}(t), t)$$

$$\vec{x}(t_0) = \vec{x}_0$$

$$\vec{y}(t) = \vec{g}(\vec{x}(t), \vec{u}(t), t)$$

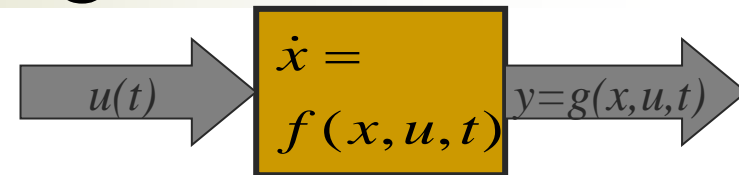
- $n$  state equations and initial conditions ( $1 \leq i \leq n$ ):

$$\dot{x}_i(t) = f_i(x_1(t), \dots, x_n(t), u_1(t), \dots, u_p(t), t),$$

$$x_i(t_0) = x_{i0}$$

- $m$  output equations ( $1 \leq j \leq m$ ):

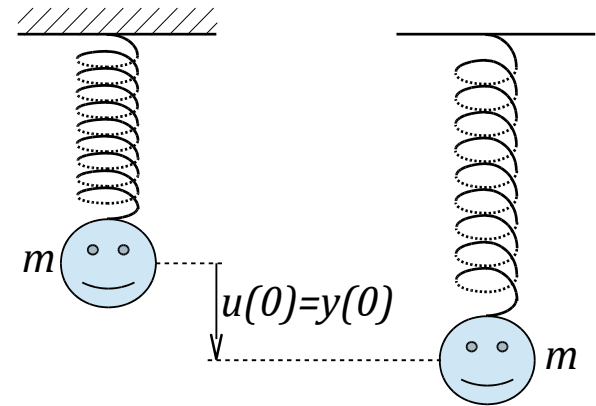
$$y_j(t) = g_j(x_1(t), \dots, x_n(t), u_1(t), \dots, u_p(t), t)$$





# State space model example

- Spring-mass system
  - a simple harmonic oscillator
- Hooke's law
  - $F = -ky$  or  $m\ddot{y} = -ky$
- Initial conditions
  - $y(0) = u_0, \dot{y}(0) = 0$
- State space model ( $x_1(t)$  instead of  $y$ )
  - $\dot{x}_1(t) = x_2(t)$
  - $\dot{x}_2(t) = -\frac{k}{m}x_1(t)$
  - $x_1(0) = u_0, x_2(0) = 0$
  - $y(t) = x_1(t)$



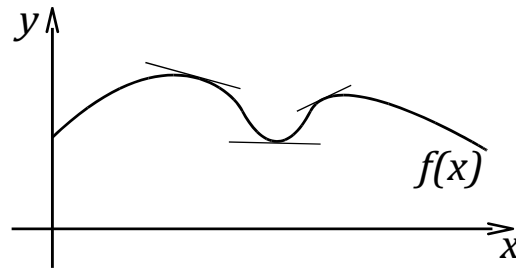
# [ Note :: Derivative I ]

- a measure of how a function changes as its input changes
- differentiation
  - process of finding a derivative of a function
- antidifferentiation
  - = integration
  - reverse of differentiation



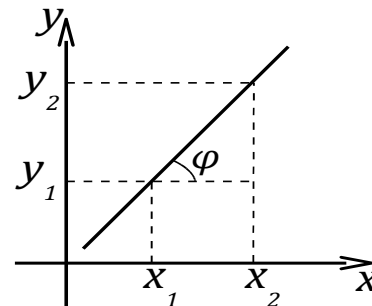
# Note :: Derivative II

- derivative of a real function of a single variable (at a point)
  - slope of the tangent line to the graph of the function (at the point)



- slope (gradient) of a line (*smernica dotyčnice*)
  - = number that describes both the direction and the steepness of the line
  - usually denoted as  $m$

$$m = \frac{\Delta y}{\Delta x} = \frac{y_2 - y_1}{x_2 - x_1} = \tan(\varphi)$$



# Note :: Derivative III

## ■ Notations for derivative of $y = f(x)$

○ Lagrange's  $f' f'' f''' f^{(n)}$

○ Leibniz's  $\frac{dy}{dx} \frac{df}{dx}(x) \frac{d}{dx} f(x) \quad \frac{d^n y}{dx^n} \frac{d^n f}{dx^n}(x) \frac{d^n}{dx^n} f(x)$

