Smart Neurofuzzy Systems

Dr Georgios K. Tairidis
Technical University of Crete

1984 - 2014
years of excellence
TECHNICAL UNIVERSITY OF CRETE

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Topics of presentation

1. Introduction
2. Fuzzy and neuro-fuzzy control strategies
3. Optimization methods
4. Natural disasters
5. Conclusions

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Introduction

Smart neurofuzzy systems consist of:

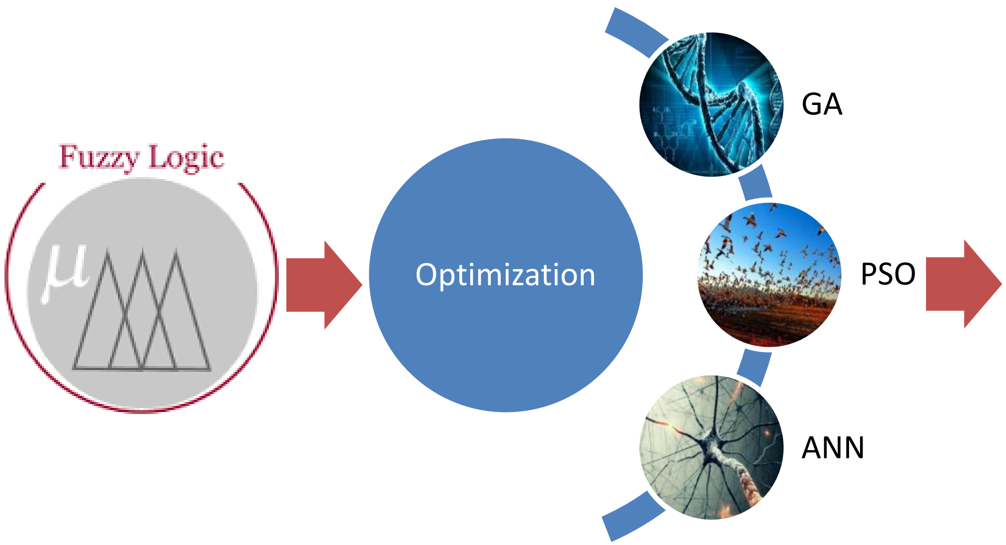
- Fuzzy inference systems and control
- Neural networks
- Adaptive techniques (e.g. ANFIS)
- Optimization (for fine-tuning)

Introduction

Neurofuzzy systems can be used for Natural Disasters Risk Management in several ways:

- Natural hazard identification
- Risk assessment
- Decision making
- Control

Presentation outline



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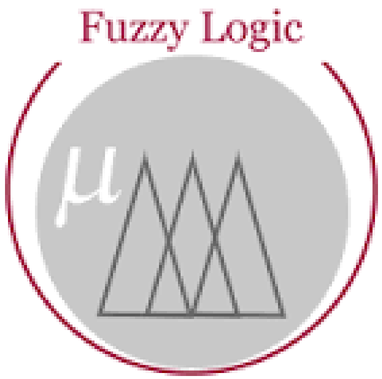

Fuzzy and neurofuzzy control strategies

- Nonlinear controllers based on fuzzy and neuro-fuzzy inference systems can provide satisfactory results in decision making systems, in control etc.
- Mamdani-type fuzzy controllers
  - Exploit kai deploy the advantages of fuzzy rule-based systems
  - Demand knowledge of the studied system
- Sugeno-type neuro-fuzzy controllers
  - Use Neural Networks for optimization (training)
  - Do not require knowledge of the system

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What are fuzzy systems

- Fuzzy inference systems are a part of the fuzzy theory with applicability to control
- Fuzzy logic is a set of mathematical principles that is used to represent an experienced operators' knowledge to a computer system
- Fuzzy logic is based on the principle that all parameters or concepts of a system are subjected to ratings
- Fuzzy logic reflects how people think, avoiding generalization errors verbalizing variables and simulating the human sense

