Outline

- ✓ Introduction to Genetic Fuzzy Systems
- ✓ Tuning Methods: Basic and Advanced Approaches
- ✓ Genetic Fuzzy Systems Application to HVAC Problems
- ✓ GFSs: Current Trends and Prospects
- ✓ Concluding Remarks

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F. Herrera, Genetic Fuzzy Systems: Taxonomy, Current Research Trends and Prospects. ***Evolutionary Intelligence* 1 (2008) 27-46 doi: 10.1007/s12065-007-0001-5.**

http://sci2s.ugr.es/gfs

1. Introduction to genetic fuzzy systems

- **Brief Introduction**
- **Taxonomy of Genetic Fuzzy Systems**
- **¿Why do we use GAs? GFSs versus Neural Fuzzy Systems**
- **The birth, GFSs roadmap, current state and most cited papers**

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1. Introduction to genetic fuzzy systems

Brief Introduction

Design of fuzzy rule-based systems:

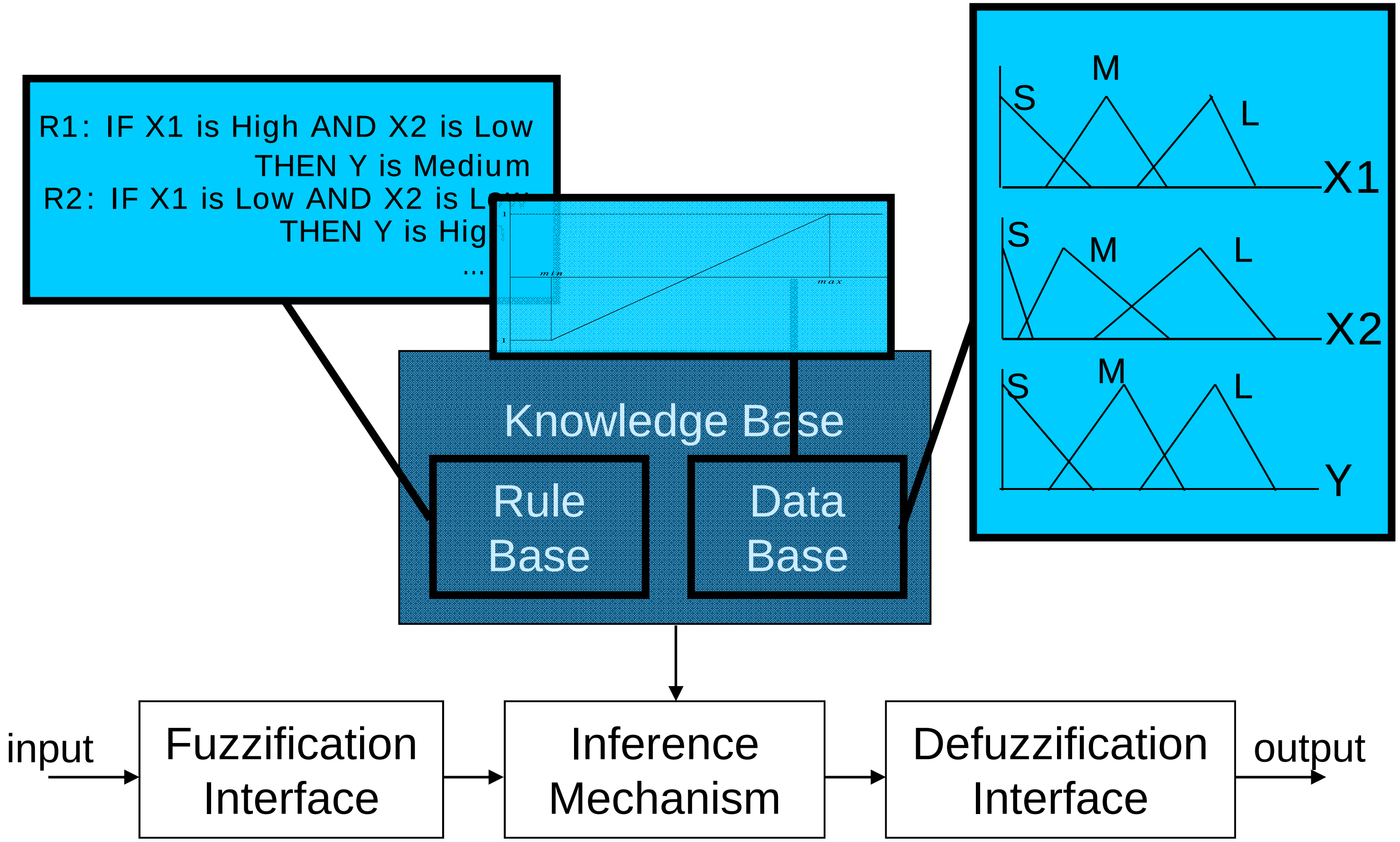
- An FRBS (regardless it is a fuzzy model, a fuzzy logic controller or a fuzzy classifier), is comprised by two main components:
  - The Knowledge Base (KB), storing the available problem knowledge in the form of fuzzy rules
  - The Inference System, applying a fuzzy reasoning method on the inputs and the KB rules to give a system output

- Both must be designed to build an FRBS for a specific application:
  - The KB is obtained from expert knowledge or by machine learning methods
  - The Inference System is set up by choosing the fuzzy operator for each component (conjunction, implication, defuzzifier, etc.)

    Sometimes, the latter operators are also parametric and can be tuned using automatic methods

1. Introduction to genetic fuzzy systems

Brief Introduction



Fuzzy rule-based system

1. Introduction to genetic fuzzy systems

Brief Introduction

The KB design involves two subproblems, related to its two subcomponents:

- Definition of the Data Base (DB):
  - Variable universes of discourse
  - Scaling factors or functions
  - Granularity (number of linguistic terms/labels) per variable
  - Membership functions associated to the labels
- Derivation of the Rule Base (RB): fuzzy rule composition

1. Introduction to genetic fuzzy systems

Brief Introduction

There are two different ways to design the KB:

- From human expert information
- By means of machine learning methods guided by the existing numerical information (fuzzy modeling and classification) or by a model of the system being controlled

1. Introduction to genetic fuzzy systems

Brief Introduction

Evolutionary algorithms and machine learning:

- Evolutionary algorithms were not specifically designed as machine learning techniques, like other approaches like neural networks
- However, it is well known that a learning task can be modelled as an optimization problem, and thus solved through evolution
- Their powerful search in complex, ill-defined problem spaces has permitted applying evolutionary algorithms successfully to a huge variety of machine learning and knowledge discovery tasks
- Their flexibility and capability to incorporate existing knowledge are also very interesting characteristics for the problem solving.

1. Introduction to genetic fuzzy systems

Brief Introduction

- The use of genetic/evolutionary algorithms (GAs) to design fuzzy systems constitutes one of the branches of the Soft Computing paradigm: genetic fuzzy systems (GFSs)

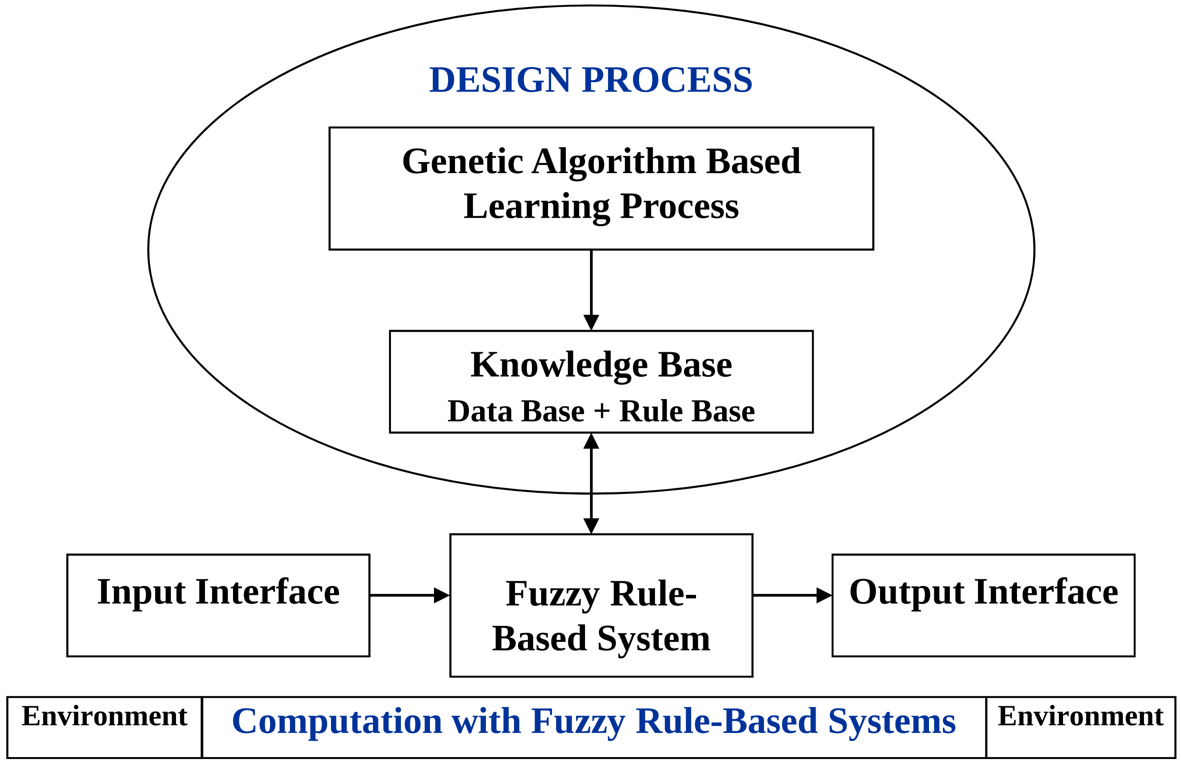
- The most known approach is that of genetic fuzzy rule-based systems, where some components of a fuzzy rule-based system (FRBS) are derived (adapted or learnt) using a GA

- Some other approaches include genetic fuzzy neural networks and genetic fuzzy clustering, among others

1. Introduction to genetic fuzzy systems

Brief Introduction

Genetic Fuzzy Rule-Based Systems:



