Application of Computational Intelligence to Mechanical Engineering

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Sapienza University of Rome,

founded in 1303
by Pope Boniface VIII

Department of Mechanical and Aerospace Engineering

created in 2010 by merging the former Department of Mechanical and Aeronautical Engineering (DMA) with part of the Department of Aerospace and Astronautical Engineering (DIAA)

Outline of this presentation

Part I

- Computational Intelligence (CI)
  - Methods and Tools (brief review)
- Topics in Mechanical Engineering (ME)
  - Topics
- Applications of CI to ME

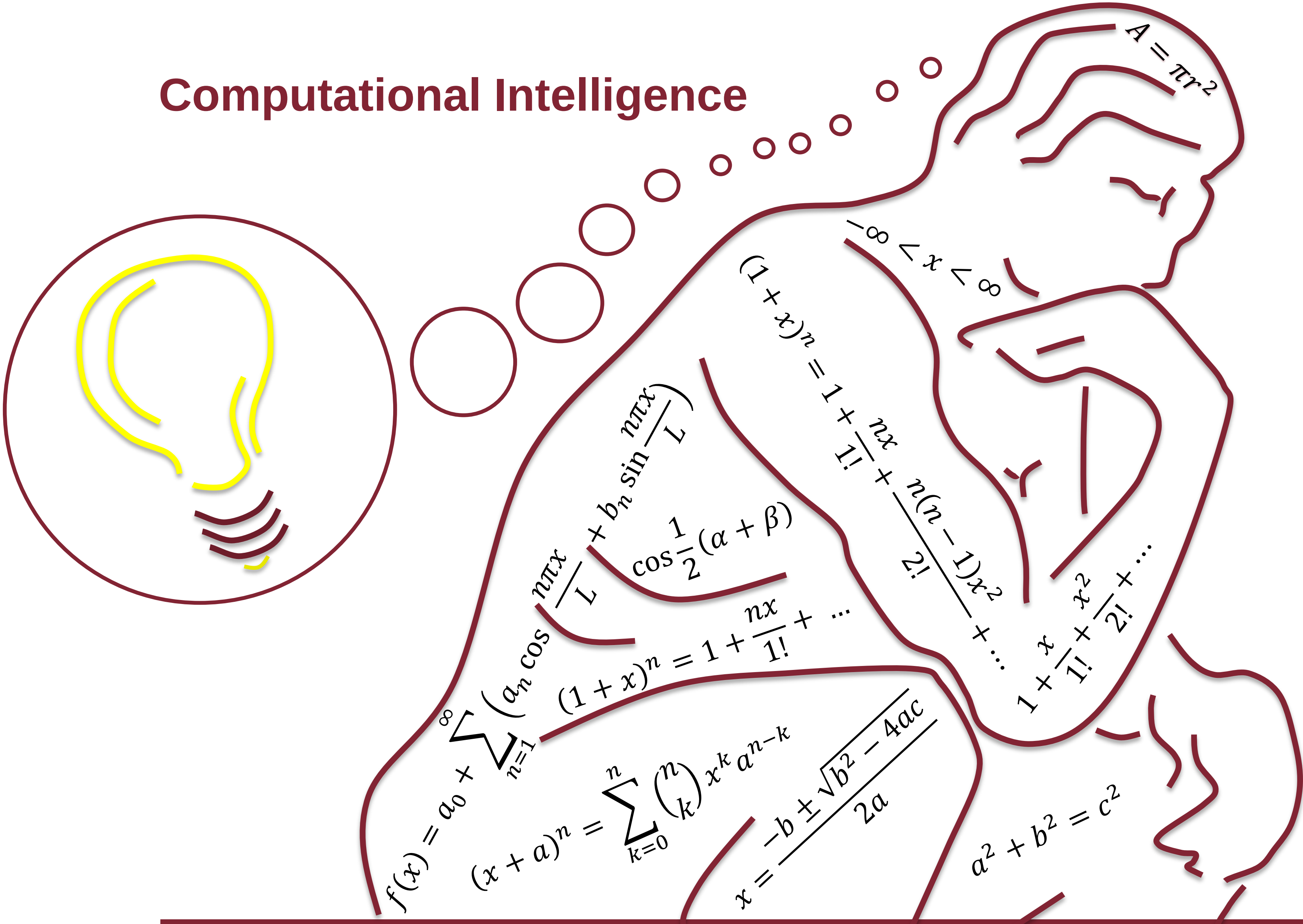
Part II

- NN and Wear Prediction
- GA and MEMS Design

Part I
Applications of Computational Intelligence to Mechanical Engineering

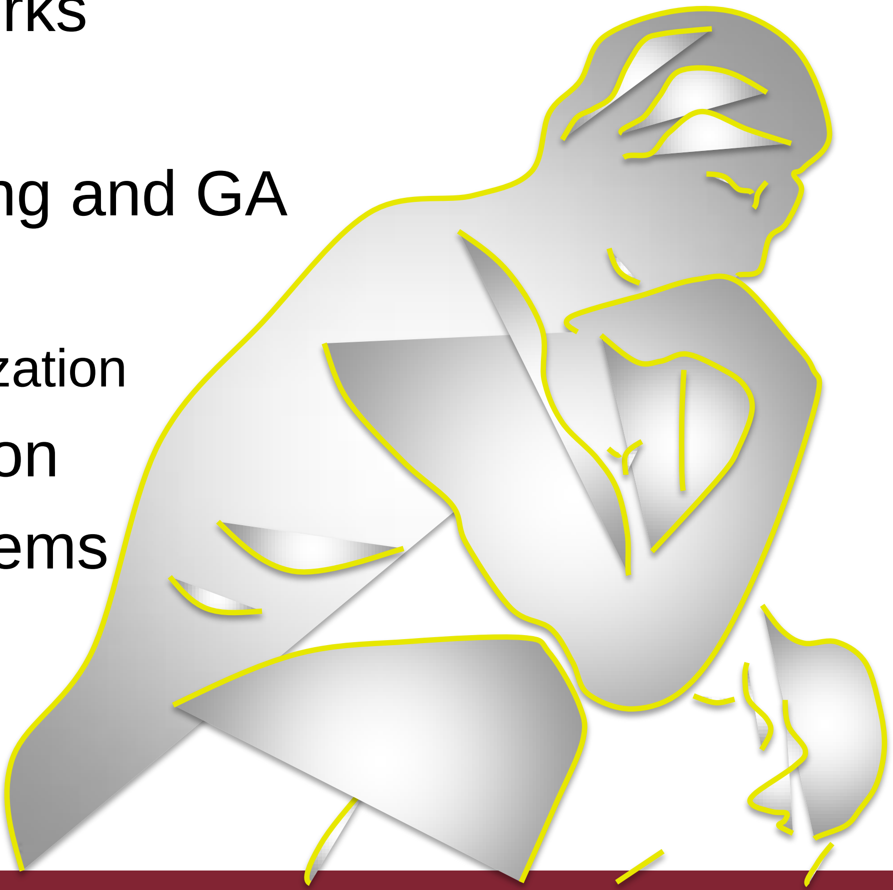
based on Ref. [1]

Computational Intelligence



Tools and Methods of Computational intelligence
(a selection)

- Artificial Neural Networks
- Fuzzy Logic
- Evolutionary Computing and GA
- Swarm Intelligence
  - Particle Swarm Optimization
- Ant Colony Optimization
- Artificial Immune Systems

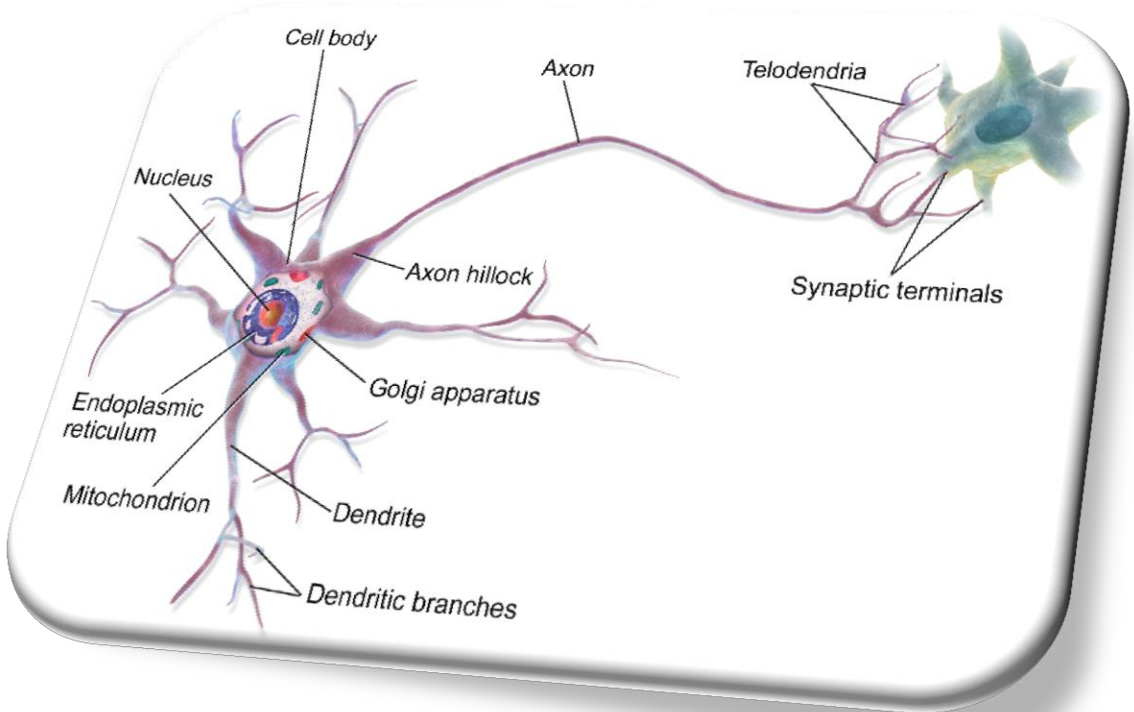


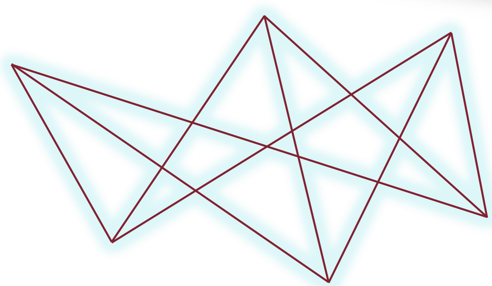
Artificial Neural Networks

Topology

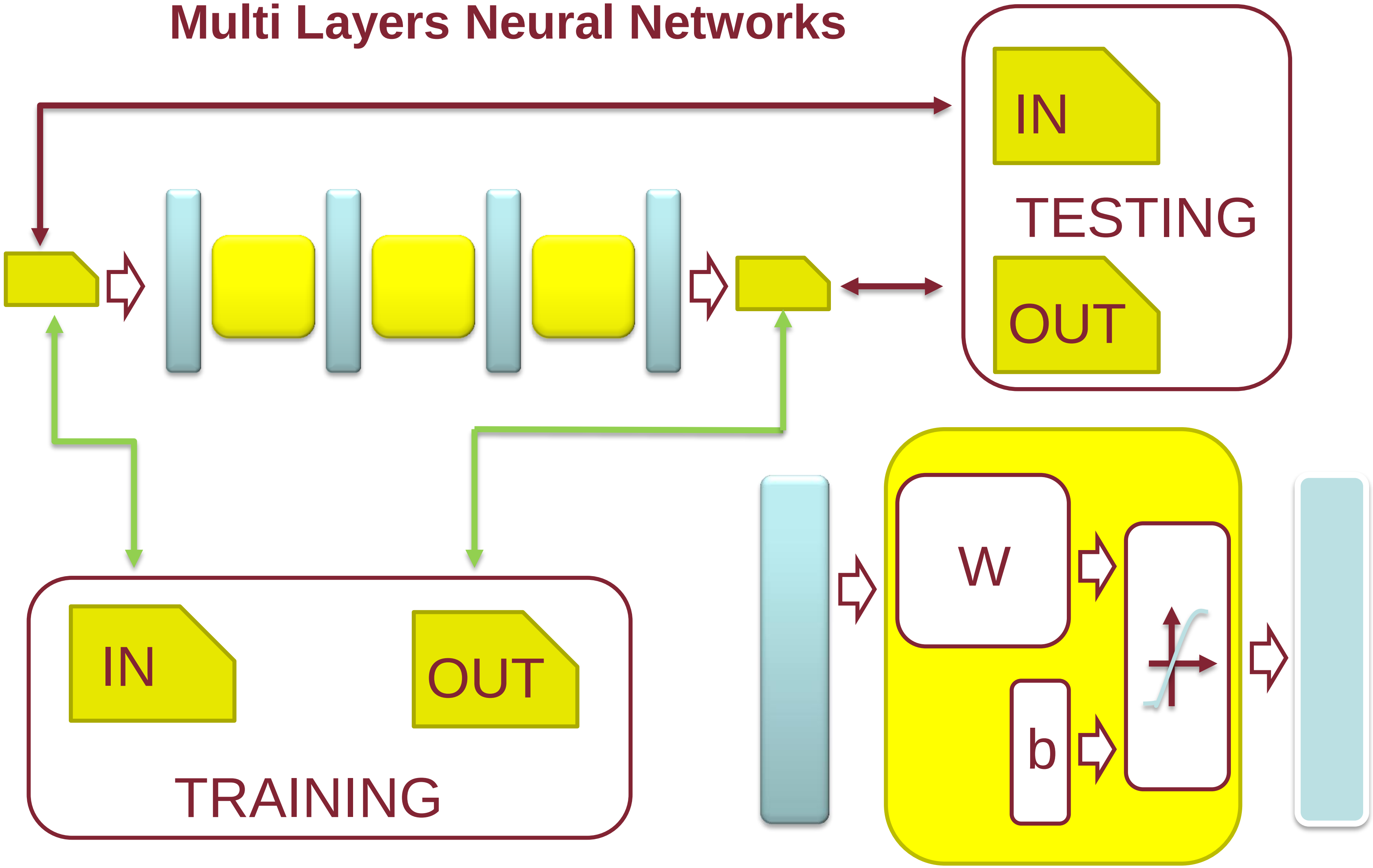
- Single or
- Multi-layers

- Feed-back
- Feed-forward
- Recurrent





Multi Layers Neural Networks



ANN Parameters and Procedures

Weight Matrices and Bias Arrays

- Bias functions:
  - sigmoid, hyperbolic tangent, signum, linear
- Training:
  - Levenberg-Marquardt backpropagation, Bayesian regulation backpropagation, Scaled conjugate gradient backpropagation, Resilient backpropagation

Neural Networks

Usual Applications

- Data fitting
- Patterns classification
- Prediction and modeling
- Time series prediction and modeling
- Data clustering

Fuzzy Logic







Old ?

Young ?

Cold ?

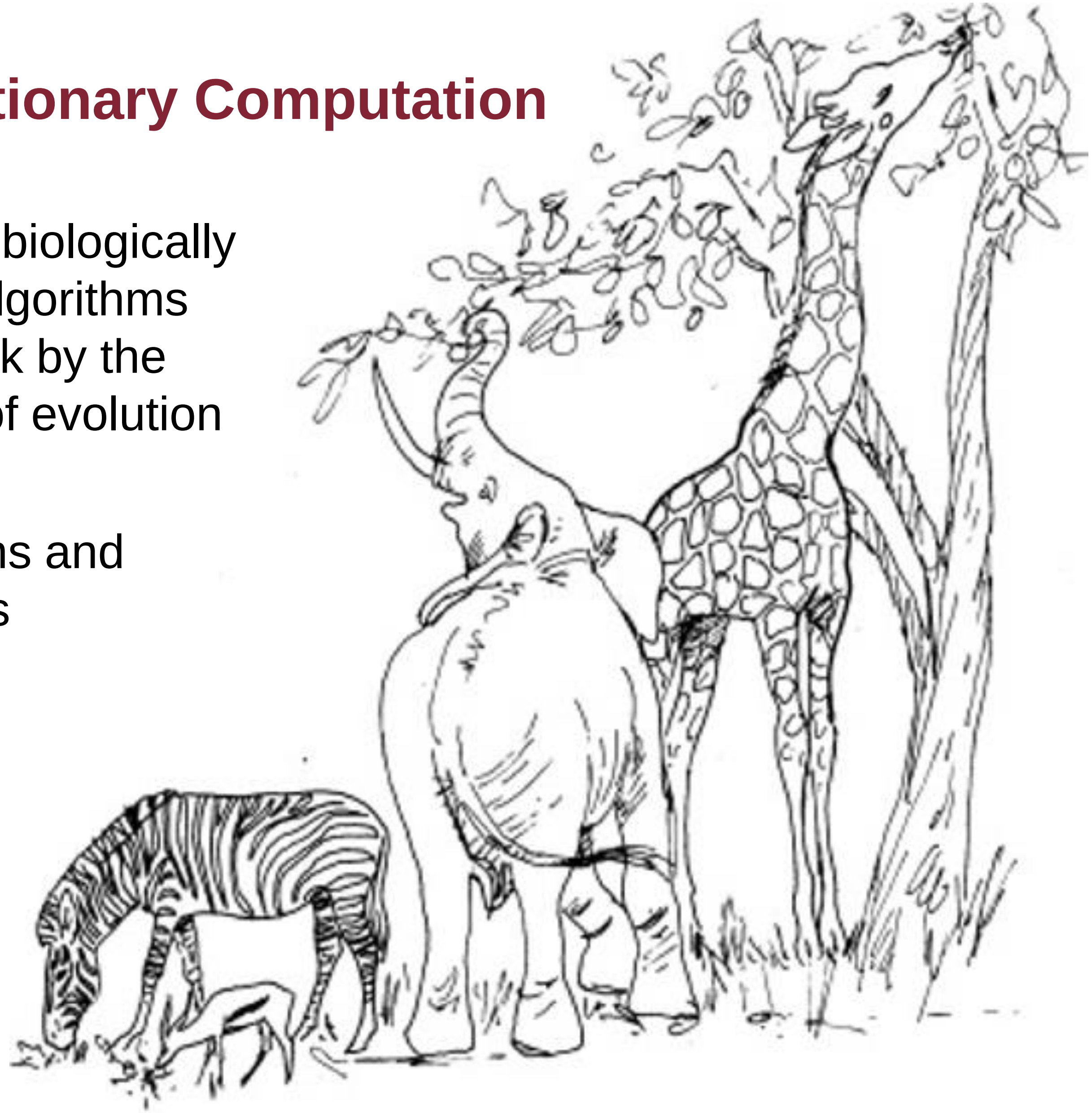
Warm ?

