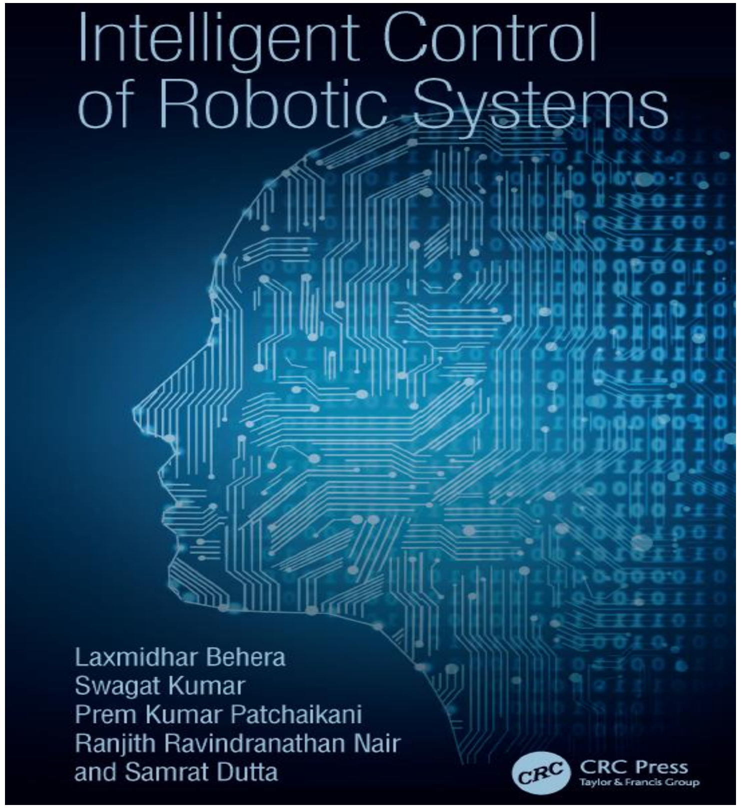
Introduction to intelligent control systems (knowledge-based vs data-driven systems)

Course Objectives	The goals of this lecture are as follows: to introduce intelligent-based control systems to overcome modeling difficulties and to use computationally efficient procedures for directing a complex system. Intelligent control systems include expert systems, machine learning, and deep learning, among others, and have a high level decision making scheme that generates the control signal based on a qualitative or heuristic understanding of the process.
Course Content	Intelligent Control Systems: Computational Thinking Tools for Control Engineers, Dynamical System Modeling, Model Predictive Control (MPC) Data-driven modeling, Data-driven methods, Data-driven control techniques, Introduction to machine learning, Introduction to deep learning, Introduction to reinforcement learning, General Applications on System Modelling and Control Design, Thermal Systems, Robotic Control Systems, and Control System performance.

Recommended or Required Reading - English

1. Liu, Jinkun. (2017). Intelligent control design and MATLAB simulation. 10.1007/978-981-10-5263-7.
2. Behera, Lingaraj & Kumar, Swagat & Patchaikani, Prem & Ravindranathan Nair, Ranjith & Dutta, Samrat. (2020). Intelligent Control of Robotic Systems. 10.1201/9780429486784.
3. Ponce, Pedro & Ramirez Figueroa, Fernando David. (2010). Intelligent control systems with LabVIEW™. 10.1007/978-1-84882-684-7.

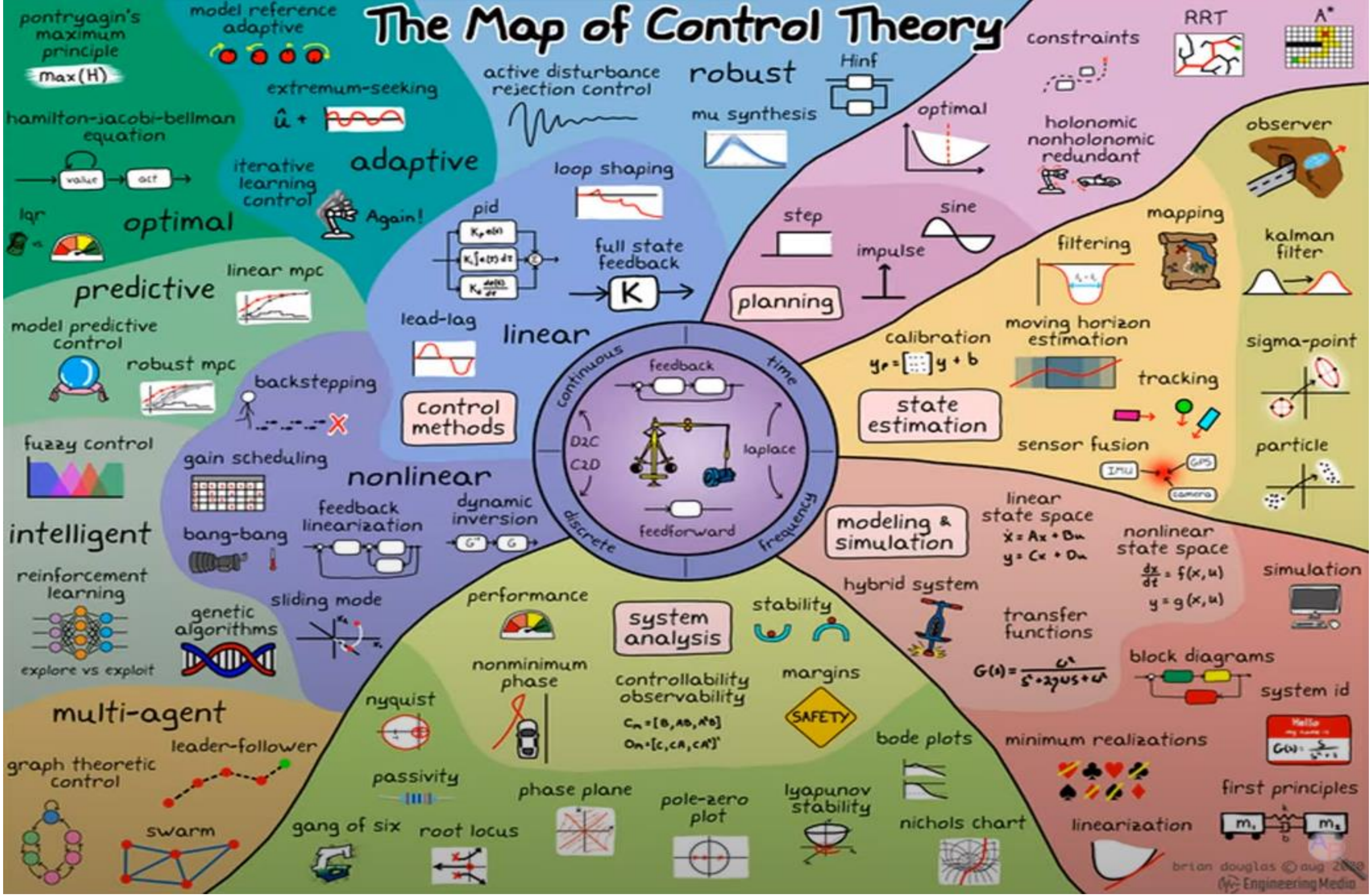
https://drive.google.com/drive/folders/1C4icnxJ4JDyjtu1w8Hvp1nErg89IUfc1?usp=sharing



	Intelligent Control System KOM 5101
1	Introduction to Intelligent Control Systems (knowledge-based vs data-driven systems)
2	Computational Thinking Tools
3	Dynamical Systems Modelling (Control System Toolbox could be used to transfer functions, state space models)
4	Model Predictive Control MPC (MPC Toolbox can be used)
5	Intro to Machine Learning (Stats & Machine Learning Toolbox could be used)
6	Data-driven Modeling -with machine learning (Stats & Machine Learning Toolbox could be used)
7	Data-driven Modeling -with system Identification (SysID toolbox could be used)
8	Midterm Exam
9	Data-driven Control Techniques -Extremum seeking (Simulink Control Design could be used)
10	Data-driven Control Techniques -Model reference adaptive control (Simulink Control Design could be used)
11	Intro to Deep Learning (Deep Learning Toolbox could be used)
12	Reinforcement Learning (RL Toolbox could be used)
13	Student's Projects
14	Student's Projects
15	Final Exam