○ Euler's  $D_x y \quad D_x f(x) \quad D_x^n y \quad D_x^n f(x)$

○ Newton's  $\dot{y} \quad \ddot{y}$

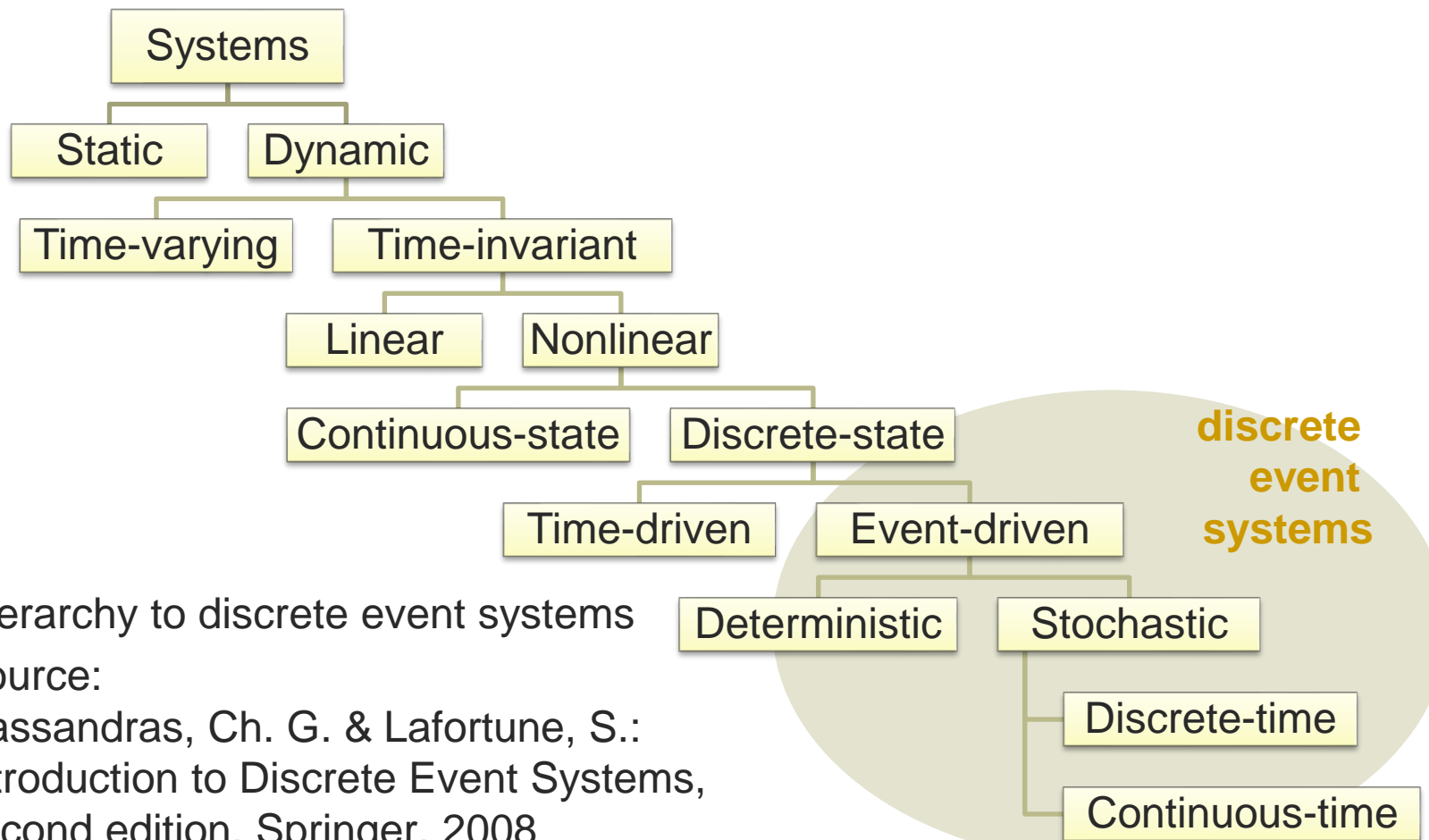
■ for time derivatives  $y = f(t)$

## ■ Definition

$$f'(a) = \lim_{h \rightarrow 0} \frac{f(a+h) - f(a)}{h}$$

$$\dot{y}(t) = \lim_{\tau \rightarrow 0} \frac{f(t+\tau) - f(t)}{\tau}$$

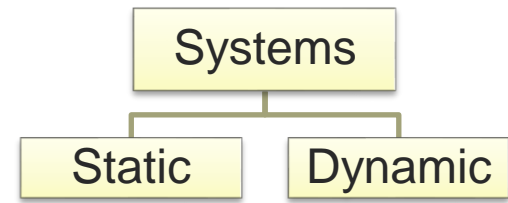
# Taxonomy of models and systems



- Hierarchy to discrete event systems
- Source:  
Cassandras, Ch. G. & Lafortune, S.:  
Introduction to Discrete Event Systems,  
second edition, Springer, 2008