Fuzzy Systems and Fuzzy Sets

- Membership grade and functions
  - Discrete or Continuous (Gaussian, triangular, S-function, L-function, Π-function or γ-function)
- Operations
  - T-Norm and S-Norm, Complementation
- Compositions
  - Max- Min or Max-Product
- Sets
  - Support, Core, Normal, α-cut

Evolutionary Computation

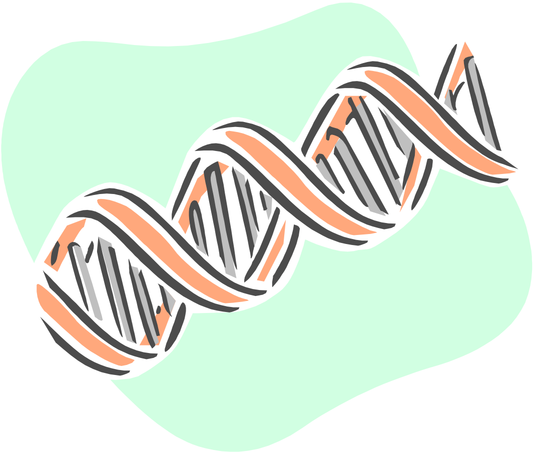
- a class of biologically inspired algorithms which work by the principle of evolution
- populations and individuals
- fitness



http://cnx.org/contents/

Genetic Algorithms

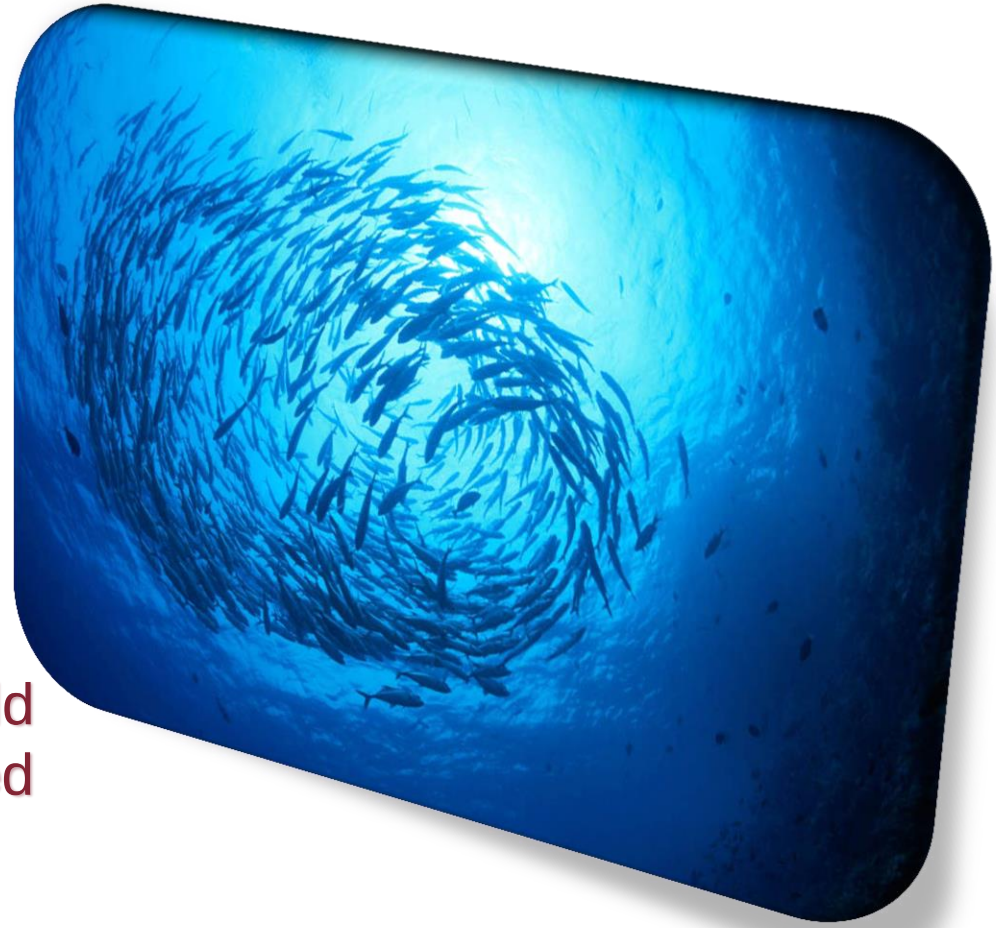
- Genotype and phenotype
- Genotype encodings (binary, real)
- Genotype operators (crossover, mutation, elitism)
- Natural selection
- Generations



Swarm Intelligence – Particle Swarm Optimization

- Collective system capable of accomplishing difficult tasks in dynamic and varied environments without any external or central control

- Achieving a collective performance which could not normally be achieved by an individual acting alone



http://www.speedmango.com/

Swarm Intelligence – Particle Swarm Optimization

Member of the family of Evolutionary Computing

Swarm moves within a multi-dimensional space in search of a global minimum

Swarm moves according to rules (repulsion, attraction and aligning)

Motion strategy (position, velocity and acceleration)

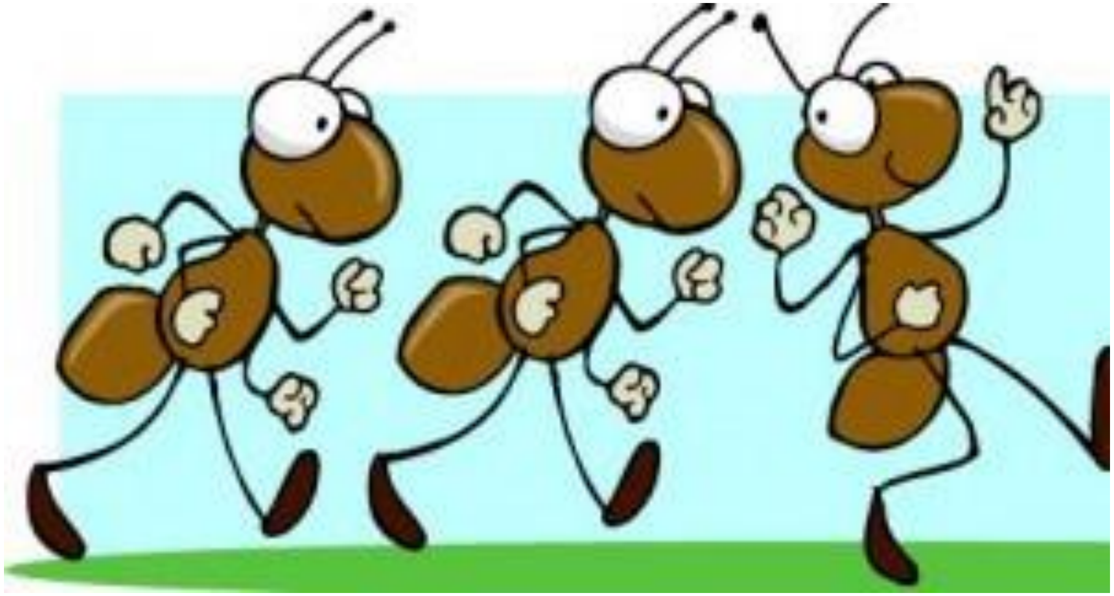
Possible body characteristics for individuals

Memory of individual and global best position

http://www.thepistrophy.com/bird-ballet-swarming-video-by-neels-castillon/

Ant Colony Optimization

Member of Swarm Intelligence



http://rollingtstores.net/sugar-ants-in-the-kitchen/

Ant Colony Optimization

Basic mechanisms

- Pheromones marking
- Pheromones accumulation on the fastest path from the nest to food

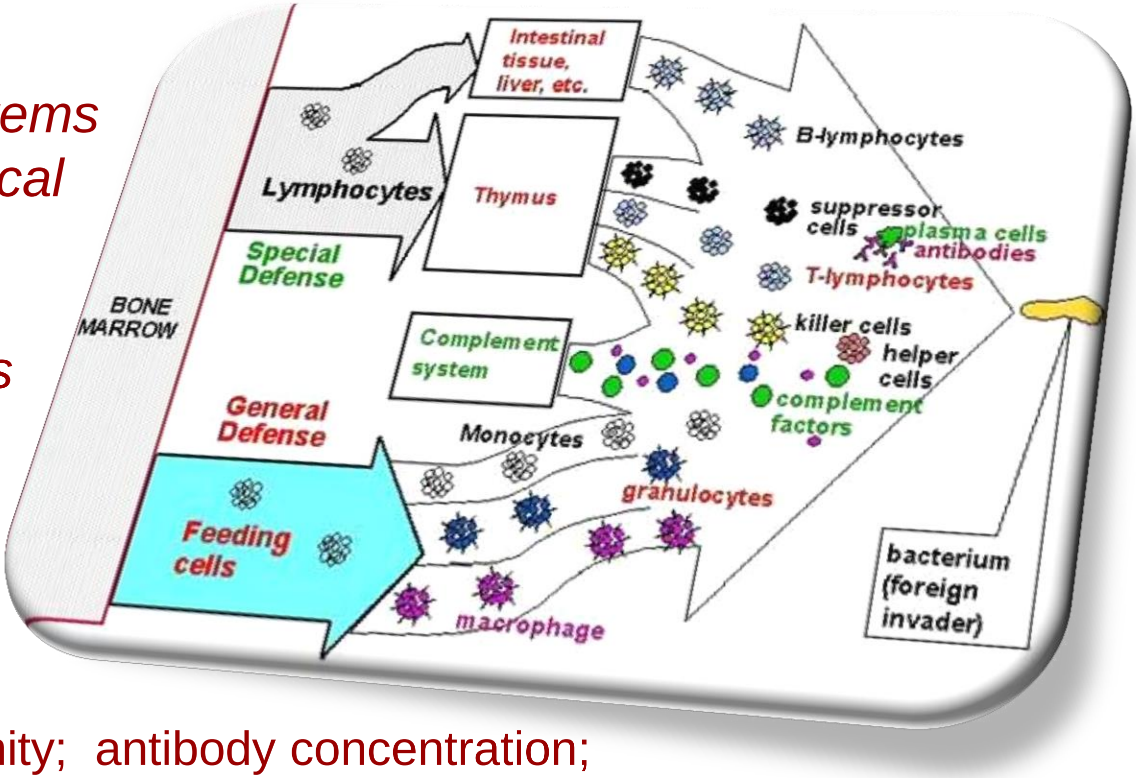
Typical applications

- Traveling Salesman
- vehicle routing
- sequential ordering
- graph coloring

http://knowledgefeed.blogspot.it/

Artificial Immune Systems

Computational systems inspired by theoretical immunology and imitating immune functions, principles and models, to solve problems



http://www.cheniere.org/images/rife/rife20.jpg

Antibody mutual affinity; antibody concentration;
antibody-antigen affinity;
Antibody natural decay
Antibody stimulation or suppression

Soft Computing

a collection of methodologies, complementary and synergistic, which provides effective tools for the development of intelligent systems

- neuro-fuzzy,
- neuro-genetic,
- fuzzy-genetic,
- neuro-belief networks,
- fuzzy-belief networks,
- neuro-fuzzy-genetic
- ... … …

Selected topics from Mechanical Engineering

- Robotics
- Mechanisms, Machine Theory and Design
- Tribology
- Energetic Systems and Power Production
- Fluid Dynamics
- Materials
- Mechanical Vibrations

Adopted queries

Main search criteria (restrictive)

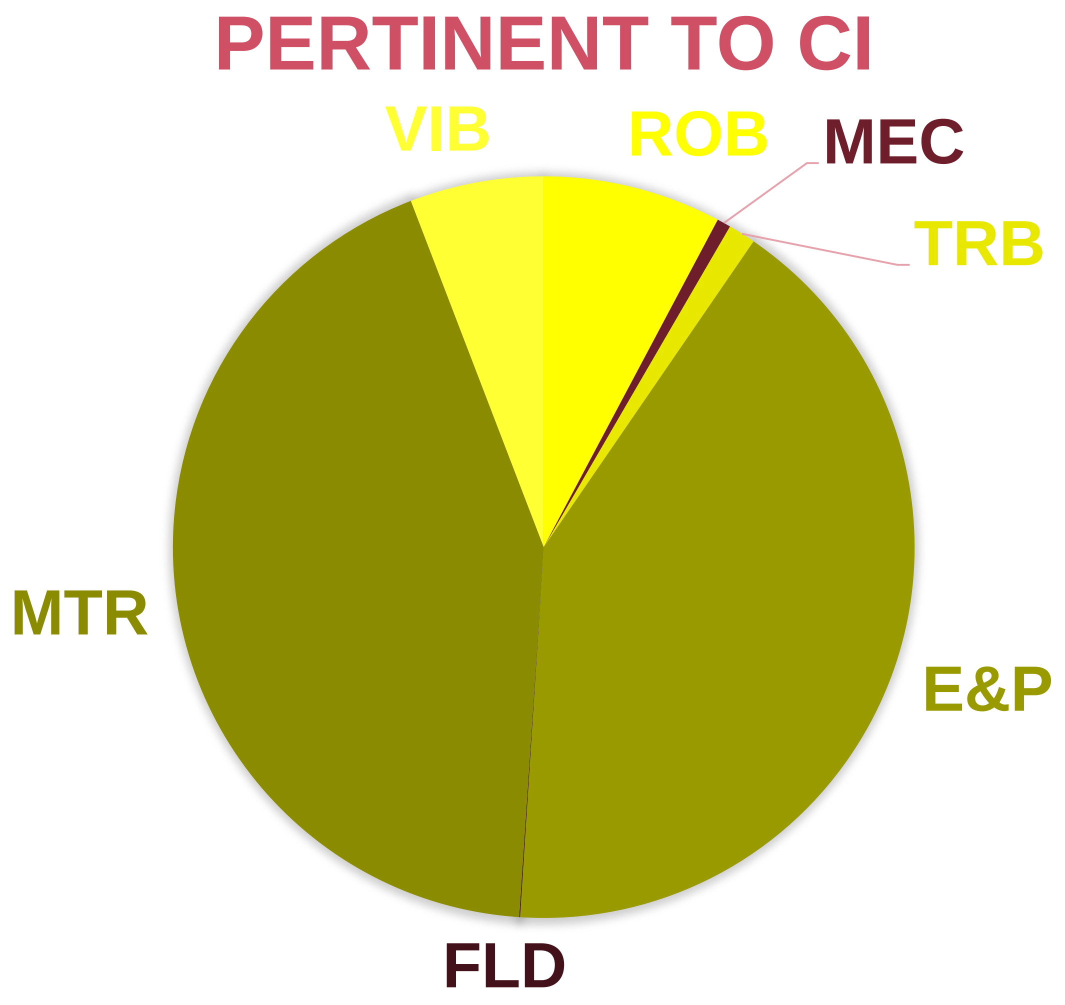
1. paper *topic* has been identified by the journal or conference title (namely, by the presence of keywords in the *source title*) where the article has been published
2. paper *relevancy to CI methods or tools* has been detected by article *title*