Fuzzy inference

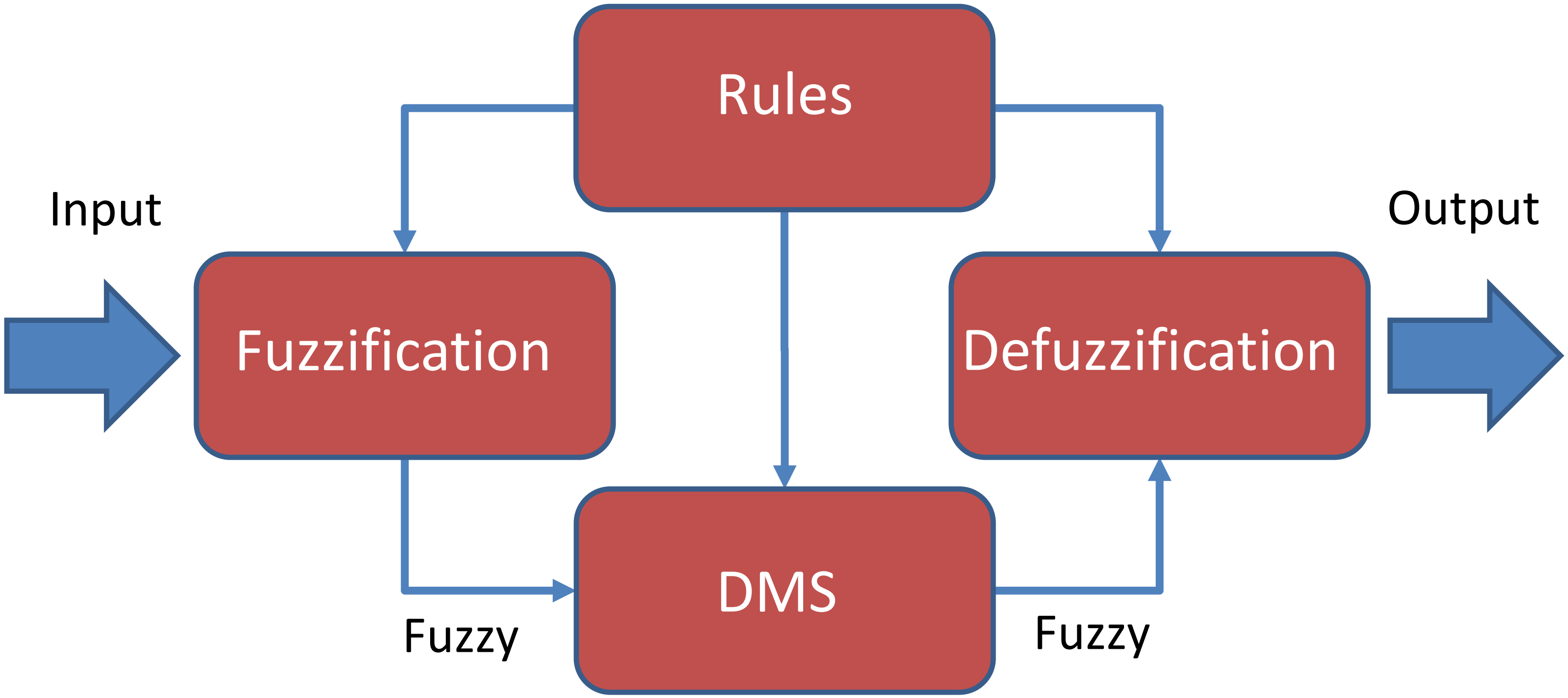

Fig. 1: The structure of a fuzzy inference system

Types of fuzzy membership functions

The membership functions can have any parameterized form, either symmetric or asymmetric.

a) Triangular membership functions
b) Trapezoidal membership functions
c) Bell membership functions
d) Gaussian membership functions
e) Sigmoid membership functions
f) Polynomial membership functions

