Glossary

"I learned very early the difference between knowing the name of something and knowing something."

- Richard Feynman

Active control – A controller that expends energy to accomplish a control task. For example, an automobile cruise-controller will actively control the fuel and brakes to regulate forward velocity.

Adaptive control – A controller that modifies its action to optimize performance or account for varying system parameters or externally varying conditions.

Actuator – A device that modifies the system according to the control input. The actuation effect is typically modeled by the structure of the **B** matrix in a control system.

Crossover – A genetic operation where two individuals exchange a portion of their expression, thereby increasing diversity of the future generation. Crossover tends to exploit successful patterns in the parent individuals to produce more fit offspring in future generations.

Closed-loop control – The process of controlling actuators based on sensor measurements.

Clustering – Identifying groups of similar data. If the data are labeled, this is called *supervised*, and if the data is not labeled, it is *unsupervised*.

Coherent structures – A structure in a dynamical system that remains coherent, or spatially correlated, for some time; here spatial correlation typically refers to the state of the dynamical system. In fluids, coherent structures often refer to persistent vortical structures that stay intact despite turbulent fluctuations.

Control theory – The theory of processes which modify a system for an engineering goal, often with actuators and sensors.

Cost function – A function that quantifies the cost or penalty of a given control law or estimator.

Disturbance – An external perturbation to the system that passes through the dynamics, also known as *process noise*. Disturbances are typically seen as unwanted perturbations that degrade performance, such as unreliable or unpredictable environmental conditions.

Dynamical system – A model for how a state evolves in time, possibly in response to an actuation signal and external disturbances. The dynamical system may have an *output equation* that consists of a set of measurements of the state and actuation signal. A dynamical system may either be *nonlinear* or *linear*, and they are often represented as a system of ordinary differential equations.

Elitism – A genetic operation whereby the best individual(s) from a generation are automatically copied to the next generation without probabilistic selection based on fitness.

Estimator – A dynamical system that estimates the state of another dynamical system from a limited set of measurements. See *Kalman filter*.

Evolutionary algorithm – An algorithm that adapts over time (generations) according to a fitness or cost function.

Exploitation – The process in an evolutionary algorithm whereby successful patterns in individuals of a given generation are *exploited* to produce more fit individuals in the next generation. Crossover is a genetic operation that promotes exploitation.

Exploration – The process in an evolutionary algorithm whereby new, unexplored patterns are sought out for individuals in future generations. Mutation is a genetic operation that promotes exploration.

Expression tree – A function or expression that may be expressed as a tree, where each node represents a unary or binary mathematical operation, such as $+$, $-$, $\times$, $/$, sin, cos, etc. Function trees may be quickly evaluated using recursion.

Feedback control – A closed-loop control architecture, whereby a downstream sensor measurement is fed back to an upstream actuator.

Feedforward control – A control architecture, whereby an upstream sensor measurement is fed forward to a downstream actuator. Often feedforward control is used to measure an incoming disturbance and apply preventative control downstream; this is known as *disturbance feedforward control*.

Fitness function – A function that measures the success of an individual expression in achieving some goal. Often inversely related to the *cost function*. In genetic algorithms and genetic programming, the fitness function determines the probability that an individual will be selected for the next generation.

Flow control – The process of modifying a fluid system to achieve some engineering goal. This is often accomplished by *active* control, whereby energy is expended to actuate the flow. High-level goals often include lift increase, drag reduction, mixing enhancement, and these goals may be achieved by physical mechanisms such as relaminarizing a boundary layer or stabilizing an unstable shear layer.

Frequency crosstalk – A phenomena in nonlinear dynamics where a signal or behavior at one frequency can effect or modify a signal or behavior at another frequency. In a linear system, input forcing at a single fixed frequency will result in an output response with the same frequency and a new magnitude and phase. However, in a nonlinear system, forcing a system at a single fixed frequency may result in an output response where multiple frequencies are modified through nonlinear coupling mechanisms.

