What is this course about?

\[ u \rightarrow \text{System} \rightarrow y \]

\[ v = \text{disturbance} \]

\[ r + \sum e = \text{control error} \]

The control problem: Minimize \( e \), including the effect of \( v \), and keep \( u \) small \((u_{\text{min}} \leq u \leq u_{\text{max}})\).

Ultimate course goal: Find the optimal solution!
Example 1: Mission to Mars (Bring’em back alive)

Predefined optimal trajectory minimizes required amount of fuel. Steer the rocket so that the deviation from the optimal trajectory is minimized, with minimal fuel consumption (we want to get back!).
Example 2: Wastewater treatment

A wastewater treatment plant removes contaminants from sewage, e.g. nutrients like ammonia and phosphorus.
One step (of many) is nitrogen removal in a bioreactor:

- **Output**: Concentrations of ammonia and nitrate in effluent water
- **Input**: Air flow, external carbon, recirculation...
- **Disturbance**: Variations of flow rates and concentrations of nutrients in the incoming water...

Remove as much contaminants as possible, to as low cost as possible.

*Characteristics*: Multivariable system, disturbances to a large extent periodical (on daily, weekly and yearly bases),...
How do we solve the problem? Course goal in parts

Optimal controllers:
Minimize a cost function \( V = \|y\|^2 + \rho \|u\|^2 \), \( \rho > 0 \) design parameter.

- \textit{LQG} gives a linear, observer based state feedback controller. Truly optimal under idealized conditions. \((\text{Chap. 9})\)

- \textit{MPC} exploits numerical optimization. Constraints on \(u\) and \(y\) are easily handled. Gives a nonlinear controller. \((\text{Chap. 16})\)
Course goal in parts, cont’d

 DISTURBANCE MODELS:

With a good characterization of the disturbances, a better performance can be achieved. *(Chap. 5)*

- Regard disturbances as random signals = stochastic processes.
- Characterize them by their frequency content = their spectrum.
- Model them as output from a linear system with a totally random input (= white noise).
- Their behaviour can be predicted by an optimal observer = the Kalman filter.
Discrete-time systems: Controllers are generally implemented in computers. A computer cannot handle continuous-time signals, only numbers ⇒ use uniform sampling. (Chap. 2, 3, 4, 5, 9, 16)

- All signals are discrete in time, i.e. sequences.
- Discrete-time models are described by difference equations = recurrence relations (rather than differential equations).
- Use the Z-transform (instead of the Laplace transform).
- A continuous-time system can be represented by a discrete-time model
  - exactly if the inputs are piecewise constant,
  - approximately using a discrete-time approximation of the time derivative.
**Multivariable systems:**

Typically a system has more than one input and more than one output. MIMO = Multi-Input Multi-Output (and SISO = Single-Input Single-Output). *(Chap. 3)*

- In the model $Y(s) = G(s)U(s)$ of a MIMO system $Y(s)$ and $U(s)$ are vectors, and $G(s)$ is a matrix.

- Convenient to use state space models for MIMO systems, looks and works the same way as for SISO systems.

- The bioreactor in example 2 is a MIMO system.
Course outline

- **F1–F2, Ö1:** Intro, repetition
- **F3–F5, Ö2–Ö3:** Discrete-time system, sampling, MIMO
- **F6–F8, Ö4–Ö5, BL1:** Disturbance models
- **F9–F11, Ö6, BL2–BL3, Lab:** Optimal control (LQG, MPC)
- **F12:** Guest lecture, repetition
- **Compulsory parts:** Process labs, final exam