Fuzzy membership functions

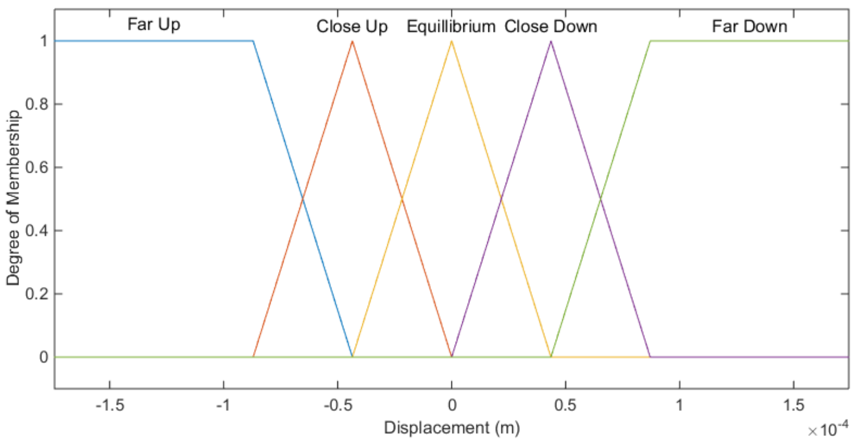

Fig. 2: Membership function of input 1

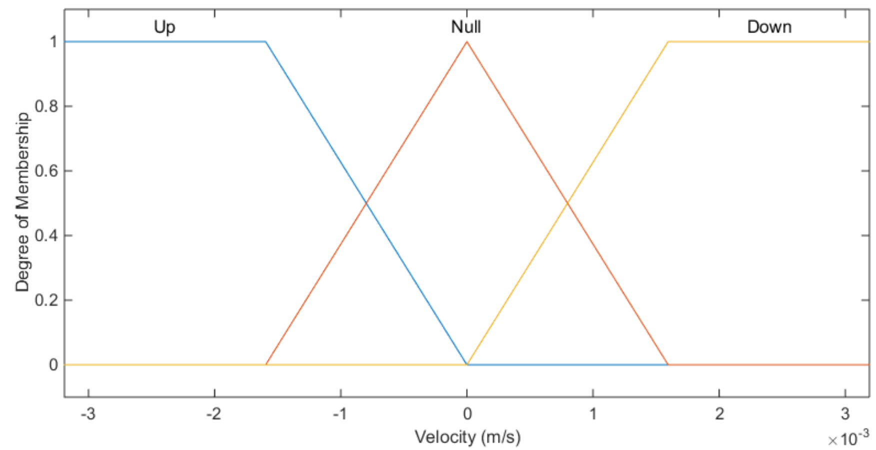

Fig. 3: Membership function of input 2

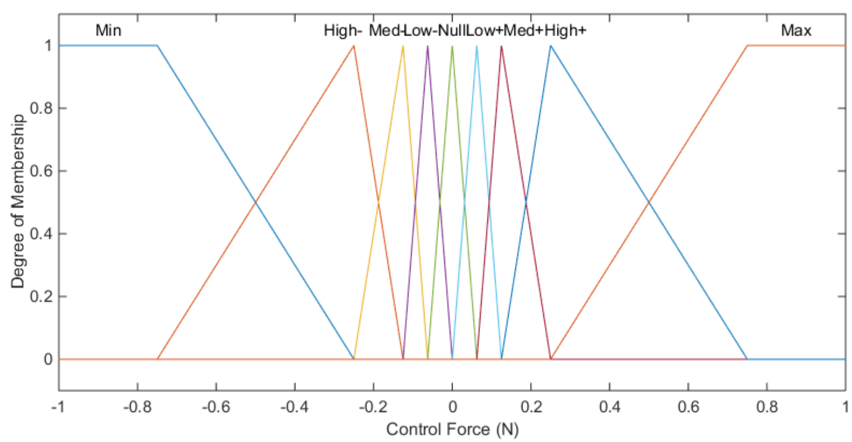

Fig. 4: Membership function of output

Membership functions vs Crisp sets

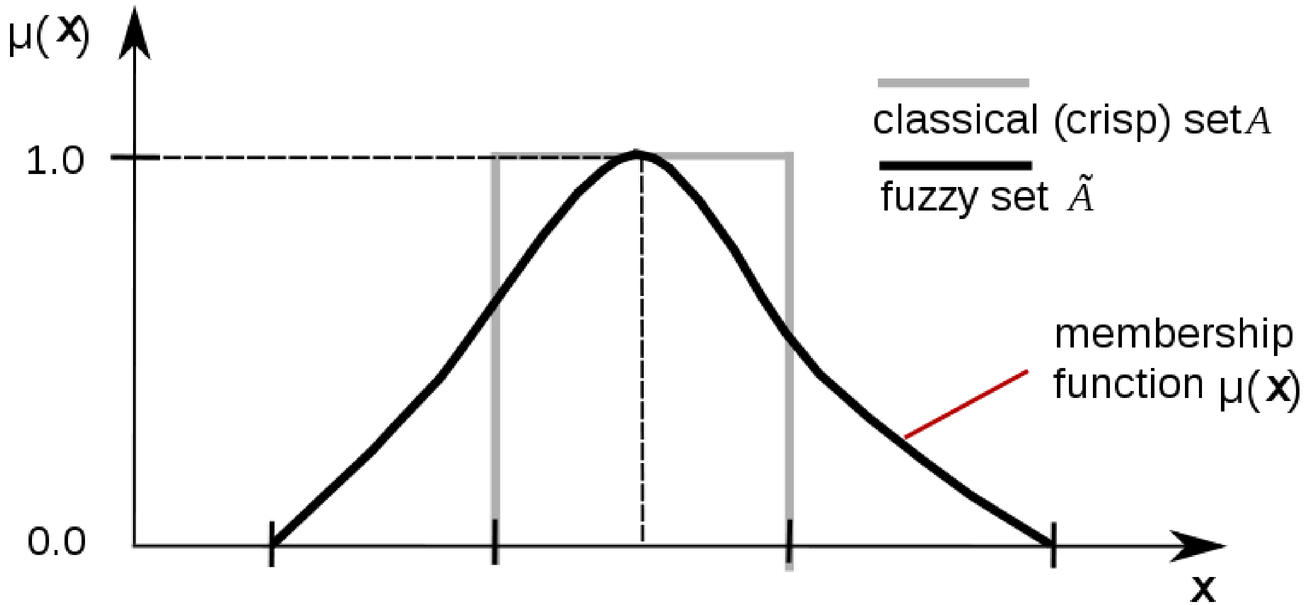

Figure 5: A fuzzy membership function in comparison to a crisp set

Fuzzy linguistic rules

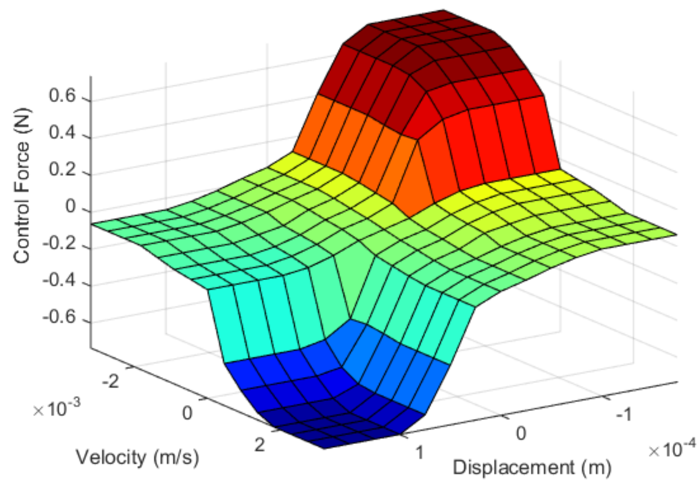

Fig. 6: Graphic representation of the fuzzy rules

