Chapter 3

Examples of mechatronic systems and signals

Τοῦ δὲ ποσουτὸ μέν 'εστι διωρισμένον, τὸ δὲ συνεξές.

Aristotle (384 BC — †322 BC), *Kathegoriai*, VI

In this chapter we discuss different types of mechatronic signals and systems, and present examples of each.

3.1 Systems

In chapter 1 we have already defined system as the part of the Universe we want to study.

A system made up of physical components may be called a **plant**. A system which is a combination of operations may be called a **process**. *Plant* *Process*

Example 3.1. WECs, mentioned in Example 1.1, are plants. Figures 3.1, 3.2 and 3.3 show three different WECs; many other such devices exist. □

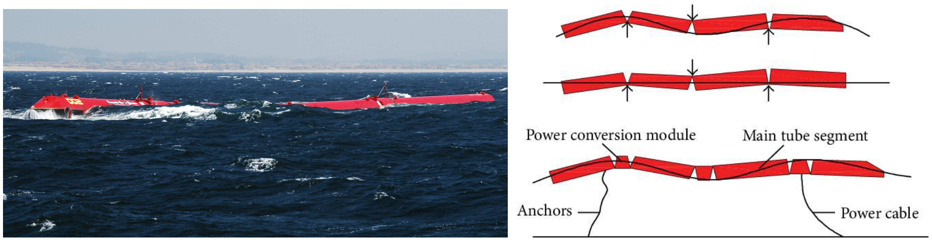

Figure 3.1: The Pelamis, a floating near-shore Wave Energy Converter, at Aguçadoura, Portugal (source: left, Wikimedia; right, DOI 10.1155/2013/186056). Waves cause an angular movement of the several sections of the device. This movement pumps oil in a closed circuit; high pressure oil is then used to run a turbine driving a usual rotational generator.

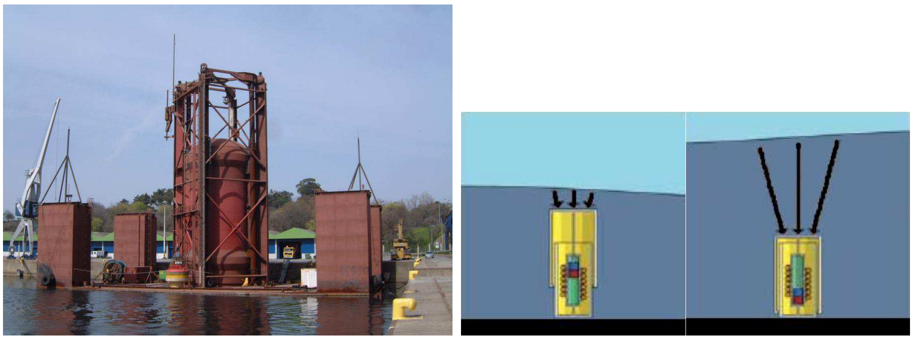

Figure 3.2: The Archimedes Wave Swing, a submerged offshore Wave Energy Converter before submersion, at Viana do Castelo, Portugal. The device is filled with air which is compressed when wave crests pass and expands during wave troughs. The heaving movement of the AWS upper part moves an electrical linear generator.

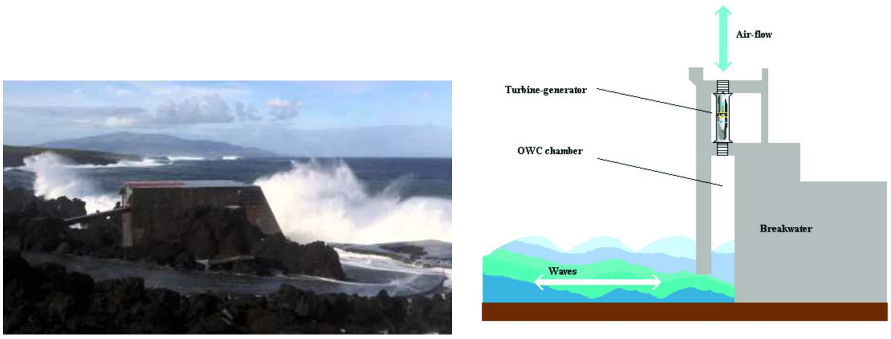

Figure 3.3: The Pico Power Plant (concluded in 1999, decommissioned in 2018), an onshore Wave Energy Converter of the Oscillating Water Column (OWC) type (source: left, WavEC; right, DOI 10.3390/en11112939). In an OWC, the heaving movement of the water inside a chamber compresses and expands the air, which can flow in and out the chamber through a turbine designed to always rotate in the same direction irrespective of the sense of the flow. The turbine drives a usual rotational generator.

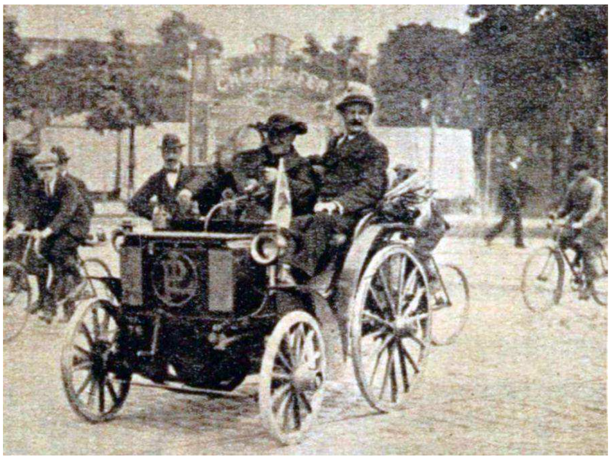

Figure 3.4: A Panhard & Levassor Type A motorcar, the first mass produced car in the world, driven by the French priest Jules Gavois (1863 – †1946) in 1891 (source: Wikimedia). This car still does not have a steering wheel (first introduced in 1894), but only a tiller.