1. Introduction to genetic fuzzy systems

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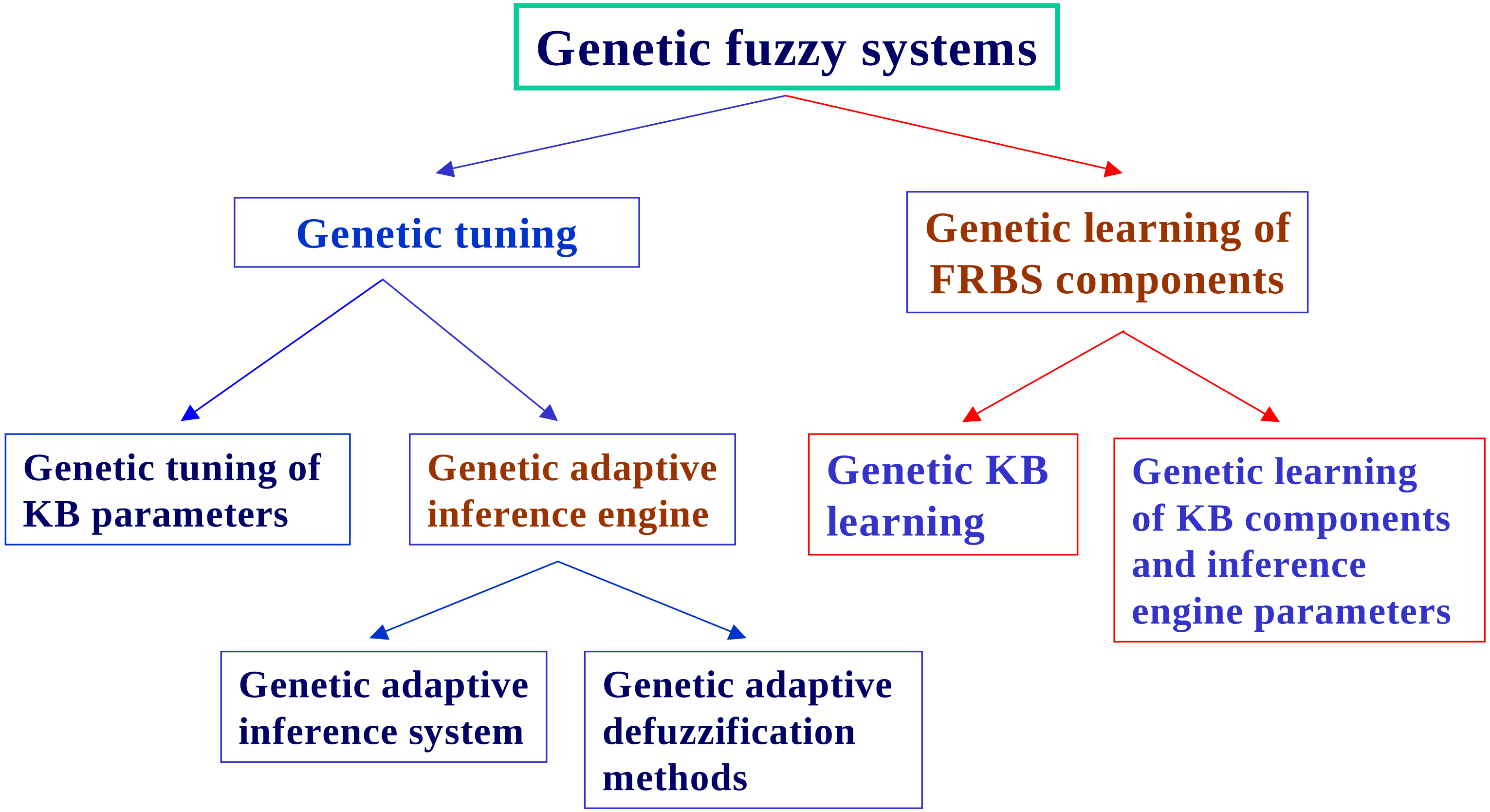
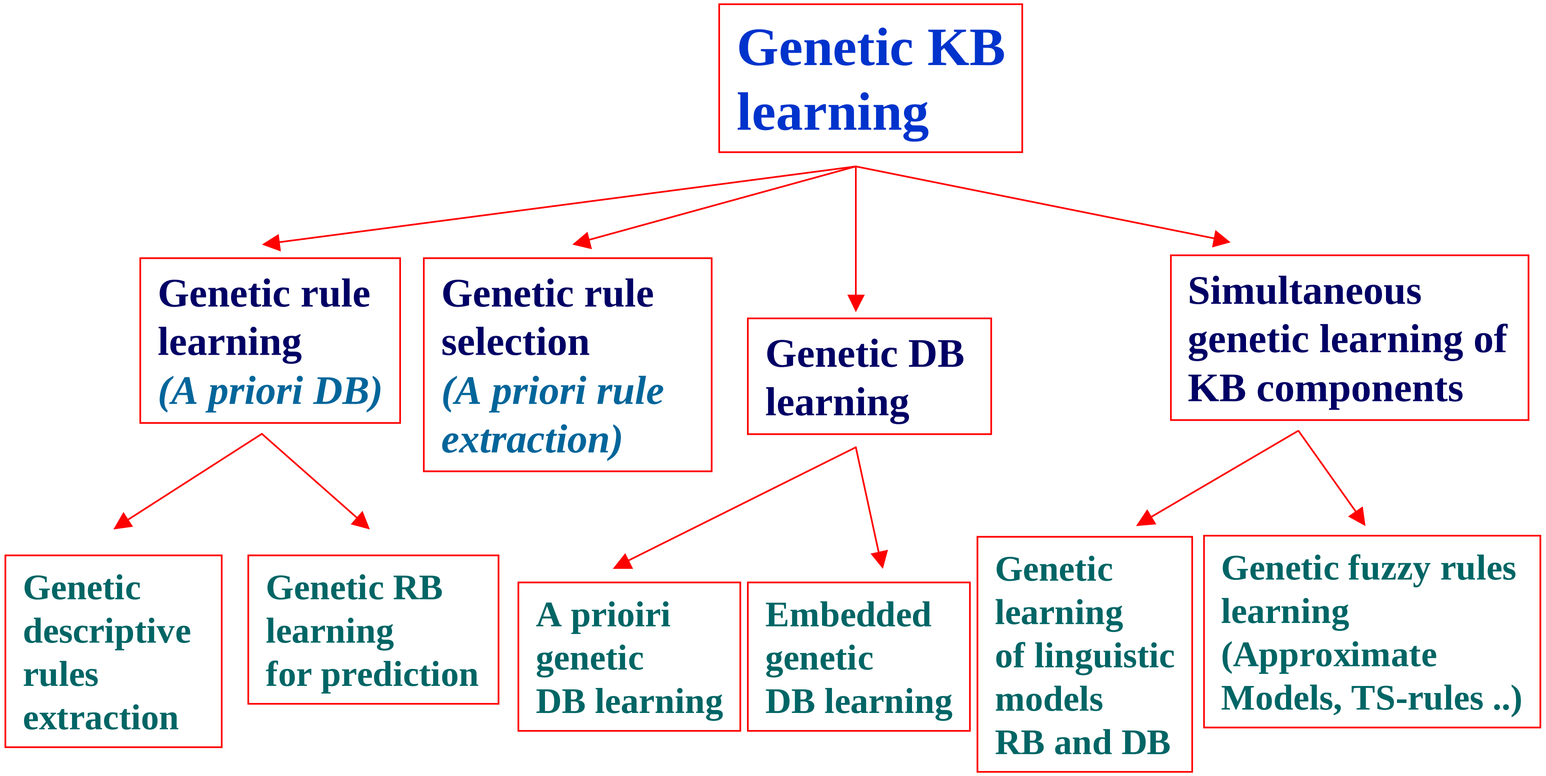
1. Introduction to genetic fuzzy systems

Taxonomy of Genetic Fuzzy Systems



1. Introduction to genetic fuzzy systems

Taxonomy of Genetic Fuzzy Systems



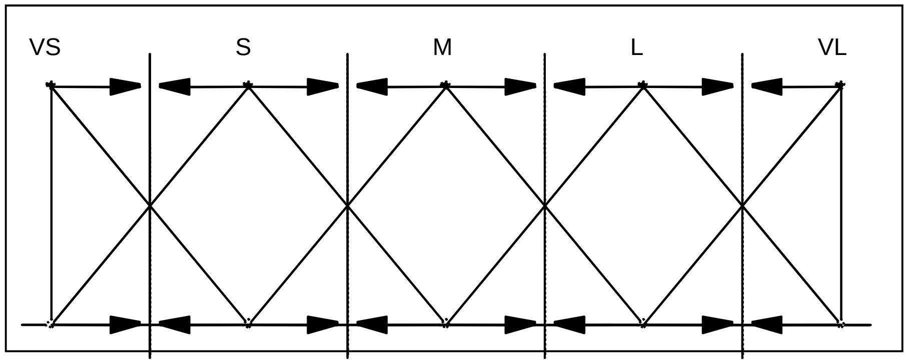
1. Introduction to genetic fuzzy systems

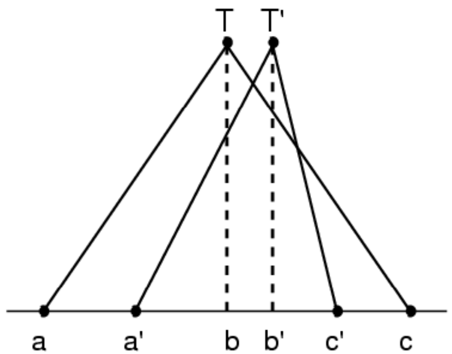
1. Genetic Tuning

Classically:

– performed on a predefined DB definition

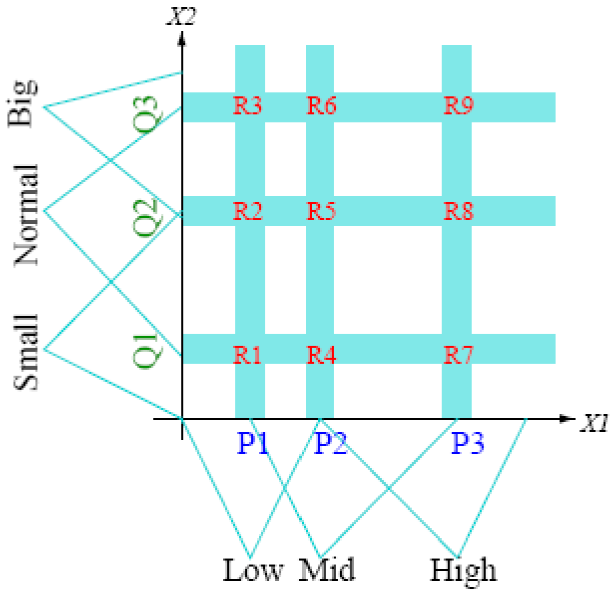
– tuning of the membership function shapes by a GA