Table 1: Fuzzy rules

Displacement / Velocity	Far up	Close up	Equilibrium	Close down	Far down
Up	Max	Med+	Low+	Null	Low-
Null	Med+	Low+	Null	Low-	Med-
Down	High+	Null	Low+	Med-	Min

How fuzzy works

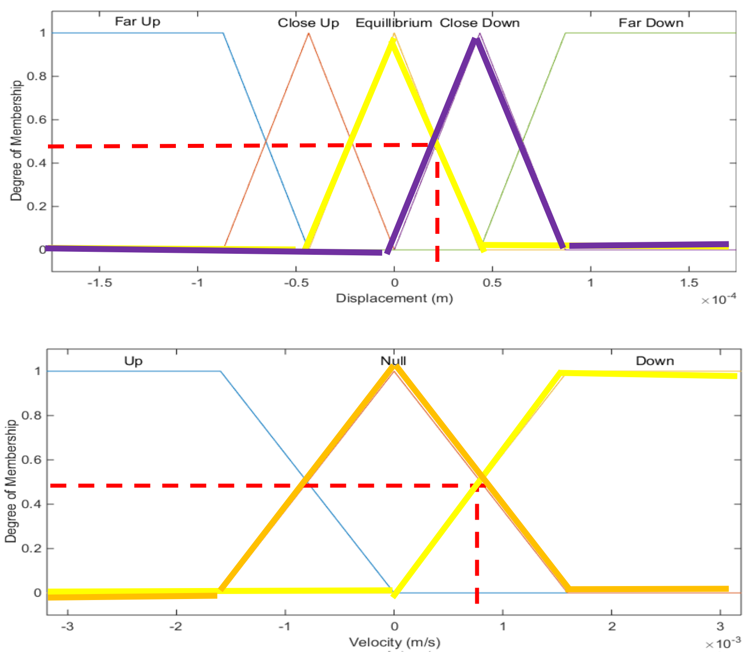

Fig. 7: Interpretation of fuzzy rules

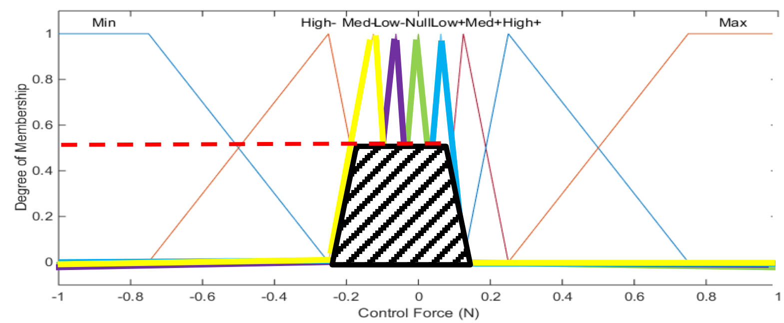

Table 2: Fuzzy rules

Displ. / Velocity	Far up	Close up	Equilibrium	Close down	Far down
Up	Max	Med+	Low+	Null	Low-
Null	Med+	Low+	Null	Low-	Med-
Down	High+	Null	Low+	Med-	Min