# Static and Dynamic Systems



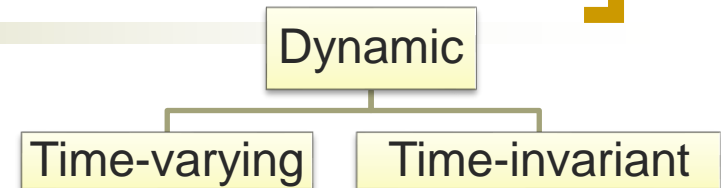
## ■ Static

- for all  $t$  the output  $y(t)$  doesn't depend on past values of the input  $u(t_b), t_b < t$ .
- the state is fixed  $\dot{\vec{x}}(t) = \vec{0}$

## ■ Dynamic

- the output depends on some past values of the input.

# Time-varying and Time-invariant Systems



## ■ Time-invariant

- the output is always the same when the same input is applied

$$\dot{\vec{x}}(t) = \vec{f}(\vec{x}(t), \vec{u}(t))$$

$$\vec{y}(t) = \vec{g}(\vec{x}(t), \vec{u}(t))$$

## ■ Time-varying

- explicit time dependence

$$\dot{\vec{x}}(t) = \vec{f}(\vec{x}(t), \vec{u}(t), t)$$

$$\vec{y}(t) = \vec{g}(\vec{x}(t), \vec{u}(t), t)$$

# Linear and non-linear systems

- Linear:  $\vec{f}$  and  $\vec{g}$  are linear
- Nonlinear:  $\vec{f}$  or  $\vec{g}$  is not linear
- The function  $\vec{g}$  is linear if it satisfies the superposition principle

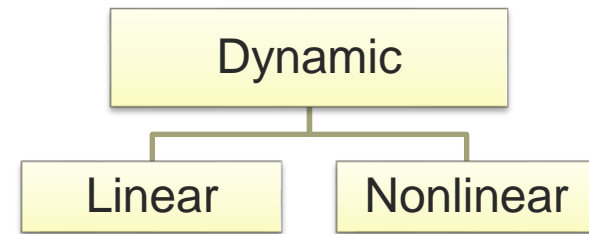
$$\vec{g}(a_1\vec{u}_1 + a_2\vec{u}_2) = a_1\vec{g}(\vec{u}_1) + a_2\vec{g}(\vec{u}_2)$$

- the state model of a linear system

$$\dot{\vec{x}}(t) = A(t)\vec{x}(t) + B(t)\vec{u}(t)$$

$$\vec{y}(t) = C(t)\vec{x}(t) + D(t)\vec{u}(t)$$

- $A(t)$  is an  $n \times n$  matrix,  $B(t)$  is an  $n \times p$  matrix,  $C(t)$  is an  $m \times n$  matrix and  $D(t)$  is an  $m \times p$  matrix.





# [ Linear system example ]

## Spring – mass system

$$\begin{aligned}\dot{\vec{x}}(t) &= A(t)\vec{x}(t) + B(t)\vec{u}(t) \\ \vec{y}(t) &= C(t)\vec{x}(t) + D(t)\vec{u}(t)\end{aligned}$$

$$\begin{aligned}\dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= -\frac{k}{m}x_1(t)\end{aligned}$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$A = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & 0 \end{bmatrix}, \quad B = 0_{2,2}$$

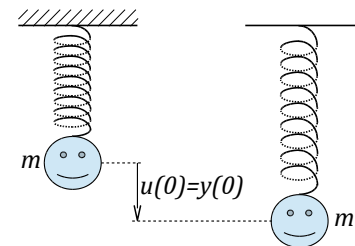
$$y(t) = x_1(t)$$

$$y = [1 \quad 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$C = [1 \quad 0], \quad D = 0_{1,2}$$