MathWorks®

Dr. Julia Hoerner
Dr. Marco Rossi
Dr. Melda Ulusoy


The Map of Control Theory
pontryagin's maximum principle
max(H)
model reference adaptive
extremum-seeking
hamilton-jacobi-bellman equation
value
act
iterative learning control
Again!
adaptive
active disturbance rejection control
robust
Hinf
mu synthesis
loop shaping
lqr
optimal
predictive
linear mpc
model predictive control
robust mpc
pid
full state feedback
K
lead-lag
linear
backstepping
control methods
fuzzy control
gain scheduling
nonlinear
intelligent
bang-bang
feedback linearization
dynamic inversion
reinforcement learning
explore vs exploit
genetic algorithms
sliding mode
multi-agent
leader-follower
graph theoretic control
swarm
continuous
time
feedback
D2C
C2D
laplace
discrete
feedforward
frequency
constraints
RRT
A*
optimal
holonomic
nonholonomic
redundant
observer
step
sine
impulse
planning
mapping
filtering
kalman filter
calibration
moving horizon estimation
sigma-point
tracking
state estimation
sensor fusion
IMU
GPS
camera
particle
modeling & simulation
linear state space
$\dot{x} = Ax + Bu$
$y = Cx + Du$
nonlinear state space
$\frac{dx}{dt} = f(x,u)$
$y = g(x,u)$
simulation
hybrid system
transfer functions
block diagrams
system id
minimum realizations
first principles
m_1
m_2
linearization
performance
system analysis
stability
nonminimum phase
controllability observability
$C_n = [B, AB, A^nB]$
$O_n = [C, CA, CA^n]'$
margins
SAFETY
nyquist
bode plots
passivity
phase plane
pole-zero plot
lyapunov stability
nichols chart
gang of six
root locus
brian douglas © aug 2020
Engineering Media

Evaluation System

Activities	Number	Percentage of Grade
Mid-Term	1	20
Attendance/Participation	1	10
Homework Assignments	1	30
Work Presentation	1	10
Project	1	30
	Percentage of In-Term Studies	100
	TOTAL	100

My recommended online training:

•Week 1 (pre-requisites)

- MATLAB Onramp (2h) and Simulink Onramp (2h) + MATLAB Fundamental (15h, *potential extra assignment for top-students*)

- Control Design Onramp with Simulink (20min - Chapter 1,2,3)
  - Toolboxes: Control System Toolbox & Simulink Control Design
- Machine Learning Onramp (2h) + Machine Learning with MATLAB (13h, *potential extra assignment for top-students*)
  - Toolboxes: Statistics and Machine Learning Toolbox
- Control Design Onramp with Simulink (30min - Chapter 4,5,6,7) + Simscape Onramp (1.5h, *potential extra assignment for top-students*)
  - Toolboxes: Control System Toolbox & Simulink Control Design
- Deep Learning Onramp (2h) + Deep Learning with MATLAB (8h, *potential extra assignment for top-students*)
  - Toolboxes: Deep Learning Toolbox
- Reinforcement Learning Onramp (3h)
  - Toolboxes: Reinforcement Learning Toolbox

Evaluation System

Homework Assignments	30%

- Week 2 (start) – Week 8(deadline)
    - Control Design Onramp with Simulink (20min - Chapter 1,2,3)
- Week 4 (start) – Week 8 (deadline)
    - Control Design Onramp with Simulink (30min - Chapter 4,5,6,7)
- Week 5 (start) – Week 8 (deadline)
    - Machine Learning Onramp (2h)
- Week 8 (start) - Week 11 (deadline)

    Deep Learning Onramp (2h)

Week 9 (start) –Week 11 (deadline)

- Reinforcement Learning Onramp (3h)

Homework Assignments 30%

Control Design Onramp with Simulink

7 modules | 1 hour | Languages

Get started quickly with the basics of feedback control design in Simulink.

Machine Learning Onramp

6 modules | 2 hours | Languages

Learn the basics of practical machine learning methods for classification problems.

Deep Learning Onramp

5 modules | 2 hours | Languages

Get started quickly using deep learning methods to perform image recognition.

Reinforcement Learning Onramp

5 modules | 3 hours | Languages

Master the basics of creating intelligent controllers that learn from experience.

MathWorks Excellence in Innovation Projects

Contribute to the progress of engineering and science by solving key industry challenges!

a list of inspiring projects based on industry trends for your capstone, senior design project, or final year assignment. These projects help you learn about technology trends while becoming an important and valued contributor to the advancement of technical computing and Model-Based Design with MATLAB and Simulink. Even more, you gain official recognition for your problem-solving skills from technology leaders at MathWorks.

- 5G
- Artificial Intelligence
- Autonomous Vehicles
- Big Data
- Computer Vision
- Drones
- Industry 4.0
- Robotics
- Sustainability and Renewable Energy

https://github.com/mathworks/MathWorks-Excellence-in-Innovation

Presentations/Jury	1	10
Project (Manuscript and Programs)	1	30

- 5G
- Artificial Intelligence
- Autonomous Vehicles
- Big Data
- Computer Vision
- Drones
- Industry 4.0
- Robotics
- Sustainability and Renewable Energy

The project can be done by max. 2 students.

https://github.com/mathworks/MathWorks-Excellence-in-Innovation

Intelligent control is a computationally efficient procedure of directing a complex system that typically combines planning with on-line error compensation; it requires learning of both the system and the environment.

https://www.sciencedirect.com/topics/computer-science/intelligent-control-system

Intelligent control is derived from conventional control, but is used to deal with complex processes that cannot be controlled by traditional methods.

The intelligent controls mainly have the following function: learning, adaptive and organizing function.

https://www.sciencedirect.com/topics/computer-science/intelligent-control-system

Intelligent Control Approach

The main paths of Intelligent Control may include, for example, expert systems, fuzzy logic, machine learning, deep learning, etc.

An intelligent control mechanism, for example, replaces the analytic controller in a conventional control system with a high-level decision making scheme that generates the control signal based on a qualitative or heuristic understanding of the process.

https://www.sciencedirect.com/topics/computer-science/intelligent-control-system

What are Heuristics?

Heuristics are strategies often used to find a solution that is not perfect, but is within an acceptable degree of accuracy for the needs of the process.

In computing, heuristics are especially useful when finding an optimal solution to a problem is impractical because of slow speed or processing power limitations.

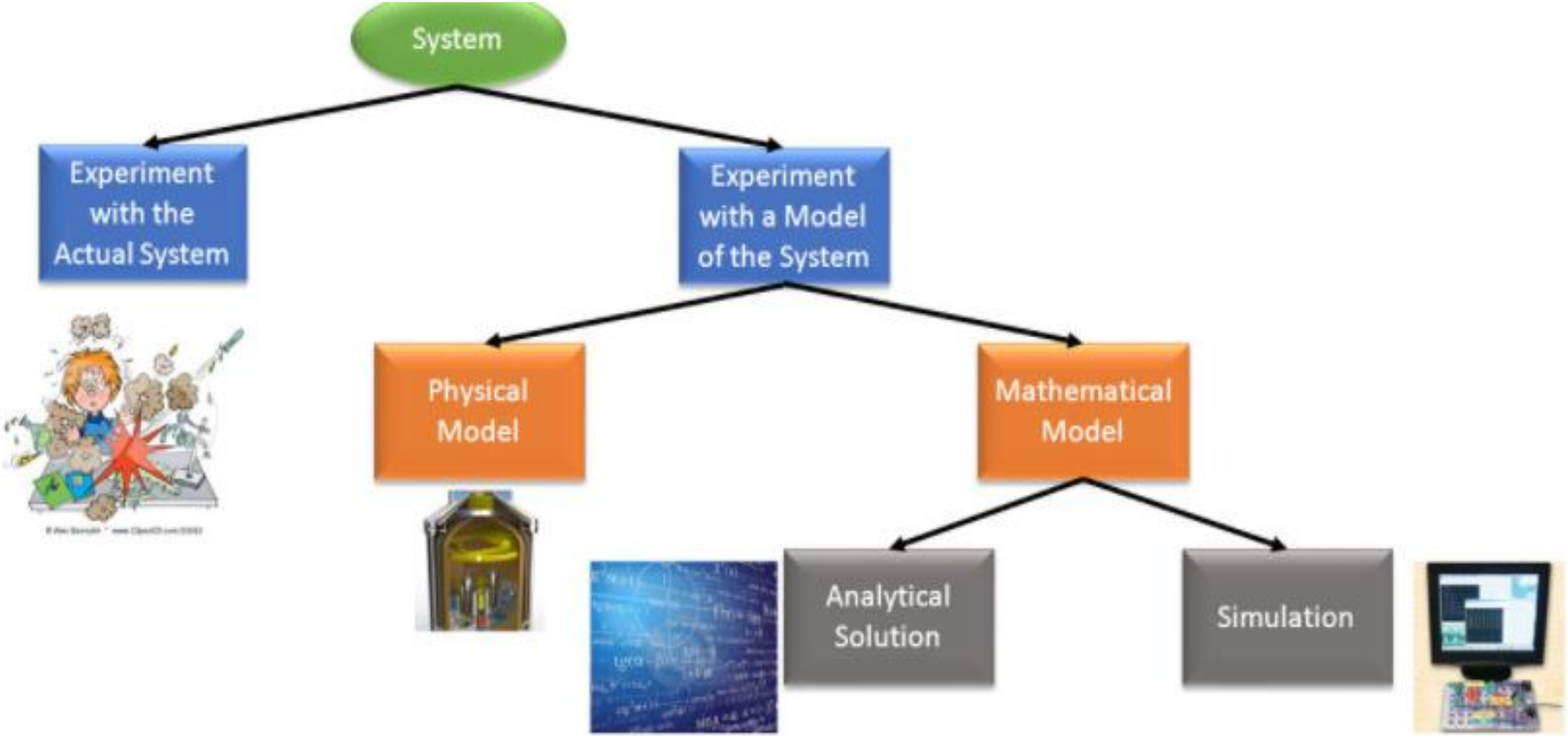
Intelligent control covers everything that is not characterized as conventional control.