Defuzzification Methods

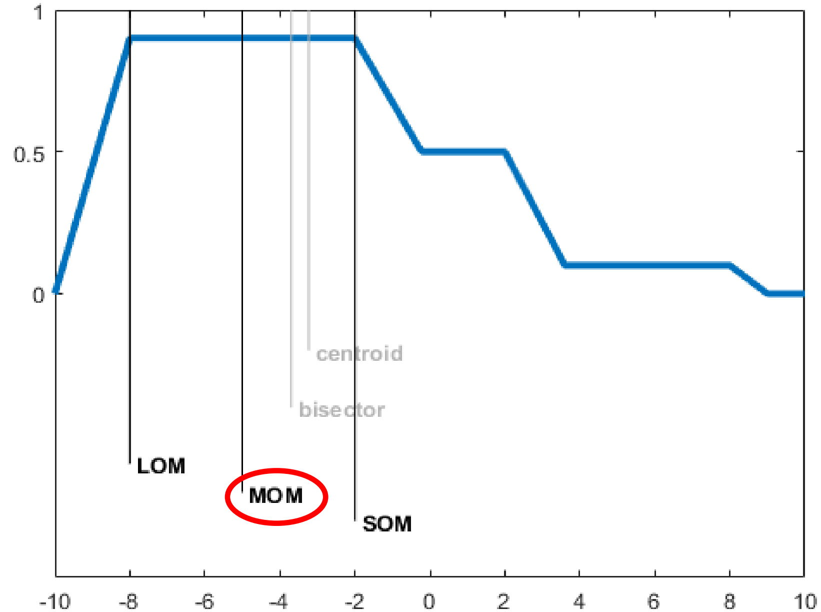

Fig. 8: Defuzzification methods

Artificial Neural Networks (ANN)

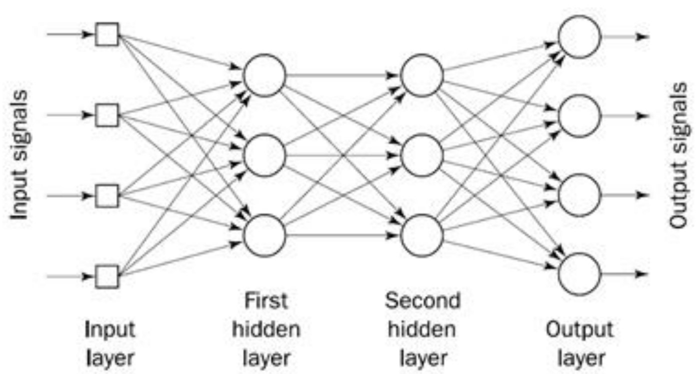

Fig. 9: An ANN with four layers

Neural networks consist of neurons which are connected with synapses which in turn are characterized by synaptic weights.

An ANN can be trained in order to produce outputs for given inputs

How to train an ANN

Back-propagation of errors method:

1. Initialization of weights and biases
2. Activation of neurons
   - Calculation of actual outputs of neurons
3. Calculation of synaptic weights
   - Calculation of derivatives of errors from the output to the hidden layers
   - Calculation of the correction of the errors
4. Iteration of the process

Adaptive Neurofuzzy Inference Systems (ANFIS)

What is ANFIS:

- The architecture of ANFIS is based on a fuzzy inference system which is implemented inside the framework of adaptive neural networks (Jang, 1993).
- It is one of the best adaptive fuzzy systems in terms of stability and adaptivity (Wang, 1994).
- ANFIS consists of fuzzy rules which, in contrast to classical fuzzy systems, are local mappings instead of global ones (Jang & Sun, 1995).
- Instead of modelling, ANFIS require training which can be done within an automated process.