About the 1,705,201 analyzed papers

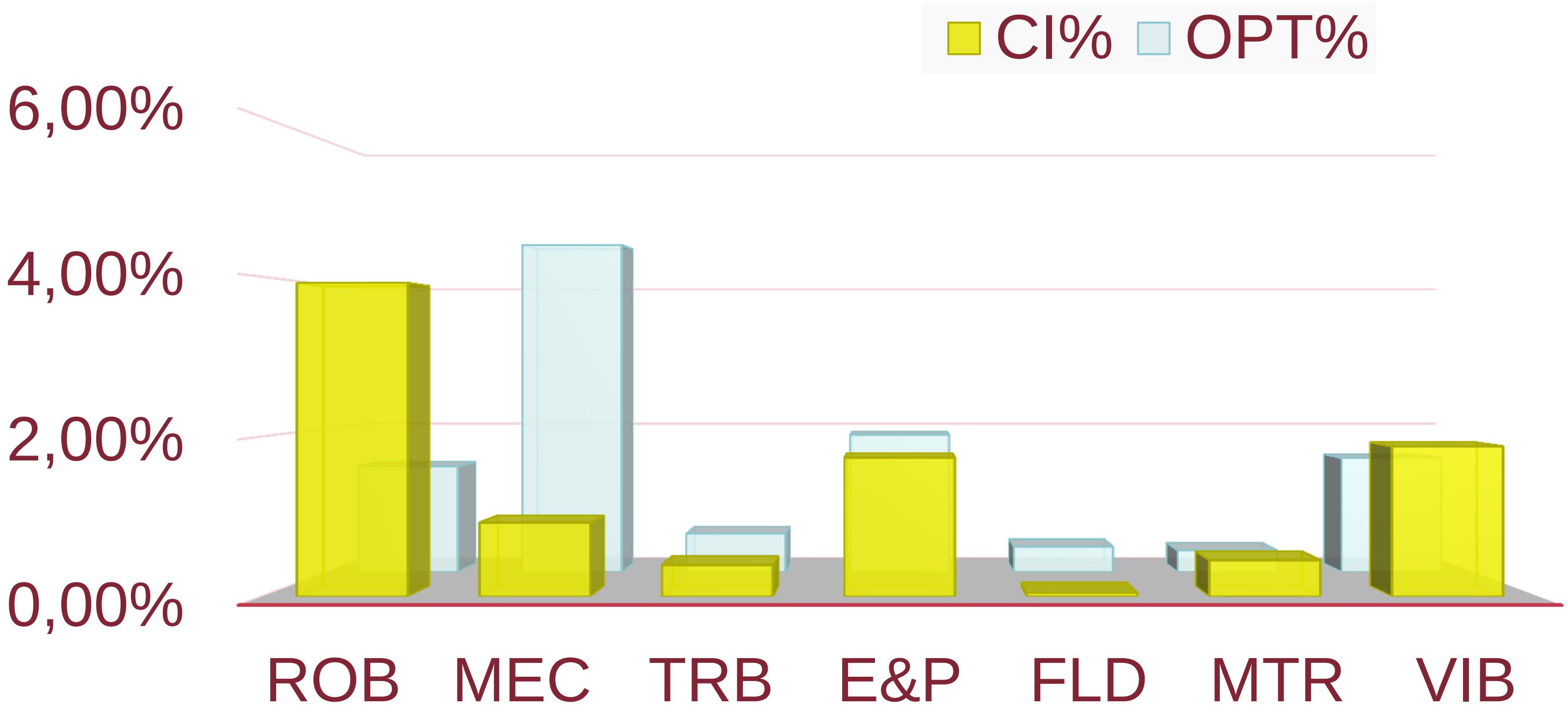
	TOT	CI	CI%	OPT	OPT%
ROB	26,390	1,035	3.92%	389	1.47%
MEC	8,646	80	0.93%	394	4.56%
TRB	40,402	159	0.39%	216	0.53%
E&P	317,230	5,515	1.74%	6,061	1.91%
FLD	10,849	5	0.05%	38	0.35%
MTR	1,260,384	5,737	0.45%	3,805	0.30%
VIB	41,300	776	1.88%	655	1.59%

Legend (first column): ROB = Robotics; MEC = Mechanisms, machines and Design; TRB = Tribology; E&P = Energy and Power; FLD = Fluid dynamics; MTR = Materials; VIB = Vibrations. Legend (first row): TOT = total analyzed; CI = pertinent to Computational Intelligence; OPT = reference standard search concerning optimization

About 13,307 papers



About the 1,705,201 analyzed papers



Statistical data concerning 13,307 out of 1,705,201 analyzed papers (detail)

	CI	NN	EC&GA	SW	AS	FZ	TOT-P
ROB	3	362	144	52	4	470	1,035
MEC	1	17	38	2	0	22	80
TRB	0	110	18	3	0	28	159
E&P	13	1,947	941	512	13	2,089	5,515
FLD	0	3	2	0	0	0	5
MTR	14	3,624	1,664	57	18	360	5,737
VIB	2	318	156	47	1	252	776

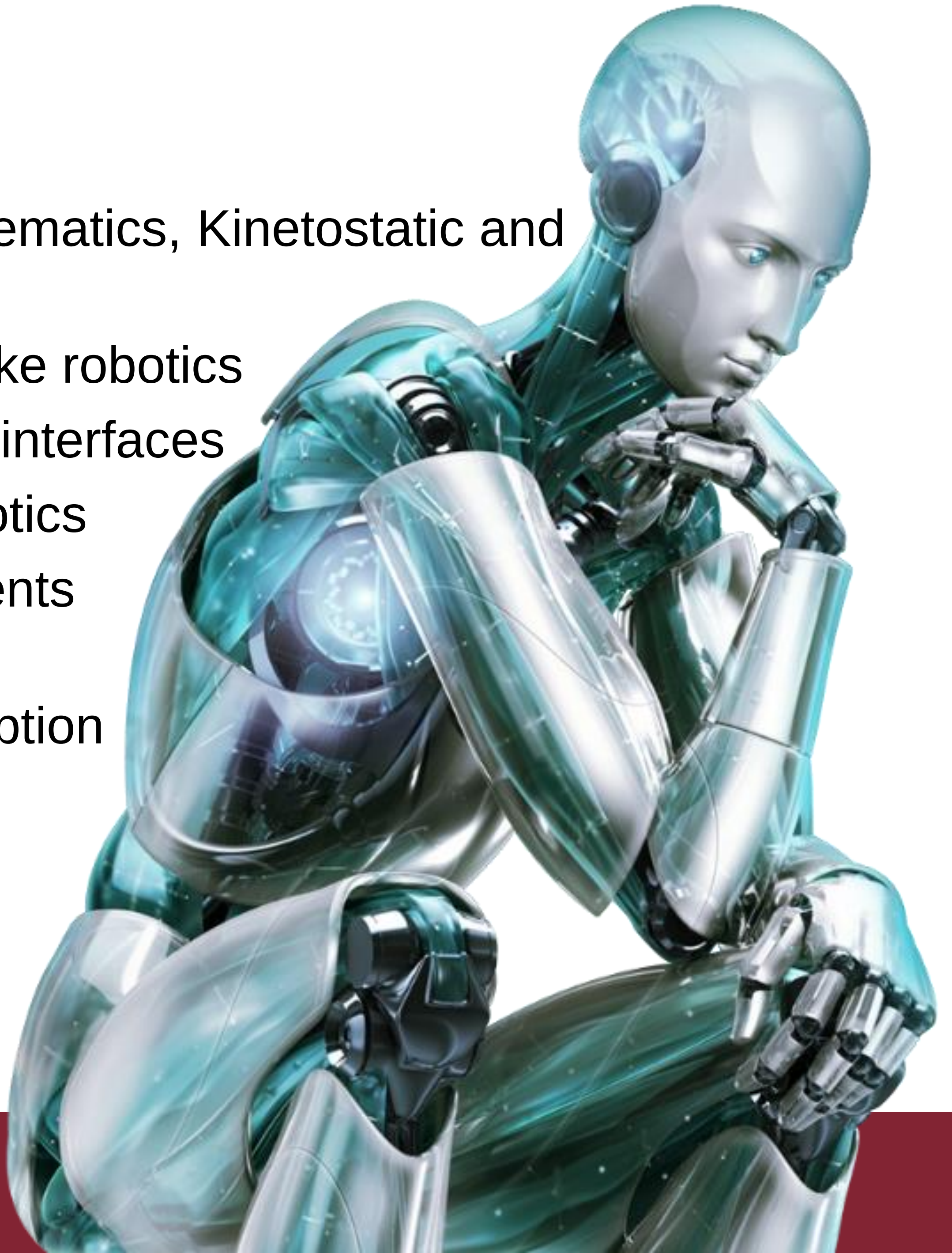
Legend (first row) CI= general approaches based on Computational Intelligence; NN = (Artificial) Neural Networks; EC and GA = Evolutionary Computing and Genetic Algorithms; SW= Swarm Intelligence; AS = Artificial Immune Systems; FZ = fuzzy; TOT-P = total pertinent works

References

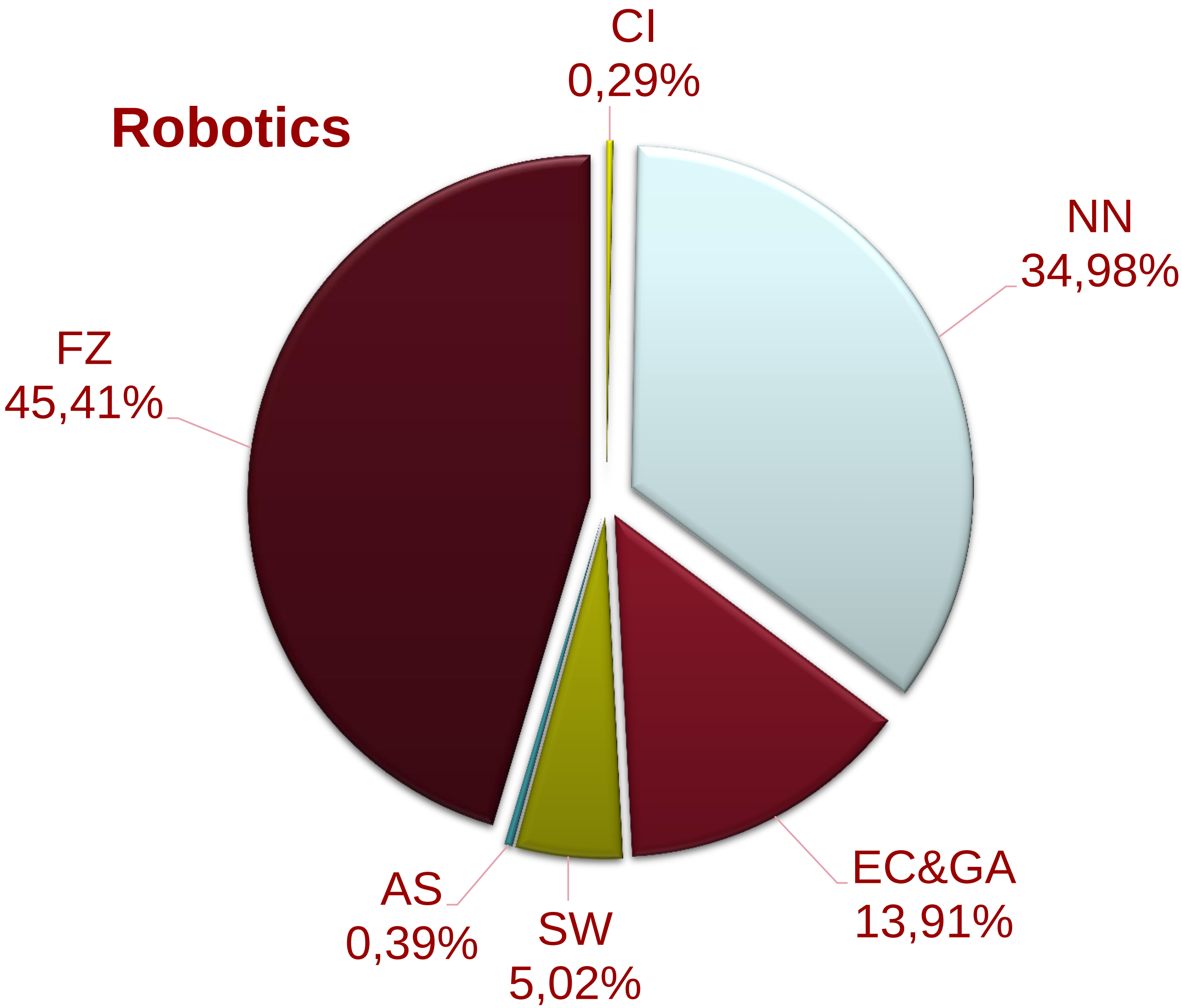
	CI	NN	EC&GA	SW	AS	FZ
ROB	[110-112]	[124-134]	[135-159]	[166-175]	[163-165]	[117-123]
MEC	[176]	[218-229]	[197-217]	[244-245]	-	[230-243]
TRB	-	[247-260]	[261-266]	[272-273]	-	[267-271]
E&P	[275-280]	[283-301]	[321-330]	[331-351]	[352-364]	[302-318]
FLD	0	[369-371]	[372-373]	-	-	-
MTR	[374-377]	[384-391]	[392-403]	[418-423]	[424-427]	[404-410]
VIB	-	[434-442]	[443-451]	[461-465]	-	[452-460]
(HM)	-	[466-468]	[469-471]	-	-	-

Robotics

- Workspace, Topology, Kinematics, Kinetostatic and Dynamics
- Human-centered and life-like robotics
- Manipulation, Contact and interfaces
- Mobile and distributed robotics
- Robot structures, components and actuators
- Sensing, Vision and Perception
- Field and service robotics
- Mechanical Design
- Control



http://www.viewwallpaper.com/eset-nod32-robot-render.html


Robotics
CI
0,29%
NN
34,98%
FZ
45,41%
EC&GA
13,91%
AS
0,39%
SW
5,02%

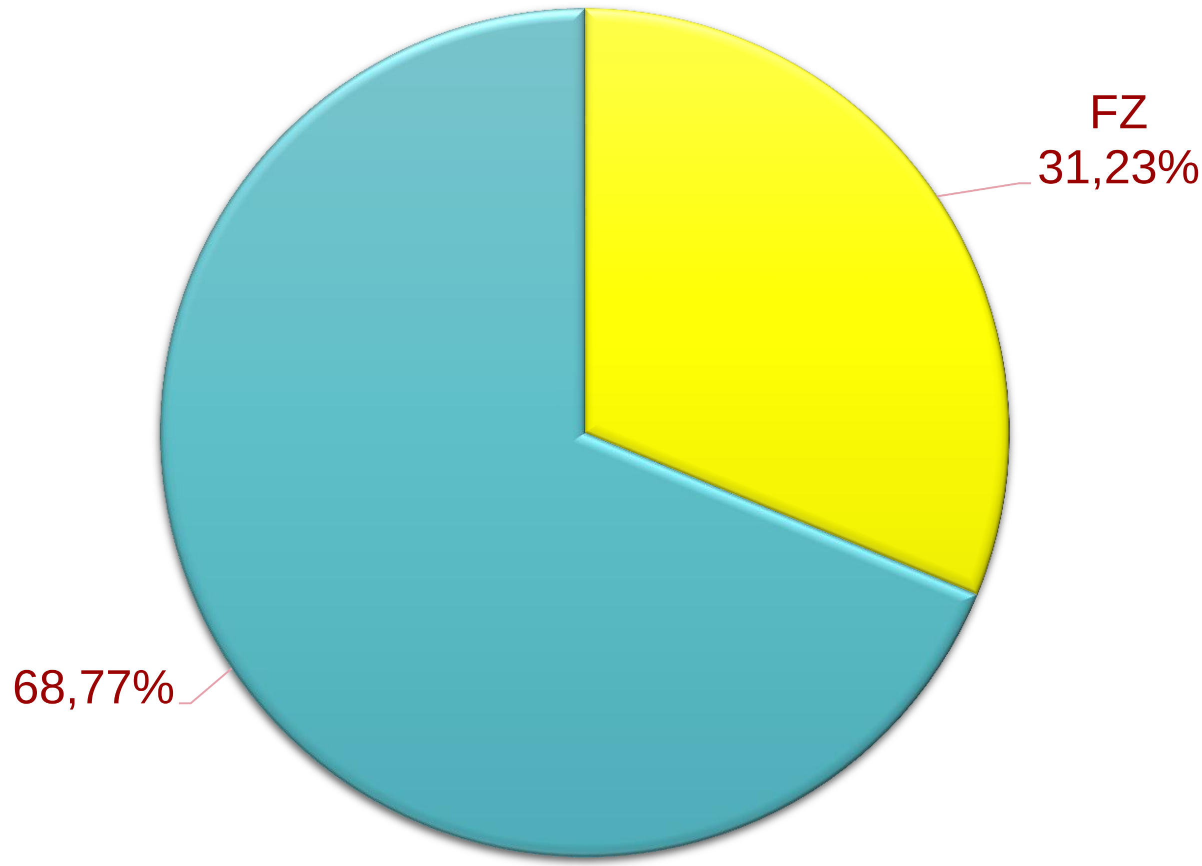
Mechanisms, machines and Design *(no thermodynamics)*

- Mechanisms Science (topology, kinematic analysis and synthesis, kinetostatics, dynamic analysis)
- MBS Dynamics
- Transmissions
- Bearings
- Brakes
- Creative Design
- Cams-Follower Systems
- Gears