- Intelligent control is interdisciplinary as it combines and extends theories and methods from areas such as control, computer science, and operations research. It uses theories from mathematics and seeks inspiration and ideas from biological systems.

- Intelligent control methodologies are being applied to robotics and automation, communications, manufacturing, and traffic control, to mention a few areas of application.

Ways to Study a System

Ways to Study a System



Model

A simplified representation or abstraction of reality.

- Reality is generally too complex to copy exactly.
- Much of the complexity is irrelevant in problem solving.

Approach to model dynamic systems

- Define the system and its components.
- Formulate the mathematical model and list the necessary assumptions.
- Write the differential equations describing the model.
- Solve the equations for the desired output with the given input variables.
- Examine the solutions and the assumptions.
- Simulate the model and analyze the results.
- If necessary, reanalyze or redesign previous steps.

Mathematical Model

A set of equations (e.g., differential eqs.) that describes the input-output behavior of a system.

WHAT IS A MODEL USED FOR?

- Simulation
- Prediction/Forecasting
- Prognostics/Diagnostics
- Design/Performance Evaluation
- Control System Design

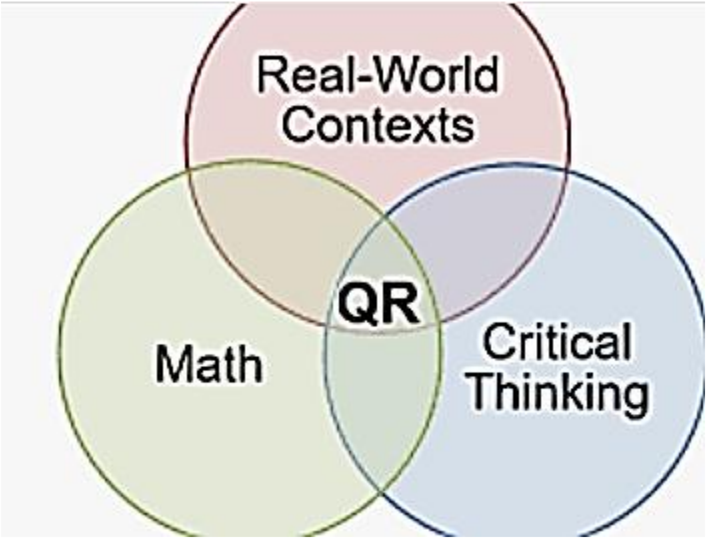
CLASSIFICATION OF MODELS

- Linear vs. Non-linear
- Deterministic vs. Probabilistic (Stochastic)
- Static vs. Dynamic
- Discrete vs. Continuous
- White box, black box and gray box

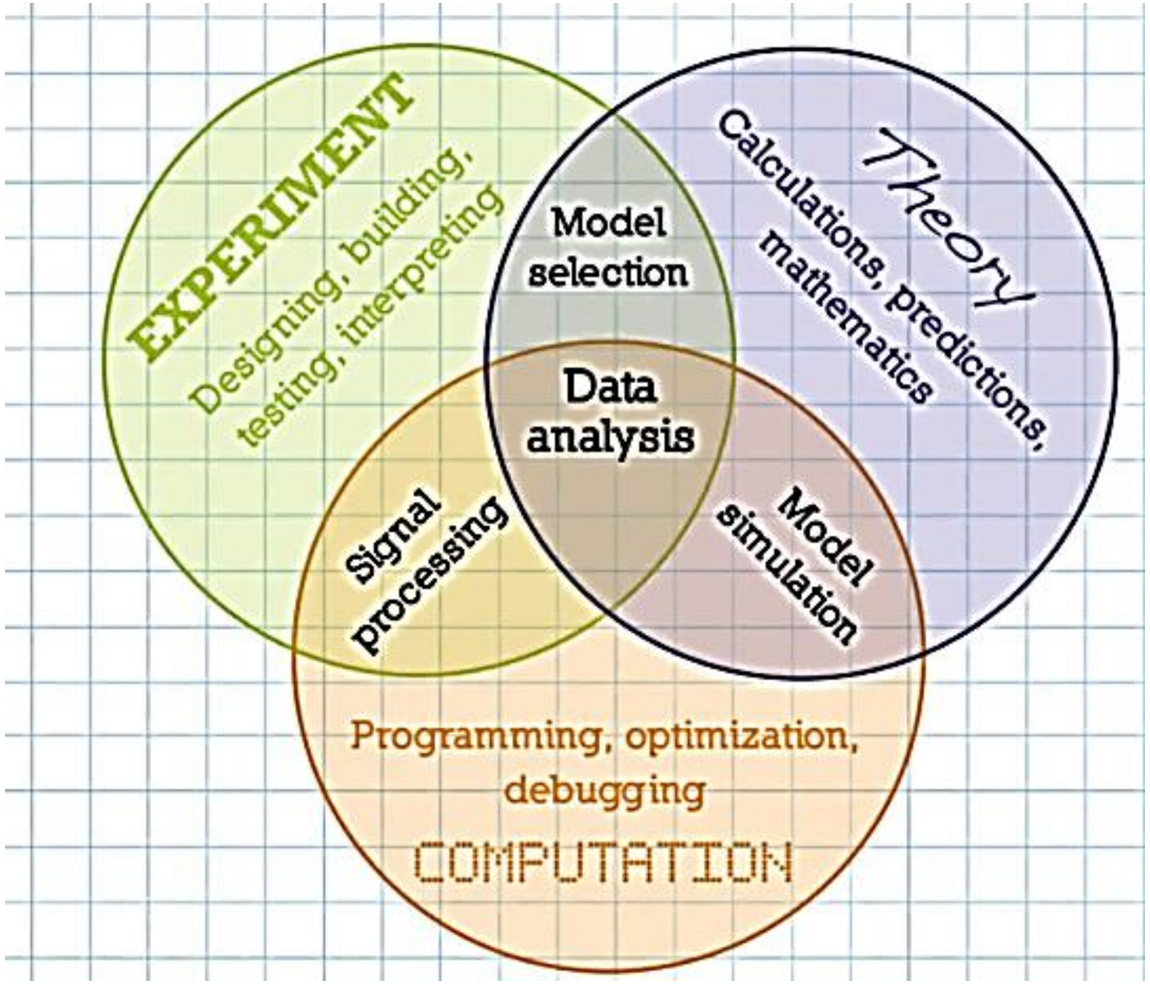
Mathematical models are an essential for simulation and design of control systems.

The purpose of the mathematical model is to be a simplified representation of reality, to mimic the relevant features of the system being analyzed.

This process is initiated by observing the phenomena, applying a mathematical model to it and predicting its behavior through simulation.