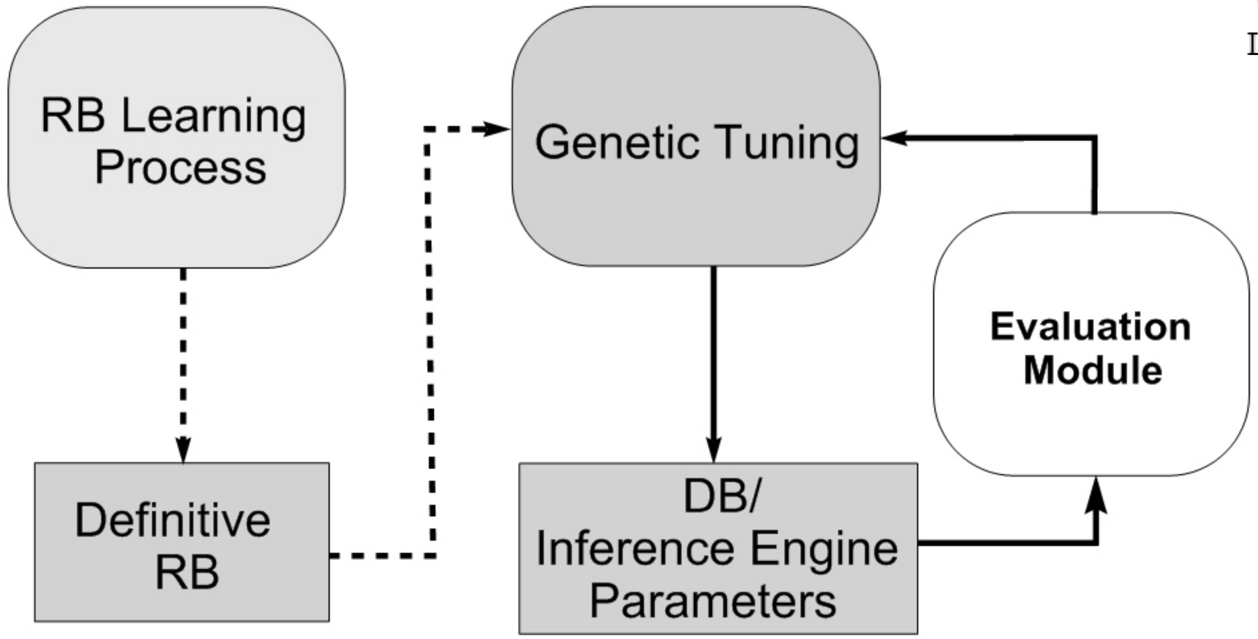




– tuning of the inference parameters

1. Introduction to genetic fuzzy systems



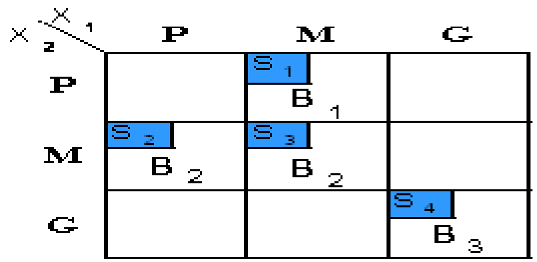


1. Introduction to genetic fuzzy systems

2. Genetic Rule Learning

– A predefined Data Base definition is assumed

– The fuzzy rules (usually Mamdani-type) are derived by a GA



Rule Base

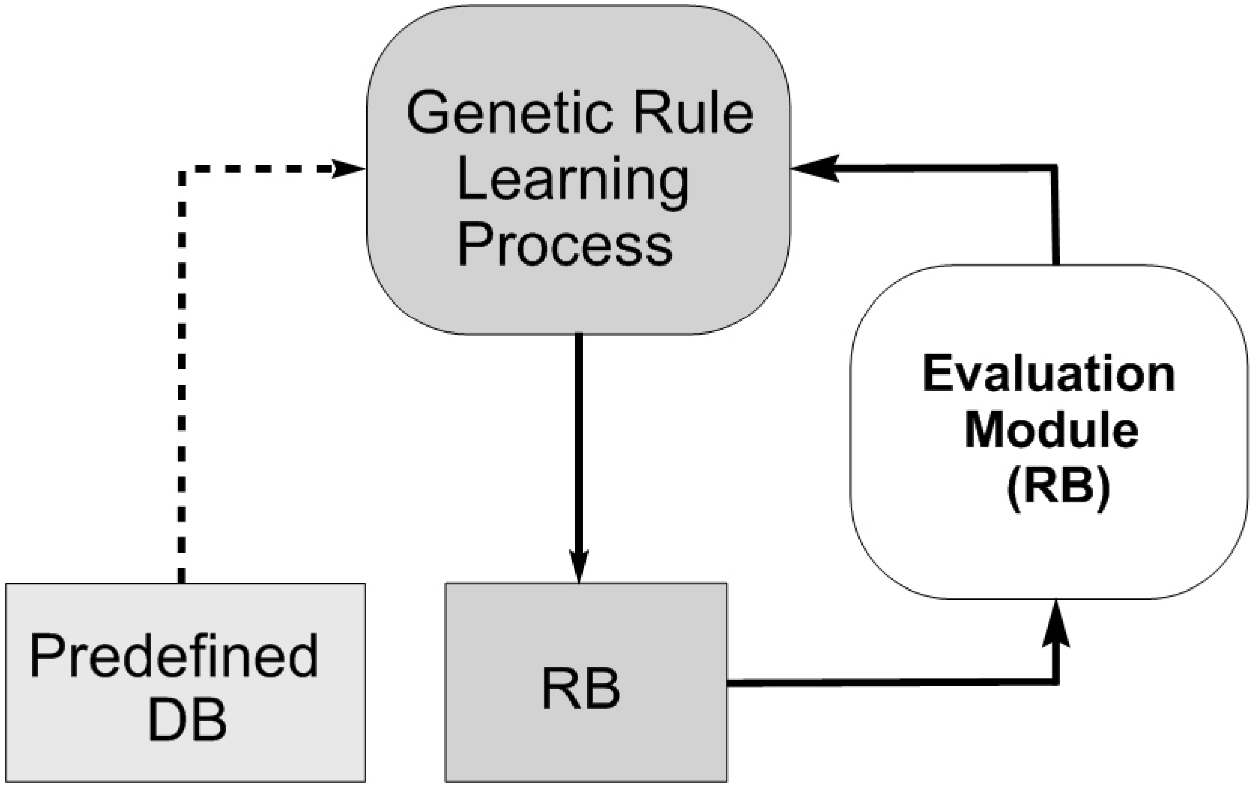
R_1 = IF X_1 is **M** and X_2 is **P** THEN Y is $\mathbf{B}_1$

R_2 = IF X_1 is **P** and X_2 is **M** THEN Y is $\mathbf{B}_2$

R_3 = IF X_1 is **M** and X_2 is **M** THEN Y is $\mathbf{B}_2$

R_4 = IF X_1 is **G** and X_2 is **G** THEN Y is $\mathbf{B}_3$

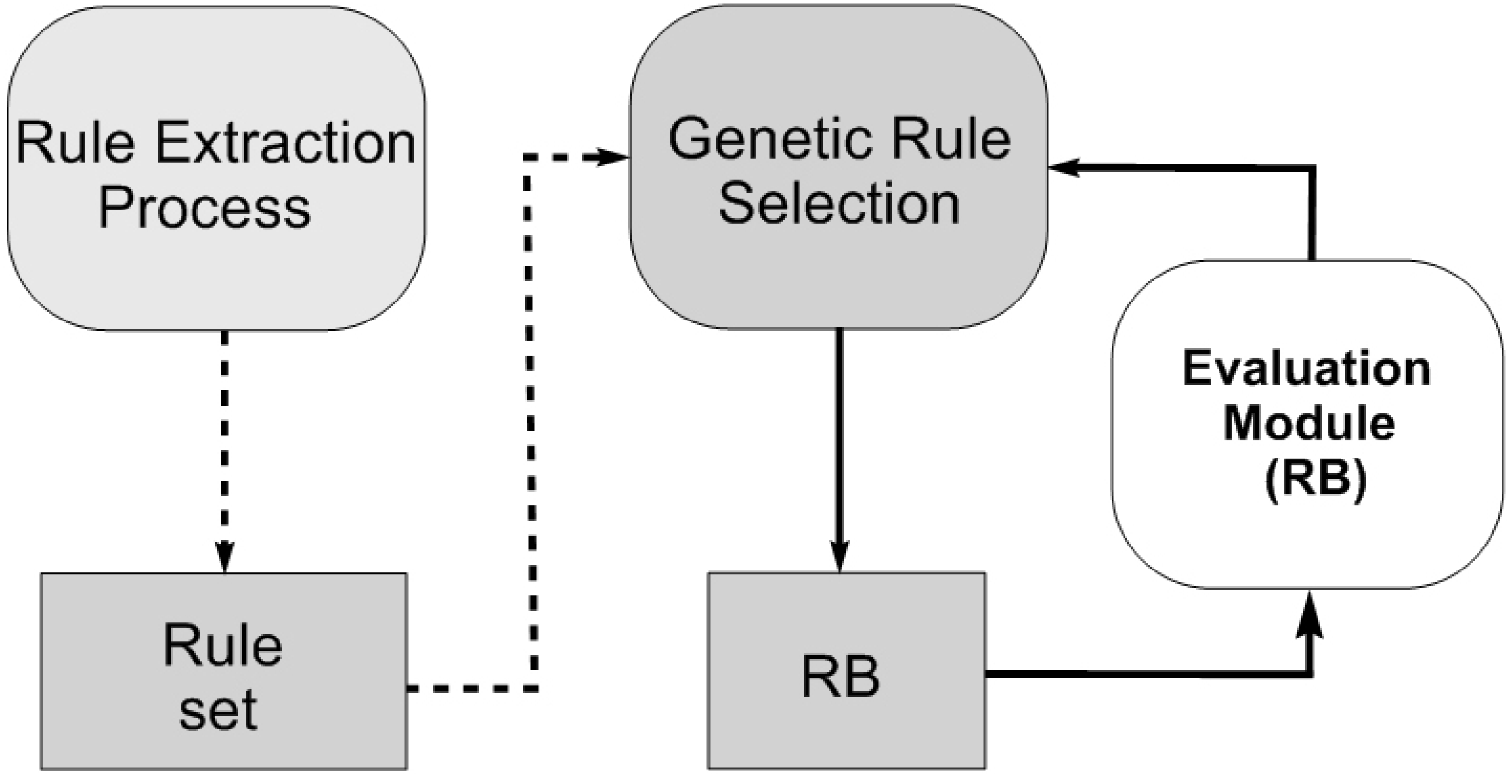
1. Introduction to genetic fuzzy systems



3. Genetic Rule Selection

- A predefined Rule Bases definition is assumed
- The fuzzy rules are selection by a GA for getting a compact rule base (more interpretable, more precise)