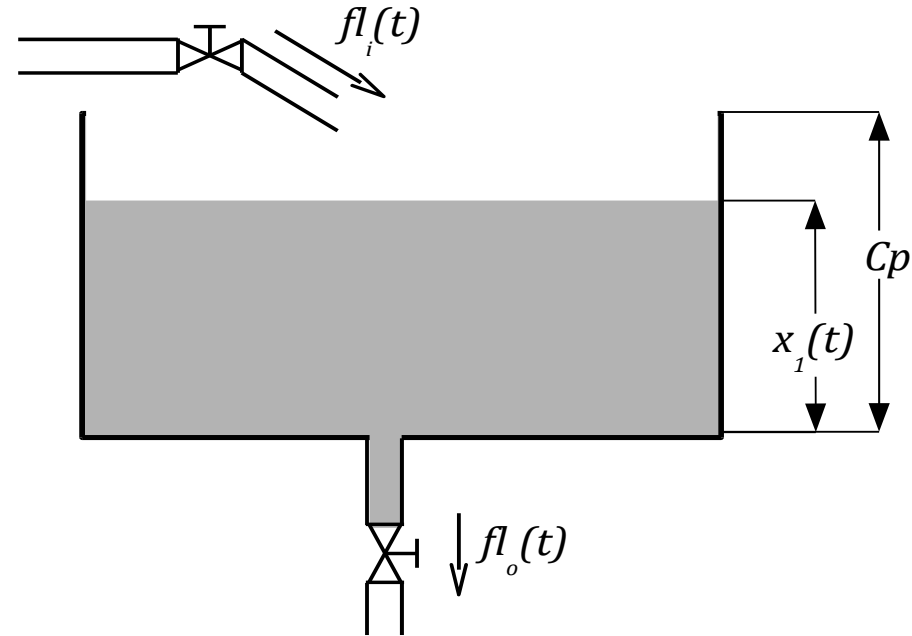
$$\begin{aligned}x_1(0) &= u_0, \\ x_2(0) &= 0\end{aligned}$$

$$\begin{bmatrix} x_1(0) \\ x_2(0) \end{bmatrix} = \begin{bmatrix} u_0 \\ 0 \end{bmatrix}$$



# [ Nonlinear system example ]

## Flow system



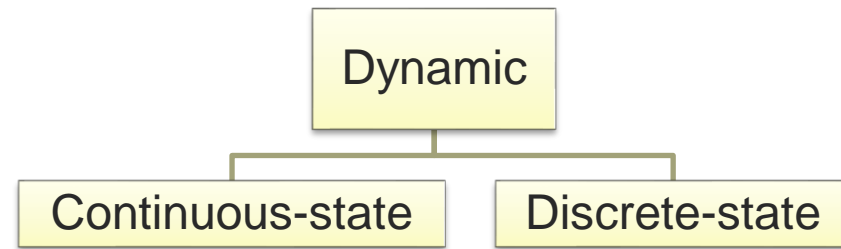
$$u_1(t) = fl_i(t)$$
$$u_2(t) = fl_o(t)$$

$$y_1(t) = x_1(t)$$

$$x_1(0) = 0$$

$$\dot{x}_1(t) = \begin{cases} 0 & (x_1(t) = 0 \wedge fl_i(t) \leq fl_o(t)) \vee \\ & \vee (x_1(t) = Cp \wedge fl_i(t) \geq fl_o(t)) \\ fl_i(t) - fl_o(t) & otherwise \end{cases}$$

# Continuous and Discrete-State



## ■ Continuous-State

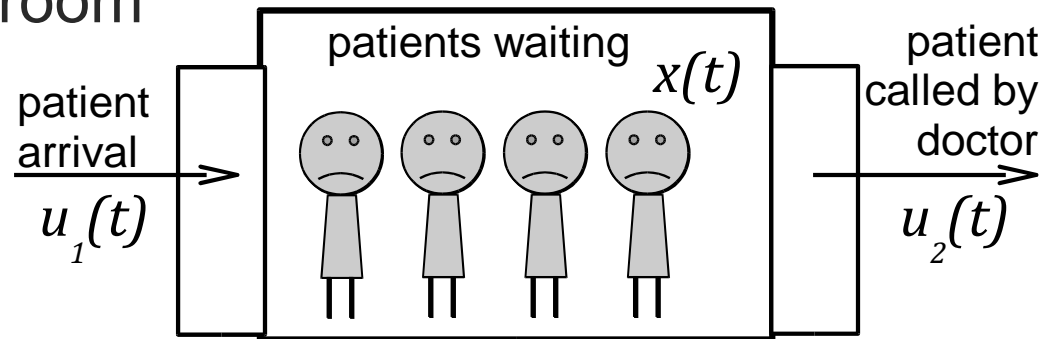
- state variables can generally take on any real (or complex) value