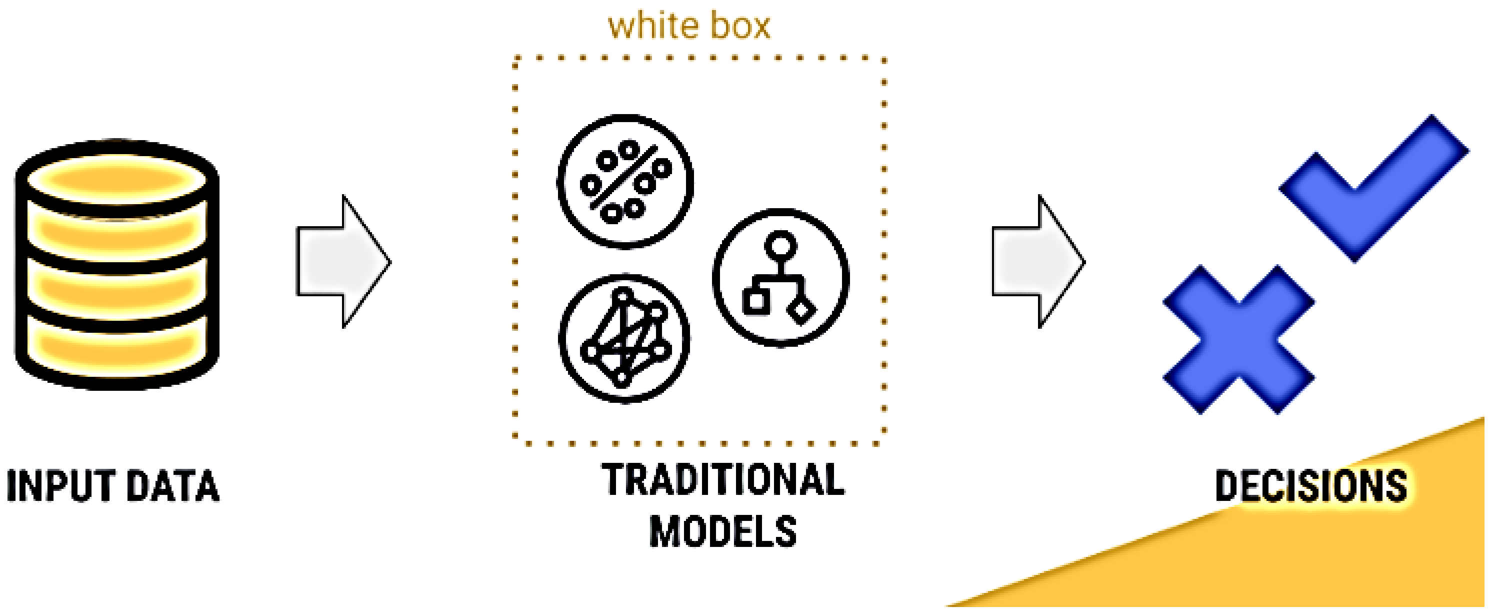


There are two main categories of mathematical modeling: theoretical and experimental.



In **theoretical modeling**, the system is described using **equations and** several simplifications have to be applied.

Systems which are modeled entirely based on physical/chemical principles are called **white-box models**.
The user has all the details concerning how the system works.

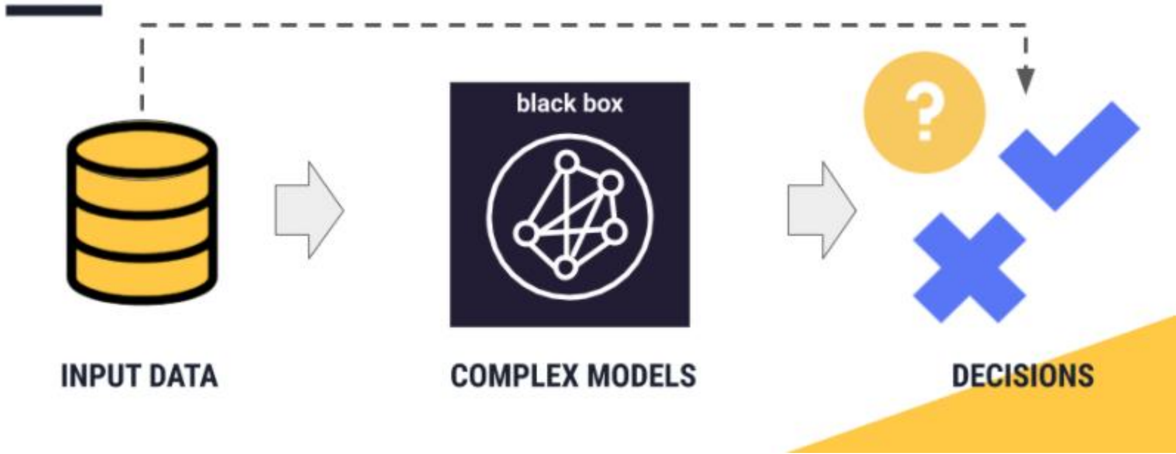


Experimental modeling, also called **system identification**.

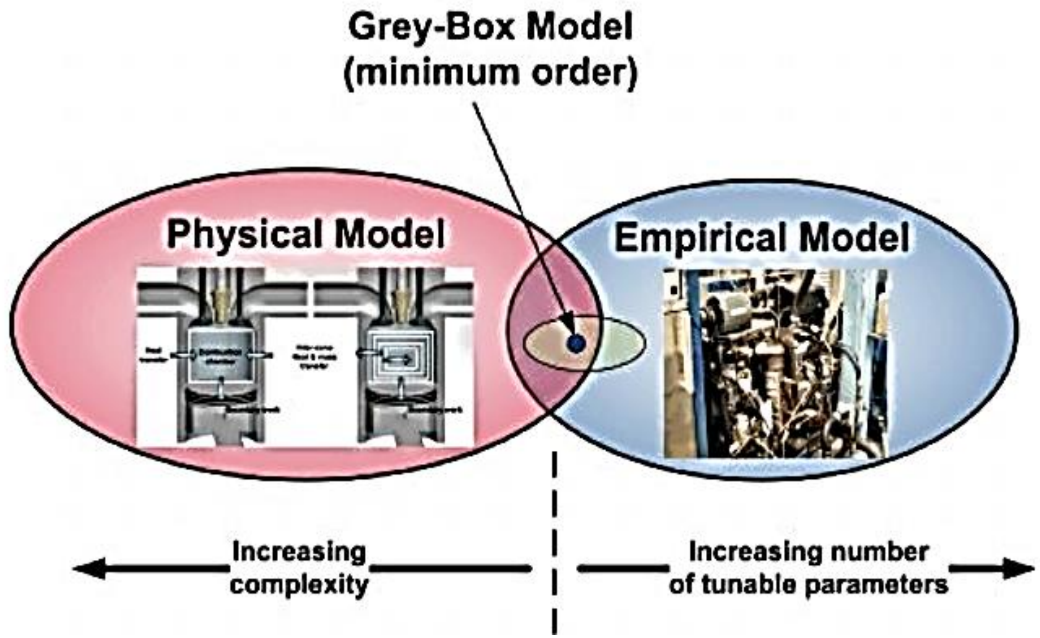
The mathematical model is derived from several sets of measurements, each recording the system's response (output) for different stimulus and perturbations (inputs).

Systems modeled entirely based on experimental data (input-output measurements) are called **black-box models**. The user can observe the response (output) of the model for a certain stimulus (input) but has no information about the internal mechanism (principles).

Black-box models can be constructed as **artificial neural networks**, trained based on the input-output measurements of the system.



Gray-box Models: **The benefit from the advantages of both methods.** For this type of models we know what structure of system we are analyzing but we do not have the right parameters for it.



A gray-box model is for example a **transfer function** or a **state-space model**. We can have a system that it's behaving as a first-order system, with the transfer function *H(s)*, but we do not know the gain (*K*) and the time constant (*T*). By using experimental data we can estimate the parameter *K* and *T*.

$$H(s) = \frac{K}{T \cdot s + 1}$$

Black box, Gray box and White box

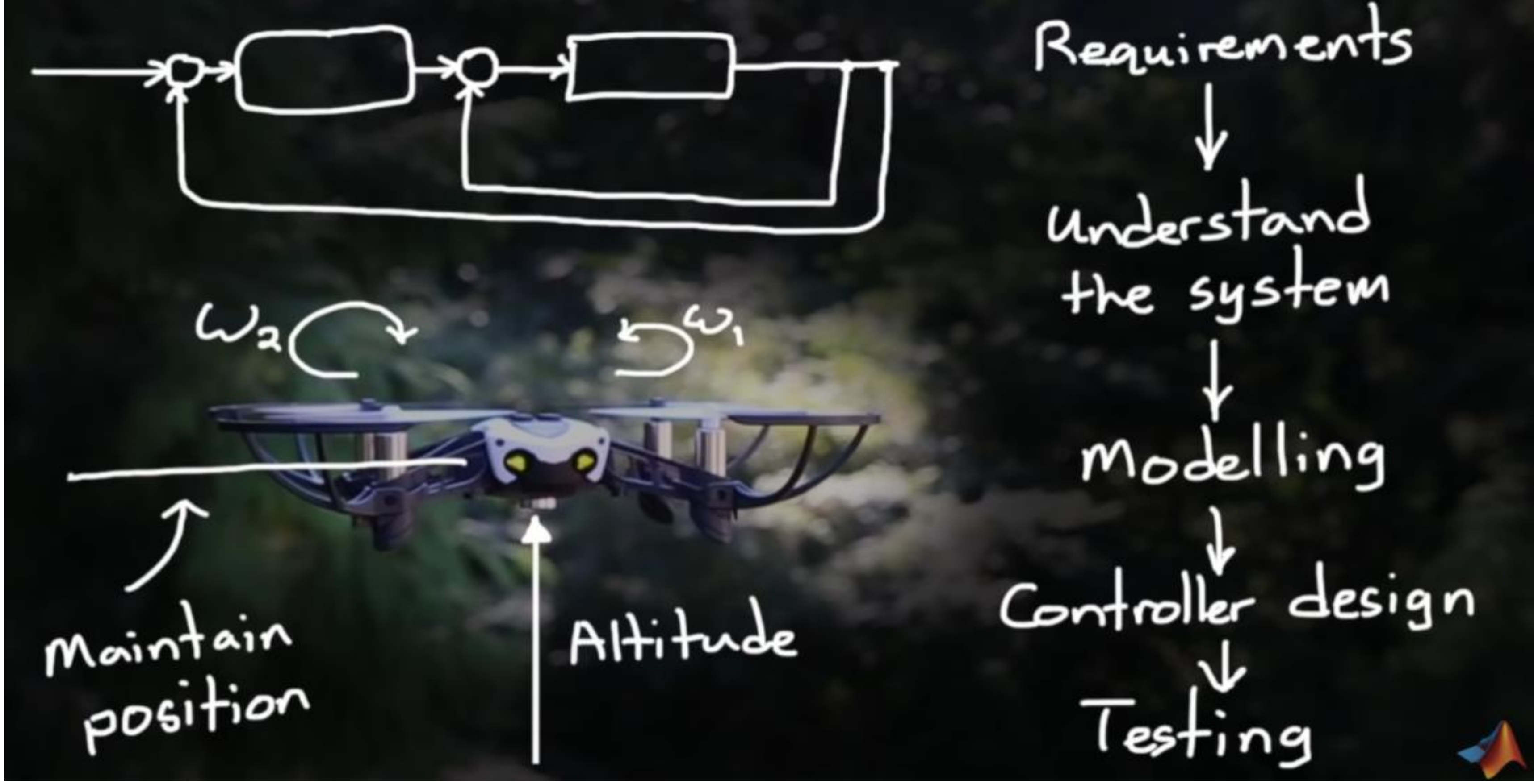
Model type	Characteristics	Consists of
White-box	•governing physical laws know •parameters know	•set of linear / non-linear differential equations
Light-gray-box	•some of the physical governing laws known •model structure known •parameters unknown	•set of linear / non-linear differential equations with parameters estimation •transfer function with parameters estimation •state-space model with parameters estimation
Dark-gray-box	•some of the physical governing laws known •model structure unknown •parameters unknown	•neuro-fuzzy models with parameters estimation
Black-box	•physical governing laws known •model structure unknown •parameters unknown	•artificial neural networks