Generation – A collection of individuals to be tested in a genetic algorithm or in genetic programming. The performance of these individuals are evaluated, and each individual's *fitness function* determines the probability of advancing to the next generation via the *genetic operations*.

Genetic algorithm – An evolutionary algorithm to optimize the parameters of an expression with a pre-specified structure.

Genetic operation – A set of operations to advance individuals from one generation to the next. These operations include *elitism*, *replication*, *crossover*, and *mutation*. Individuals are selected for these operations depending on their *fitness function*.

Genetic programming – An evolutionary algorithm to optimize both the structure and parameters of an expression or a function; often referred to as *semantic regression*.

Genetic programming control – The process of discovering an effective control law by using genetic programming to construct functions relating sensor measurements to an actuation signal.

Individual – A candidate expression in a genetic algorithm or genetic programming. Each individual is tested, resulting in a fitness function that determines its probability of propagating to the next generation.

Kalman filter – A dynamical system that estimates the full-state of another dynamical system from measurements of the sensor outputs and actuation inputs. The Kalman filter is an optimal state estimator for a linear system with additive Gaussian process and measurement noise.

Linear system – A dynamical system where superposition holds for solutions. This implies that doubling the initial condition and the control input signal will result in exactly twice the output. Often, the system will be a *linear time invariant* (LTI) system, so that the dynamics may be characterized entirely by linear operators (matrices).

Linear quadratic Gaussian (LQG) – An optimal sensor-based feedback control law that consists of a linear quadratic regular feedback law applied to the full-state estimate from a Kalman filter. The LQG controller is optimal for a linear system with the same quadratic cost function as in LQR and additive Gaussian white process and measurement noise of known magnitude.

Linear quadratic regulator (LQR) – An optimal full-state feedback control law to stabilize the state of a linear system while not expending too much actuation energy. LQR is optimal with respect to a quadratic cost function that balances deviation of the state and control expenditure.

Linearization – The process of approximating a nonlinear dynamical system by a linear dynamical system near a fixed point or periodic orbit by truncating a Taylor series of the dynamics at first order. Linearization is valid for small state perturbations in a small neighborhood of the fixed point or periodic orbit.

Machine learning – A set of techniques to automatically generate models from data that may be generalized and improve with more data. Machine learning is often applied to high-dimensional data where it is difficult to identify patterns and relationships in the data. Common techniques include classification and regression tasks, and these may be either supervised by expert input or unsupervised algorithms.

Machine learning control – The process of determining effective control laws through the use of machine learning methods. Controllers are *learned* through a guided process that is informed by measured performance data as opposed to being derived from first principles or optimization routines.

Mean-field model – In fluid mechanics, a mean-field model is a low-order Galerkin model linking base-flow changes with fluctuations. In the most simple case, a mean-field model describes the soft onset of an oscillation via a supercritical Hopf bifurcation. This is also referred to as *Watson-Stuart model* or *weakly nonlinear theory* and implies the famous *Landau equation* for a supercritical Hopf bifurcation. Generalized models may incorporate several frequencies and do not require the closeness of a bifurcation.

Measurement noise – Noise that is added to the output equation of a dynamical system, thus not being affected by the dynamics. Often simply referred to as *noise*.

Model – A mathematical expression that describes a system. Often, a model is derived from first-principles by physical arguments, such as conservation of mass, momentum and energy. Alternatively, a model may be derived from observational data about the system, as in statistics, system identification, and machine learning. Dynamic models are often represented as a coupled system of differential equations relating the various quantities under observation.

Model reduction – The process of approximating a high-fidelity model with a smaller, more computationally efficient model in terms of fewer states. Model reduction is an important step when controlling high-dimensional systems, since determining and evaluating control laws based on high-fidelity models is often computationally prohibitive. Moreover, control performance may be limited by the latency of a control decision, so faster decisions resulting from reduced-order models are often beneficial.

Mutation – A genetic operation where a portion of an individual in the current generation is randomly altered to produce a new individual in the next generation. Mutation tends to promote exploration in the search space of possible individuals.