More in general

- Design
- FEA
- Fatigue

Mechanisms, Machines and Design



Tribology

Wear, Friction and Lubrication

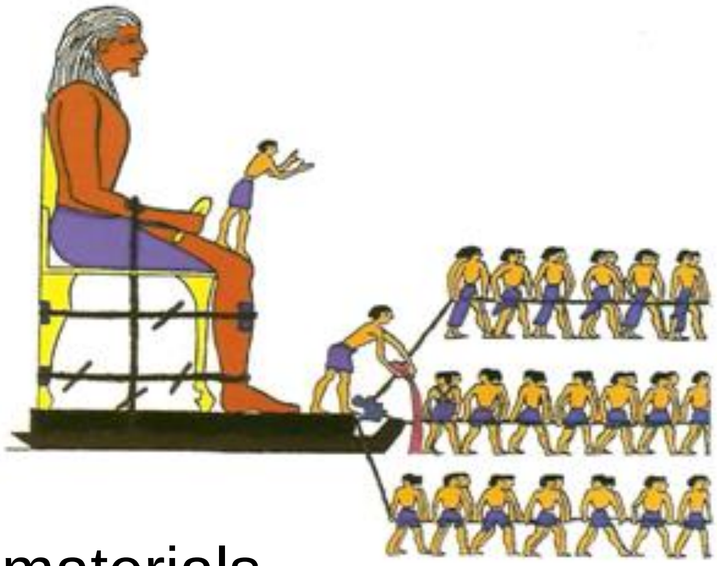
Contact mechanics

Nano-tribology

Bio-tribology

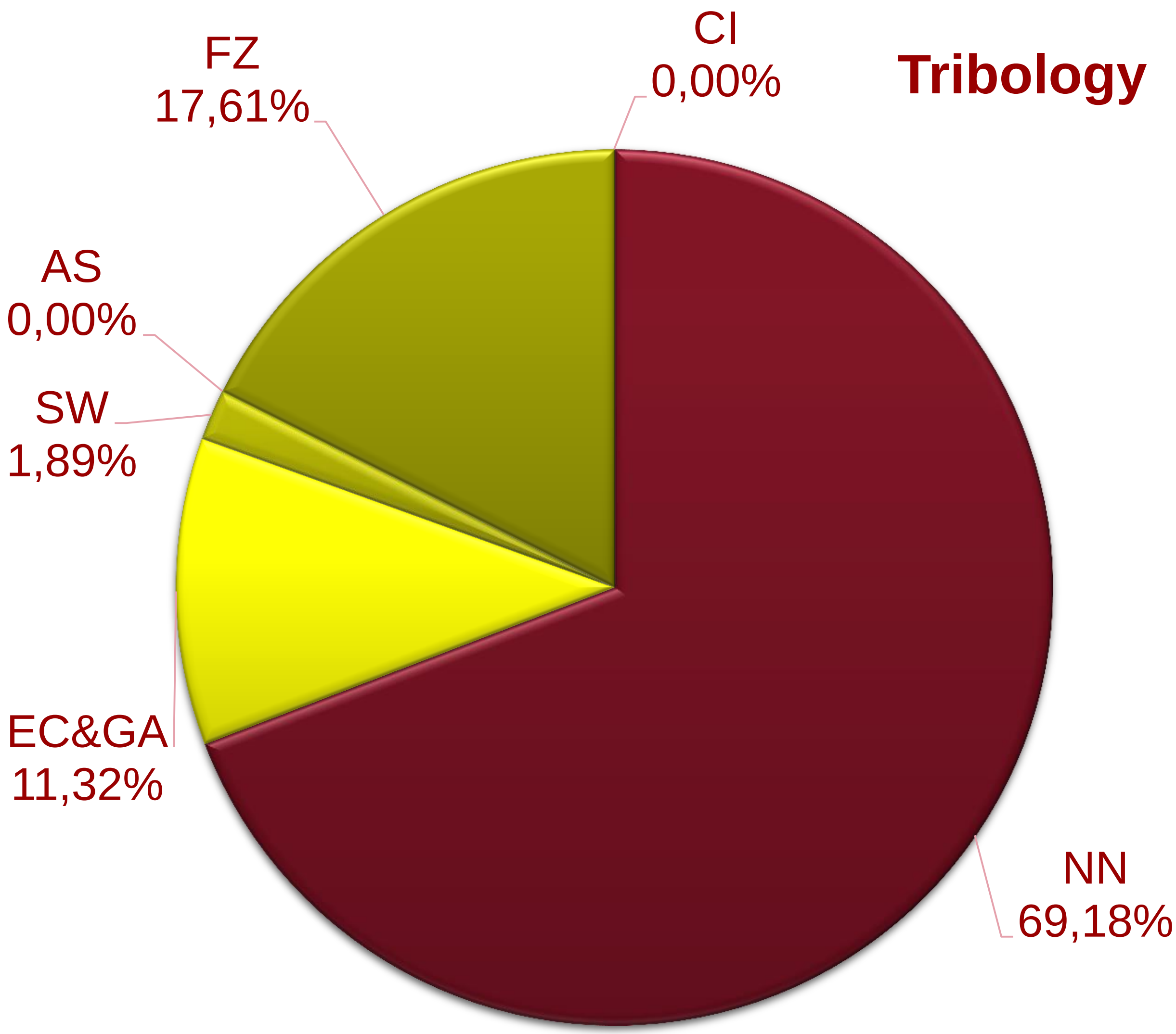
Lubricants

HD and EHD lubrication



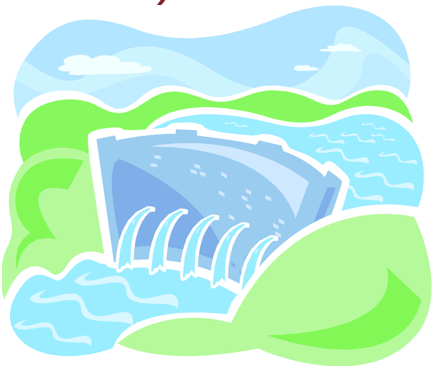
Surface engineering and materials

Physics and Chemistry of tribo-surfaces

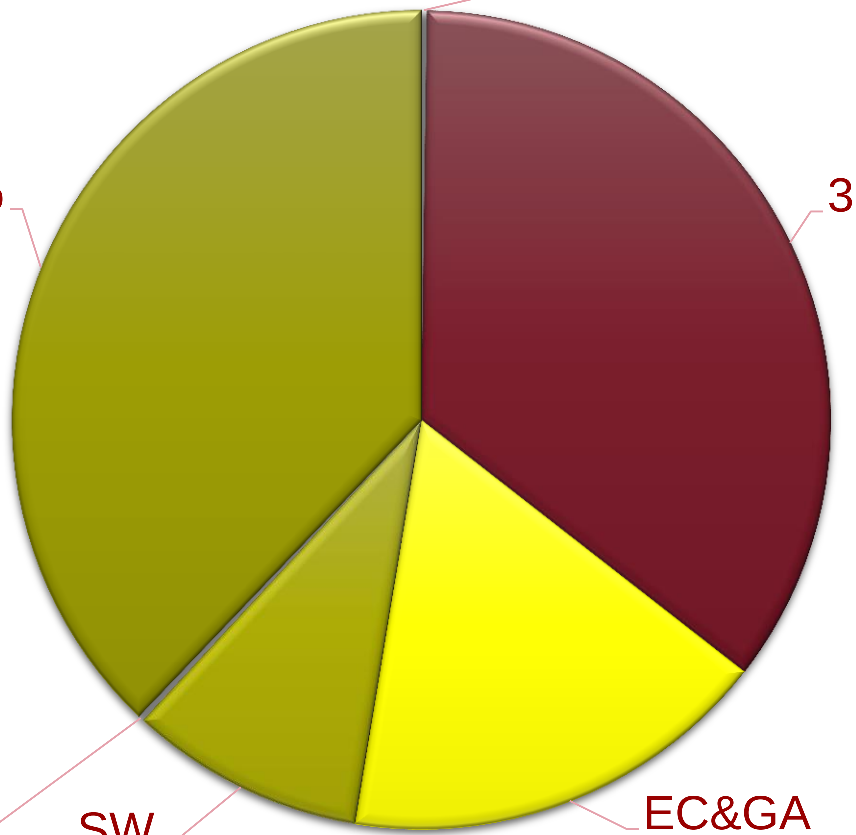

Tribology
CI
0,00%
FZ
17,61%
AS
0,00%
SW
1,89%
EC&GA
11,32%
NN
69,18%

Energetic Systems and Power Production

- Fuels, Combustion & Material Handling
- Renewable Energy (Wind, Solar & Geothermal)
- Sustainability
- Steam Generators
- Heat Exchangers & Cooling Systems
- Turbines, Generators & Auxiliaries
- Plant Operations & Maintenance
- Reliability, Availability & Maintenance
- Plant Systems, Structures, Components & Materials
- Simple & Combined Cycles
- Low/Emission Power Plants and Carbon Capture & Sequestration



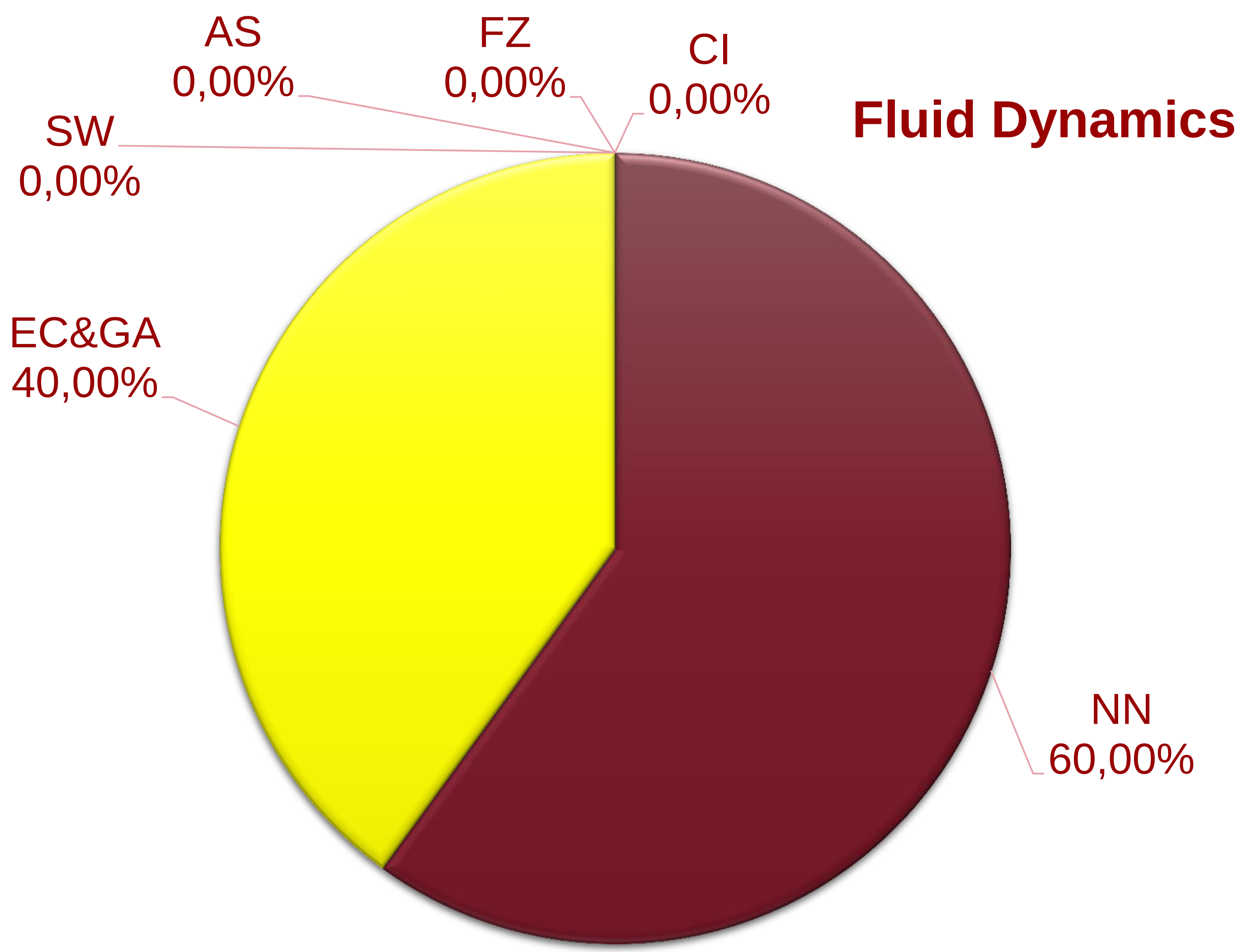
Energetic Systems and Power Plants



Fluid Dynamics

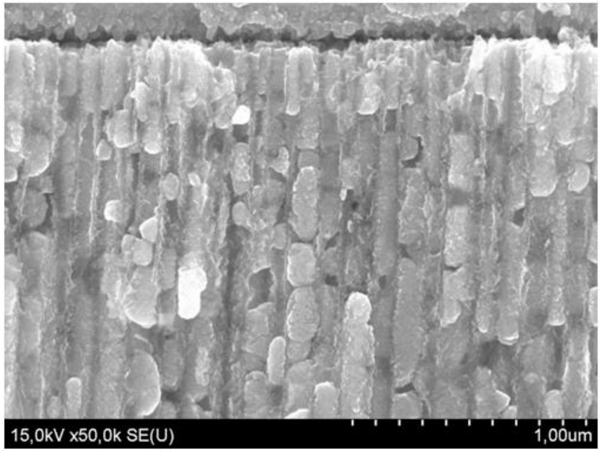
- Numerical Methods in Fluid Flow and Heat Transfer
- Laminar and Turbulent Flow
- Experimental Fluid Dynamics
- Boundary Layer and Free Surface Flows
- Combustion and Reacting Flows
- Industrial Fluid Mechanics
- Heat Transfer, Air Conditioning and Refrigeration
- Micro / Nano Heat Transfer and Fluid Mechanics
- Multi-Phase Flow

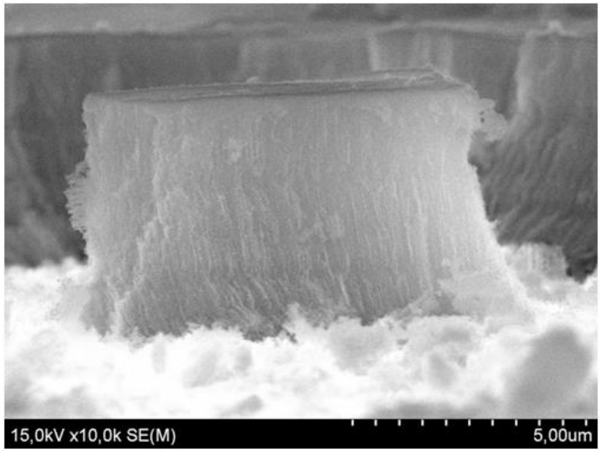
http://www.blosint.com/dir/wp-content/uploads/2013/04/computational-fluid-dynamics.png


AS
0,00%
FZ
0,00%
CI
0,00%
Fluid Dynamics
SW
0,00%
EC&GA
40,00%
NN
60,00%

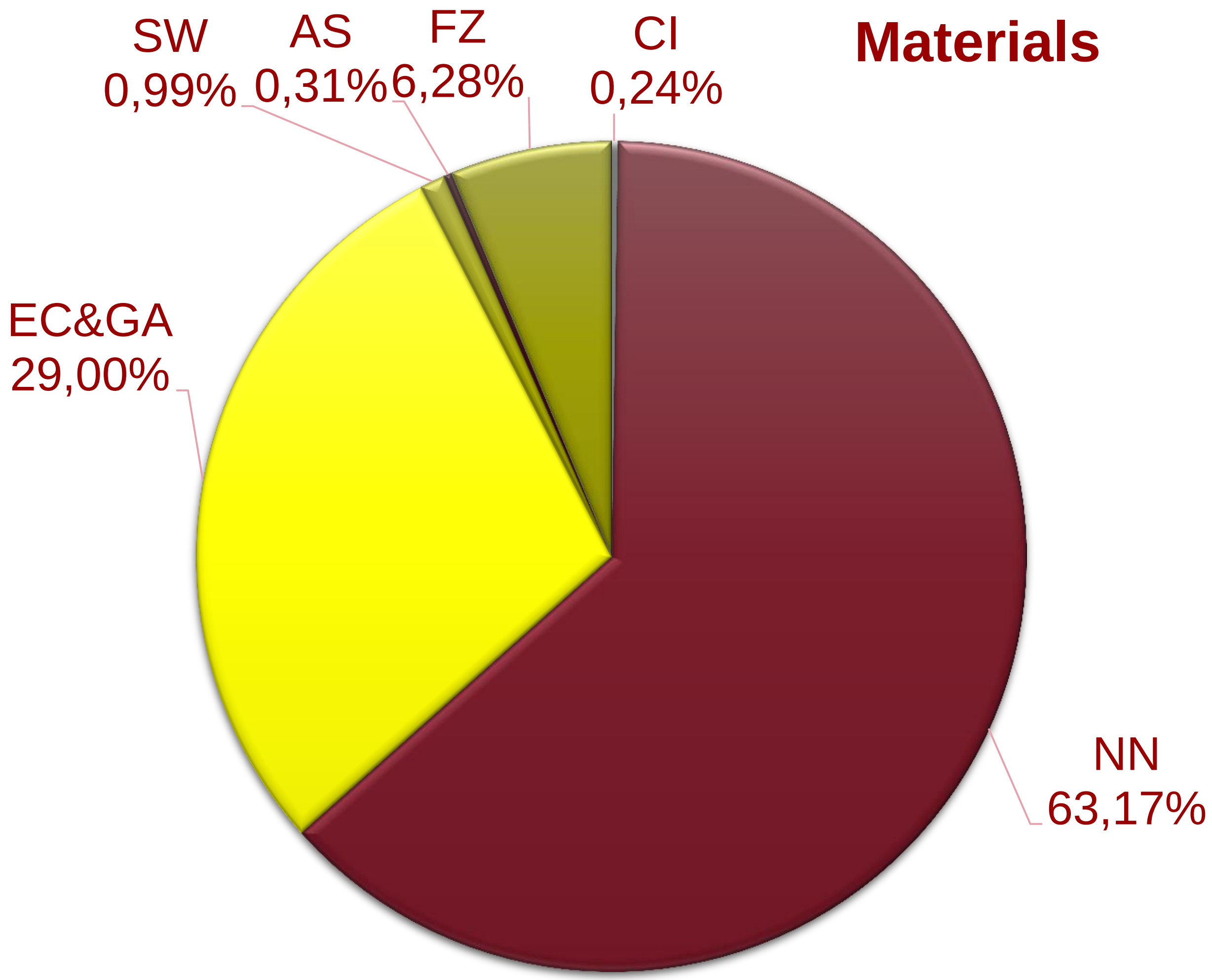
Materials

- Material science
- Material characterization
- Nanoscience and nanotechnology
- Bio and bio inspired materials
- Materials for energy
- New materials for specific applications
- Magnetic and electronics materials
- Metallurgy and Metallography