What is the Role of Process Simulation Today?

Process simulation is today applied in almost all disciplines of engineering in general. It is the inevitable part of disciplines from process design, research and development, production planning, optimization, training and education to decision-making processes.

“This is why it is considered one of the most important disciplines of engineering”

Modeling and simulation today!



Drone Simulation and Control https://www.youtube.com/watch?v=hGcGPUqB67Q&list=RDCMUCgdHSFcXvkN6O3NXvif0-pA&index=2

How to Build a Model for Simulation https://www.youtube.com/watch?v=gEmGfo36INc

What does it mean to build “a successful simulation project”?

A successful simulation project is one that delivers **useful information** or **a result** at **the appropriate time** to **support** a **meaningful decision** or **task.**

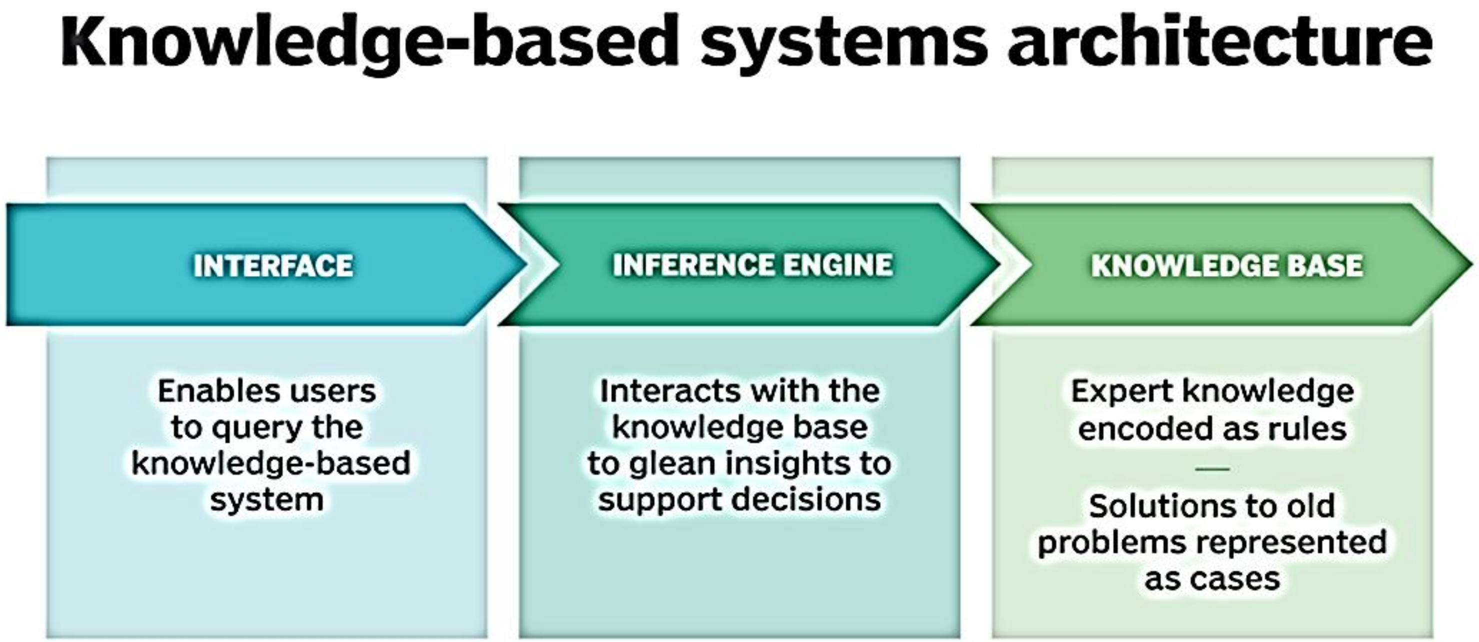
http://www.simulatelive.com/product-reviews/simulation/review-of-open-source-process-simulators

Knowledge-based Systems

It is a form of artificial intelligence (AI) that aims to capture the knowledge of human experts to support decision-making. Examples of knowledge-based systems include expert systems, which are so called because of their **reliance on human expertise.**

Example: clinical decision-support systems

Healthcare is an important market for knowledge-based systems

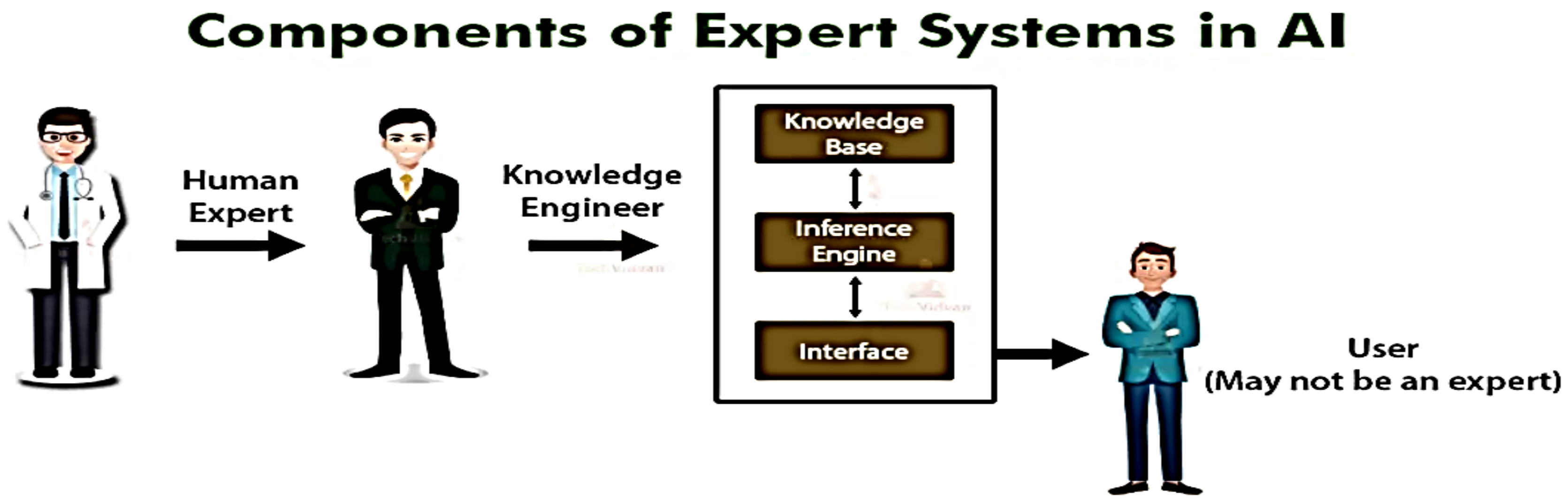


Knowledge-based Systems and Artificial Intelligence

"Top-down-organized, bureaucratically efficient know-it-all"

- Systems that harness Big Data
- Statistical pattern-finding techniques, such as data-mining and deep learning.