Example 3.2. If we want to study the wave elevation at a certain onshore location as a function of the weather on the middle of the ocean, we will be studying a process.

The variables describing the characteristics of the system that we are interested in are its **outputs**. The variables on which the outputs depend are the system's **inputs**.

Outputs

Inputs in the general sense

Example 3.3. An internal combustion engine motorcar (see Figure 3.4) is a plant. We are usually interested in its position, velocity, and attitude. We also may want to know the rotation speed of the motor, the temperature of the oil, the fuel consumption, or other such values. All these are outputs. They depend on the position of the steering wheel, the position of the accelerator and brake pedals, the gear selected, the condition and inclination of the road the car in running on, the direction and speed of the wind, the outside temperature, and other such values. These are the inputs. Not all the outputs depend on all the inputs. □

A **control system** is one devised to make one or more of the system's outputs follow some **reference**.

Control system

Reference

Example 3.4. An air conditioning (AC) unit (see Figure 3.5) is a mechatronic system that heats or cools a room to a temperature set by the user. It is consequently a control system. The value of the temperature selected by the AC user is the reference. The room's temperature is the output of the plant that has to follow this reference. □

Example 3.5. The wind at the location of a wind turbine is related to the temperature, the solar exposition, and the atmospheric pressure, among other variables. This is a process we cannot control. It is not a control system. □

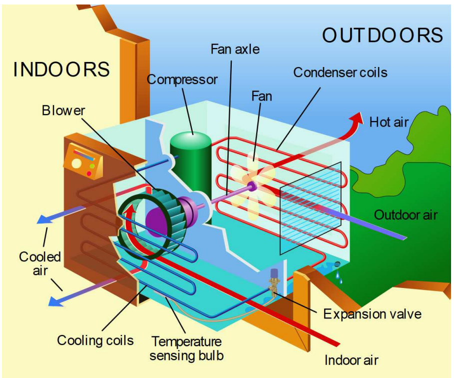

Figure 3.5: A window unit air conditioning system (source: Wikimedia). There are many other types of AC units.

Inputs in the strict sense

Disturbances

For a control system to exist, it must be possible to modify one or more of the inputs, so as to affect the desired outputs and thereby cause them to follow the reference. Such inputs are called **manipulated variables** or **inputs in the strict sense**. The inputs of the system that cannot be modified are called **disturbances**. When studying control systems, it is usual to call simply inputs to the inputs in the strict sense, and to call outputs only to the variable or variables that have to follow a reference.

Example 3.6. In the case of the OWC from Example 3.1 and Figure 3.3, the sea waves are disturbances, since we cannot control them. The rotation speed of the turbine is an input in the strict sense, since we can manipulate it (e.g. varying the resistance of the electrical generator). If the OWC chamber has a relief valve, the pressure in the chamber will be also an input, since we can change it opening or closing the relief valve. □

Example 3.7. In the case of the car from Example 3.3, the positions of the steering wheel and of the pedals are inputs. If the car has a manual gear box, the gear selected is an input too; if the gear box is automatic, it is not. The gusts of wind are a disturbance, since we cannot modify them. If we are studying the temperature of the motor of the car, this will depend on the outside temperature, which we cannot control and is therefore a disturbance. □

SISO system

MIMO system

A system with only one input and only one output is a Single-Input, Single-Output (**SISO**) system. A system with more than one input and more than one output is a Multi-Input, Multi-Output (**MIMO**) system. It is of course possible to have Single-Input, Multiple-Output (**SIMO**) systems, and Multiple-Input, Single-Output (**MISO**) systems. These are usually considered as particular cases of MIMO systems.

Example 3.8. Both the OWC of Example 3.1 and the car of Example 3.3 are MIMO plants. □

Example 3.9. The lever in Figure 3.6 is a SISO system: if the extremities are at heights $x(t)$ and $y(t)$, and the first is actuated, then $y(t)$, the output, depends on position $x(t)$, the input, and nothing more. □

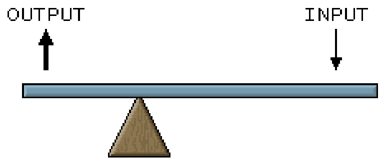

Figure 3.6: A lever, an example of a linear SISO system without dynamics (source: Wikimedia).

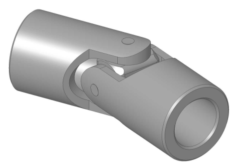

Figure 3.7: A Cardan joint, a non-linear mechanical system without dynamics (source: Wikimedia).

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A system's **model** is the mathematical relation between its outputs, on the one hand, and its inputs in the general sense (inputs in the strict sense and disturbances), on the other.

A system is **linear** if its exact model is linear, and **non-linear** if its exact model is non-linear. Of course, exact non-linear models can be approximated by linear models, and often are, to simplify calculations.

Linear system
Non-linear system

Example 3.10. The lever of Figure 3.6 is a linear plant, since, if its arm lengths are L_x and L_y for the extremities at heights $x(t)$ and $y(t)$ respectively,

$$y(t) = \frac{L_y}{L_x} x(t). \quad \square \tag{3.1}$$

Example 3.11. A Cardan joint (see Figure 3.7) connecting two rotating shafts, with a bent corresponding to angle β, is a non-linear plant, since a rotation of $\theta_1(t)$ in one shaft corresponds to a rotation of the other shaft given by

$$\theta_2(t) = \arctan \frac{\tan \theta_1(t)}{\cos \beta}. \tag{3.2}$$

If $\beta \approx 0$, (3.2) can be approximated by

$$\theta_2(t) = \arctan \frac{\tan \theta_1(t)}{1} = \theta_1(t). \tag{3.3}$$

The error incurred in approximating (3.2) by (3.3) depends on how close $\cos \beta$ is to 1. There will be no error at all if the two shafts are perfectly aligned ($\beta = 0$). □

Example 3.12. A car is also an example of a non-linear plant, as any driver knows. □

A system is **time-varying** if its exact model changes with time, and **time-invariant** otherwise.