Open-loop control – A method of control that specifies a pre-determined input sequence without correction or adaptation via sensors. A common method of open-loop control is periodic forcing.

Neural network – A network representation of an input–output function that attempts to mimic the computational flexibility observed in biological networks of neurons. A neural network consists of a group of individual computational components, or neurons, that are connected in a network or graph structure to perform some computation. Neural networks are typically characterized by their *adaptability* and *trainability* to new stimulus.

Noise – A quantity that varies randomly in time and is added to some variable in a dynamical system. If added to the state equation, it is also known as a *disturbance* or *process noise*, and if added to the output equation, it is also known as *measurement noise*. Noise is often assumed to follow a Gaussian white noise process, although it may also be correlated or *colored*.

Nonlinear system – A system of equations or a dynamical system that is characterized by nonlinear dynamics. As opposed to a linear system, a nonlinear system does not satisfy superposition of solutions, resulting in complex behavior, including frequency crosstalk and chaos.

Passive control – A controller that modifies a system without energy expenditure. Examples include vortex generators on wings that passively delays flow separation over a wing.

Plant – In control theory, the plant refers to the model system being controlled along with the actuator.

Process noise – Noise that is added to the state equation of a dynamical system, thereby passing through the dynamics. Also called a *disturbance*.

Real-time control – A control law that modifies the system on a time scale that is fast compared with the natural time scale. Also referred to as *in-time* control.

Reduced-order model – An approximate model with fewer states than the full high-fidelity system. Reduced-order models are often desirable in the control of high-dimensional systems, such as fluids, to reduce computational overhead, leading to faster, lower-latency control decisions.

Regression – A statistical model that relates multiple variables from measurement data. The method of least squares is a simple *linear* regression that determines a best-fit line relating data. Least-squares regression may be generalized to higher dimensions in what is known as the principal components analysis (PCA). More generally, nonlinear regression, dynamic regression, and functional or semantic regression are used to determine complex and possibly time-varying relationships between variables. Regression is commonly used in both *system identification*, *model reduction*, and *machine learning*.

Regulator – A control law that maintains a set-point in the state variable. See *linear quadratic regulator*.

Replication – A genetic operation where individuals are copied directly from one generation to the next. These individuals are selected probabilistically based on their fitness, so that the most fit individuals are more likely to advance.

Reynolds number – A dimensionless quantity that measures the ratio of inertial and viscous forces in a fluid. The Reynolds number may also be thought of as a rough measure of the ratio of the size of the largest vortices and the smallest vortices in a flow. Thus, a volcanic eruption will constitute an extremely high Reynolds number flow, as there are both very large and very small eddies.

Robust control – The field of control theory where controllers are designed to be inherently robust to model uncertainty, unmodeled dynamics, and disturbances. Often referred to as $\mathscr{H}_\infty$ *optimal control*.

Selection – The process of selecting individuals from one generation for the next generation via a genetic operation. The individuals are selected randomly but with a bias for individuals with a higher fitness, and these individuals are advanced using one of the *genetic operations*.

Sensor – A device that measures the system, producing an output. The sensor effect is typically modeled by the structure of the **C** matrix in a control system.

Stability – A property of a system, referring to how it behaves for long times or when it is perturbed. For example, a fixed point of a dynamical system is *stable* if small perturbations around this fixed point result in trajectories that stay near the fixed point and do not leave a neighborhood of the fixed point. A fixed point of a linear system is unstable if some initial conditions near the fixed point result in trajectories that grow and leave the neighborhood.

State-space system – A model consisting of a coupled system of ordinary differential equations in terms of a collection of variables known as the *state variable*. The state variable represents the state of the system, and it is an element of a vector space or manifold, known as the *state space*.

System identification – The process of determining a model for a physical process based on measurement data. Typically, system identification involves measuring the sensor output of a system in response to certain actuation inputs, and a model for the underlying state dynamics (i.e., hidden variables) is constructed. Most methods of system identification may be viewed as a form of dynamic regression of data onto models.