How ANFIS works

- ANFIS works with Sugeno-type controllers
- The initial fuzzy inference system can be either loaded or generated if an appropriate set of data is available
- The generation of clusters (mfs) can be done by using:
  - Grid partitioning on the data, if the form and the number of the membership functions is known (manual)
  - Subtractive clustering, if there is no such information (auto)
- Methods for training of the system:
  - Back propagation method (Artificial Neural Networks)
  - Hybrid method (Back propagation and LSE method)

Clusters (membership functions)

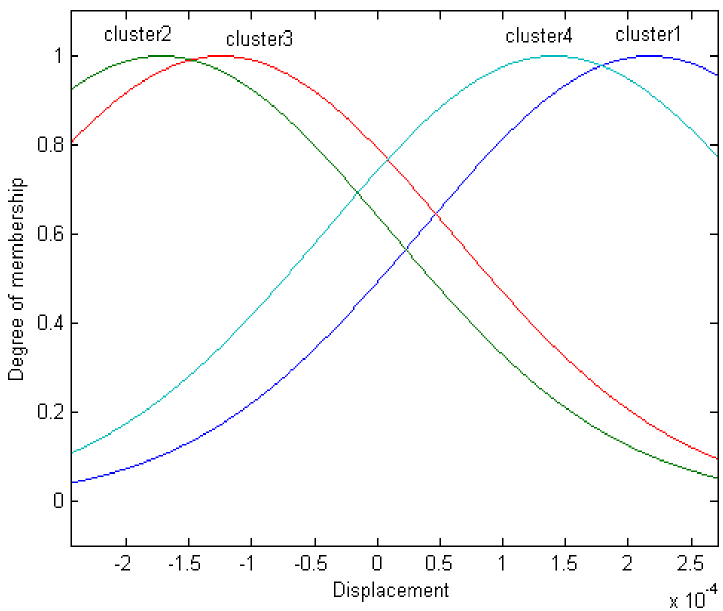

Fig. 10: Cluster of input 1 (displacement in m)

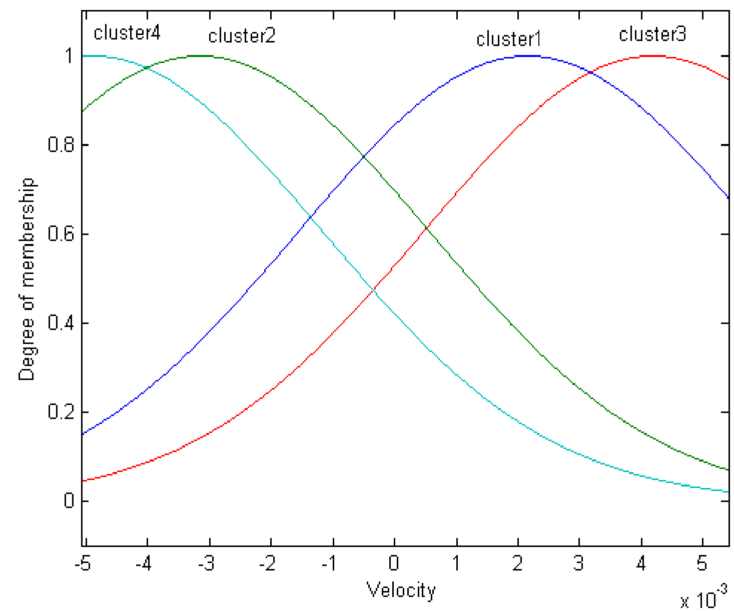

Fig. 11: Cluster of input 2 (velocity in m/s)