Time-varying system
Time-invariant system

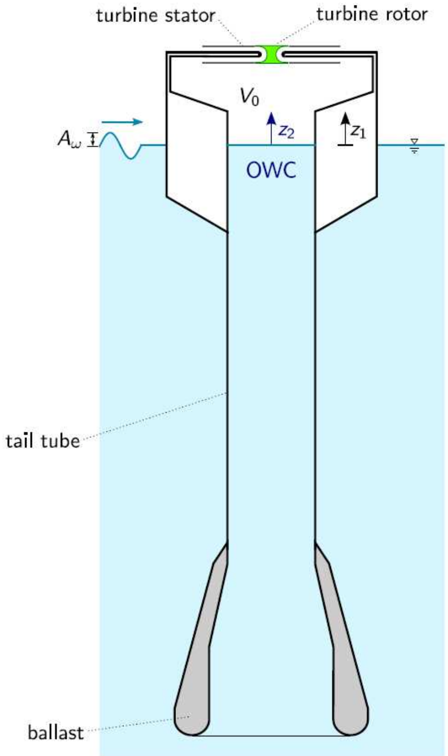

Figure 3.8: A floating OWC (source: DOI 10.1016/j.energy.2016.06.054).

Example 3.13. An airplane consumes enormous amounts of fuel. Thus its mass changes significantly from take-off to landing. Any reasonable model of a plane will have to have a time-varying mass. But it is possible to study a plane, for a short period of time, using an approximation consisting of a time-invariant model, as the mass variation is neglectable in that case. □

Example 3.14. A drone powered by a battery will not have a similar variation of mass. It is a time-invariant system (unless e.g. its mass changes because it is a parcel-delivering drone). □

Example 3.15. WECs can have time-varying parameters due to the effects of tides. This is the case of the AWS in Figure 3.2, which is submerged and fixed to the ocean bottom. Consequently, the average height of sea water above it varies from low tide to high time, even if the sea waves remain the same. Other WECs are time-invariant, at least with respect to tides. That is the case of the floating OWC in Figure 3.8, which, precisely because it floats, is not affected by tides. □

Dynamic system
Static system

A system has no dynamics if its outputs in a certain time instant do not depend on past values of the inputs or on past values of the disturbances. Otherwise, it is a **dynamic system**. A system without dynamics is called **static system**, which does not mean that it never changes; it means that, if its inputs do not change, neither do the outputs.

Example 3.16. Both mechanical systems in Figures 3.6 and 3.7 have no dynamics, since the output $y(t)$ only depends on the current value of the input $u(t)$. Past values of the input are irrelevant. □

Example 3.17. Consider a pipe with a tap (or a valve) that delivers a flow rate $Q(t)$ given by

$$Q(t) = k_Q f(t) \tag{3.4}$$

where $f(t) \in [0, 1]$ is a variable that tells is if the tap is open ($f(t) = 1$) or closed ($f(t) = 0$). This system is static. But a tap placed far from the point where the flow exits the pipe will deliver a flow given by

$$Q(t) = k_Q f(t - \tau) \tag{3.5}$$

Here, τ is the time the water takes from the tap to the exit of the pipe. This is an example of a dynamic plant, since its output at time instant t depends on a past value of $f(t)$. □

A system is **deterministic** if the same inputs starting from the same initial condition always lead to the same output. A system is **stochastic** if its outputs are not necessarily the same when it is subject to the same inputs beginning with the same initial conditions, or, in other words, if its output is random.

Deterministic system
Stochastic system

Example 3.18. The process from Example 3.5 is stochastic. Even though we may know all those variables, it is impossible to precisely predict the wind speed. The same happens with the process from Example 3.2, and even more so. □

Example 3.19. Figure 3.9 shows a laboratory setup to test controllers for the lithography industry (which produces microchips with components positioned with precisions of the order of 1 nm). This is a deterministic system. If lithography plants and processes were not deterministic, it would be far more difficult to mass produce microchips. □

In this course we will only address deterministic, SISO, linear time-invariant (**LTI**) systems.

LTI systems

3.2 Signals

In chapter 1 we have already defined signal as a function of time or space that conveys information about a system. In other words, it is the evolution with time or with space of some variable that conveys information about a system. Most of the signals we will meet depend on time but not on space.

Example 3.20. An image given by a camera is a signal that depends on space, but not on time. A video is a signal that depends on both space and time. □

Some signals can only take values in a discrete set; they are called **quantised signals**. Others can take values in a continuous set; they are called **analogical signals**.

Quantised signal
Analogical signal

Example 3.21. Consider a turbine, such as the turbine in Figure 3.10, of the Wells type, installed in the Pico Power Plant (shown above in Figure 3.3). Its rotation speed is real valued; it takes values in a continuous set. So the signal consisting in the turbine's rotation speed as a function of time is an analogical signal. □

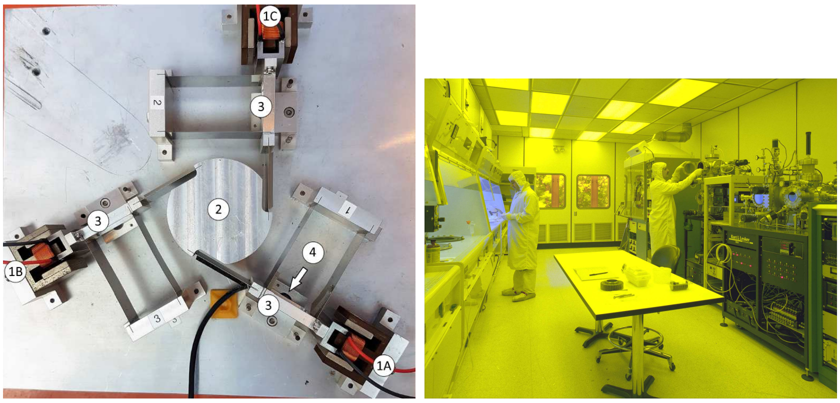

Figure 3.9: Left: precision positioning system used at the Delft University of Technology (source: DOI 10.1007/s11071-019-05130-2). Coil actuators 1 move masses 2, which are connected through flexures to mass 3, the position of which is measured using sensors (encoders) 4. Mass 2 can be positioned with a precision of 1 μm or less. Right: NASA clean room for lithography (source: Wikimedia).