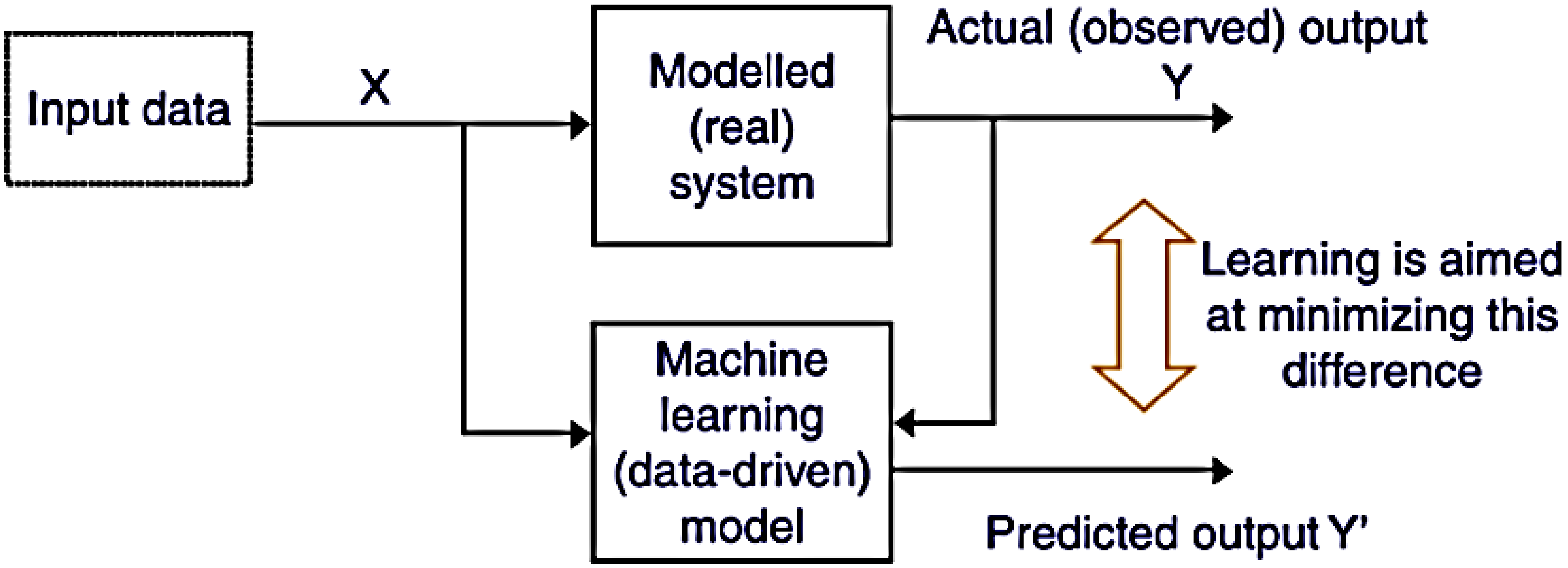
Some examples are: approaches that include neural network systems, a type of deep-learning technology for signal processing, and pattern recognition problems such as facial recognition.



Data-driven Modeling is based on the analysis of the data of a specific system to find relationships between the system state variables (input and output) without explicit knowledge of the physical behavior of the system.

Some examples of data-driven models apply statistical models (that include Linear regression, Autoregressive moving average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models) and Machine Learning (ML) models.