Turbulence – A fluid phenomena characterized by multi-scale coherent vorticity in space and time and strongly nonlinear, chaotic dynamics. Turbulence is often a characteristic of real-world or industrial flows at high *Reynolds number*.

Symbols

$\mathbf{A}$; $\mathbf{A}_d$; $\tilde{\mathbf{A}}$	State matrix (continuous time ; discrete time ; reduced).
$\mathbf{a}$; $\mathbf{a_k}$; a_m ; a	State (vector, continuous time ; vector, discrete time k^{th} step ; m^{th} component ; scalar).
$\hat{\mathbf{a}}$; $\hat{\mathbf{a}}_k$	Full state estimate (continuous ; discrete time).
$\mathbf{B}$; $\mathbf{B}_d$; $\tilde{\mathbf{B}}$	Input matrix (continuous ; discrete time ; reduced).
B	Amplitude of periodic forcing.
$\mathbf{b}$; $\mathbf{b_k}$; b_m ; b	Actuation command (vector, continuous time ; vector, discrete time k^{th} step ; m^{th} component ; scalar).
$\mathscr{B}$	Matrix of control inputs.
$\mathbf{C}$; $\mathbf{C}_d$; $\tilde{\mathbf{C}}$	Output matrix (continuous ; discrete time ; reduced).
c_μ	Momentum coefficient.
$\mathscr{C}$; $\mathscr{C}_d$	Controllability matrix (continuous ; discrete time).
$\mathbf{D}$; $\mathbf{D}_d$; $\tilde{\mathbf{D}}$	Feedthrough matrix (continuous ; discrete time, reduced).
D	Characteristic distance.
d_c	Duty cycle.
$\mathbf{e}_x$, $\mathbf{e}_y$, $\mathbf{e}_z$	Unity vectors associated with directions x, y and z.
$\mathbb{E}$	Expectation operator.
$\mathbf{F}$	Dynamics.
F_D	Drag force.
$\mathbf{G}$	Measurement function.
g	Gain of control command in a generalized mean-field model.
$\mathbf{H}$	Hankel matrix.
H	Heavyside function.
H_{section}	Height of the test section.
$h_i(t)$; $h_{i,u}$; $h_{i,\max}$	hot-wire or hot-film signal number i (raw signal ; average value of the unactuated measurement ; average measurement under constant maximal actuation).
h_{step} ; h_{ramp}	Height (of the step ; of the ramp).

$\mathbf{I}$	Identity matrix.
i	Index of individual (or other counter).
J ; J_i^j	Cost function value ; of individual i in generation j.
J_a	Cost on states.
J_b	Cost on actuation.
j	Index of generation.
$\mathbf{K}$	Control function.
$\mathbf{K}_f$	Kalman filter gain.
$\mathbf{K}_r$	Regulator gain, full-state control matrix.
L	Length of the experimental test section.
L_{sep}	Separation length.
l	Width of the experimental test section.
ℓ	Ramp length.
N_a	Number of states.
N_b	Number of actuation commands.
N_e	Number of individuals concerned by elitism.
N_g	Number of generations.
N_i	Number of individuals.
N_p	Tournament size.
N_s	Number of sensors.
$\mathscr{O}$; $\mathscr{O}_d$	Observability matrix (continuous time ; discrete time).
P_c	Probability of crossover.
P_m	Probability of mutation.
P_r	Probability of replication.
p	Pressure.
$p(\mathbf{a})$	Probability density of states.
$\mathbf{Q}$	State cost weight matrix for LQR.
Q ; Q_u	Flow rate to actuator jets (instantaneous ; average value under constant blowing).
$\mathbf{R}$	Actuation cost weight matrix for LQR.
$r_\bullet$, $r_\circ$	Amplitude of oscillators of a generalized mean-field model (Tab. 5.1).
Re	Reynolds number.
$S_a(t)$; $S_{a,u}$	Area of backflow (instantaneous ; unactuated average value).
S_b	Actuator cross section.
S_j	Jet cross section.
S_{ref}	Ramp reference surface.
$\mathbf{s}$; $\mathbf{s}_k$; s_m ; s	Sensor signal (vector, continuous time ; vector, discrete time k^{th} step ; m^{th} component ; scalar).
$\hat{\mathbf{s}}$; $\hat{\mathbf{a}}_k$	Expected sensor value (continuous time ; discrete time).
$\mathscr{S}$; $\bar{\mathscr{S}}$	Markov parameters ; of the augmented system.
T	Evaluation time.
T_{rms}	Time period used to compute RMS of hot-wire signal fluctuations.
t, t_0	Time, initial time.