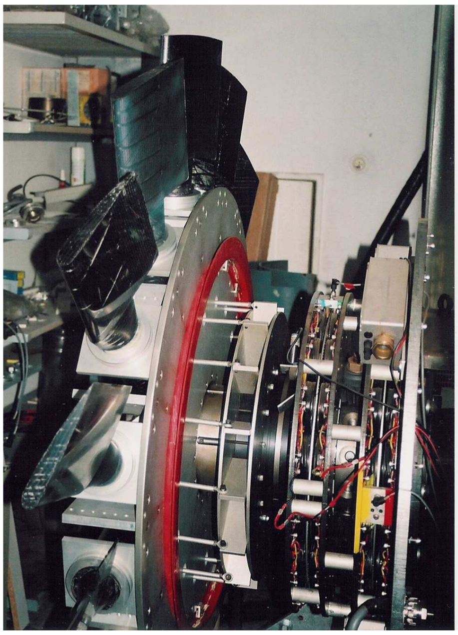

Figure 3.10: The Wells turbine of the Pico Power Plant OWC in Figure 3.3 (source: DOI 10.1016/j.renene.2015.07.086).

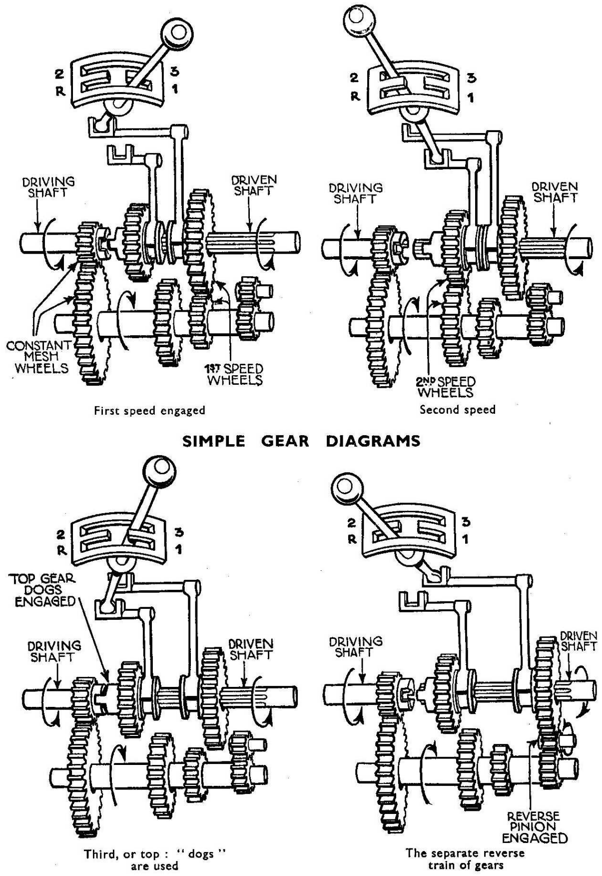

Figure 3.11: Three-speed manual gearbox, typical of cars in the 1930s (source: Wikimedia).

Example 3.22. Consider the gearbox of a car (see Figure 3.11). The signal consisting in the speed engaged as a function of time (neutral, reverse, 1st, 2nd, etc.) takes values in a discrete set. It is a quantised signal. □

Remark 3.1. It is possible, and sometimes desirable, to approximate a quantised signal by an analogical signal, and vice-versa. □

Example 3.23. The rotation of a shaft $\theta(t)$ is an analogical signal; it is of course possible to rotate the shaft by an angle as small as desired. But it is often useful to replace it by a discrete signal $\vartheta(t)$ which is the number of revolutions (i.e. the number of 360° rotations of the shaft). This corresponds to an approximation given by $\vartheta(t) = \lceil \theta(t) \rceil$. Figure 3.12 shows a mechanical revolution counter. □

Example 3.24. A population — be it the number of persons in a country, the number of rabbits in a field, or the number of bacteria on a Petri dish — is a quantised signal. It always increases or decreases in multiples of one, since it is

Figure 3.12: Mechanical 19th century revolution counter, from the former Barbadinhos water pumping station (currently the Water Museum), Lisbon. Nowadays mechanical revolution counters are still used, though electronic ones exist.

impossible that half a child be born, or that $\frac{3}{4}$ of a rabbit dies. However, if the population is large enough, a variation of one individual is so small that it is possible to assume that it is an analogical signal, and write equations such as

$$\frac{\mathrm{d}p(t)}{\mathrm{d}t} = b(t)p(t) - d(t)p(t), \tag{3.6}$$

where $p(t)$ is the population, $b(t)$ is the birth rate, and $d(t)$ is the death rate. (Terms for immigration and emigration rates must be included if the population is not isolated.) Such models (and others more complicated, that we will mention in passing below in Chapter 14) are used for instance in Bioengineering and in many other areas. □

Example 3.25. Strictly speaking, variables such as the fuel admitted to one of the cylinders of an internal combustion engine are also quantised, since the number of molecules of fuel admitted is integer. Of course, in practice an analogical value is assumed. □

Continuous signal
Discrete signal
Sampling time
Sampling frequency

Some signals take values for all time instants: they are said to be **continuous**. Others take values only at some time instants: they are said to be discrete in time, or, in short, **discrete**. The time interval between two consecutive values of a discrete signal is the **sampling time**. The sampling time may be variable (if it changes between different samples), or constant. In the later case, which makes mathematical treatment far more simple, the inverse of the sampling time is the **sampling frequency**.