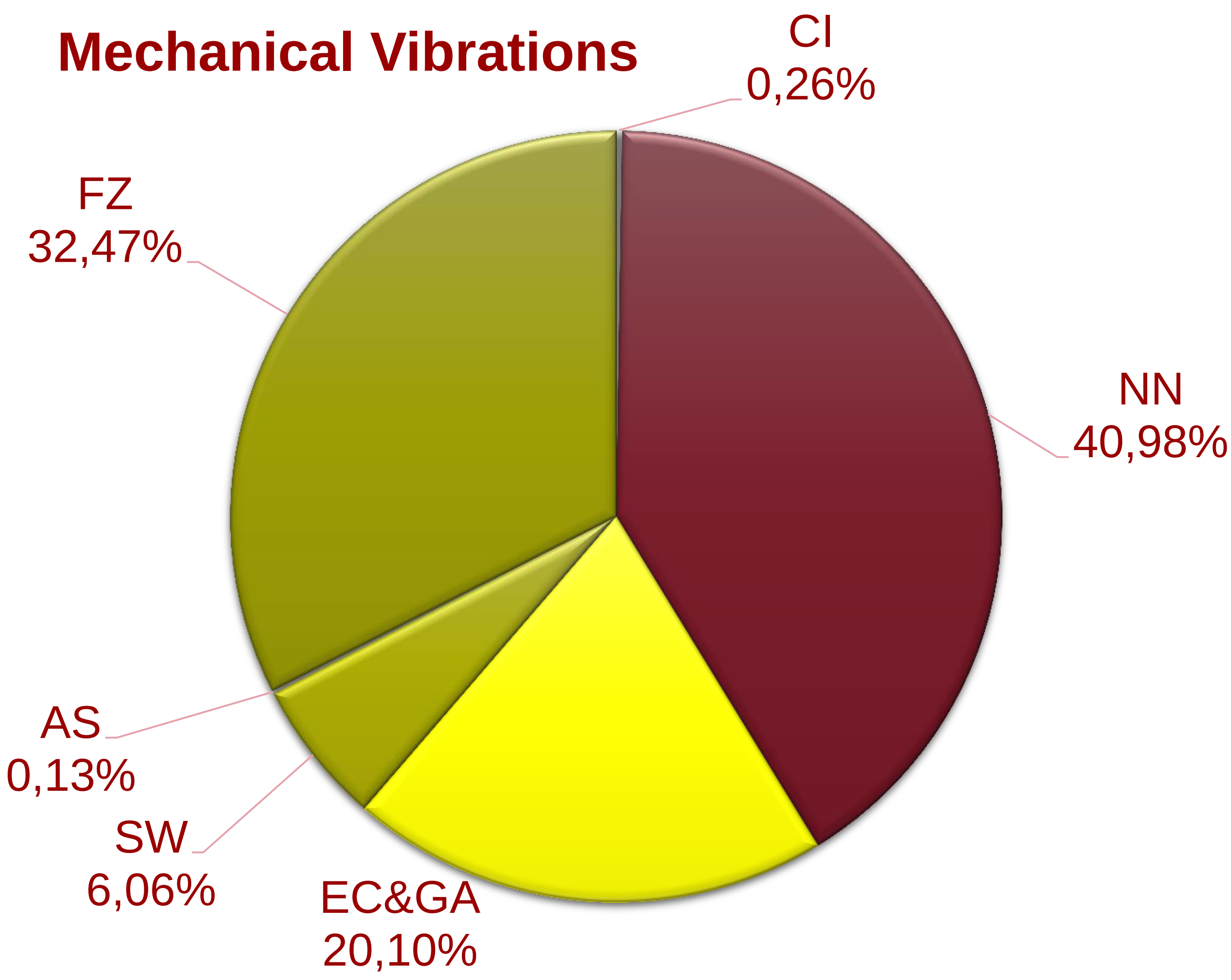
Materials



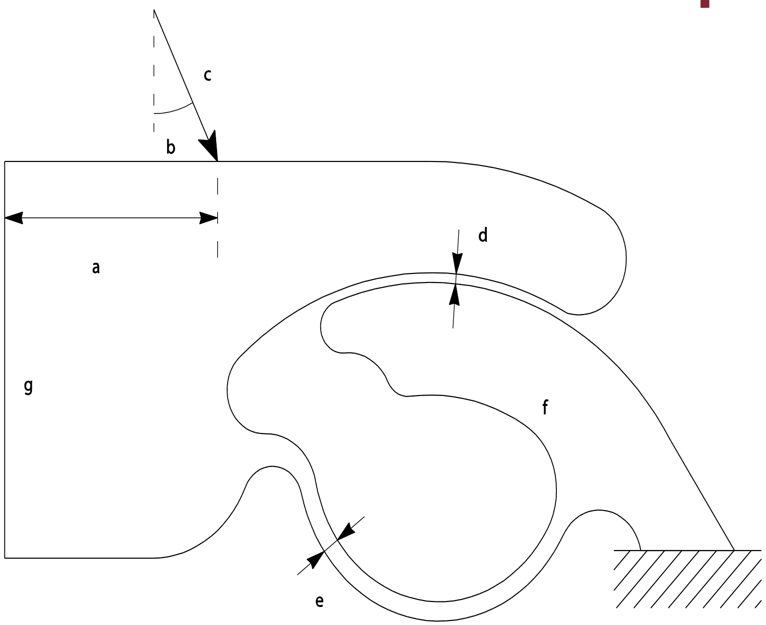
Mechanical Vibrations

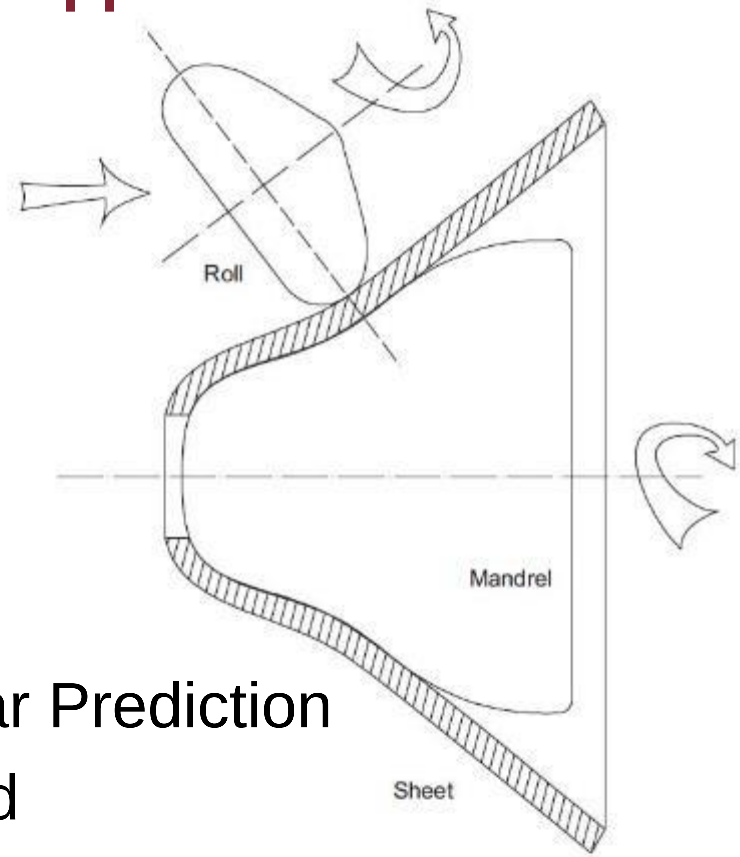
- Modal testing and Frequency Response Function
- Operational modal analysis
- Self-excited vibrations
- Damage detection and condition monitoring
- Noise and vibration control
- Measurement techniques
- Signal processing
- Medium and high frequency techniques
- Damping and ground vibration
- Structures dynamics
- Non-linearities: identification and modelling
- Sound quality engineering

https://www.gipom.com/search/Vibrations/


Mechanical Vibrations
CI
0,26%
FZ
32,47%
NN
40,98%
AS
0,13%
SW
6,06%
EC&GA
20,10%

Part II
Two examples of application





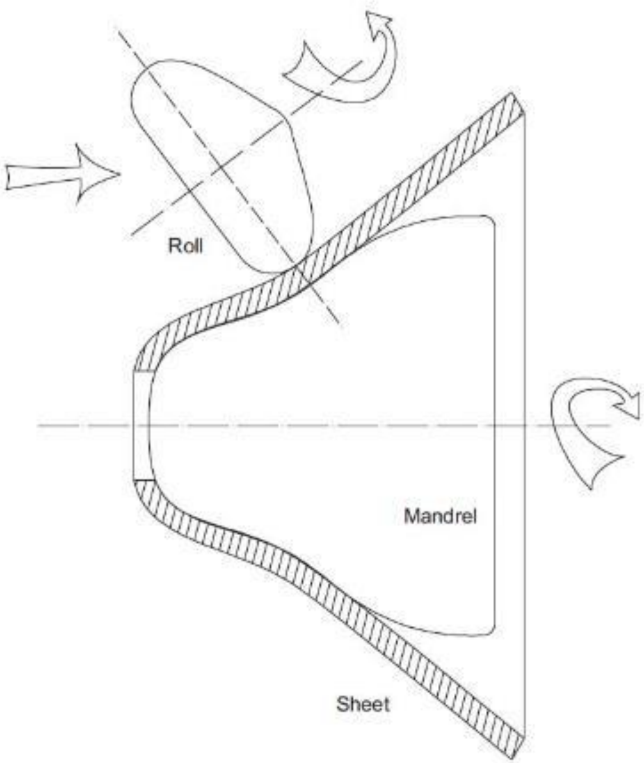
ANN and Wear Prediction

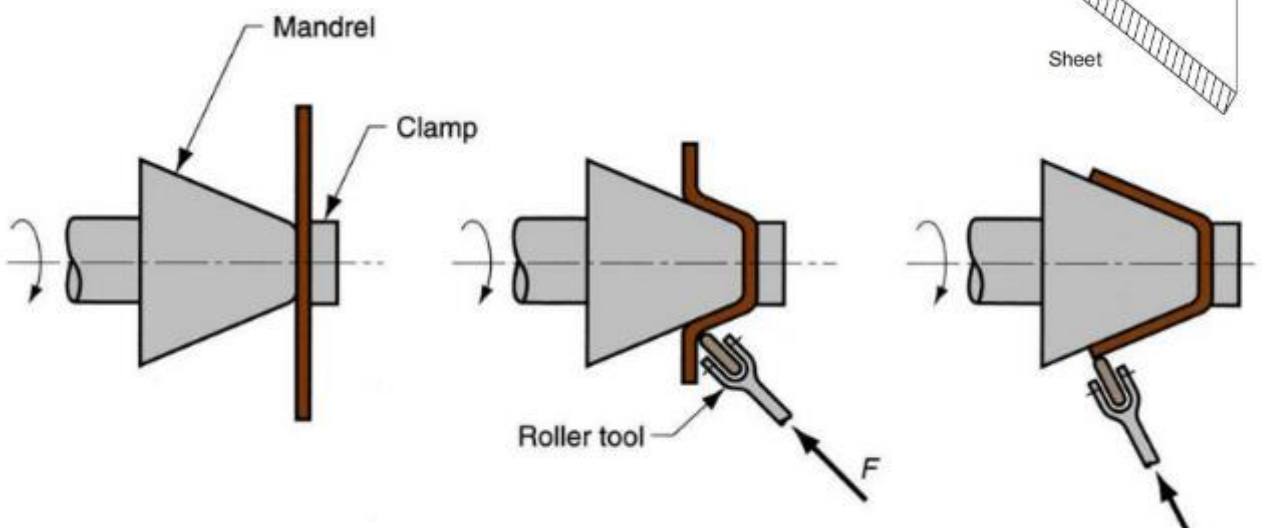
and

GA and MEMS Design

Wear prediction in metal forming

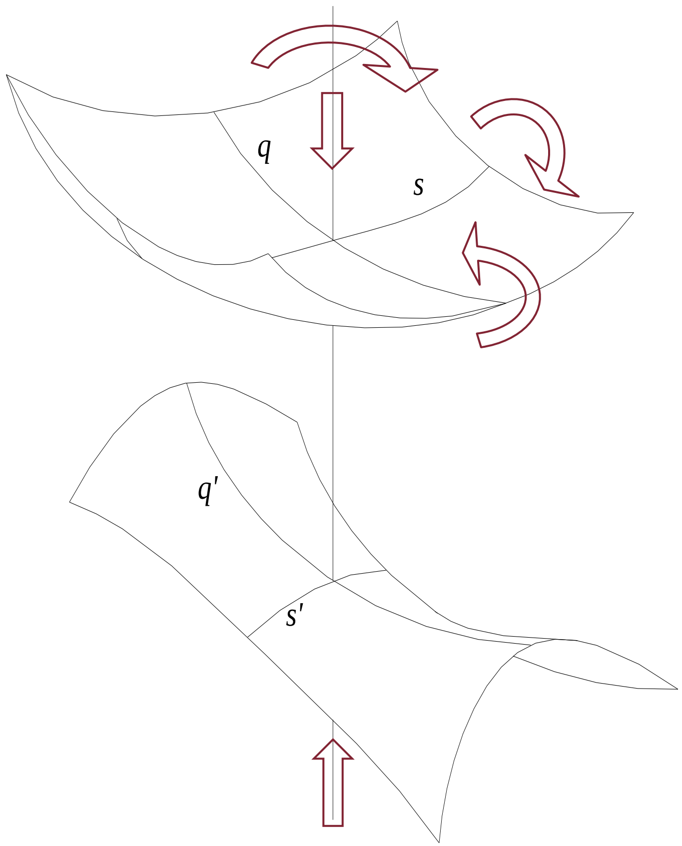
based on Ref. [2]





http://*www.quia.com/files/quia/users/brownfieldreview/Spinning.jpg*

Modeling wear in surface contacts with lubrication and high loads



Wear basic mechanisms

- Adhesion
- Abrasion
- Fatigue
- Mild-Severe wear transitions
- Running in

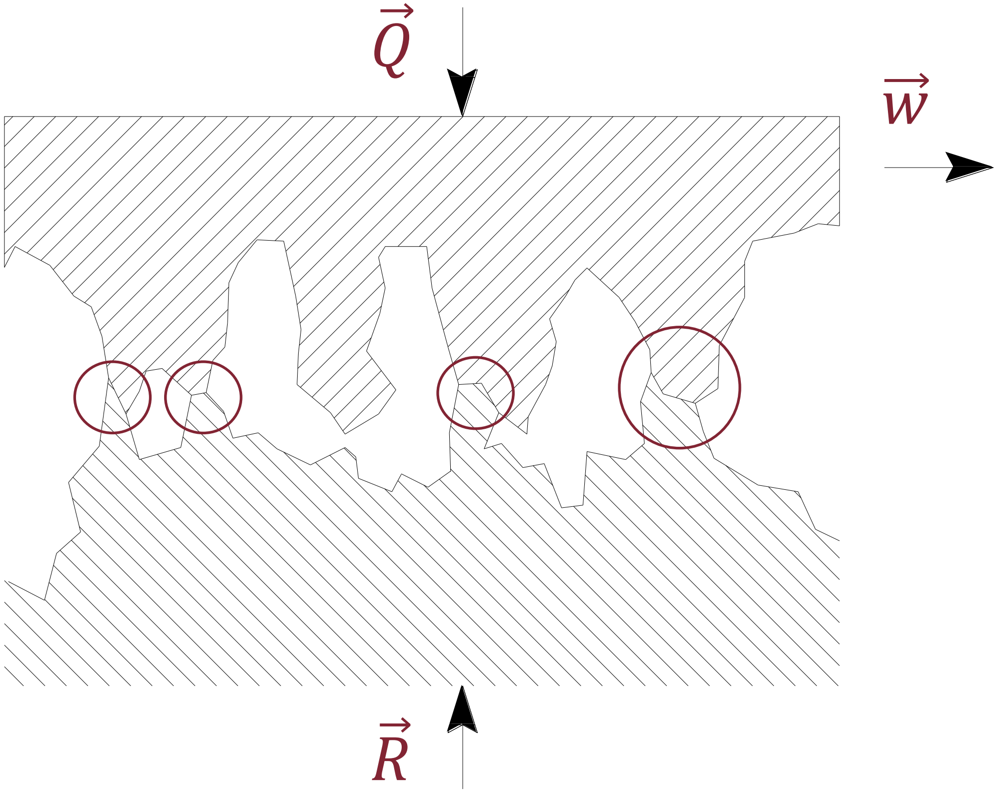
Relative Motion

- Sliding
- Spin
- Roll

Contribution of adhesion to the overall wear damage

$$\frac{\delta h}{s} = k_{ad} \frac{p}{\aleph}$$

$$k_{ad} = \frac{f\aleph}{\tau_k} = \frac{\tau_{\max}}{\tau_k}\aleph^2$$

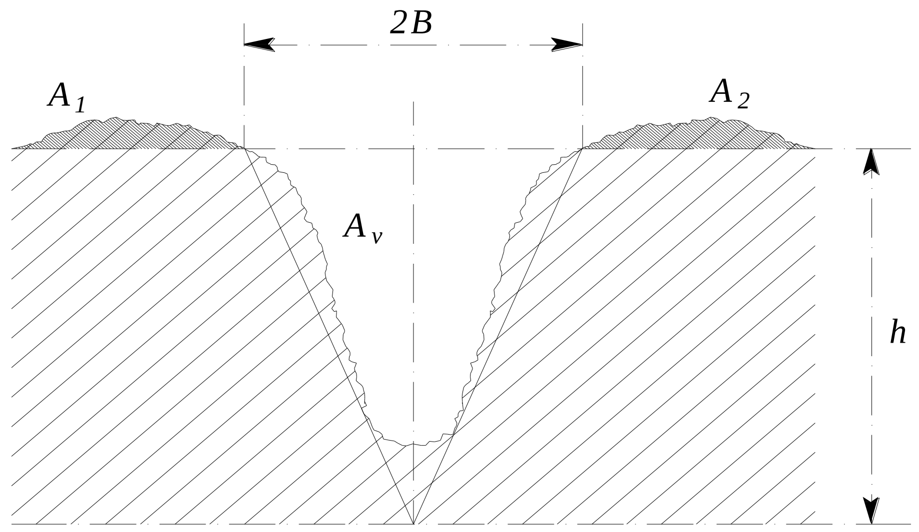


Contribution of abrasion to the overall wear damage

$$\frac{\delta h}{s} = k_{ab} \frac{p}{\aleph}$$

$$k_{ab} = \rho_{ab} \frac{A_v \aleph}{N}$$

$$\rho_{ab} = \frac{A_v - (A_1 + A_2)}{A_v}$$



Contribution of fatigue to the overall wear damage

the increment of the number of micro-defects per each cycle is proportional to the actual number of micro-defects

$$\frac{\delta h}{s} = C_f 1.58 \sigma_o^{-0.085} e^{k_e \frac{R_q}{R} n} \left(\frac{\sigma_f}{\sigma_o} \right)^m \frac{p}{\aleph}$$