In Sugeno controllers the outputs take only linear or constant values

The rules in ANFIS

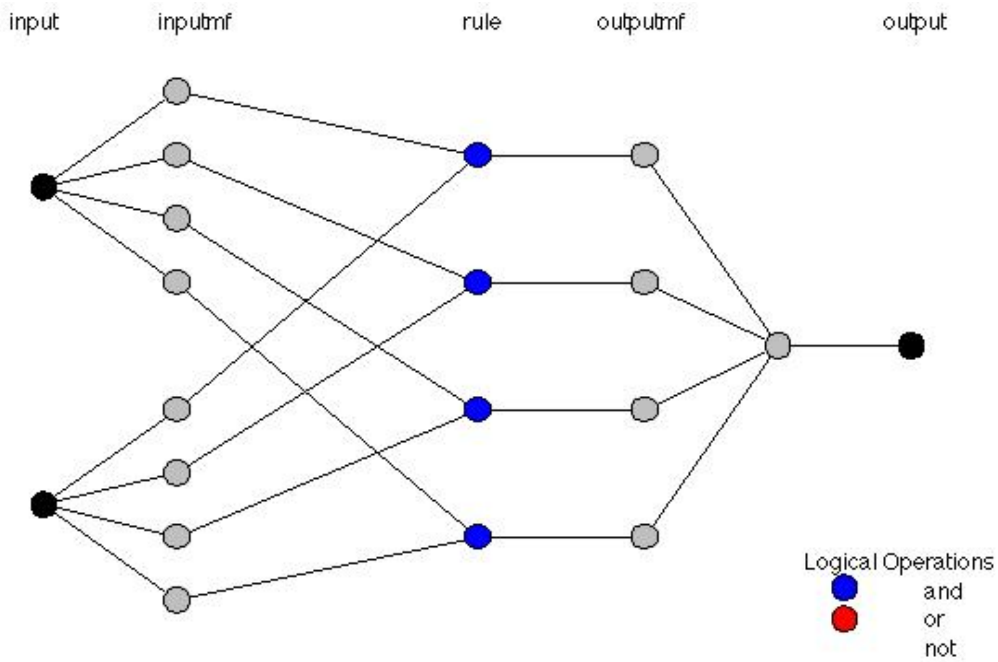

Fig. 12: The structure of rules in ANFIS

Linguistic rules of ANFIS controller

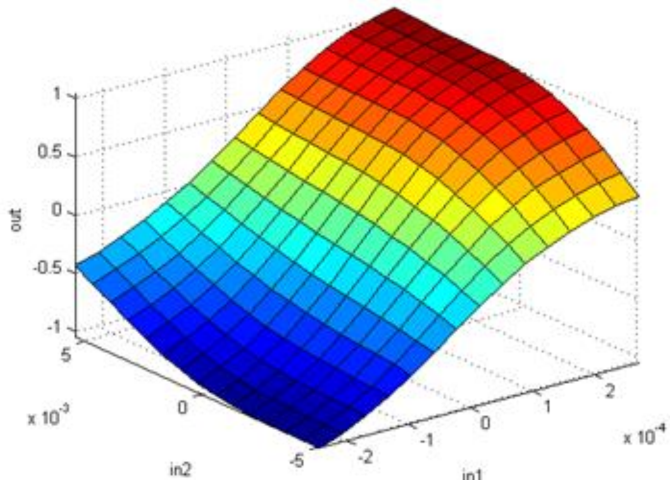

Fig. 13: Graphic representation of the fuzzy rules

Defuzzification method:
Weighted average

$$z_0 = \frac{\sum_{i=1}^{n} a_i C_i}{\sum_{i=1}^{n} a_i}$$

where α_i are the trigger points of mfs and C_i the individual values of outputs

Table 3: Fuzzy rules

Displacement / Velocity	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	Out1	-	-	-
Cluster 2	-	Out2	-	-
Cluster 3	-	-	Out3	
Cluster 4	-	-	-	Out4

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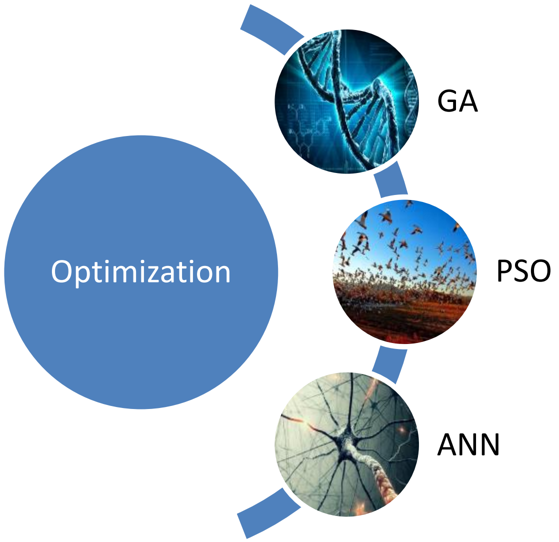

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Optimization methods

- Classic optimization drawbacks:
  - Classic optimization can be proved quite unreliable due to the fact that the range of the parameters of the optimization could considerably vary
  - Classic optimization tools are quite sensitive to local optima
- Nature inspired global optimization methods:
  - Genetic algorithms
  - Particle swarm optimization
- Global optimization benefits:
  - Provide simplicity and smooth behavior
  - Can be used for fine-tuning of fuzzy controllers (e.g. membership functions, ranges of the fuzzy variables (inputs/outputs), etc.