Example 3.26. The air pressure inside the chamber of an OWC is a continuous signal: it takes a value for every time instant. □

Example 3.27. The number of students attending the several classes of this course along the semester is a discrete signal: there is a value for each class, and the sampling time is the time between consecutive classes. The sampling time may be constant (if there is e.g. one practical class every Monday) or variable (if there are e.g. two lectures per week on Mondays and Wednesdays). □

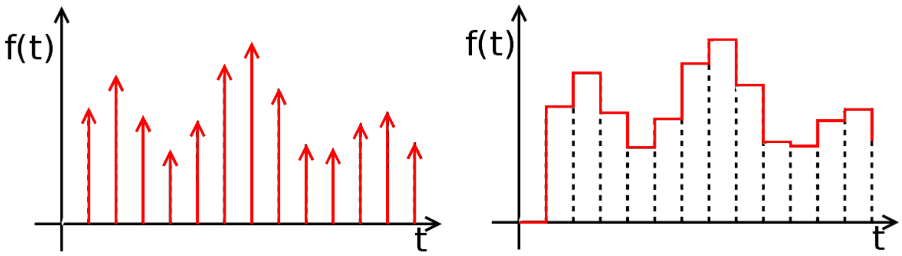

Figure 3.13: Left: discrete signal; right: continuous signal obtained from the discrete signal by keeping the previous value between sampling times (source: Wikimedia, modified).

Example 3.28. One of the controllers used with the laboratory setup from Example 3.19 in Figure 3.9 provided a discrete control action with sampling frequency 20 kHz. So the sampling time was

$$T_s = \frac{1}{20 \times 10^3} = 50 \times 10^{-6} \text{ s} = 50 \ \mu\text{s}, \tag{3.7}$$

or, in other words, every 50×10^{-6} s the control action for the coil actuators was updated; or, again, the control action was updated 20×10^3 times per second. The sampling frequency could also be given as

$$\omega_s = \frac{2\pi}{50 \times 10^{-6}} = 2\pi \times 20 \times 10^3 = 125.7 \times 10^3 \text{ rad/s}. \quad \square \tag{3.8}$$

Remark 3.2. Mind the numerical difference between the value of the sampling frequency in Hertz and in radians per second. It is a common source of mistakes in calculations. □

Remark 3.3. It is possible, and sometimes desirable, to approximate a discrete signal by a continuous signal, and vice-versa. Approximating a continuous signal by a discrete one is an operation called **discretisation**. We will study this issue in more detail below in Chapter 11. □ *Discretisation*

Example 3.29. The control action from Example 3.28 had in fact to be converted into a continuous signal to be applied by the coil actuators. As described, this was done by keeping the control action signal constant between sampling times. The operation corresponds to converting a discrete signal as seen in the left of Figure 3.13 into a continuous signal as seen in the right diagram of that Figure. □

Example 3.30. Figure 3.14 illustrates the operation of discretisation. □

A signal which is both discrete and quantised is a **digital signal**. *Digital signal*

A system, too, is said to be continuous, discrete, or digital, if all its inputs and outputs are respectively continuous, discrete, or digital. *Continuous system* *Discrete system*

Electronic components are nowadays ubiquitous. As a result of sensors, actuators, controllers, etc. being electronic, most signals are digital. Likewise, systems that incorporate such components are digital, inasmuch their inputs and outputs are all digital. *Digital system*

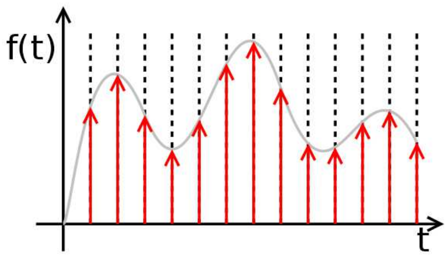

Figure 3.14: Discretising a signal (source: Wikimedia), i.e. approximating a continuous signal (grey) by a discrete one (red).

Figure 3.15: Industrial oven for aircraft component manufacture (source: Wikimedia).

Example 3.31. Consider an industrial oven, seen in Figure 3.15, with a control system to regulate its temperature. The output of this system is the actual temperature inside the oven, and the input is the desired temperature (i.e. the reference of the control system). The oven is heated by gas, and so the gas flow is the manipulated variable that allows controlling the oven. This is a continuous system, since all variables exist in all time instants. But, in all likelihood, a digital sensor will be used for the temperature, and changes in gas flow will also take place at sampling times, after the temperature reading is compared with the reference and processed to find the control action that will better eliminate the error between actual and desired temperatures. So in practice the system will probably be digital. □

Example 3.32. A flush tank for a toilet equipped with a float valve as seen in the top scheme of Figure 3.16 is a control system devoid of any electronic component, and for which all signals are continuous. (See also Figure 3.17.) This is a continuous control system. □

Bounded signal

A signal is **bounded** if it can only assume values in a bounded interval. In engineering, most signals (if not all) are bounded.

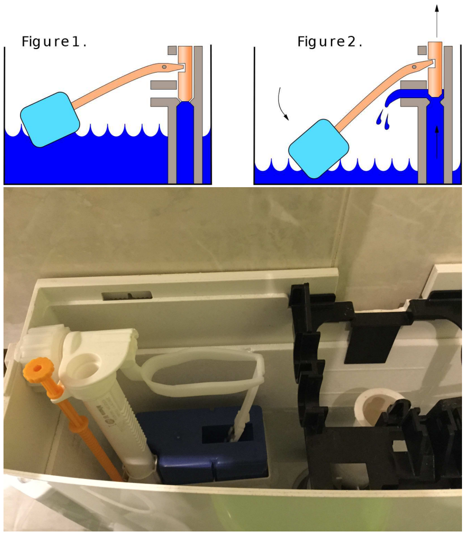

Figure 3.16: Top: float valve mechanism, well known by its use in flush tanks (source: Wikimedia). Bottom: flush tank with a float valve (notice that the lever has two arms, to increase the speed with which the water flow is interrupted as soon as the float raises the level from the lower end of stroke).