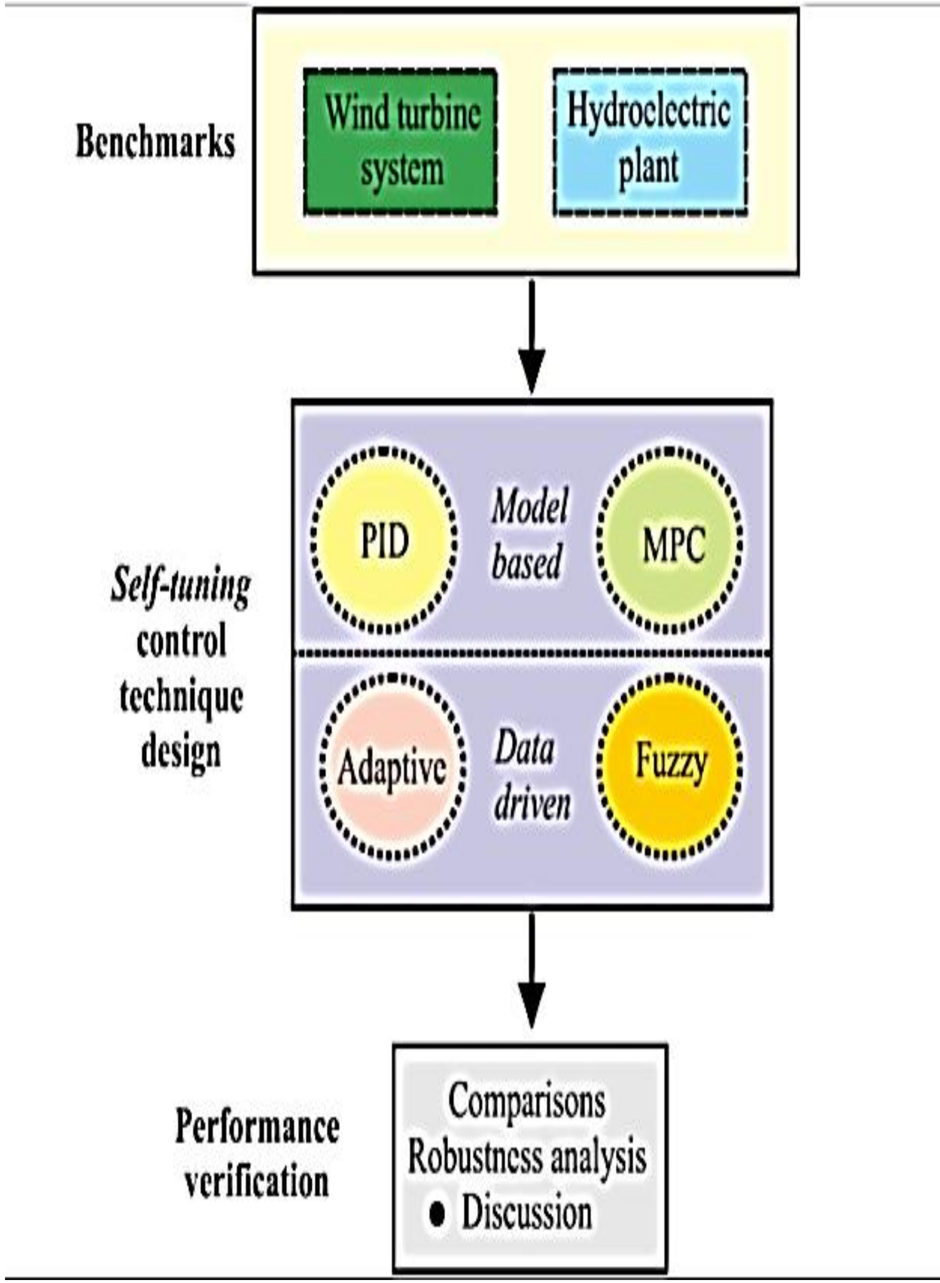
Data-driven modeling



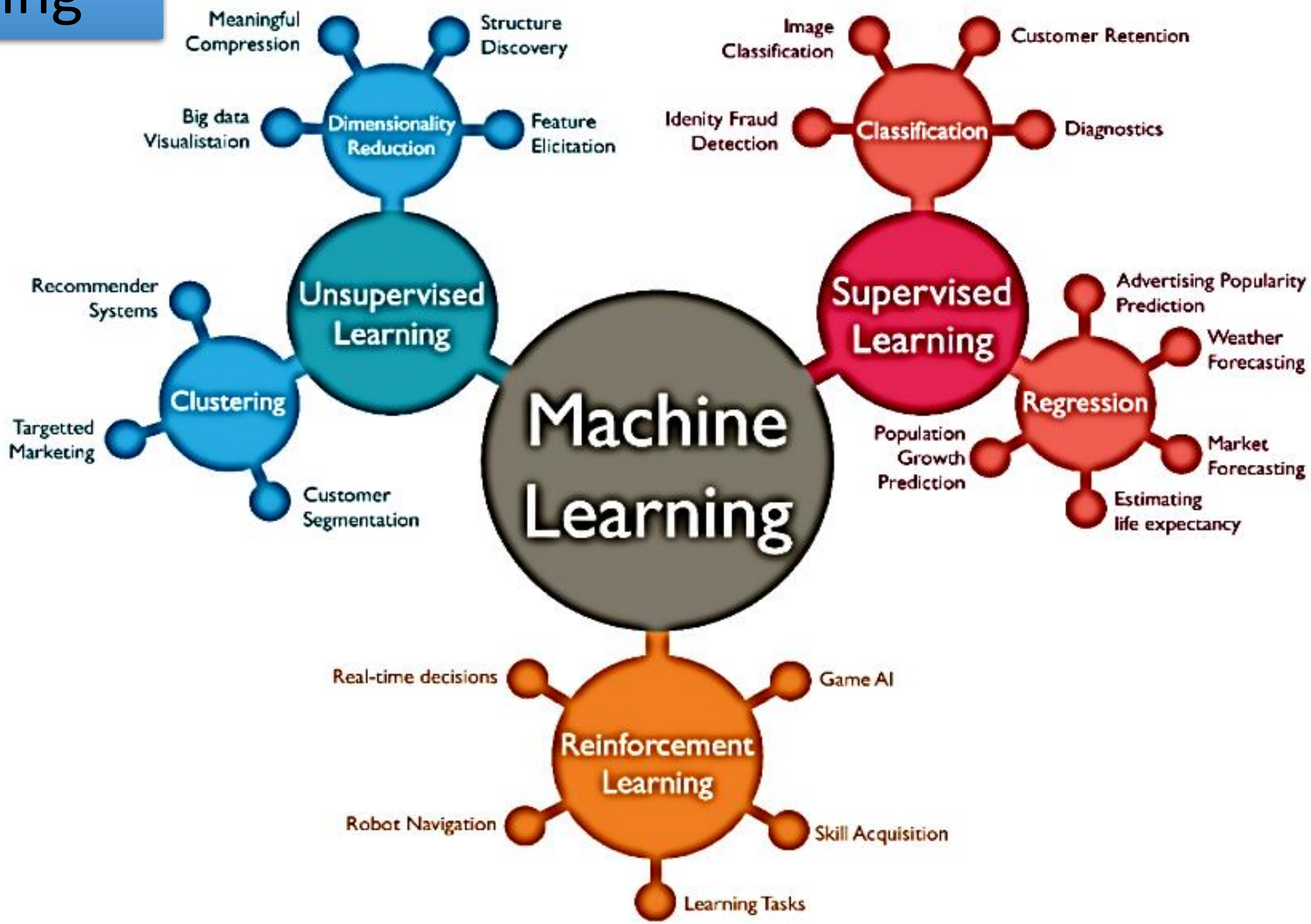
Data-driven Control Systems

A control systems in which the identification of the process model and/or the design of the controller are based entirely on experimental data collected from the plant.

- It is difficult to find a simple reliable model for a physical system and control specifications.
- Direct data-driven methods allow to tune a controller without an identified model of the system.
- It can also simply weight process dynamics of interest inside a cost function, and exclude those dynamics that are out of interest.



Machine Learning



Machine Learning is Everywhere

Solution is too complex for hand written rules or equations

Speech Recognition

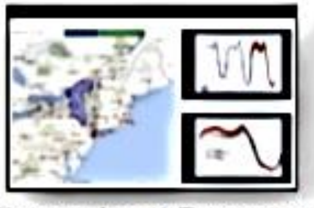

Object Recognition

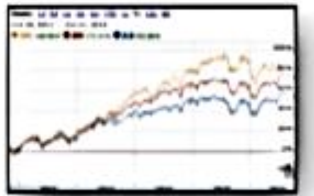

Engine Health Monitoring

learn complex non-linear relationships

Solution needs to adapt with changing data

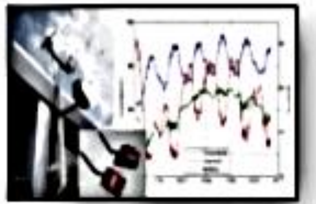

Weather Forecasting

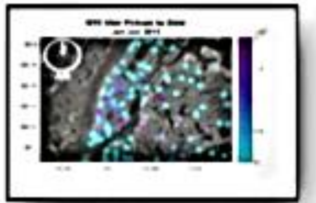

Energy Load Forecasting

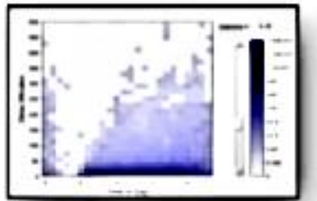

Stock Market Prediction

update as more data becomes available

Solution needs to scale

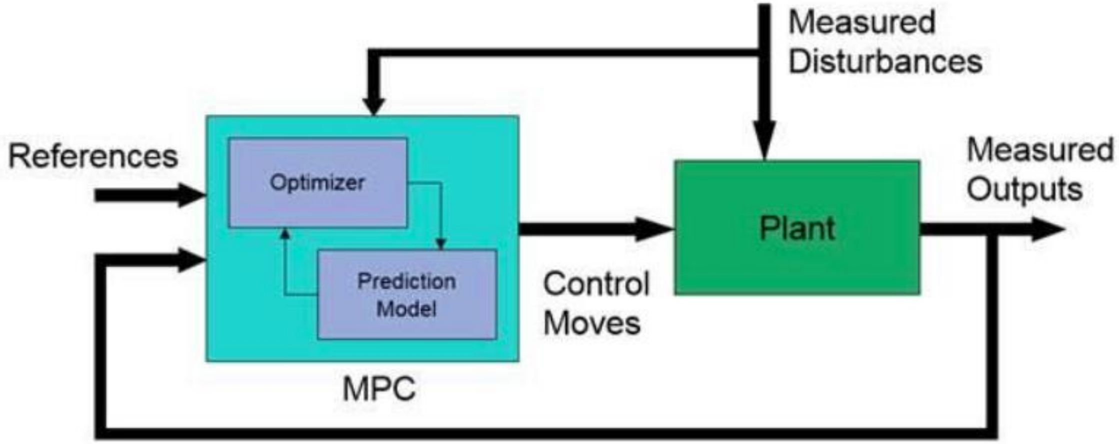

IoT Analytics


Taxi Availability


Airline Flight Delays

learn efficiently from very large data sets

Model Predictive Control (MPC)

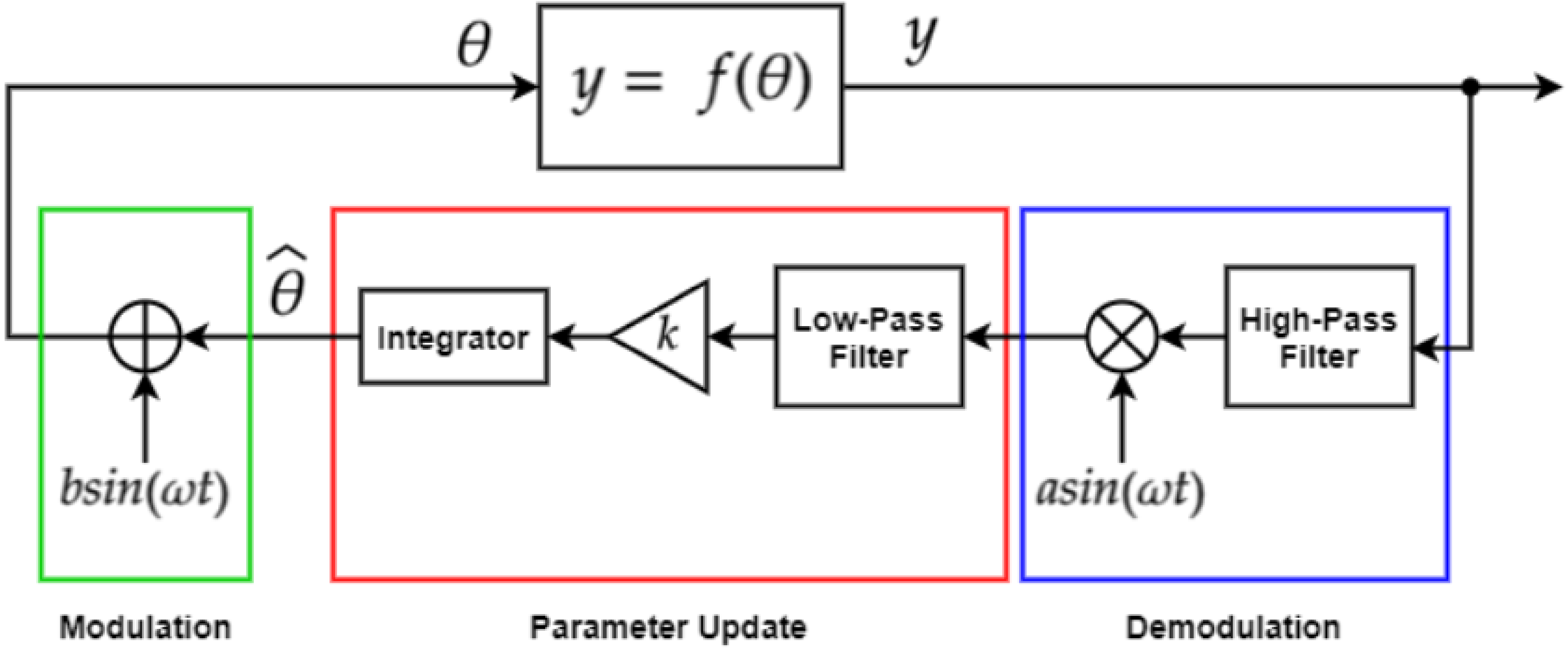


Model predictive control (MPC) is an optimal control technique in which the calculated control actions minimize a cost function for a constrained dynamical system over a finite, receding, horizon.