1. Introduction to genetic fuzzy systems



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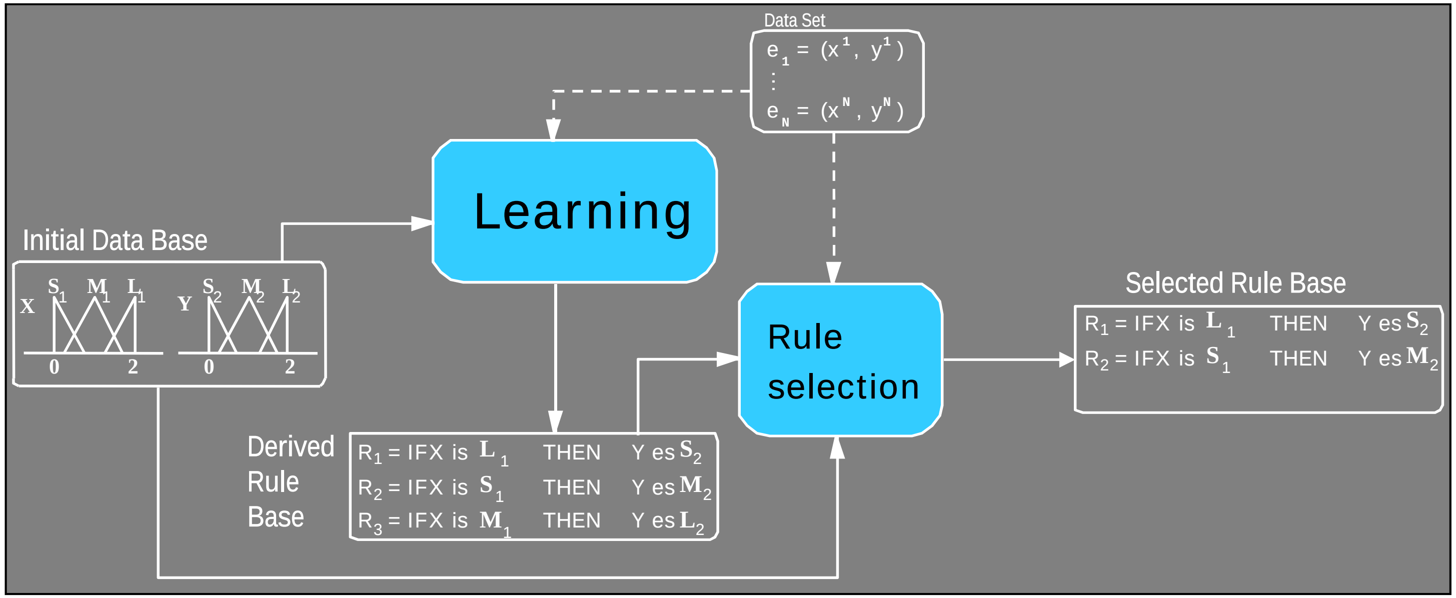
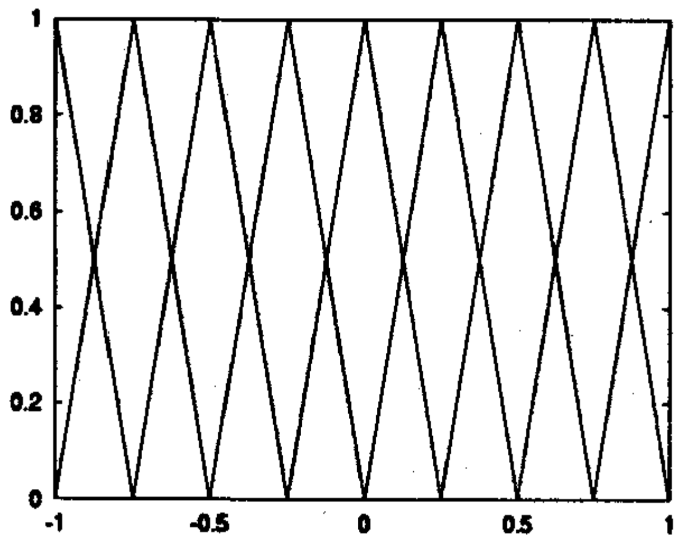


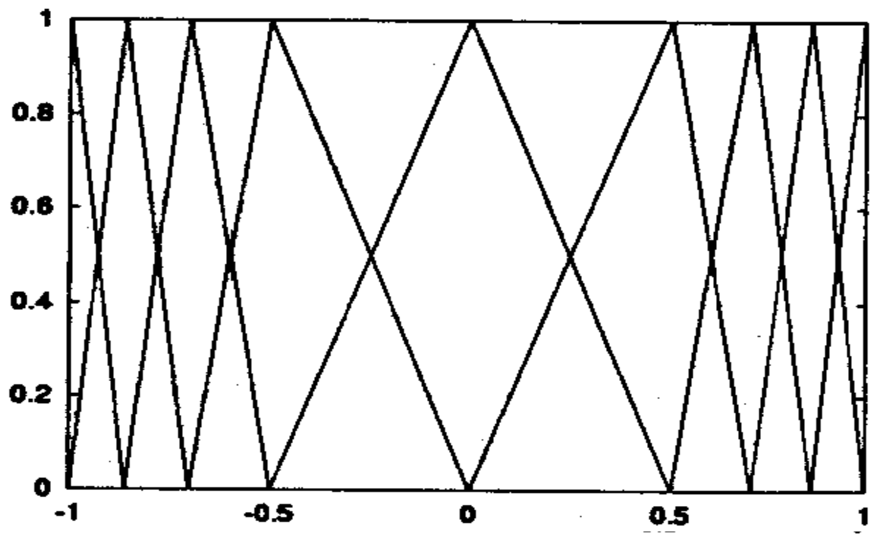
Example of genetic rule selection

1. Introduction to genetic fuzzy systems

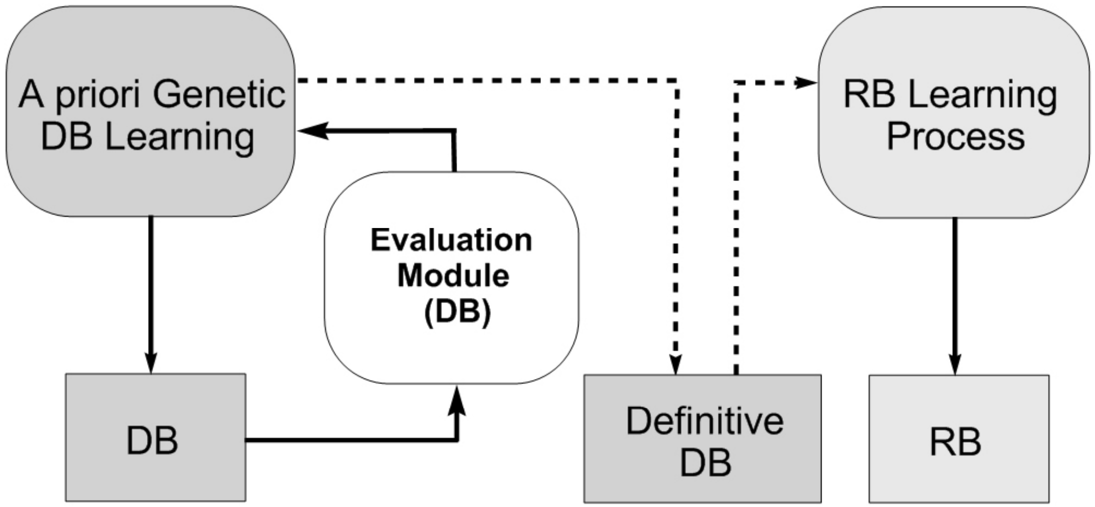
4. Genetic DB Learning

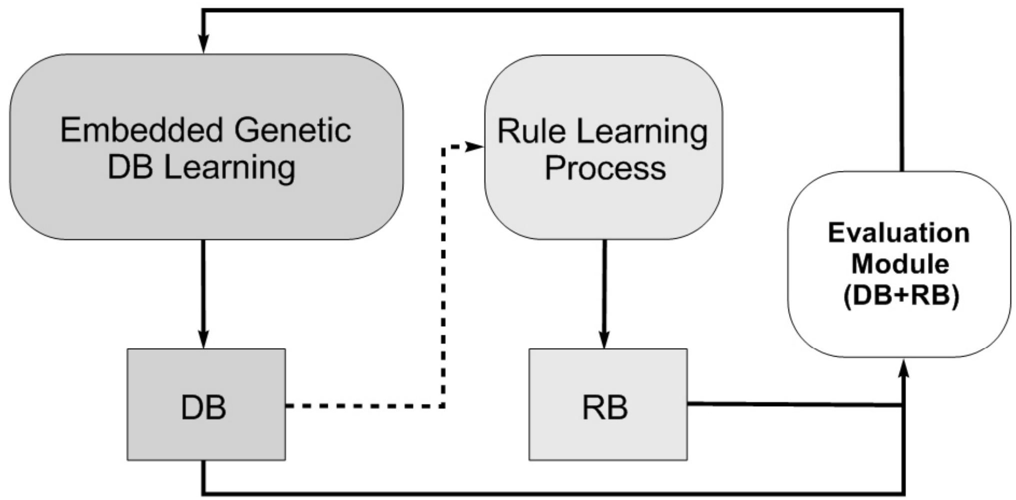
– Learning of the membership function shapes by a GA





1. Introduction to genetic fuzzy systems

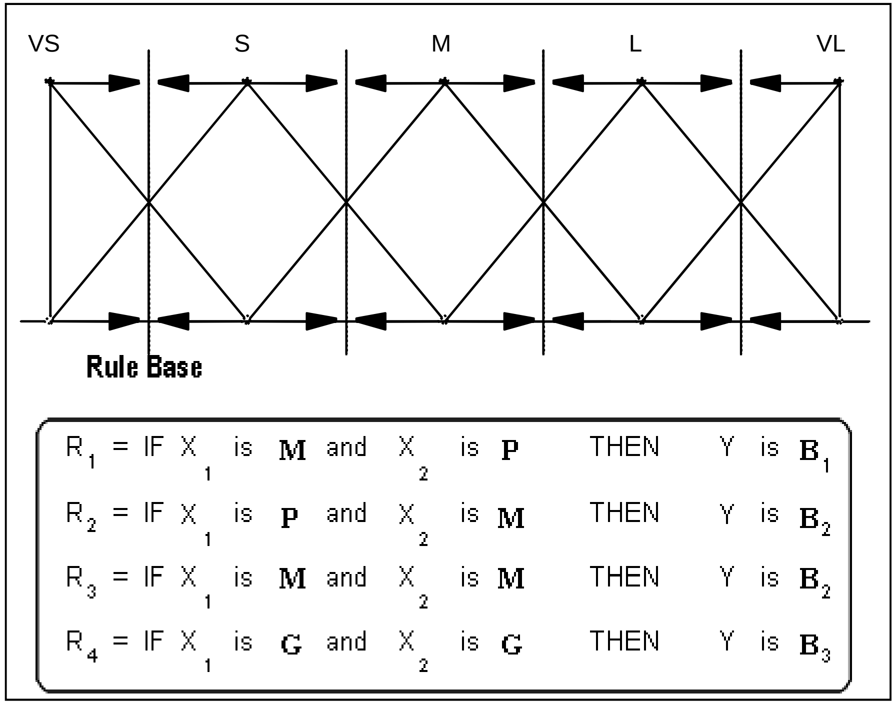




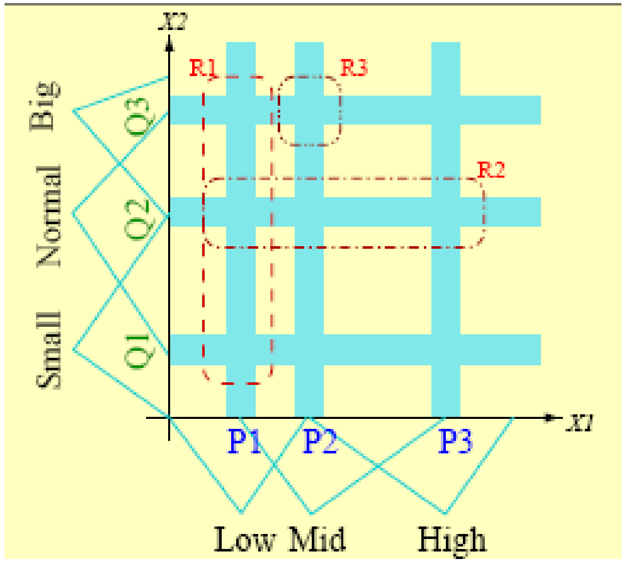
1. Introduction to genetic fuzzy systems