## ■ Discrete-State

- state variables are elements of a discrete set (e.g., the non-negative integers)

# Discrete-state system example

- Doctor's waiting room



$$u_1(t) = \begin{cases} 1 & \text{if a patient arrives at time } t \\ 0 & \text{otherwise} \end{cases}$$

$$u_2(t) = \begin{cases} 1 & \text{if a patient is called at time } t \\ 0 & \text{otherwise} \end{cases}$$

$$x(t+1) = \begin{cases} x(t) + 1 & u_1(t) = 1 \wedge u_2(t) = 0 \\ x(t) - 1 & u_1(t) = 0 \wedge u_2(t) = 1 \wedge x(t) > 0 \\ x(t) & \text{otherwise} \end{cases}$$

# [ Continuous and discrete-time ]

- Continuous-time
  - all input, state, and output variables are defined for all possible values of time
- Discrete-time
  - one or more of these variables are defined at discrete points in time only (usually as the result of some sampling process)
  - time is a **discrete** variable
- each real system is a continuous-time system
  - inputs and outputs can be observed at any time instant
  - their models can be discrete-time



# [ Discrete-time systems I ]

- Good for models
  - where output and state variables can change only at exactly defined time instants
    - digital circuits
  - based on a finite set of data, recorded at certain time moments
    - a model is discrete-time because we cannot construct a continuous-time one
- Continuous-time systems become de-facto discrete-time systems when simulated on digital computers



# Discrete-time systems II

- Time = sequence of time values  $t_0, t_1, \dots, t_k, \dots$

- $\forall i(i \geq 0): t_i < t_{i+1}$

- $T$  – sampling interval  $\forall i(i \geq 0): t_{i+1} = t_i + T$

- State space model uses *difference equations*

$$\vec{x}(k+1) = \vec{f}(\vec{x}(k), \vec{u}(k), k)$$

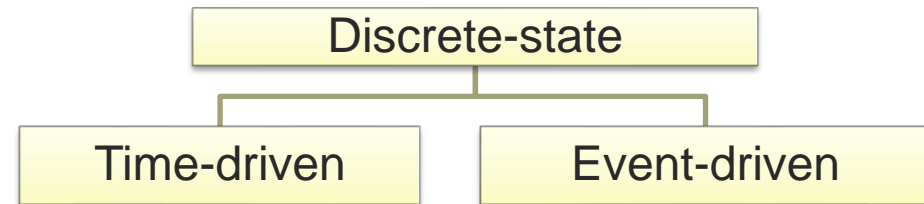
$$\vec{x}(0) = x_0$$

$$\vec{y}(k) = \vec{g}(\vec{x}(k), \vec{u}(k), k)$$

- $k$  – integer variable, replaces  $t$

- number of intervals of the length  $T$  that passed since the initial time point  $t_0$

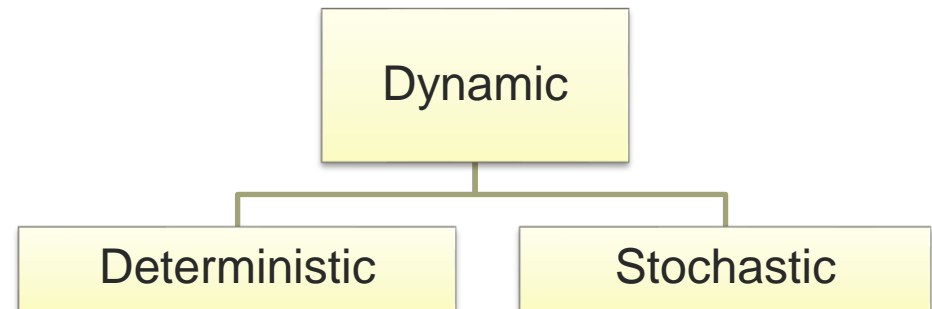
# [ Time-driven vs. Event-driven ]



- Time-driven
  - state continuously changes as time changes
  - time advance causes state change
- Event-driven
  - only an occurrence of an asynchronously generated discrete event forces instantaneous state transition.
  - event occurrence causes state change



# Stochastic vs. Deterministic



- Stochastic
  - one or more of its output variables is a random variable
- Deterministic
  - no random variable

# Discrete Event Systems