Example 3.33. The wave elevation at given coordinates cannot be less than the depth of the sea there. Similarly, the rotation speed of a turbine, or the linear velocity of a shaft, or a voltage in a circuit, are always limited by physical constraints. □

Remark 3.4. Bounded continuous signals can assume infinite values, but bounded quantised signals can only assume a finite number of values. □

3.3 Models

In Section 3.1 we have already defined a system's model as a mathematical relation between its inputs and outputs. There are basically two ways of modelling a system:

1. A model based upon **first principles** is a theoretical construction, resulting from the application of physical laws to the components of the plant. *First principles model*

2. A model based upon **experimental data** results from applying identification methods to data experimentally obtained with the plant. *Experimental model*

It is also possible to combine both these methods.

In this course we will concentrate on models based upon first principles, and you will find abundant examples thereof in Chapters 4 through 8. They can be obtained whenever the way the system works is known. They are the only possibility if the system does not exist yet because it is still being designed and built, or if no experimental data is available. They may be quite hard to obtain *When to use first principles models*

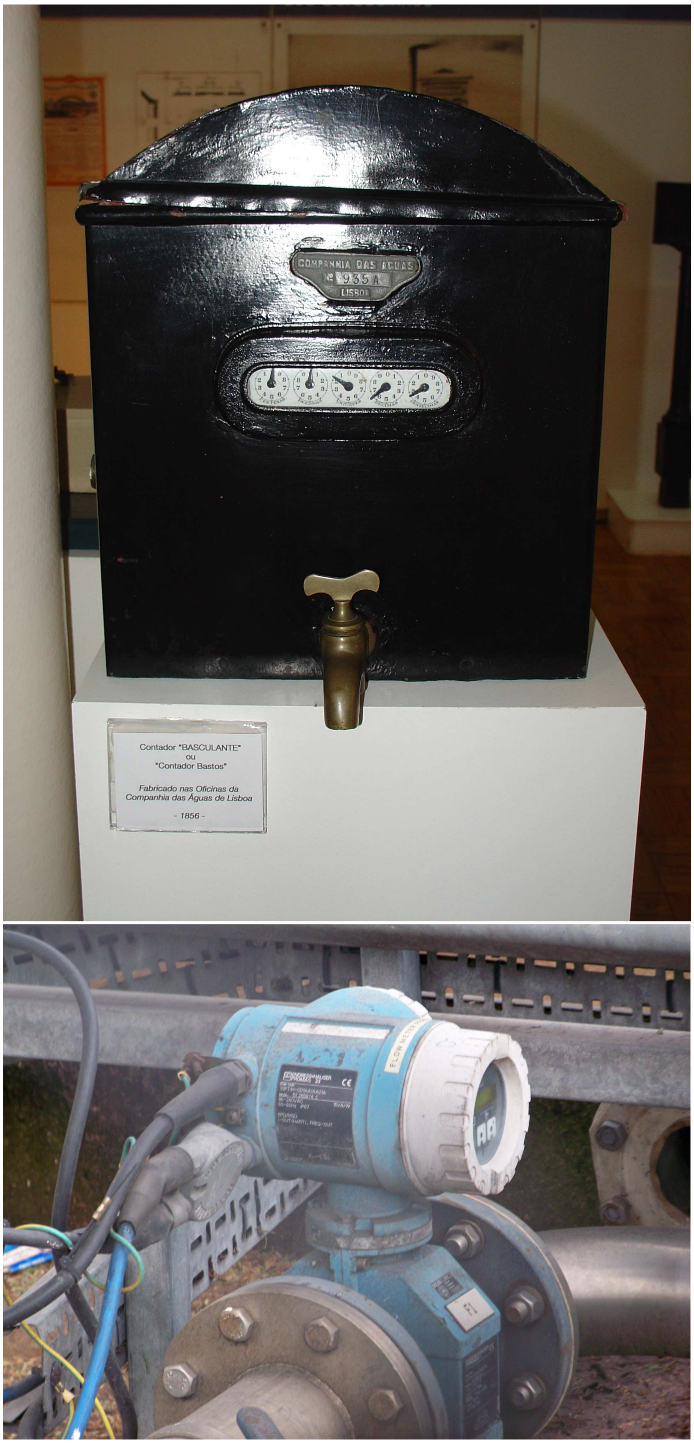

Figure 3.17: Top: a float valve (see Figure 3.16) was also used in water meters devised by António Pinto Bastos in the 1850s, which were used in Lisbon until the 1960s in spite of being obsolescent for a long time by then (source: Wikimedia). These meters were purely mechanical. Bottom: electromagnetic flow meters have no mechanical components; the reading can be sent elsewhere rather than having to be read in the dials *in loco* (source: Wikimedia). We will address sensors for flow measurements in Chapter 12.

if the system comprises many complicated interacting sub-parts. Simplifications can bring down the model to more manageable configurations, but its theoretical origin may mean that results will differ significantly from reality if parameters are wrongly estimated, if too many simplifications are assumed, or if many phenomena are neglected.

Differential equations

Difference equations

The models of dynamic continuous LTI systems are given by linear **differential equations**. The models of dynamic digital LTI systems are given by linear **difference equations**. The models of static LTI systems are linear and have neither derivatives nor time differences.