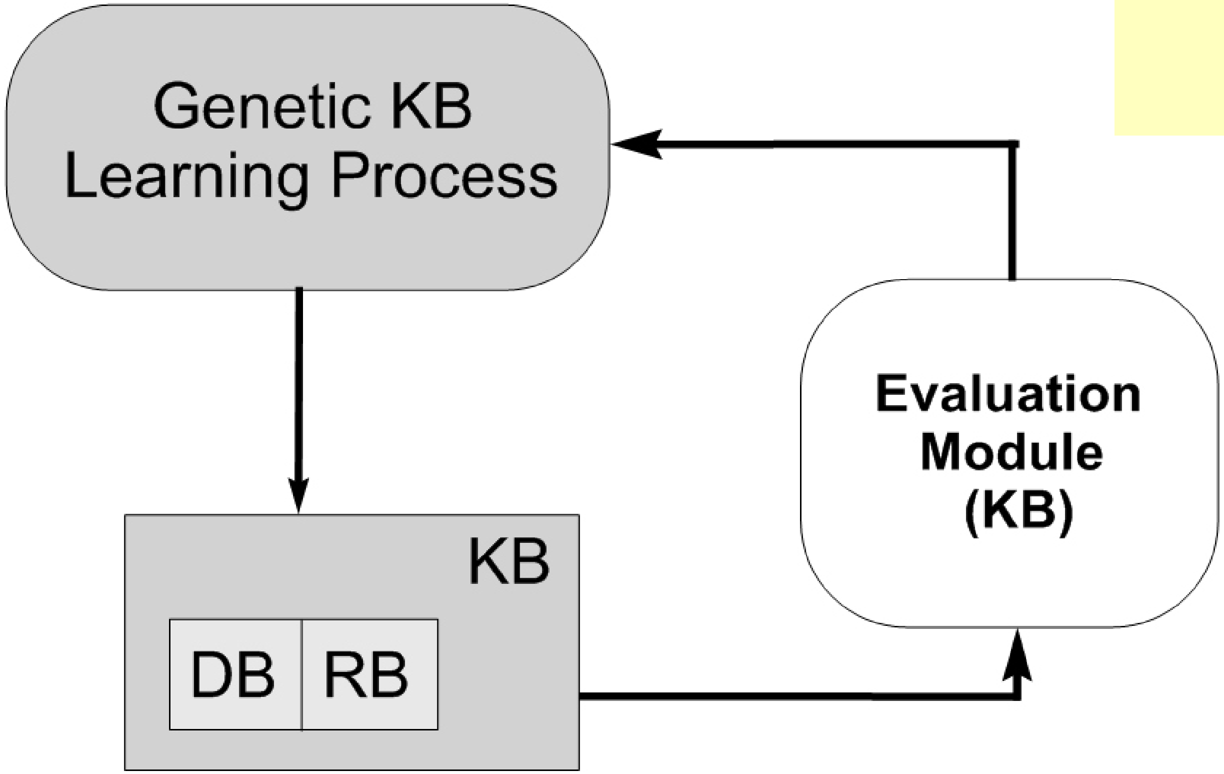
5. Simultaneous Genetic Learning of KB Components

– The simultaneous derivation properly addresses the strong dependency existing between the RB and the DB

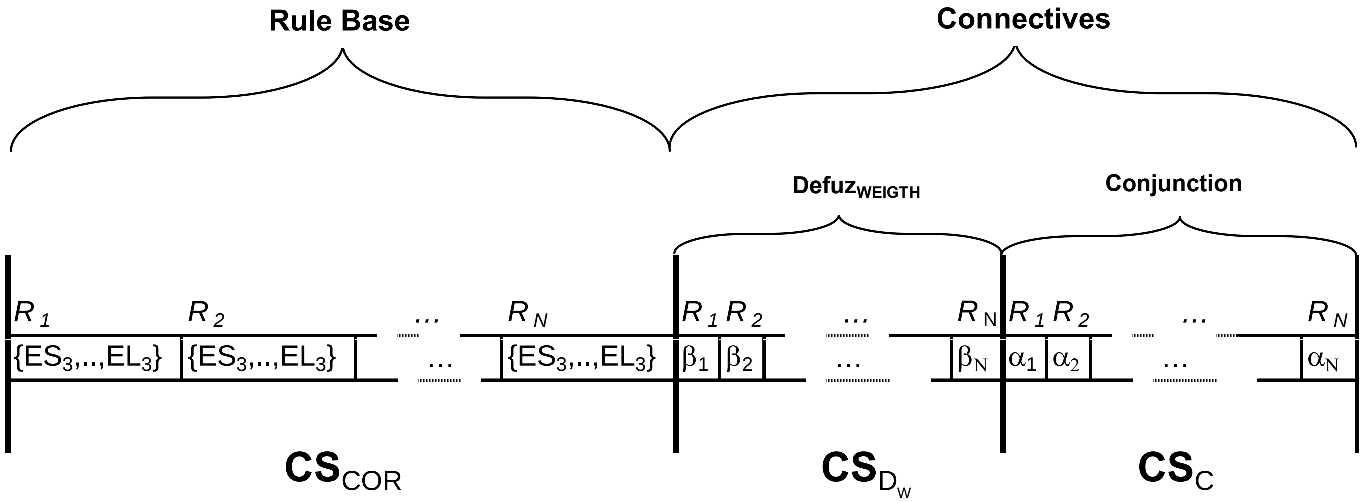


1. Introduction to genetic fuzzy systems



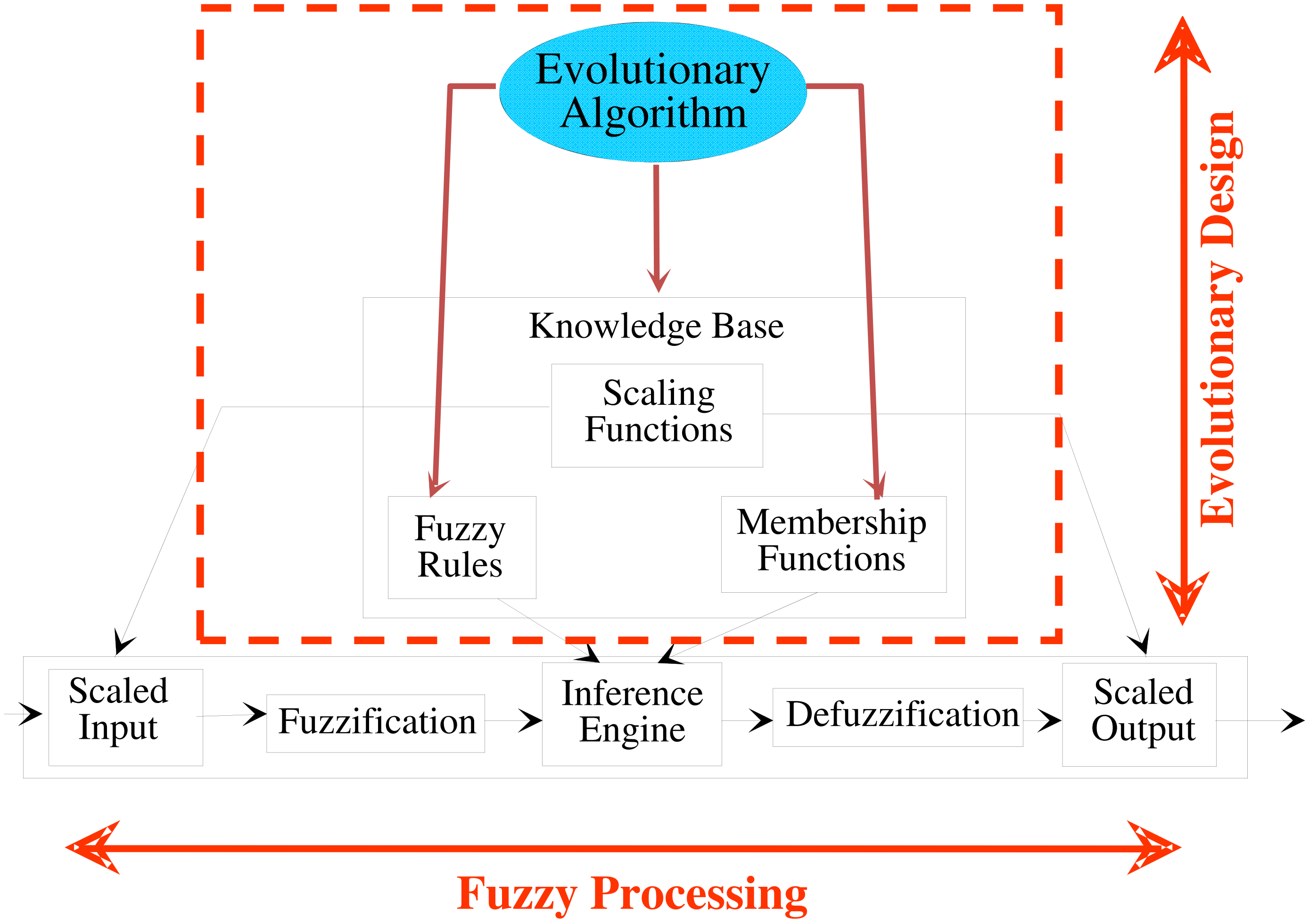


6. Genetic Learning of KB Components and Inference Engine Parameters



Example of the coding scheme for learning an RB and the inference connective parameters

1. Introduction to genetic fuzzy systems



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1. Introduction to genetic fuzzy systems

The birth, GFSs roadmap, current status and most cited papers

The birth of GFSs: 1991

- Thrift's ICGA91 paper (Mamdani-type Rule Base Learning. Pittsburgh approach)
- Thrift P (1991) **Fuzzy logic synthesis with genetic algorithms.** *In: Proc. of 4th International Conference on Genetic Algorithms (ICGA'91), pp 509-513*
- Valenzuela-Rendón's PPSN-I paper (Scatter Mamdani-type KB Learning. Michigan approach)
- Valenzuela-Rendon M (1991) **The fuzzy classifier system: A classifier system for continuously varying variables**. *In: Proc. of 4th International Conference on Genetic Algorithms (ICGA'91), pp 346-353*
- Pham and Karaboga's Journal of Systems Engineering paper (Relational matrix-based FRBS learning. Pittsburgh approach)
- Pham DT, Karaboga D (1991) **Optimum design of fuzzy logic controllers using genetic algorithms**. *Journal of Systems Engineering 1:114-118*).
- Karr's AI Expert paper (Mamdani-type Data Base Tuning)
- Karr C (1991) **Genetic algorithms for fuzzy controllers**. *AI Expert 6(2):26-33*.