$\mathbf{U}$; $\mathbf{U}_r$	Left singular vectors of SVD (complete ; reduced) .
U	Characteristic velocity.
$\mathbf{u}$; $\mathbf{u}_s$, $\mathbf{u}_\Delta$, $\mathbf{u}_\bullet$, $\mathbf{u}_\circ$	Velocity (vector field ; steady solution ; deviation due to Reynolds stresses ; contribution of frequency $\omega_\bullet$; contribution of frequency $\omega_\circ$).
$\overline{\mathbf{u}}$	Slow varying mean flow.
$\mathbf{u}'$	Flow fluctuations.
u	Streamwise velocity component.
$\mathbf{V}$; $\mathbf{V}_r$	Right singular vectors of SVD (complete ; reduced).
$\mathbf{V}_d$	Disturbance variance.
$\mathbf{V}_n$	Noise variance.
V_{Jet}	Characteristic velocity of jets.
$\mathbf{v}$	Velocity vector initial condition.
v	Transverse velocity component.
$\mathbf{W}^d_{\mathscr{C}}$	Discrete time controllability Gramian.
$\mathbf{W}^d_{\mathscr{O}}$	Discrete time observability Gramian.
W	mixing layer width.
$\mathbf{w}$	Disturbance array.
$\mathbf{w}_r$	External reference signal.
$\mathbf{w}_d$	External disturbance, process noise.
$\mathbf{w}_n$	Measurement noise.
w	Spanwise velocity component.
$\mathbf{X}$	Solution to the Riccati equation for LQR.
$\mathbf{x}$	Space vector.
x	Streamwise coordinate.
$\mathbf{Y}$	Solution to the Riccati equation for Kalman filter.
y	Transverse coordinate.
$\mathbf{z}$	System output.
z	Spanwise coordinate.
$\beta_{\bullet\bullet}$, $\beta_{\bullet\circ}$, $\beta_{\circ\bullet}$, $\beta_{\circ\circ}$	Parameter for growth-rate change in oscillators of a generalized mean-field model (Tab. 5.1).
γ	Penalization coefficient.
$\gamma_{\bullet\bullet}$, $\gamma_{\bullet\circ}$, $\gamma_{\circ\bullet}$, $\gamma_{\circ\circ}$	Parameter for frequency change in oscillators for a generalized mean-field model (Tab. 5.1).
$\delta(\cdot)$	Dirac delta function.
ε	Nonlinearity strength coefficient or state stabilisation error.
κ	Gain of the generalized mean-field model.

ν	Kinematic viscosity.
ρ	Fluid density.
Σ ; Σ_r	Singular values matrix of SVD, (complete ; reduced) .
σ	Oscillator growth rate.
$\sigma_\bullet$; $\sigma_{\bullet\star}$; $\sigma_\circ$; $\sigma_{\circ\star}$	Growth rate of oscillators of a generalized mean-field model (Tab. 5.1).
τ ; τ_a ; τ_u	Period of time (with actuated system ; with unactuated system).
$\phi_\bullet$, $\phi_\circ$	Phase of oscillators in a generalized mean-field model (Tab. 5.1).
χ	Back-flow coefficient.
Ω	Space domain.
ω	Oscillator pulsation.
$\omega_\bullet$; $\omega_{\bullet\star}$; $\omega_\circ$; $\omega_{\circ\star}$	Frequency of oscillators in a generalized mean-field model (Tab. 5.1).