Please, refer to the above mentioned paper for the Nomenclature

Influence of Mild Wear to Severe Wear Transition

$$\delta h = k\frac{p}{\aleph}\left(n\Delta T\right)\cdot k_w\frac{\ln\left(w+1\right)}{\left(w+1\right)}$$

Including the influence of the initial transient period

Run in

$$\delta h = \left(-k_2n^2 + k_1n\right)\frac{\Delta T}{\aleph}\frac{\ln(w+1)}{(w+1)}\,p$$

The adopted overall model

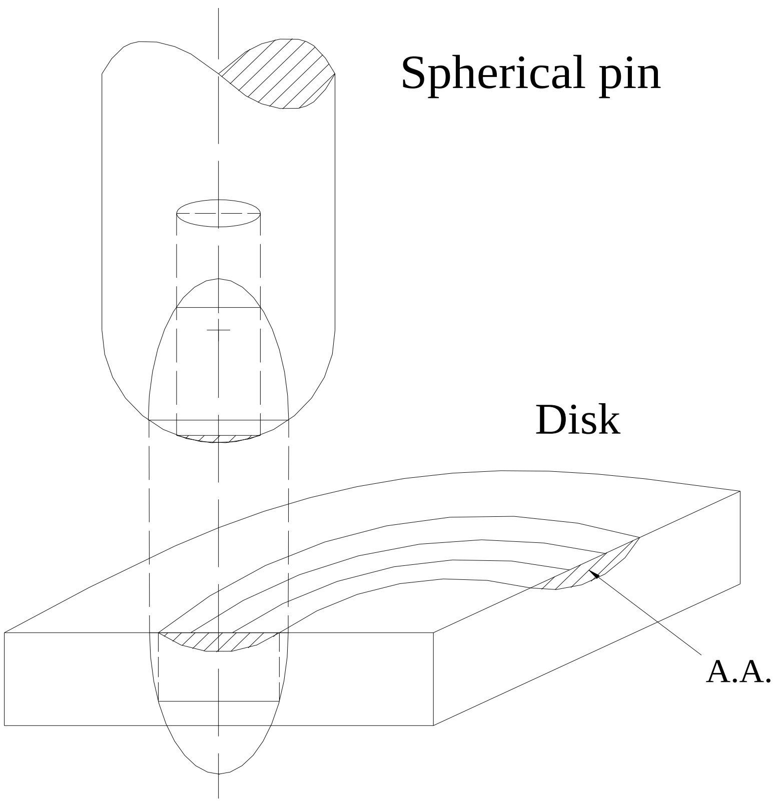
for $0 < n < n_o = 300000$ cycles

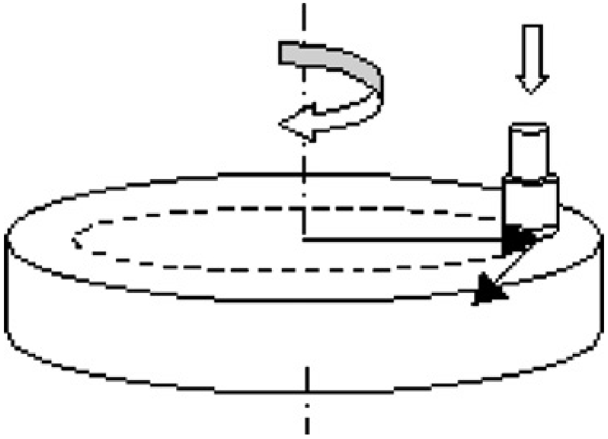
$$\delta h = \left(-k_2 n^2 + k_1 n\right)\frac{\Delta T}{\aleph}\,\frac{\ln(w+1)}{(w+1)}\,p$$

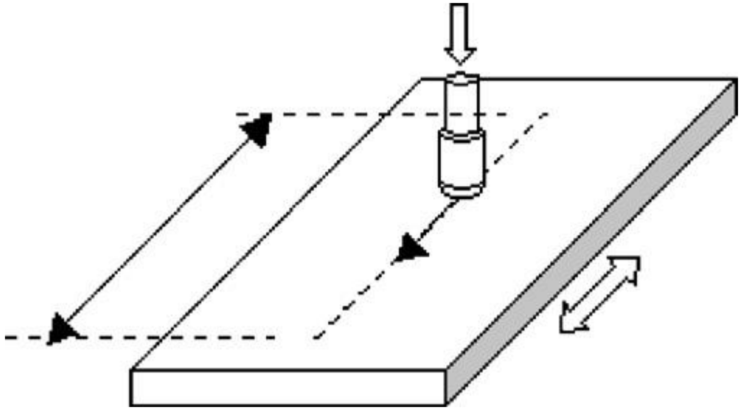
for $n > n_o$

$$\delta h = \delta h(n_o) + \left(k_a + C_f\,1.58\,\sigma_o^{-0.085}\,e^{k_e \frac{R_q}{R}(n-n_o)}\left(\frac{\sigma_f}{\sigma_o}\right)^m\right)\frac{\Delta T}{\aleph}\,\frac{\ln(w+1)}{(w+1)}\,p(n-n_o)$$

Experimental set up

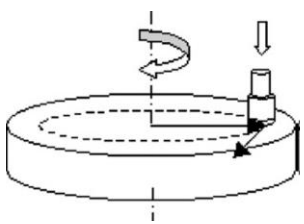






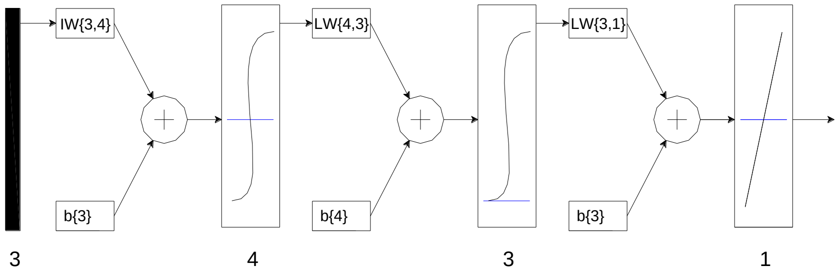
Hybridization

- Data produced by the theoretical model have been used to enlarge the amount of experimental data
- Both the Training and Test Sets have been built by using hybridization

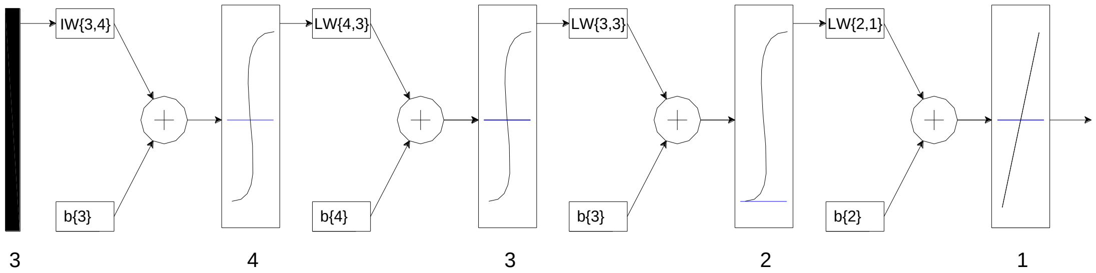


$$\delta h = \delta h(n_o) + \left(k_a + C_f 1.58 \sigma_o^{-0.085} e^{k_e \frac{R_q}{R}(n-n_o)} \left(\frac{\sigma_f}{\sigma_o} \right)^m \right) \frac{\Delta T}{\aleph} \frac{\ln(w+1)}{(w+1)} p(n-n_o)$$

Neural Network Structures



(a)



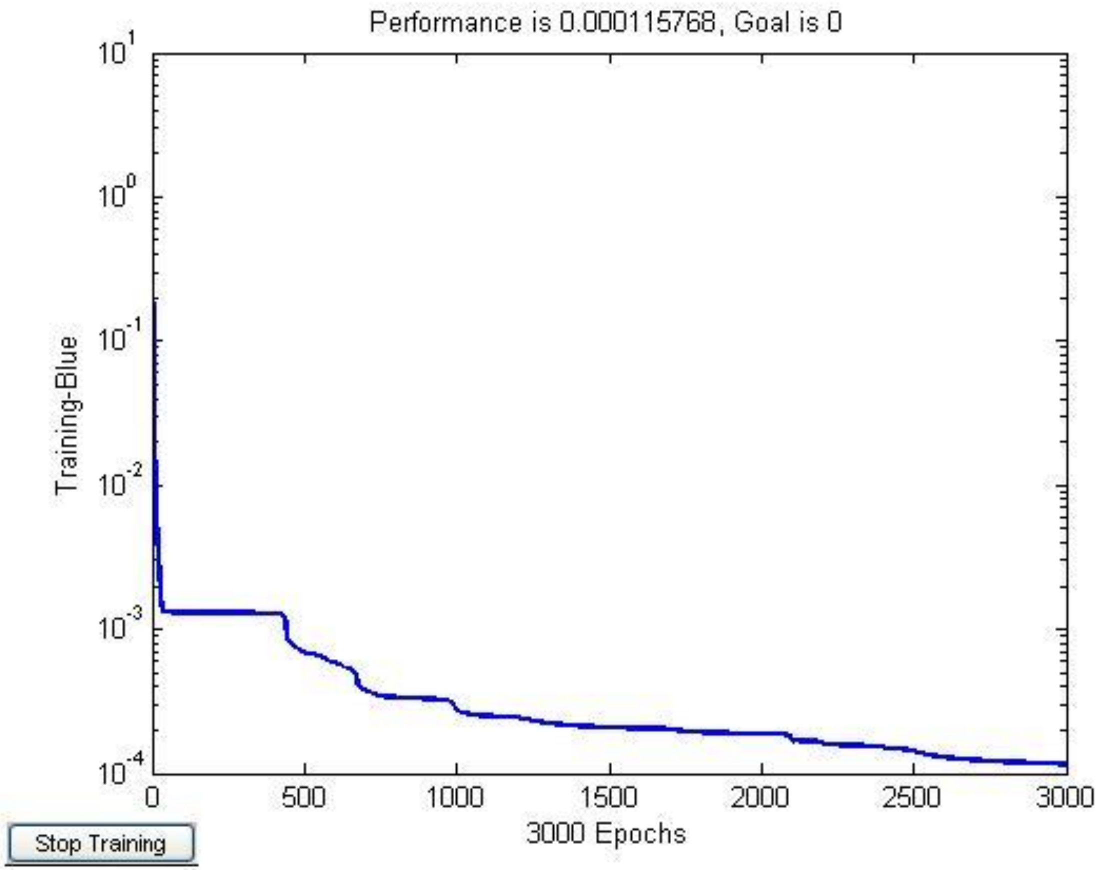
(b)

3 inputs = Thousands of revolutions, Pressure, Velocity

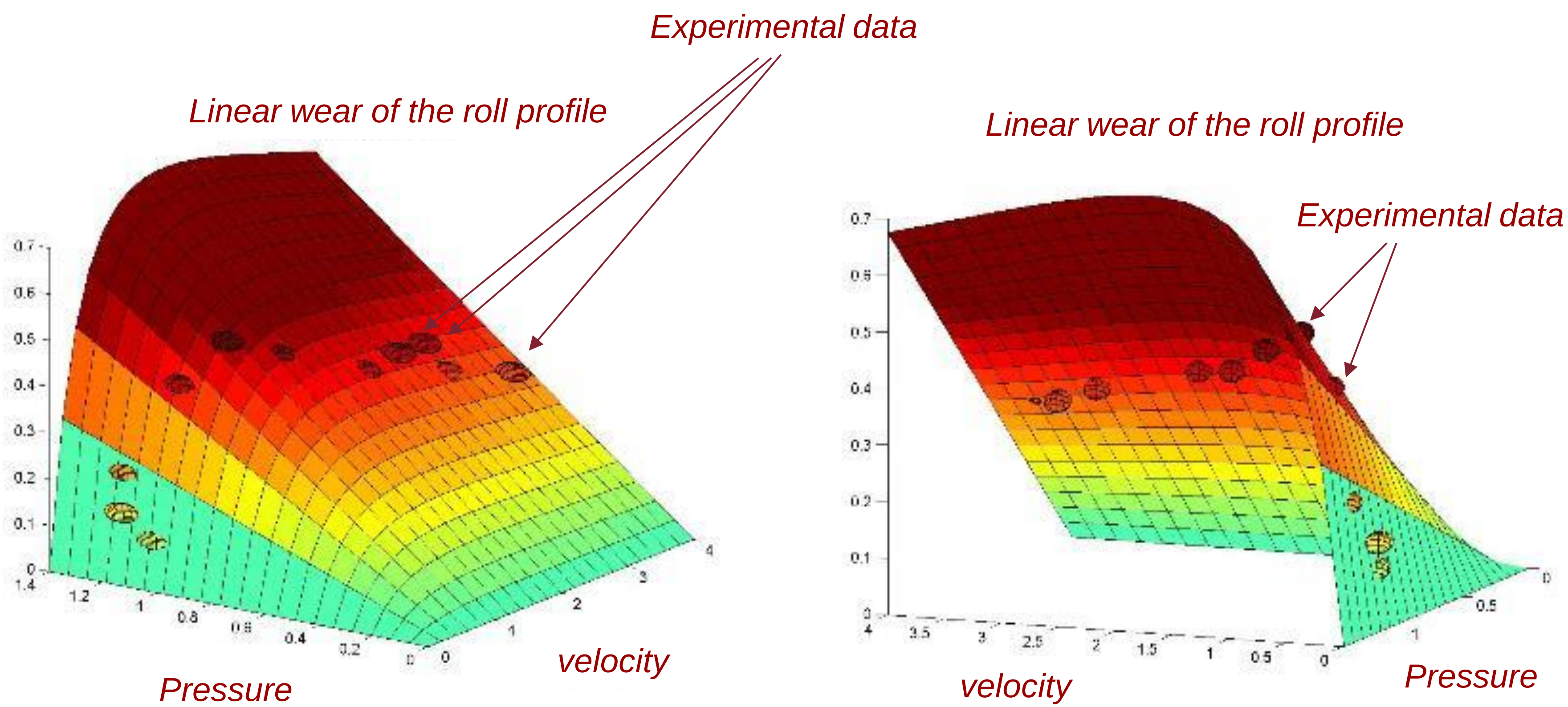
1 output = sample radius wear (mm)

$$a^3 = f^3\left(LW_{1,3} f^2\left(LW_{3,4} f^1\left(IW_{4,3} p + b^1\right) + b^2\right) + b^3\right) = y$$