At each time step, an MPC controller receives or estimates the current state of the plant. It then calculates the sequence of control actions that minimizes the cost over the horizon by solving a constrained optimization problem that relies on an internal plant model and depends on the current system state.

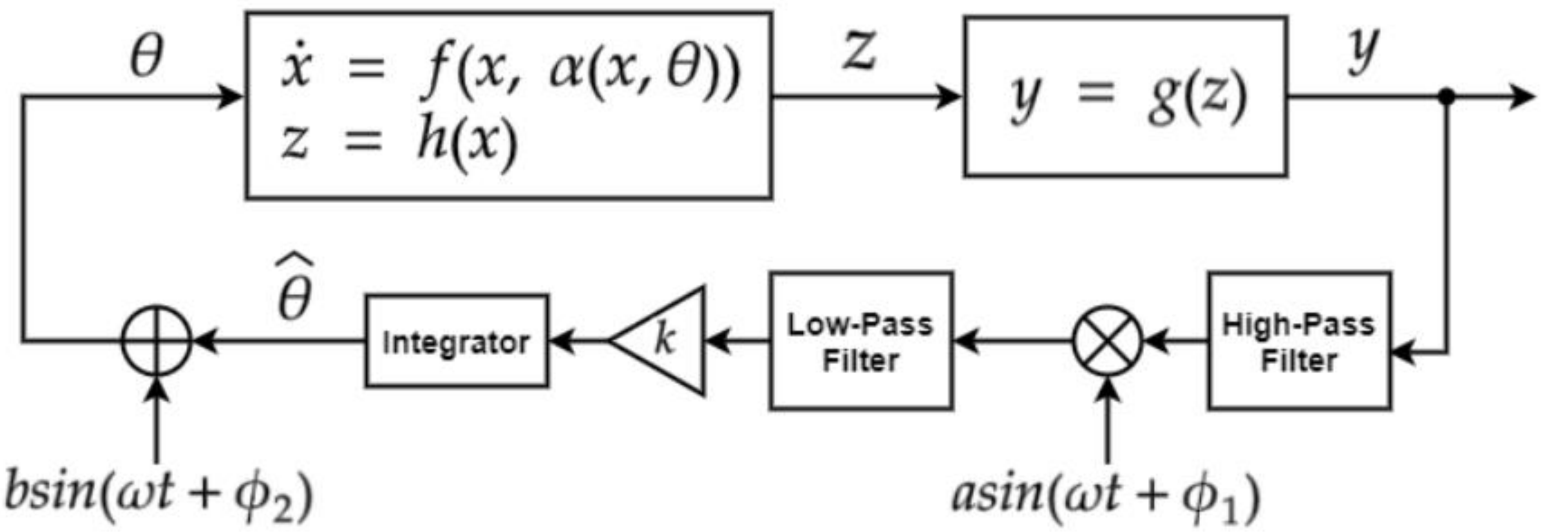
Extremum seeking Control

Extremum seeking controllers are model-free adaptive controllers that are useful for adapting to unknown system dynamics and unknown mappings from control parameters to an objective function. When seeking multiple parameters, the Extremum Seeking Control block uses a separate tuning loop for each parameter.



Dynamic System Optimization

Extremum seeking optimization of a dynamic system occurs in a similar fashion as static optimization. However, in this case, the parameter θ affects the output of a time-dependent dynamic system. The objective function to be maximized is computed from the system output. The following figure shows the general tuning loop for a dynamic system.



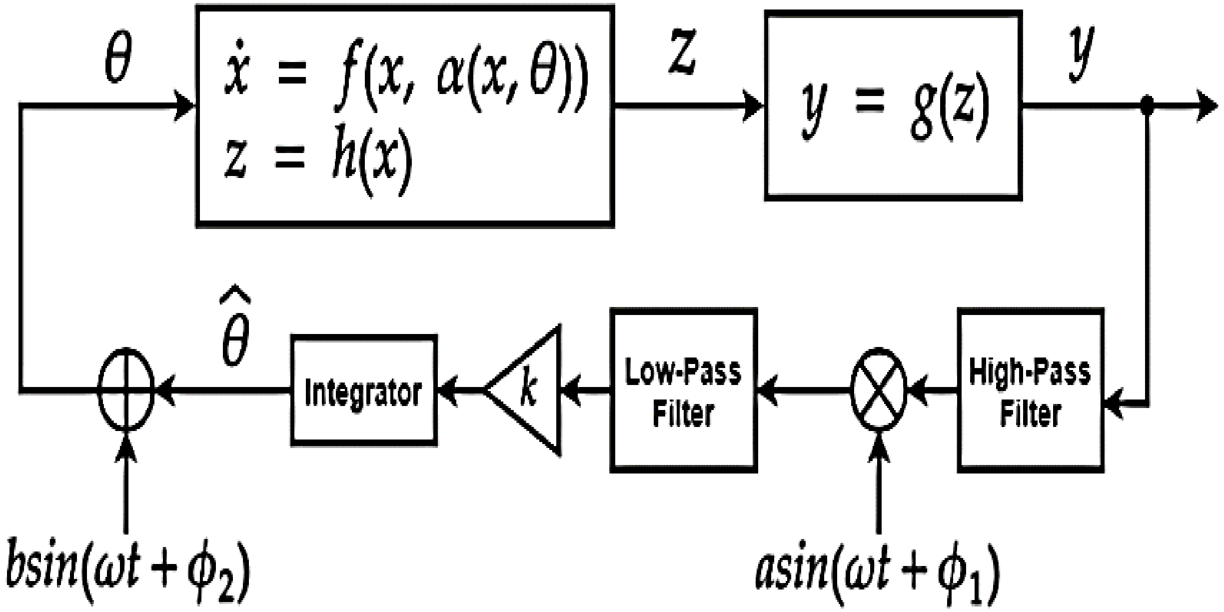
An **objective function** attempts to maximize profits or minimize losses based on a set of constraints and the relationship between one or more decision variables.

Extremum seeking optimization

- $\hat{\theta}$ is the estimated parameter value.
- θ is the modulation signal
- $y = f(\theta)$ is the function output being maximized, that is, the objective function.
- ω is the forcing frequency of the modulation and demodulation signals.
- $b \cdot \sin(\omega t)$ is the modulation signal.
- $a \cdot \sin(\omega t)$ is the demodulation signal.
- k is the learning rate.

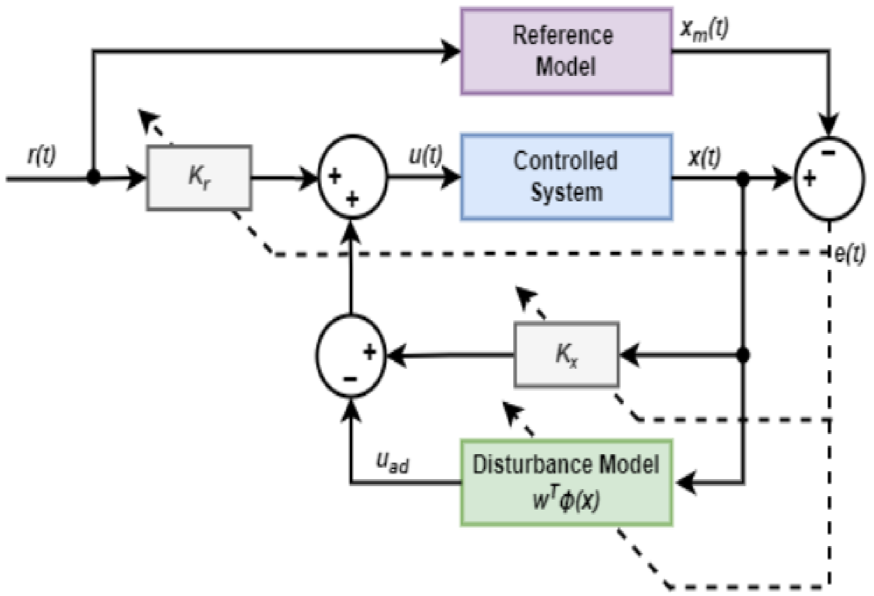
The optimum parameter value, θ^*, occurs at the maximum value of $f(\theta)$.

To optimize multiple parameters, you use a separate tuning loop for each parameter.



An **objective function** attempts to maximize profits or minimize losses based on a set of constraints and the relationship between one or more decision variables.

Model reference adaptive control



The controller adapts or is robust to plant changes, such as

Disturbances coming from the environment

Uncertainties in your system

Unaccounted in your model

Dynamics may change

Examples:

- Robust Control : the system works well even when there are unexpected variations
- Gain schedule : the controller gains will change between states
- Adaptive Control: the controller is constantly changing and optimizing parameters to adapt to variations