Abbreviations

ANN...	Artificial Neural Network
ARMA(X)...	Auto-Regressive Moving Average (with eXogenous input)
AVERT...	Aerodynamic Validation of Emission Reducing Technologies
BPOD...	Balanced Proper Orthogonal Decomposition
CROM...	Cluster-based Reduced Order Modeling
DEIM...	Discrete Empirical Interpolation Method
DMD...	Dynamic Mode Decomposition
EC...	Evolutionary Computing
EP...	Evolutionary Programming
ERA...	Eigensystem Realization Algorithm
GA...	Genetic Algorithm
GMFM...	Generalized Mean-Field Model
GP...	Genetic Programming
LQE...	Linear Quadratic Estimation
LQG...	Linear Quadratic Gaussian
LQR...	Linear Quadratic Regulator
LML...	Laboratoire de Mécanique de Lille, Université de Lille 1 Cité Scientifique, Bâtiment M3 - 59655 Villeneuve d'Ascq Cedex, France
LPV...	Linear Parameter Varying
MIMO...	Multiple Input Multiple Output
MISO...	Multiple Input Single Output
ML...	Machine Learning
MLC...	Machine Learning Control
NLSA...	Nonlinear Laplacian Spectral Analysis
OKID...	Observer Kalman filter IDentification
PCA...	Principal Component Analysis

PID...	Proportional Integral Derivative
PIV...	Particle Image Velocimetry
PMMH...	Physique et Mecanique des Millieux Hétérogènes Laboratory, 10 rue Vauquelin - 75231 Paris Cedex, France
POD...	Proper Orthogonal Decomposition
PPRIME...	Institute Pôle Poitevin de Recherche pour l'Ingénieur en Mécanique, Matériaux et Énergétique, 11 Boulevard Marie et Pierre Curie BP 30179 - 86962 Futuroscope Chasseneuil Cedex, France
PRISME...	Laboratoire Pluridisciplinaire de Recherche, Ingénierie des Systèmes, Mecanique, Energétique. Université d'Orléans 8 Rue Léonard de Vinci - 45072 Orléans, France.
ROM...	Reduced Order Model
RT...	Real-Time
SIMO...	Single Input Multiple Output
SISO...	Single Input Single Output
SSA...	Singular Spectrum Analysis
SVM...	Support Vector Machine
TUCOROM...	TUrbulence COntrol using Reduced Order Models, ANR Chair of Excellence (ANR-10-CEXC-0015), Poitiers, France.
UVG...	Unsteady Vortex Generator

Matlab® Code: **`OpenMLC`**

This appendix describes `OpenMLC`, the employed implementation of MLC in Matlab®. All examples in the book have been performed with this software.

Installation

`OpenMLC` is a Matlab® toolbox. It can be added to Matlab® by downloading the toolbox from [94] or duplicate the master branch. The root directory of the toolbox, **OpenMLC**, needs to be added to the path with subdirectories. Detailed or alternative instructions will be available from the Github repository [94] as the software is updated.

Content

`OpenMLC` contains a class defined by the file `MLC.m` in the folder **@MLC**. This class implements all methods discussed in the book. Additionally, a folder **MLCtools** is provided. It provides the *MLCparameters* class description files which implements all parameters. Also functions such as expression-tree interpreter, derivation function, common function overloading for protection are provided in this folder. Finally this folder also contains the **Examples** subfolder that contains all configuration files, evaluation function, and typical results discussed in this book.

The reader is referred to the documentation of the software:

```
help MLC            % class description and first steps. Also
                    % list all properties of the MLC class and
                    % its methods.
help MLC/parameters % will list all configuration parameters
                    % and available options
```

for a quick starting guide. Contextual help is available for each method by typing:

```
help MLC/METHOD % will provide help for METHOD
```

A full package documentation is available on the Github repository [94]. Any bug report, feature request or participation can be brought to our attention through the Github repository.

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