Convergence history

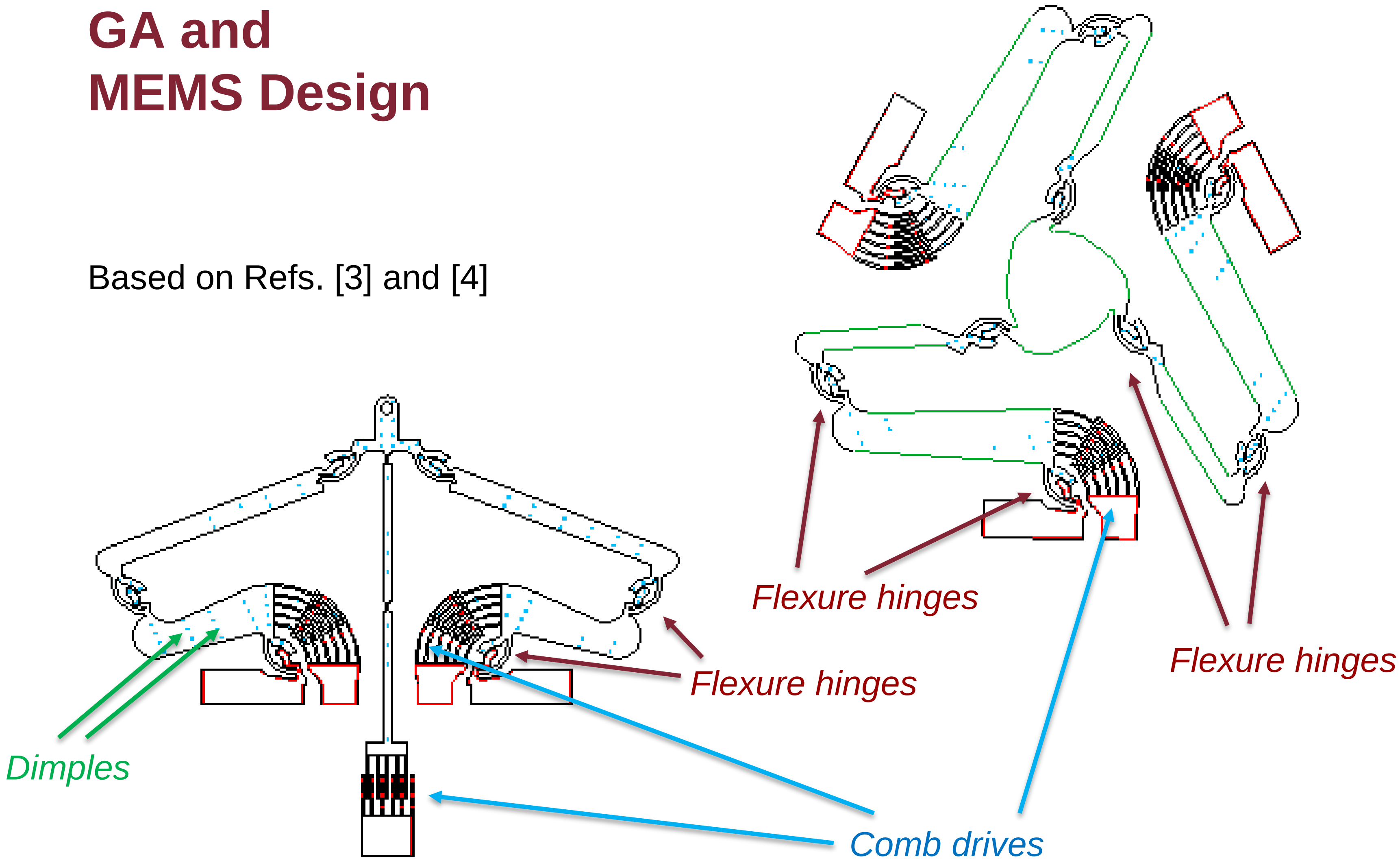


ANN vs Model Comparative Analysis of Results

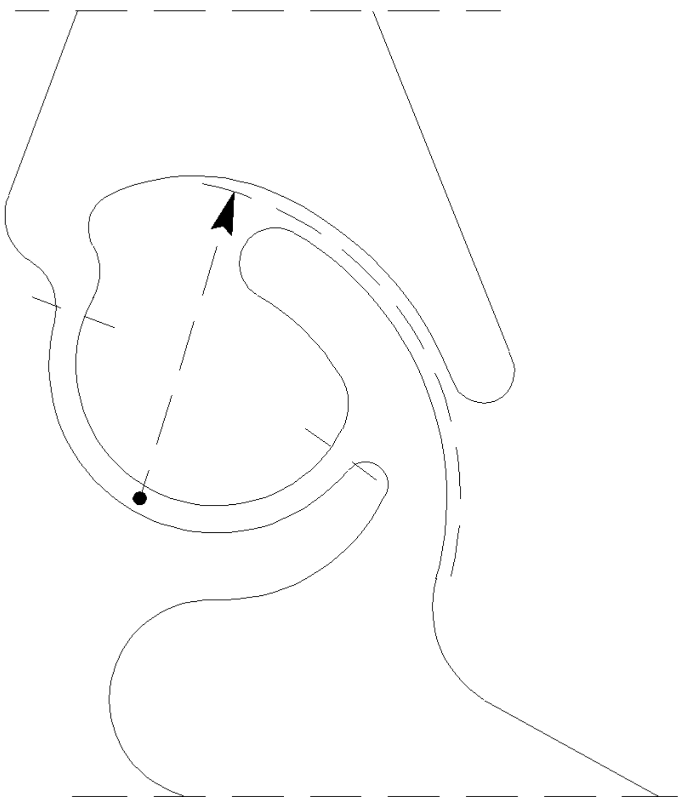


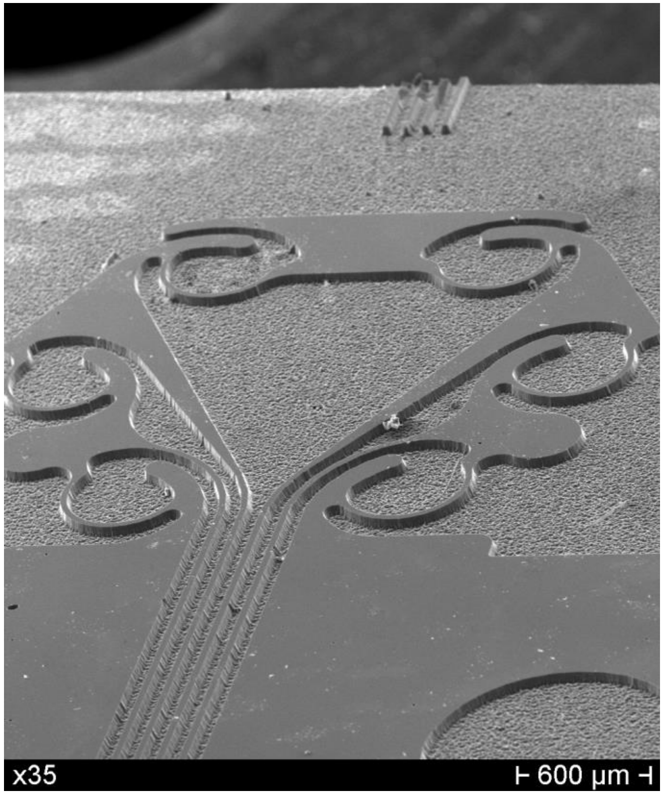
GA and MEMS Design

Based on Refs. [3] and [4]



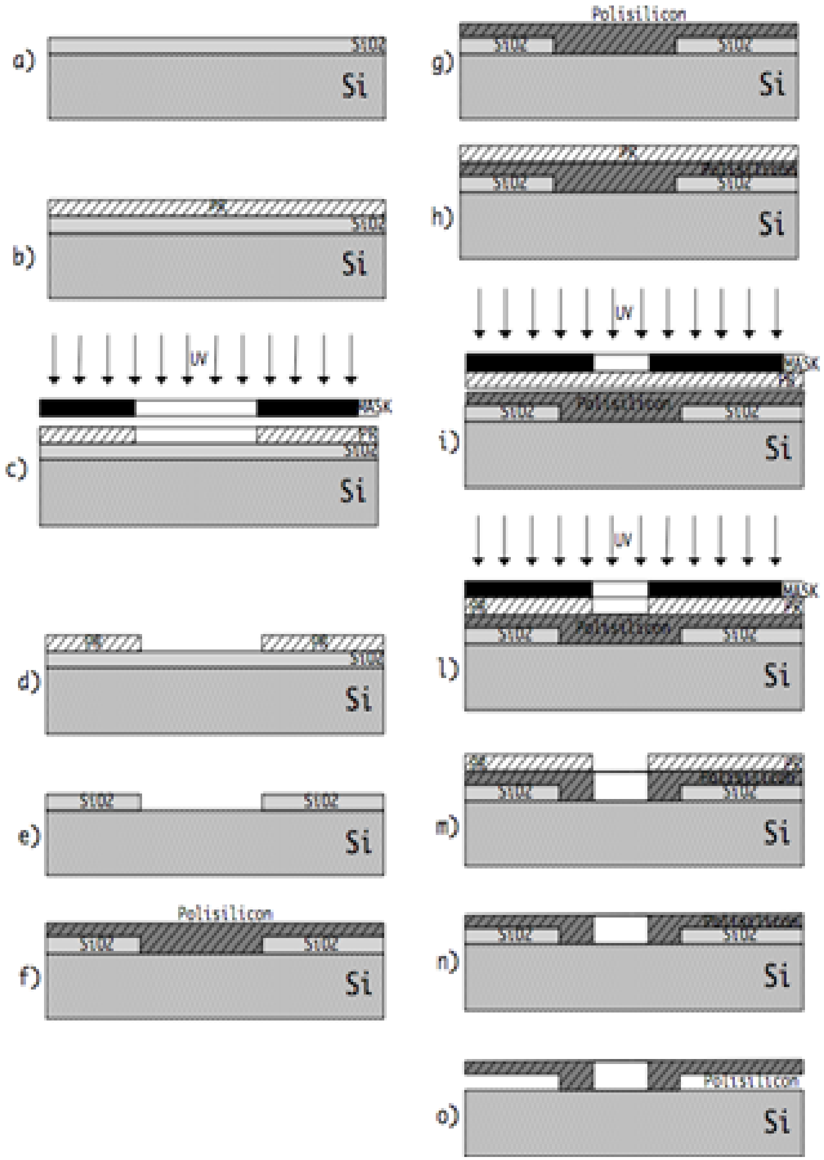
CSFH (Conjugate-Surfaces Flexure Hinge) for MEMS Design



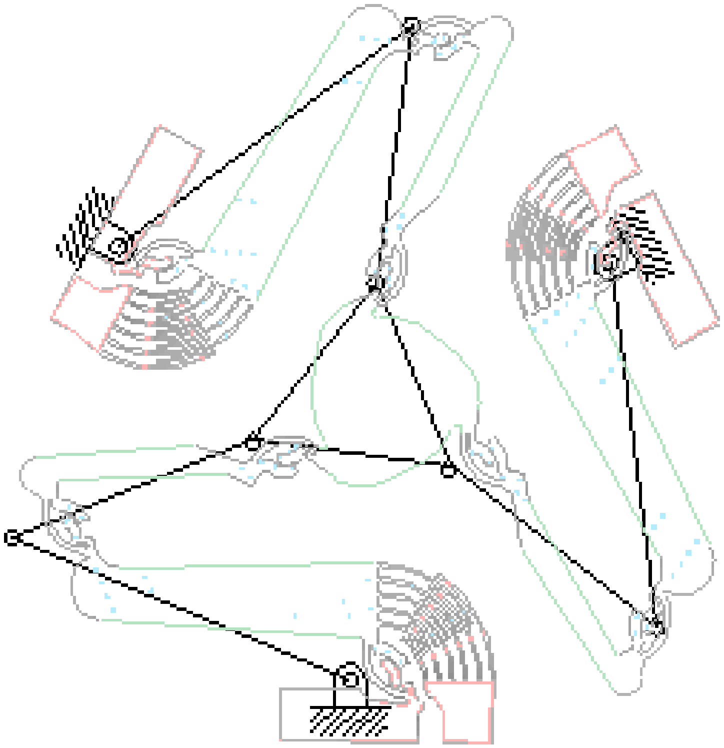


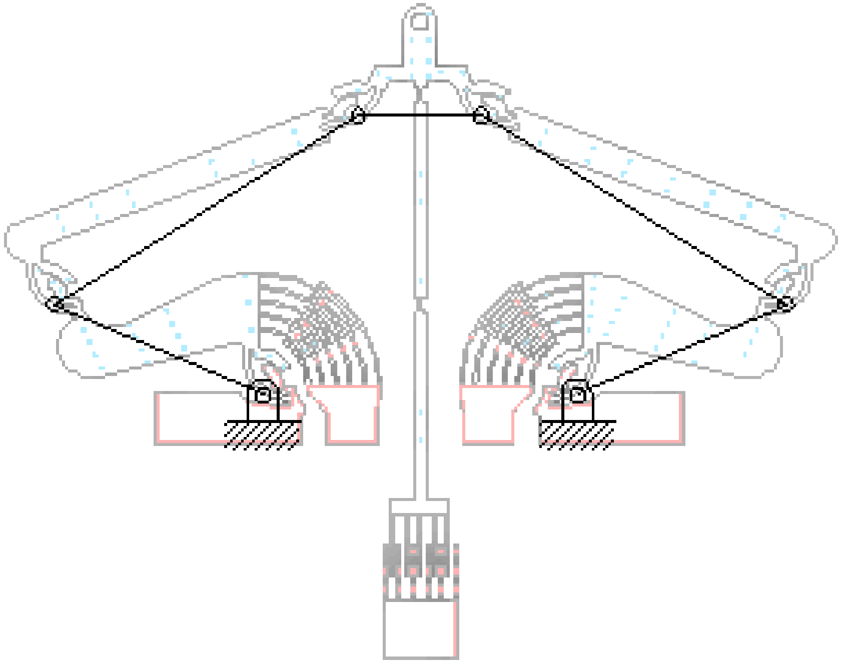
The Construction Method

a) silicon dioxide grown thermally on a silicon wafer
b) PR photoresist
c) Mask and PR developing
d) Mask removal
e) Reactive Ion Etching
f) Polisilicon deposition via Low Pressure Chemical Vapor Deposition)
g) Preparation for photolitography
    h) PR
    i) Mask
    l) PR developinig
    m) Mask removal
n) Wet etching (acetone)
o) PR removal
p) HF (hydrofluoric acid) etching for removing the silicon dioxide



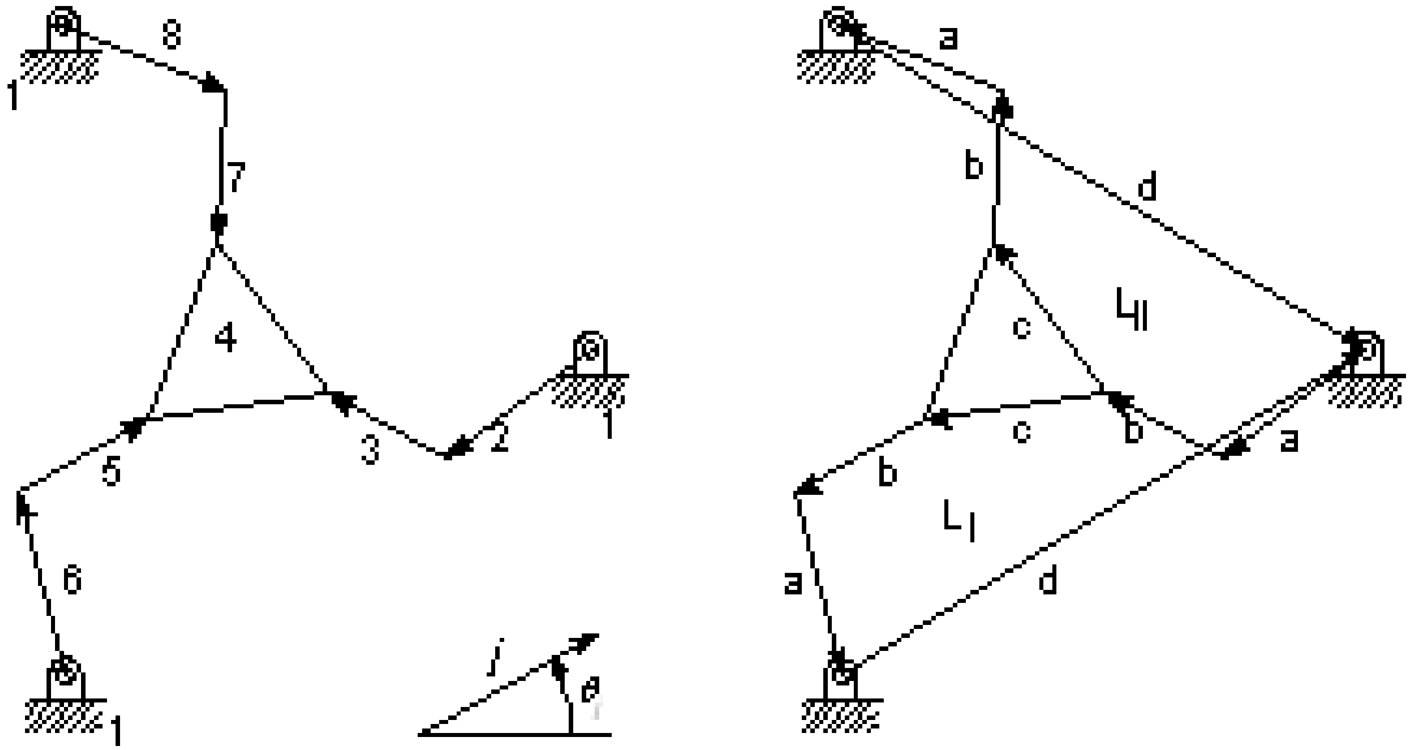
The pseudo-rigid body equivalent mechanism