Almost the whole basis of the area were established in the first year!

1. Introduction to genetic fuzzy systems

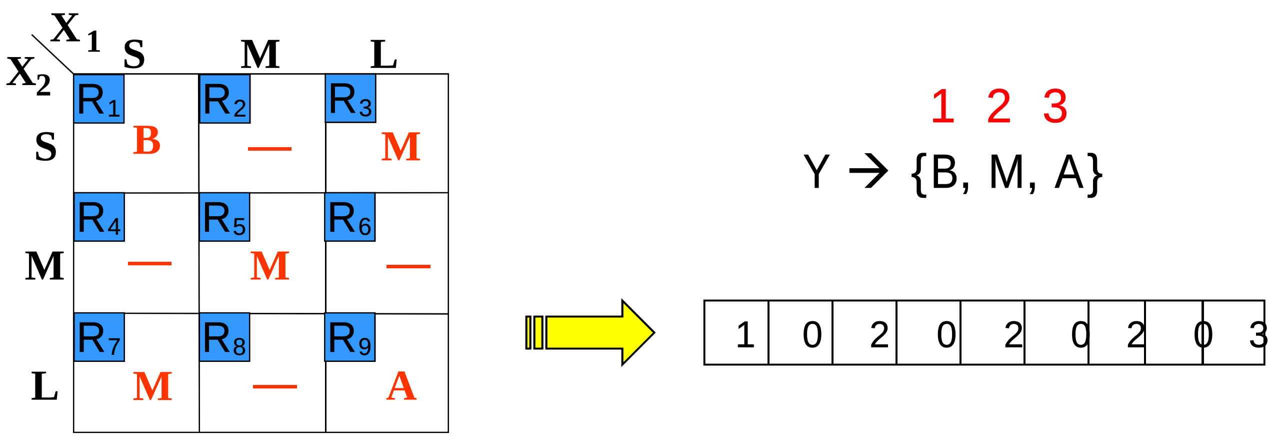
Thrift's GFS:

P. Thrift, Fuzzy logic synthesis with genetic algorithms, Proc. Fourth Intl. Conf. on Genetic Algorithms (ICGA'91), San Diego, USA, 1991, pp. 509–513

– Classical approach: Pittsburgh – the decision table is encoded in a rule consequent array

– The output variable linguistic terms are numbered from 1 to n and comprise the array values. The value 0 represents the rule absence, thus making the GA able to learn the optimal number of rules

– The ordered structure allows the GA to use simple genetic operators



1. Introduction to genetic fuzzy systems

The birth, GFSs roadmap, current status and most cited papers

GFSs roadmap

1991-1996/7: INITIAL GFS SETTING: KB LEARNING:

- Establishment of the three classical learning approaches in the GFS field: Michigan, Pittsburgh, and IRL
- Different FRBS types: Mamdani, Mamdani DNF, Scatter Mamdani, TSK
- Generic applications: Classification, Modeling, and Control

1995-...: FUZZY SYSTEM TUNING:

- First: Membership function parameter tuning
- Later: other DB components adaptation: scaling factors, context adaptation (scaling functions), linguistic hedges, ...
- Recently: interpretability consideration

1. Introduction to genetic fuzzy systems

The birth, GFSs roadmap, current status and most cited papers

GFSs roadmap

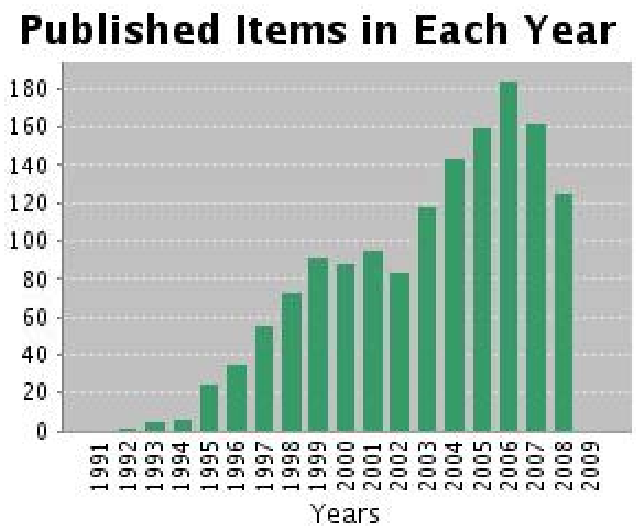
1998-...: APPROACHING TO MATURITY? NEW GFS LEARNING APPROACHES:

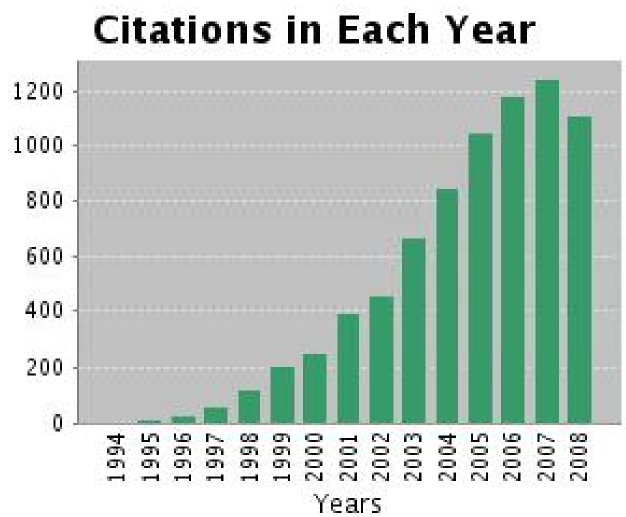
- New EAs: Bacterial genetics, DNA coding, Virus-EA, genetic local search (memetic algorithms), ...
- Hybrid learning approaches: a priori DB learning, GFNNs, Michigan-Pitt hybrids, ...
- Multiobjective evolutionary algorithms
- Interpretability-accuracy trade-off consideration
- Course of dimensionality (handling large data sets and complex problems):
  - Rule selection (1995-...)
  - Feature selection at global level and fuzzy rule level
  - Hierarchical fuzzy modeling
- “Incremental” learning

1. Brief introduction to genetic fuzzy systems

Current state of the GFS area

Number of papers on GFSs published in JCR journals





Source: The Thomson Corporation ISI Web of Knowledge

Query: (TS = (("GA-" OR "GA based" OR evolutionary OR "genetic algorithm*" OR "genetic programming" OR "evolution strate*" OR "genetic learning" OR "particle swarm" OR "differential evolutio*" OR "ant system*" OR "ant colony" OR "genetic optimi*" OR "estimation of distribution algorithm*") AND ("fuzzy rule*" OR "fuzzy system*" OR "fuzzy neural" OR "neuro-fuzzy" OR "fuzzy control*" OR "fuzzy logic cont*" OR "fuzzy class*" OR "fuzzy if" OR "fuzzy model*" OR "fuzzy association rule*" OR "fuzzy regression"))

Date: October 15, 2008 **Number of papers:** 1459

Number of citations: 5,237,630 **Average citations per paper:** 5.23

1. Brief introduction to genetic fuzzy systems

Current state of the GFS area

Most cited papers on GFSs

1. Homaifar, A., McCormick, E., Simultaneous Design of Membership Functions and rule sets for fuzzy controllers using genetic algorithms, IEEE TFS 3 (2) (1995) 129-139. **Citations: 184**

2. Ishibuchi, H., Nozaki, K., Yamamoto, N., Tanaka, H., Selecting fuzzy if-then rules for classification problems using genetic algorithms, IEEE TFS 3 (3) (1995) 260-270. **Citations: 164**

3. Setnes, M., Roubos, H., GA-fuzzy modeling and classification: complexity and performance, IEEE TFS 8 (5) (2000) 509-522 . **Citations: 101**

4. Ishibuchi, H., Nakashima, T., Murata, T., Performance evaluation of fuzzy classifier systems for multidimensional pattern classification problems, IEEE TSMC B 29 (5) (1999) 601-618. **Citations: 93**

5. Park, D., Kandel, A., Langholz, G., Genetic-based new fuzzy reasoning models with application to fuzzy control, IEEE TSMC B 24 (1) (1994) 39-47. **Citations: 86**

6. Herrera, F., Lozano, M., Verdegay, J.L., Tuning fuzzy-logic controllers by genetic algorithms, IJAR 12 (3-4) (1995) 299-315. **Citations: 71**

7. Shi, Y.H., Eberhart, R., Chen, Y.B., Implementation of evolutionary fuzzy systems, IEEE TFS 7 (2) (1999) 109-119. **Citations: 63**

8. Carse B., Fogarty, TC., Munro, A., Evolving fuzzy rule based controllers using genetic algorithms, FSS 80 (3) (1996) 273-293. **Citations: 63**

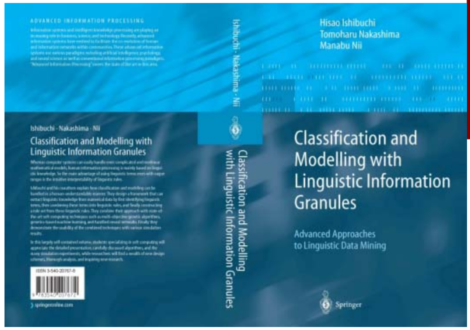
9. Juang, C.F., Lin, J.Y., Lin, C.T., Genetic reinforcement learning through symbiotic evolution for fuzzy controller design, IEEE TSMC B 30 (2) (2000) 290-302. **Citations: 59**

10. Cordon, O., Herrera, F., A three-stage evolutionary process for learning descriptive and approximate fuzzy-logic-controller knowledge bases from examples, IJAR 17 (4) (1997) 369-407. **Citations: 58**

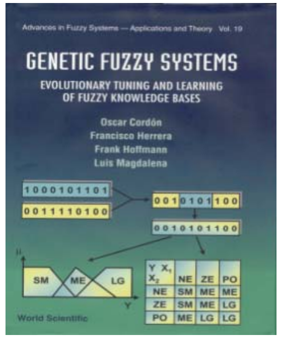
Date: September 30, 2008

1. Brief introduction to genetic fuzzy systems

Some references



GENETIC FUZZY SYSTEMS
Evolutionary Tuning and Learning of Fuzzy Knowledge Bases.
O. Cordón, F. Herrera, F. Hoffmann, L. Magdalena
World Scientific, July 2001