Example 3.34. The static model of the lever (3.1) includes neither differential nor difference equations. It is irrelevant whether $x(t)$ and $y(t)$ are discretised or not. The same happens with the non-linear static model of the Cardan joint (3.2). □

Example 3.35. Continuous model (3.6) is a differential equation. Suppose that the model is applied to the population of a country, where immigration and emigration are neglectable, and for which population data is available on a yearly basis. Also suppose that birth and death rates are constant and given by $b = 0.03/\text{year}$ and $d = 0.02/\text{year}$. So

$$\frac{\mathrm{d}p(t)}{\mathrm{d}t} = 0.01p(t) \tag{3.9}$$

Because the sampling time is $T_s = 1$ year, we can perform the following approximation:

$$\left.\frac{\mathrm{d}p(t)}{\mathrm{d}t}\right|_{t=\text{year }k} \approx \frac{p_k - p_{k-1}}{1\text{ year}}, \tag{3.10}$$

where p_k is the population in year k, and p_{k-1} is the population in the year before. Notice that this is a first order approximation for the derivative in year k, in which we use the value of the year before, and is consequently called a backward approximation. So we end up with the following difference equation:

$$p_k - p_{k-1} = 0.01p_k \Leftrightarrow p_k = \frac{1}{0.99}p_{k-1}, \tag{3.11}$$

which is an approximation of differential equation (3.9); approximations other than (3.10) could have been used instead. We will address this subject further below in Chapter 11. □

Example 3.36. Differential equation (2.53) can be approximated by difference equation

$$3y_k = 0.4y_{k-1} + 0.2y_{k-2} + 0.8e^{T_s\,k} + 1.6e^{T_s\,(k-1)} + 0.8e^{T_s\,(k-2)} \tag{3.12}$$

for sampling time T_s. □

Experimental identification of model parameters

Experimental data should, whenever available, be used to confirm, and if necessary modify, models based upon first principles. This often means that first principles are used to find a structure for a model (the orders of the derivatives in a differential equation, or the number of delays in a difference equation), and then the values of the parameters are found from experimental data: feeding the model the inputs measured, checking the results, and tuning the parameters until they are equal (or at least close) to measured outputs. This can sometimes be done using least squares; sometimes other optimisation methods, such as genetic algorithms, are resorted to. If the outputs of experimental data cannot be made to agree with those of the model, when the inputs are the same, then another model must be obtained; this often happens just because too many simplifications were assumed when deriving the model from first principles. It may be possible to find, from experimental data itself, what modifications to model structure are needed. This area is known as **identification**, and will not be addressed in this course.

White box model

Models based upon first principles can be called **white box models**, since the reason why the model has a particular structure is known. If experimental data requires changing the structure of the model, a physical interpretation of the new parameters may still be possible. The resulting model is often called a **grey box model**.

Grey box model

There are methods to find a model from experimental data that result in something that has no physical interpretation, neither is it expected to have. Still the resulting mathematical model fits the data available, providing the correct outputs for the inputs used in the experimental plant. Such models are called **black box models**, in the sense that we do not understand how they work. Such models include, among others, neural network (NN) models (see an example in Figure 3.18) and models based upon fuzzy logic, known as fuzzy models (see Figure 3.19). These modelling techniques are increasingly important, but we will not study them in this course.

Black box model

Glossary

> "Lascia stare, cerchiamo un libro greco!"
> "Questo?" chiedevo io mostrandogli un'opera dalle pagine coperte di caratteri astrusi. E Guglielmo: "No, questo è arabo, sciocco! Aveva ragione Bacone che il primo dovere del sapiente è studiare le lingue!"
> "Ma l'arabo non lo sapete neppure voi!" ribattevo piccato, al che Guglielmo mi rispondeva: "Ma almeno capisco quando è arabo!"

Umberto Eco (1932 — †2016), *Il nome della rosa*, Quinto giorno, Sesta

black box model modelo de caixa negra
bounded limitado
control system sistema de controlo
continuous contínuo
deterministic determinístico
difference equation equação às diferenças
digital digital
discrete discreto
disturbance perturbação
dynamic dinâmico
first principles primeiros princípios
grey box model modelo de caixa cinzenta
identification identificação
manipulated variable variável manipulada

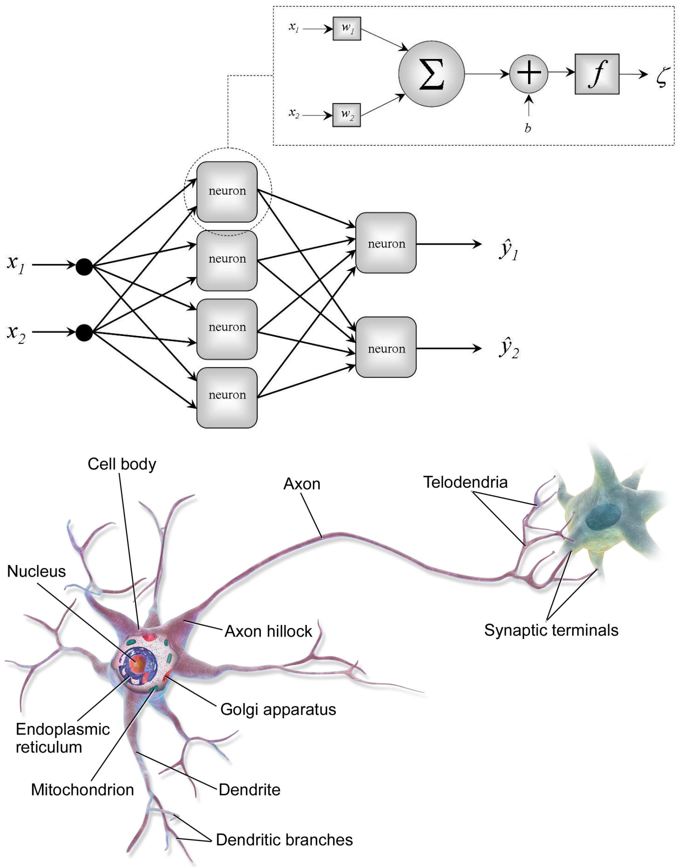

Figure 3.18: Top: scheme of an example of an artificial neural network (source: DOI 10.1016/j.apor.2008.11.002). It is made of several neurons, arranged in layers. These neurons are oversimplified models of biological neurons, seen in the bottom scheme (source: Wikimedia), which are arranged in far more complex patterns. The parameters of an artificial neural network are the configuration of its interconnections and the parameters of each neuron, which are not expected to have any physical meaning at all. Neuron parameters can be optimised from experimental data using numerical methods. The NN shown can be used to model a static MIMO system with two inputs and two outputs, or a dynamic system with one input and two outputs if $x_2(t) = x_1(t - Ts)$, in which case it provides a non-linear difference equation model with sampling time T_s. We will not study NNs in this course.