PRBM: benefits

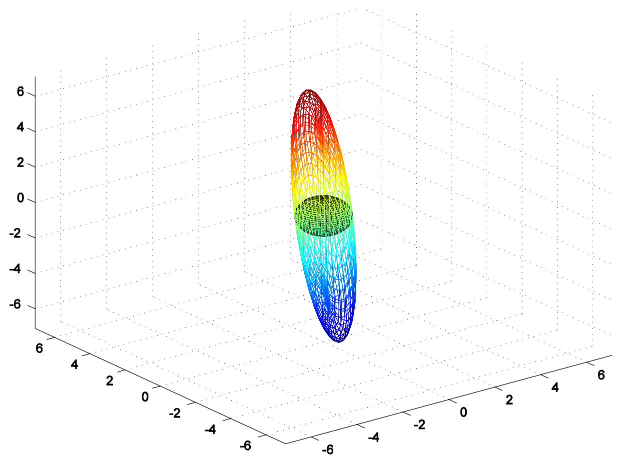
a) Configuration analysis around the neutral configuration
b) First order and Performance analysis
c) Stress minimization, isotropic compliance and mechanical advantage optimization



Main Indexes

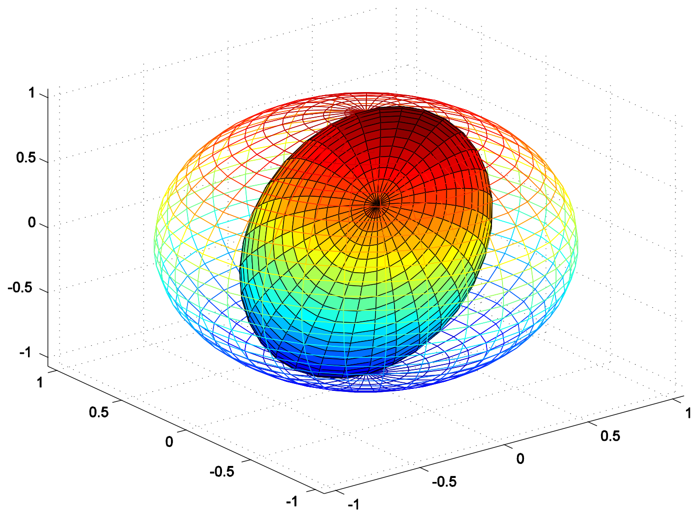
k (*J*) *Kinematic Condition Number*,
ratio of highest to lowest values of the output generalized velocity vectors;
k (J) gives a good esteem of the sensitivity of the tip velocities upon directions

Output generalized velocity

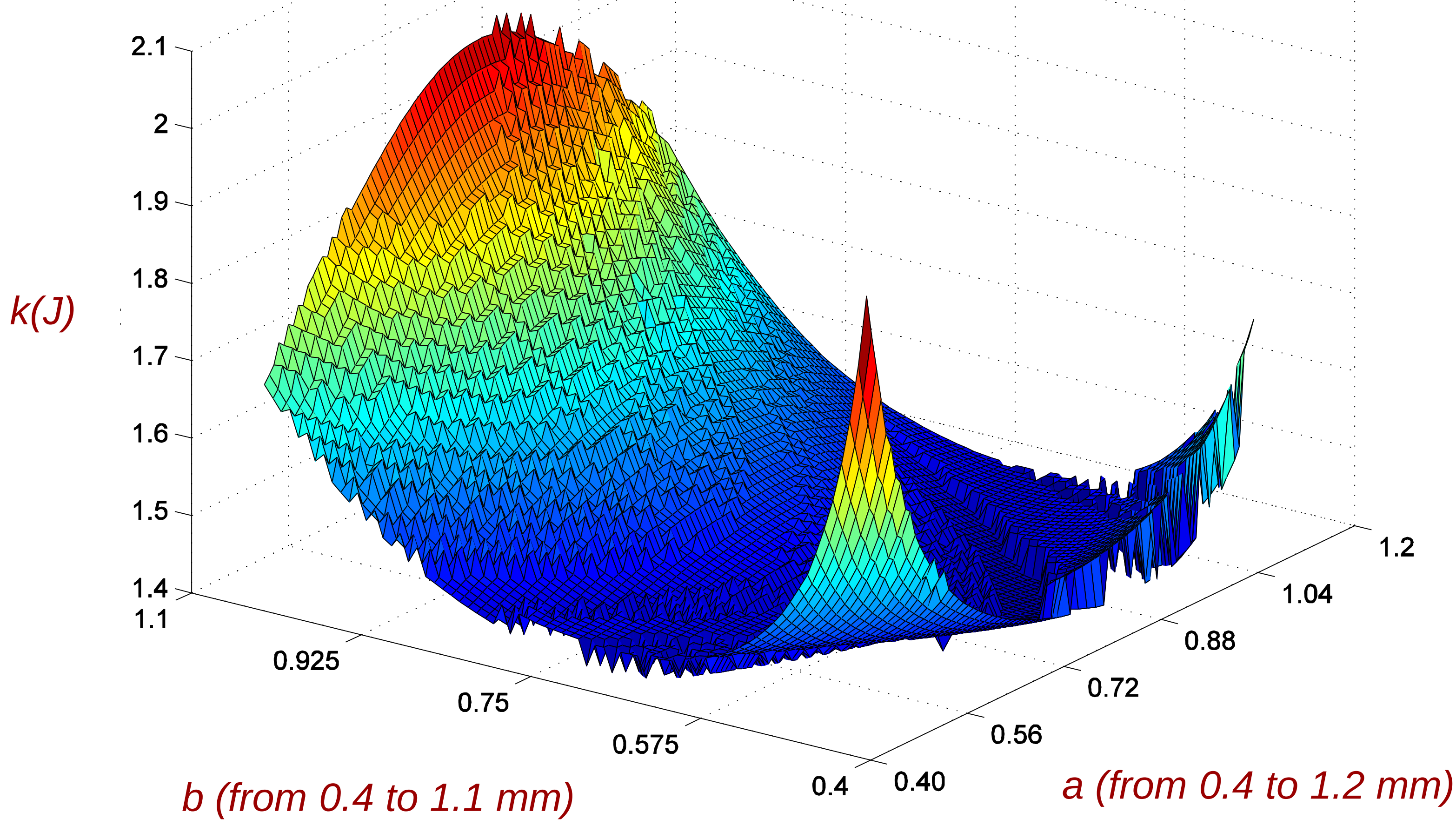


MA Mechanical Advantage,
ratio of the norm of the input generalized velocity vector (actuators) by the norm of its corresponding output generalized velocity vector (platform);
MA could be used to evaluate the overall force amplification factor in static conditions

Output generalized velocity



k(J) mapping for variable values of the lengths *a* and *b*



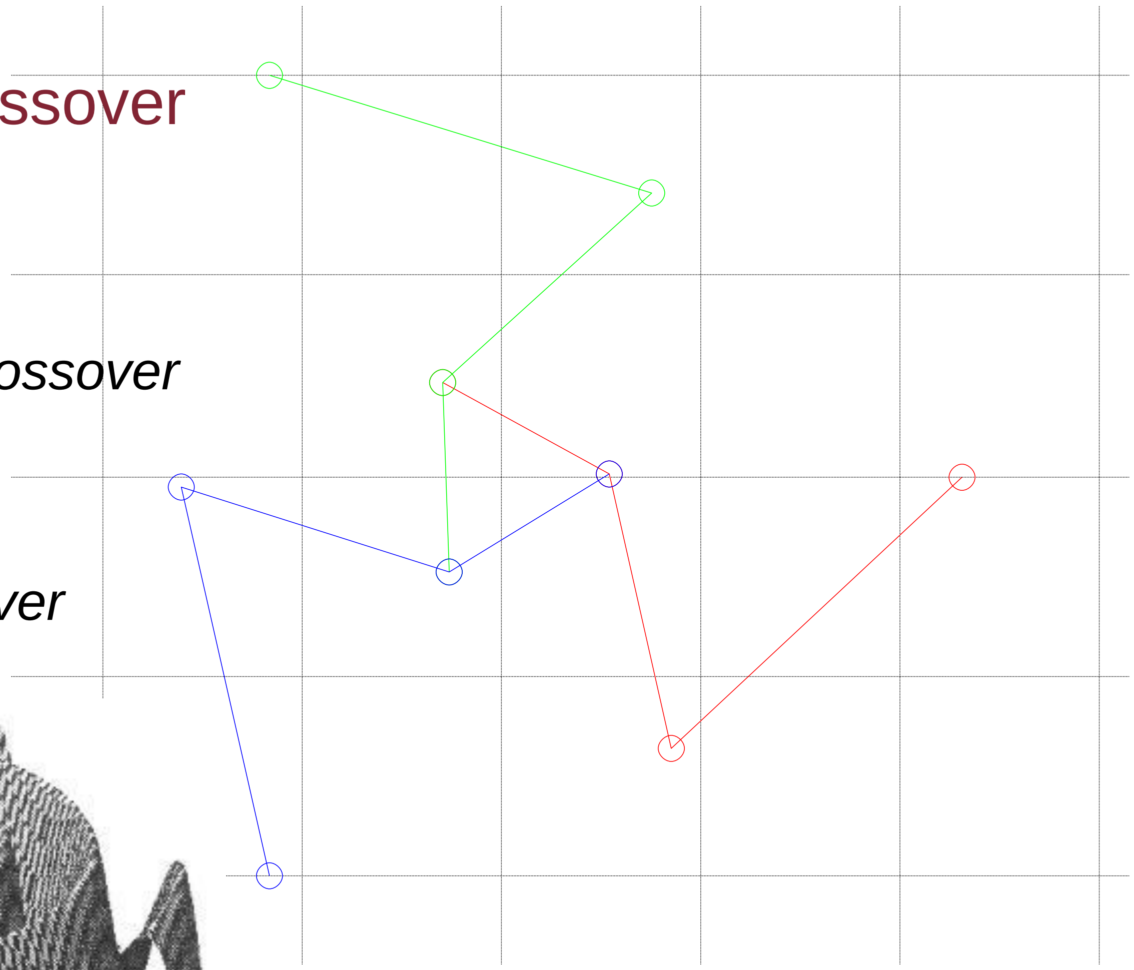
Fitness functions

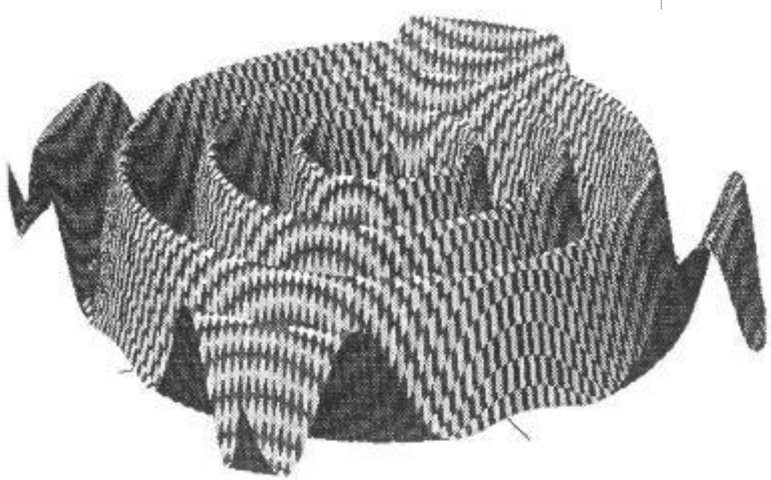
- $(k(J) - 1)^2$ → target = unit value of the *KCN*
- $(MA_{max} - 1)^2$ → target = output generalized velocity vectors $\{V\}$ are represented by an ellipsoid which is fully included within a unit radius sphere $\{\Omega_u\}$
- $(MA_{min} - 1)^2$ → target = $\{V\}$ are represented by an ellipsoid which fully includes $\{\Omega_u\}$
- $(k(J) - 1)^2 + (MA_{max} - 1)^2$ → target = $\{V\}$ is fully included within $\{\Omega_u\}$ but it similar to a sphere
- $(k(J) - 1)^2 + (MA_{min} - 1)^2$ → target = {V } includes $\{\Omega_u\}$ but it is similar to a sphere

Encoding and Crossover

Based on Ref. [5]

- *One or two point crossover*
- *Uniform crossover*
- *Flat crossover*
- *Logarithmic crossover*





Population size = 200

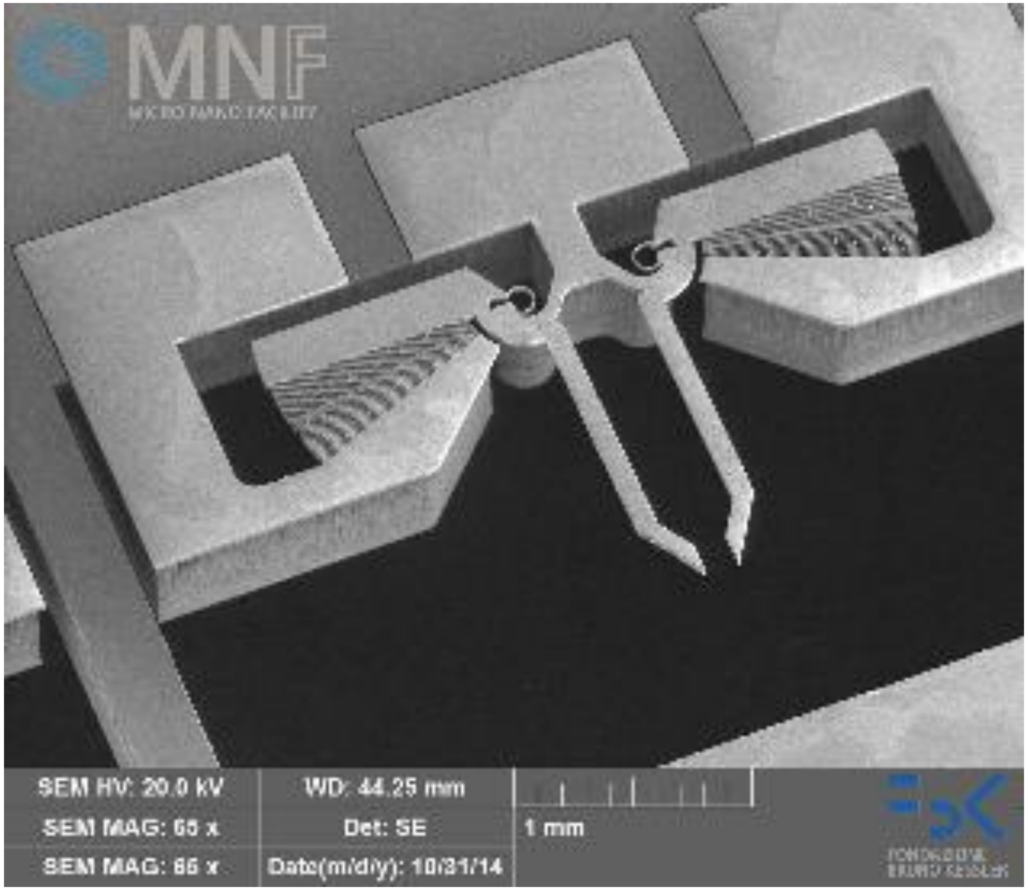
Results

Target	a (mm)	b (mm)	c (mm)	k(J)	MA_{max}	MA_{min}	CPU time (s)
K(J)	1.34	0.50	1.21	1.25	4.64	5.83	1676
MA_{max}	0.79	0.63	0.67	1.93	1.00	1.93	406
MA_{min}	1.51	0.91	1.01	7.14	0.14	1.00	245
K(J)&MA_{max}	1.15	0.28	1.22	1.47	1.00	1.46	1053
K(J)&MA_{min}	1.29	0.55	0.83	1.93	0.52	1.00	1275

Some Activities at CNIS

CNIS
Centro di ricerca per le Nanotecnologie applicate all'Ingegneria della Sapienza
cnis at uniroma1.it

The most recent prototype (November 2014)



Conclusions

- 1,705,201 analyzed papers
- 13,307 selected papers
- 473 referenced and catalogued papers
- ME subjects to CI methods and tools mapping
- Identification of areas of interest
  - Some ME subjects appear relatively ignored by CI means (with no apparent justification)
  - ANN-to-Tribology (2007)
  - GA-to-MEMS design (2014)

References (for this presentation)

[1] Belfiore, N.P., Rudas, I.J., *Applications of Computational Intelligence to Mechanical Engineering*, Proc. 15th IEEE International Symposium on Computational Intelligence and Informatics CINTI 2014, November 19-21, 2014, Budapest, Hungary, Paper No. 107

[2] Belfiore NP, et al. *A hybrid approach to the development of a multilayer neural network for wear and fatigue prediction in metal forming*. Tribology International (2007)

[3] N. P. Belfiore, M. EmamiMeibodi, M. Verotti, R. Crescenzi, M. Balucani, P, Nenzi, *Kinetostatic Optimization of a MEMS–Based Compliant 3 DOF Plane Parallel Platform*, IEEE 9th International Conference on Computational Cybernetics, Paper No. 5, IEEE PID2796439, July 8-10, 2013, Tihany, Hungary

[4] N.P. Belfiore, M. Balucani, R. Crescenzi, M. Verotti, *Performance Analysis of Compliant MEMS Parallel Robots through Pseudo-Rigid-body Model Synthesis*, Proceedings of the 11th Biennial Conference on Engineering Systems Design and Analysis, ASME-ESDA2012, July 2-4, 2012, Nantes, France

[5] *Belfiore, N.P., A., Esposito, A., Theoretical and Experimental Study of Crossover Operators of Genetic Algorithms, Journal of Optimization Theory and Applications, Vol. 99, No. 2, November 1998, Plenum Publ. Co., New York, pp. 271 – 302*