H. Ishibuchi, T. Nakashima, M. Nii, Classification and Modeling with Linguistic Information Granules. Advanced Approaches to Linguistic Data Mining. Springer (2005)

- **F. Herrera, Genetic Fuzzy Systems: Taxonomy, Current Research Trends and Prospects. *Evolutionary Intelligence 1 (2008) 27-46 doi: 10.1007/s12065-007-0001-5,***
- **F. Herrera, Genetic Fuzzy Systems: Status, Critical Considerations and Future Directions, International Journal of Computational Intelligence Research 1 (1) (2005) 59-67**
- **O. Cordón, F. Gomide, F. Herrera, F. Hoffmann, L. Magdalena, Ten Years of Genetic Fuzzy Systems: Current Framework and New Trends, FSS 141 (1) (2004) 5-31**
- **F. Hoffmann, Evolutionary Algorithms for Fuzzy Control System Design, Proceedings of the IEEE 89 (9) (2001) 1318-1333**

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2. Evolutionary Tuning of FRBSs

Tuning of membership functions

- A genetic tuning process that slightly adjusts the shapes of the membership functions of a preliminary DB definition

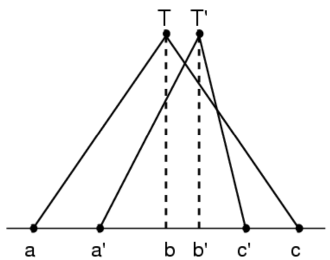
- Each chromosome encodes a whole DB definition by joining the partial coding of the different membership functions involved

- The coding scheme depends on:
  - The kind of membership function considered (triangular, trapezoidal, bell-shaped, …) $\rightarrow$ different real-coded definition parameters
  - The kind of FRBS:
    - Grid-based: Each linguistic term in the fuzzy partition has a single fuzzy set definition associated
    - Non grid-based (free semantics, scatter partitions, fuzzy graphs): each variable in each rule has a different membership function definition

2. Evolutionary Tuning of FRBSs

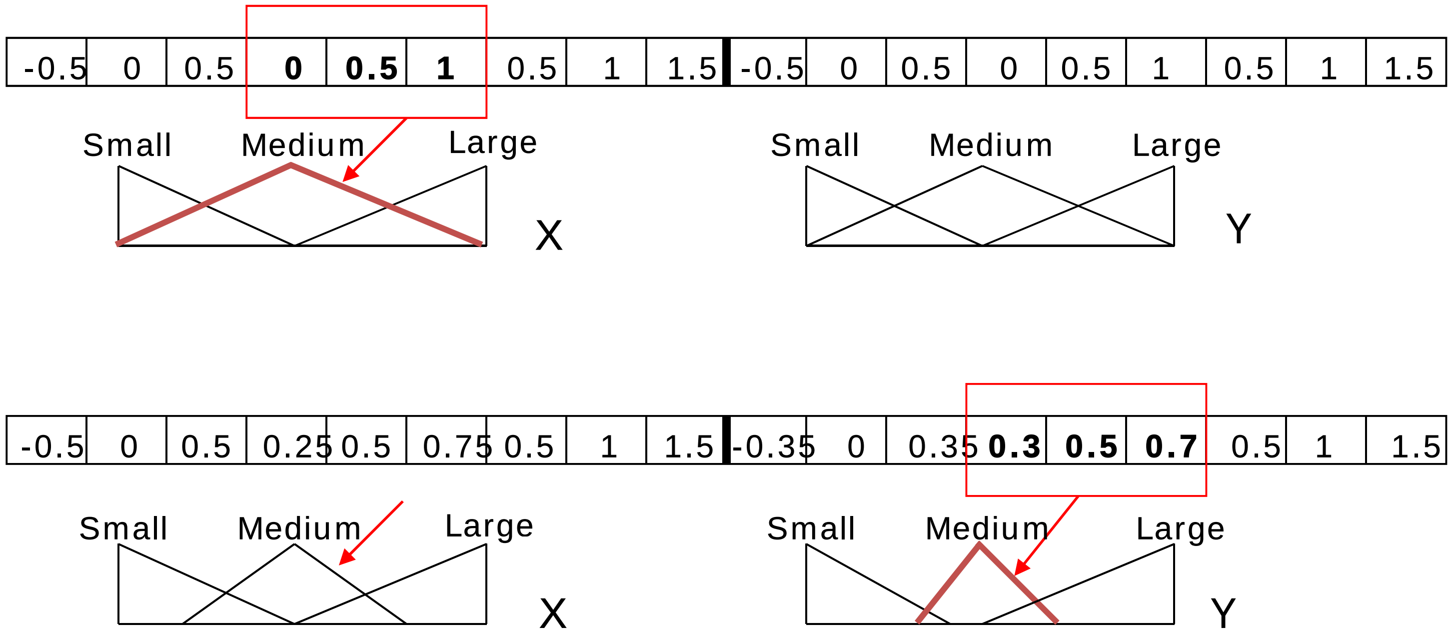
– Example: Tuning of the triangular membership functions of a grid-based SISO Mamdani-type FRBS, with three linguistic terms for each variable fuzzy partition

– Each chrosome encodes a different DB definition:
  - 2 (variables) · 3 (linguistic labels) = 6 membership functions
  - Each triangular membership function is encoded by 3 real values (the three definition points):
  - So, the chromosome length is 6 · 3 = 18 real-coded genes (binary coding can be used but but is not desirable)



– Either definition intervals have to be defined for each gene and/or appropriate genetic operators in order to obtain meaningful membership functions

2. Evolutionary Tuning of FRBSs



The RB remains unchanged!

R1: IF X1 is Small THEN Y is Large
R2: IF X1 is Medium THEN Y is Med
. . .

2. Evolutionary Tuning of FRBSs

References:

- C. Karr, Genetic algorithms for fuzzy controllers, AI Expert 6 (2) (1991) 26–33
- C. Karr, E.J. Gentry, Fuzzy control of pH using genetic algorithms, IEEE TFSs 1 (1) (1993) 46–53
- J. Kinzel, F. Klawonn, R. Kruse, Modifications of genetic algorithms for designing and optimizing fuzzy controllers, Proc. First IEEE Conf. on Evolutionary Computation (ICEC'94), Orlando, FL, USA, 1994, pp. 28–33
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- P.P. Bonissone, P.S. Khedkar, Y. Chen, Genetic algorithms for automated tuning of fuzzy controllers: a transportation application, in Proc. Fifth IEEE Int. Conf. on Fuzzy Systems (FUZZ-IEEE'96), New Orleans, USA, 1996, pp. 674–680
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- H.B. Gurocak, A genetic-algorithm-based method for tuning fuzzy logic controllers, FSS 108 (1) (1999) 39–47

2. Evolutionary Tuning of FRBSs

Genetic tuning of DB and RB using linguistic hedges

J. Casillas, O. Cordón, M.J. del Jesus, F. Herrera, Genetic tuning of fuzzy rule deep structures preserving interpretability and its interaction with fuzzy rule set reduction, IEEE TFS 13 (1) (2005) 13-29

Genetic tuning process that refines a preliminary KB working at two different levels:

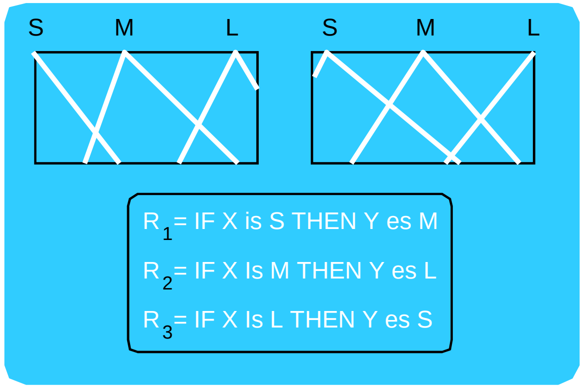
– DB level: Linearly or non-linearly adjusting the membership function shapes

– RB level: Extending the fuzzy rule structure using automatically learnt linguistic hedges

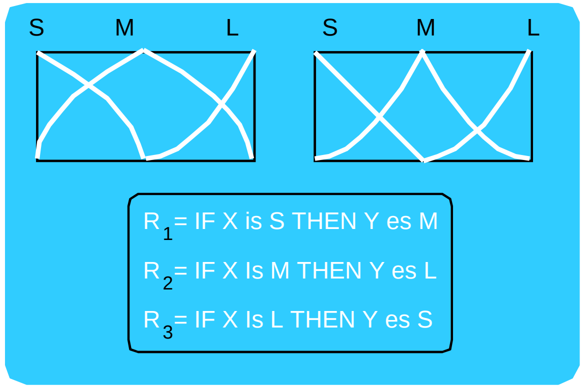
2. Evolutionary Tuning of FRBSs

- Tuning of the DB:

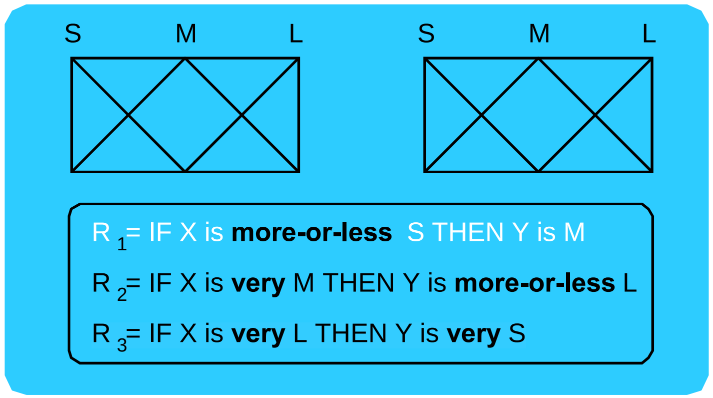
Linear tuning



Non-linear tuning



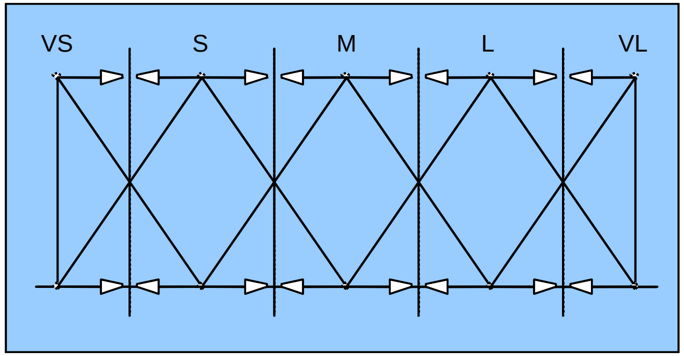
- Tuning of the RB: linguistic hedges 'very' and 'more-*or-less*'