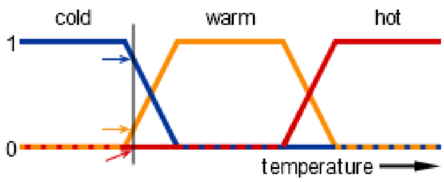

Figure 3.19: In Boolean logic, propositions are either true or false. These two cases correspond respectively to logical values 1 and 0. In fuzzy logic, all intermediate logical values can be used. The plot above shows an example of this (source: Wikimedia). For the temperature shown by the grey line, proposition "temperature is hot" has the logical value 0, proposition "temperature is warm" has the logical value 0.2, and proposition "temperature is cold" has the logical value 0.8. This type of logic can then be used to build models, both static and dynamic. We will not not study fuzzy logic or fuzzy models in this course.

mechatronic mecatrónico
mechatronics mecatrónica
multiple input entradas múltiplas
multiple output saídas múltiplas
input entrada
model modelo
output saída
plant planta
process processo
reference referência
sampling frequency frequência de amostragem
sampling time tempo de amostragem
signal sinal
single input entrada única
single output saída única
static estático
stochastic estocástico
white box model modelo de caixa branca

Exercises

1. Answer the following questions for each of the mechatronic systems below:
    - What are its outputs?
    - What are its inputs?
    - Is the system SISO or MIMO?
    - Which of the inputs can be manipulated, if any?
    - Is it a static or a dynamic system?
    - Is it time varying or time invariant?
    - Is the system continuous or digital?

    (a) An automated train system, as seen in Figure 3.20.

Figure 3.20: The Stansted Airport Transit System conveys passengers between Terminals 1 and 2 of Stansted Airport, United Kingdom (source: Wikimedia). Vehicles have no driver. They stop, open doors, close doors, and move between terminals automatically.

Figure 3.21: Physicist Stephen Hawking (1942 — †2018) attending a scientific conference in 2001 (source: Wikimedia).

(b) A power wheelchair, as seen in Figure 3.21.

(c) A motorboat, as seen in Figure 3.22.

(d) A rigged ship, as seen in Figure 3.22.

(e) A submarine, as seen in Figure 3.23.

(f) A space probe, as seen in Figure 3.24.

(g) A robotic arm, as seen in Figure 3.25.

2. Use the Laplace transform to solve (3.9) for the situation starting at a time when the country's population is 10 million inhabitants. Find the population for $t = 1, 2, 3 \ldots$ years. Then use (3.11) to find the evolution of the population starting with year $k = 1$ (corresponding to $t = 0$ years) when the country's population is 10 million inhabitants. Find the population for $k = 2, 3, 4 \ldots$ and compare the results with those obtained with (3.9).

Figure 3.22: Left: a motorboat with an outboard motor at Zanzibar, Tanzania (source: Wikimedia). Right: Portuguese Navy school ship Sagres (formerly Brazilian school ship Guanabara, formerly German school ship Albert Leo Schlageter; source: Wikimedia).

Figure 3.23: The Portuguese Navy submarine Tridente, of the Tridente class, propelled by a low noise skew back propeller and powered by hydrogen–oxygen fuel cells (source: Wikimedia).

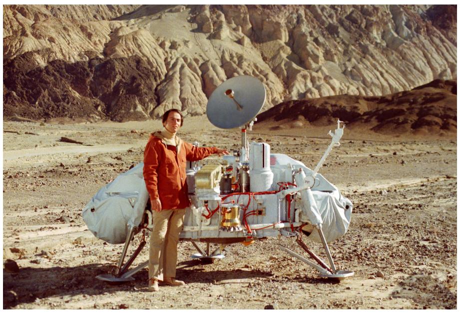

Figure 3.24: Astronomer Carl Sagan (1934 – †1996) with a model of one of the two Viking landers, space probes that descended on Mars in 1976 and worked until 1980 and 1982 (source: Wikimedia). Descent speed was controlled by deploying a parachute and launching three retrorockets (one on each leg) to ensure a soft landing. The descent control system employed an inertial reference unit, four gyroscopes, a radar altimeter, and a landing radar.

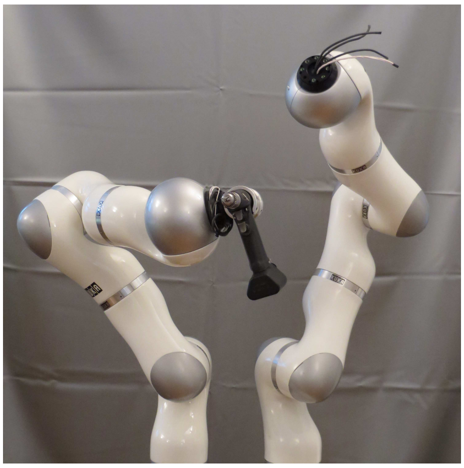

Figure 3.25: Two KUKA LWR IV robotic arms extant at the Control, Automation and Robotics Laboratory of Instituto Superior Técnico, Universidade de Lisboa, Portugal. Each robot has seven rotational joints.