Genetic Algorithms

- Nature inspired method which in turn is based on the natural selection process (simulates biological evolution)
- It is suitable for both constrained and unconstrained problems
- It creates a population of possible solutions (members) instead of a single individual solution (the optimum is approached by the best member of the whole population at each iteration)
- It is a stochastic process (the population of solutions is produced and modified in a random manner)
- As the generations pass by, the population is following an evolutionary course in order to approach the optimal solution

Genetic Algorithm Pseudocode

generation=0
Initialize
Evaluate
KeepBest
do generation = 1, MAXGENS
Select
Crossover
Mutate
Report
Evaluate
Elitist
enddo

Genetic Algorithms in structural control

Genetic algorithms (Gas) can be used among others for:

- Actuator location and voltage optimization of smart structures (Foutsitzi et al., 2013)
- Damage identification (Hadjigeorgiou et al., 2006)
- Design of fuzzy controllers in smart structures (Lu et al., 2003)
- Optimal placement of sensors and actuators (Han et al. 1999), (Nestorovic et al., 2015)
- Optimization of fuzzy controllers (Tairidis et al., 2016)

Genetic Algorithms in Natural Disasters

Genetic algorithms (Gas) can be used among others for:

- Real-coded genetic algorithm for rule-based flood control reservoir management (Chang and Chen, 1998)
- Natural disaster impact assessment using genetic algorithm (Bhalaji and Raman, 2010)
- Prediction of natural disasters based on genetic algorithms (Li and Li, 2010)
- Genetic algorithms for the optimization of network connectivity in a natural disaster scenario (Chavan and Patil, 2015)

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Particle Swarm Optimization

- Nature inspired algorithm
- Population based algorithm
- Simulates the movement of particles (e.g. flock of birds) towards the search of food
- The swarm of possible solutions “flies” towards the optimum solution
- Very simple and easy to implement method
- Adaptive to various problems
- Can be used for the optimization of the characteristics of fuzzy controllers (Marinaki et al. 2011), (Marinaki et al. 2011b)

Implementation of PSO algorithm

- The position of the particles is given as:

$$x_{ij}(t+1) = x_{ij}(t) + u_{ij}(t+1) \qquad (1)$$

- The velocity at each iteration is calculated by:

$$u_{ij}(t+1) = w\, u_{ij}(t) + c_1 r_1 \left(p_{best\ ij} - x_{ij}(t)\right) + c_2 r_2 \left(g_{best\ j} - x_{ij}(t)\right) \qquad (2)$$

- The inertia weight w is given by:

$$w = w_{max} - \frac{w_{max} - w_{min}}{max\_iteration} t \qquad (3)$$

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Identification of natural hazards using fuzzy systems

Fuzzy systems can be very successful in natural hazards identification especially if:

- A wide range of hazards in the study area is available
- The several hazards have different impact
- The risks and/or hazards are distributed
- There are many statistical data available
- There is expert knowledge

See (Najafabadi et al., 2016), (Zlateva and Velev, 2013)

Risk assessment using fuzzy systems

- Fuzzy and neurofuzzysystems can be used for Natural Disaster Risk Management (NDRM) under high uncertainty (e.g. lack of enough or appropriate statistical data, lack of knowledge of the system, etc.)
- The fuzzy framework is ideally suited for combining heterogeneous information sources, which is very important in risk assessment applications
- ND indicators are rather qualitative, than quantitative, thus linguistic (fuzzy) variables are appropriate for representation
- Expertise knowledge is necessary for assessment

Fuzzy modeling for NDRM

The number of inputs corresponds to the indicators of environmental risk and social vulnerability:

- Input 1 “Extreme temperature”
- Input 2 “Floods”
- Input 3 “Seismic hazard”
- Input 4 “Population density”
- Input 5 “Socioeconomical status”

The output represents a social risk assessment from natural disasters.

Image processing techniques

Fuzzy and neurofuzzy systems can be used along with image and/or sound identification techniques for the recognition of natural disasters:

- Identification of fire, flood etc
- Use of aerial photos or videos

(eg from unmanned vehicles/drones)

Applications of Fuzzy Systems for NDRM

- Risk assessment system of natural hazards based on fuzzy probability (Karimi and Hüllermeier, 2007)
- Risk assessment for urban area using fuzzy logic (Foroutan and Maleki, 2011)
- Social risk assessment from natural hazards using fuzzy logic (Zlateva et al., 2011)
- Fuzzy decision support model for natural disaster response under informational uncertainty (Wex et al., 2012)
- Risk assessment of natural disasters using fuzzy logic systems (Pamučar et al., 2016)

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Conclusions

Fuzzy and neurofuzzy systems

- can be used for dentification of natural hazards
- are suitable for NDRM
- can be used for decision making in case of a natural disaster
- are powerful and robust
- deploy user expertise
- can be optimized/trained

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Thank you very much for your attention!

Dr Georgios K. Tairidis
Technical University of Crete
www.comeco.tuc.gr
tairidis@gmail.com