2. Evolutionary Tuning of FRBSs

Triple coding scheme:

– Membership function parameters (P) (DB linear tuning): real coding



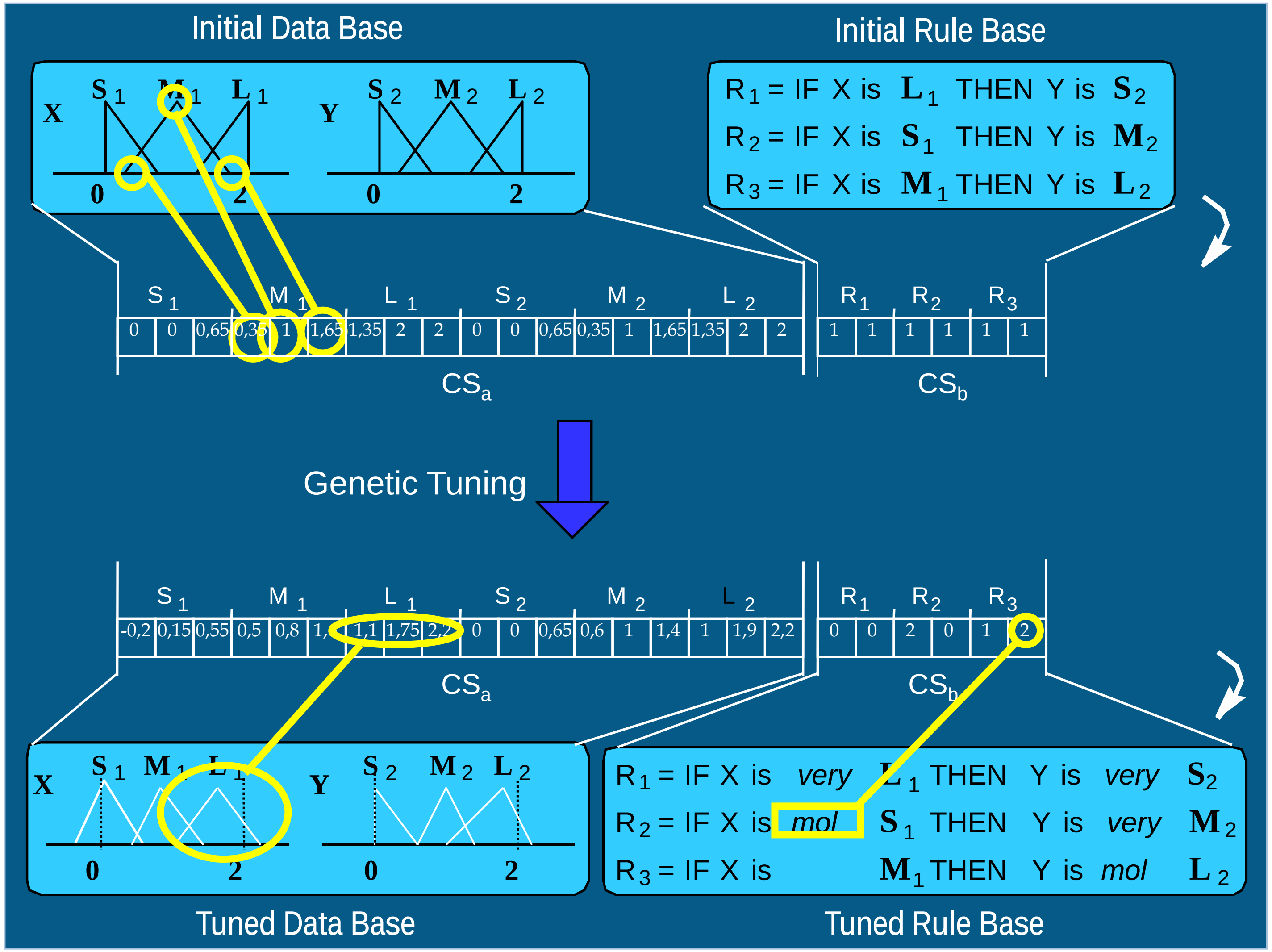
– Alpha values (A) (DB non linear tuning): real coding

$$\alpha = \begin{cases} 1 + c_{ij}^{A}, & \text{si } c_{ij}^{A} \in [-1,0] \\ 1 + 4 \cdot c_{ij}^{A}, & \text{si } c_{ij}^{A} \in]0,1] \end{cases}$$

– Linguistic hedges (L) (RB tuning): integer coding

$$\begin{array}{lll} c_{ij} = 0 & \leftrightarrow & \text{'very'} \\ c_{ij} = 1 & \leftrightarrow & \text{no hedge} \\ c_{ij} = 2 & \leftrightarrow & \text{'more-or-less'} \end{array}$$

2. Evolutionary Tuning of FRBSs



2. Evolutionary Tuning of FRBSs

Experimental study for the medium voltage line problem:

- Learning method considered: Wang-Mendel

- Tuning method variants:

TUNING PROCESSES CONSIDERED IN THIS EXPERIMENTAL STUDY

Method	Basic m.f. parameters	α m.f. parameter	Surface structure with linguistic hedges
P-tun	✓		
A-tun		✓	
L-tun			✓
PA-tun	✓	✓	
PL-tun	✓		✓
AL-tun		✓	✓
PAL-tun	✓	✓	✓

- Evaluation methodology: 5 random training-test partitions 80-20% (5-fold cross validation) $\times$ 6 runs = 30 runs per algorithm

2. Evolutionary Tuning of FRBSs

Maintenance cost estimation for low and medium voltage lines in Spain:

O. Cordón, F. Herrera, L. Sánchez, Solving electrical distribution problems using hybrid evolutionary data analysis techniques, Appl. Intell. 10 (1999) 5-24

- Spain's electrical market (before 1998): Electrical companies shared a business, Red Eléctrica Española, receiving all the client fees and distributing them among the partners

- The payment distribution was done according to some complex criteria that the government decided to change

- One of them was related to the maintenance costs of the power line belonging to each company

- The different producers were in trouble to compute them since:
  - As low voltage lines are installed in small villages, there were no actual measurement of their length
  - The goverment wanted the maintenance costs of the optimal medium voltage lines installation and not of the real one, built incrementally

2. Evolutionary Tuning of FRBSs

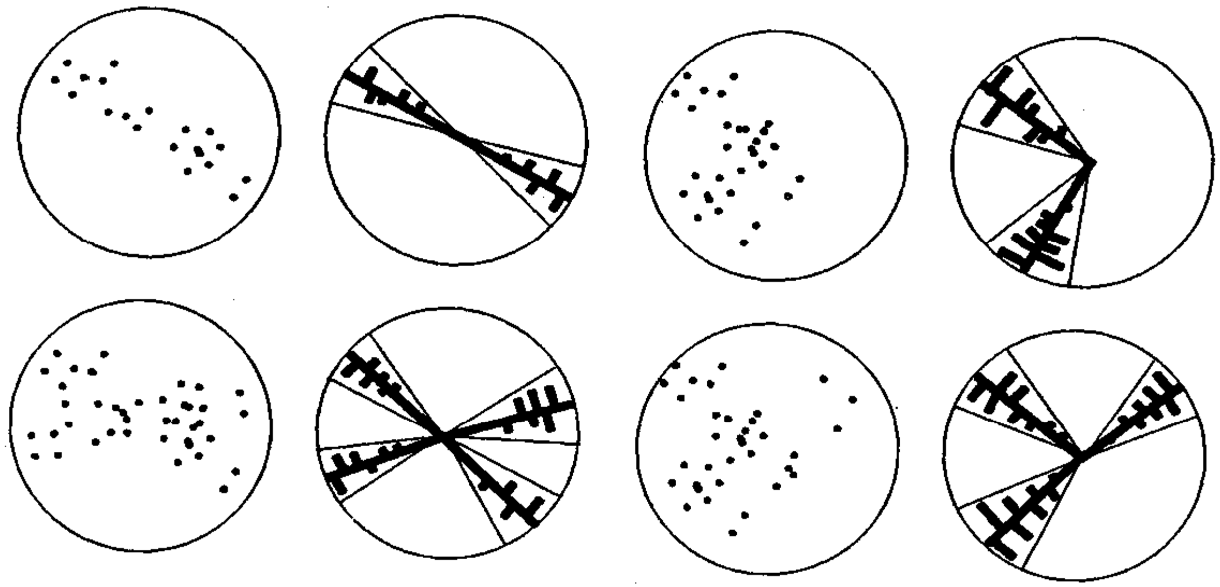
Low voltage line maintenance cost estimation:

- Goal: estimation of the low voltage electrical line length installed in 1000 rural towns in Asturias
- Two input variables: number of inhabitants and radius of village
- Output variable: length of low voltage line
- Data set composed of 495 rural nuclei, manually measured and affected by noise
- 396 (80%) examples for training and 99 (20%) examples for test randomly selected
- Seven linguistic terms for each linguistic variable

2. Evolutionary Tuning of FRBSs

Low voltage line maintenance cost estimation:

- Classical solution: numerical regression on different models of the line installation in the villages



2. Evolutionary Tuning of FRBSs

Medium voltage line maintenance cost estimation:

- Goal: estimation of the maintenance cost of the optimal medium voltage electrical line installed in the Asturias' towns
- Four input variables: street length, total area, total area occupied by buildings, and supplied energy
- Output variable: medium voltage line maintenance costs
- Data set composed of 1059 simulated cities
- 847 (80%) examples for training and 212 (20%) examples for test randomly selected
- Five linguistic terms for each linguistic variable

2. Evolutionary Tuning of FRBSs

Obtained results for the medium voltage line problem:

Tuning methods:

	Electrical Problem									
	$\bar{x}$				$\sigma_{\bar{x}_i}$			σ_{x_i}		
Method	#R	MSE_{tra}	MSE_{tst}	h:m:s	#R	MSE_{tra}	MSE_{tst}	#R	MSE_{tra}	MSE_{tst}
WM	**65**	56,135	56,359	0:00:00	**0.0**	1,498	4,685	—	—	—
WM+P-tun	65	18,395	22,136	**0:22:41**	0.0	778	3,200	—	1,110	1,988
WM+A-tun	65	37,243	38,837	0:33:58	0.0	455	1,816	—	**125**	**572**
WM+L-tun	65	20,967	23,420	0:25:16	0.0	632	3,207	—	336	1,439
WM+PA-tun	65	17,967	21,377	0:38:02	0.0	1,078	1,625	—	2,133	2,628
WM+PL-tun	65	**9,617**	**13,519**	0:25:33	0.0	**263**	3,153	—	694	1,509
WM+AL-tun	65	20,544	23,207	0:34:55	0.0	834	2,701	—	797	1,430
WM+PAL-tun	65	11,222	14,741	0:38:12	0.0	380	**1,315**	—	801	2,136

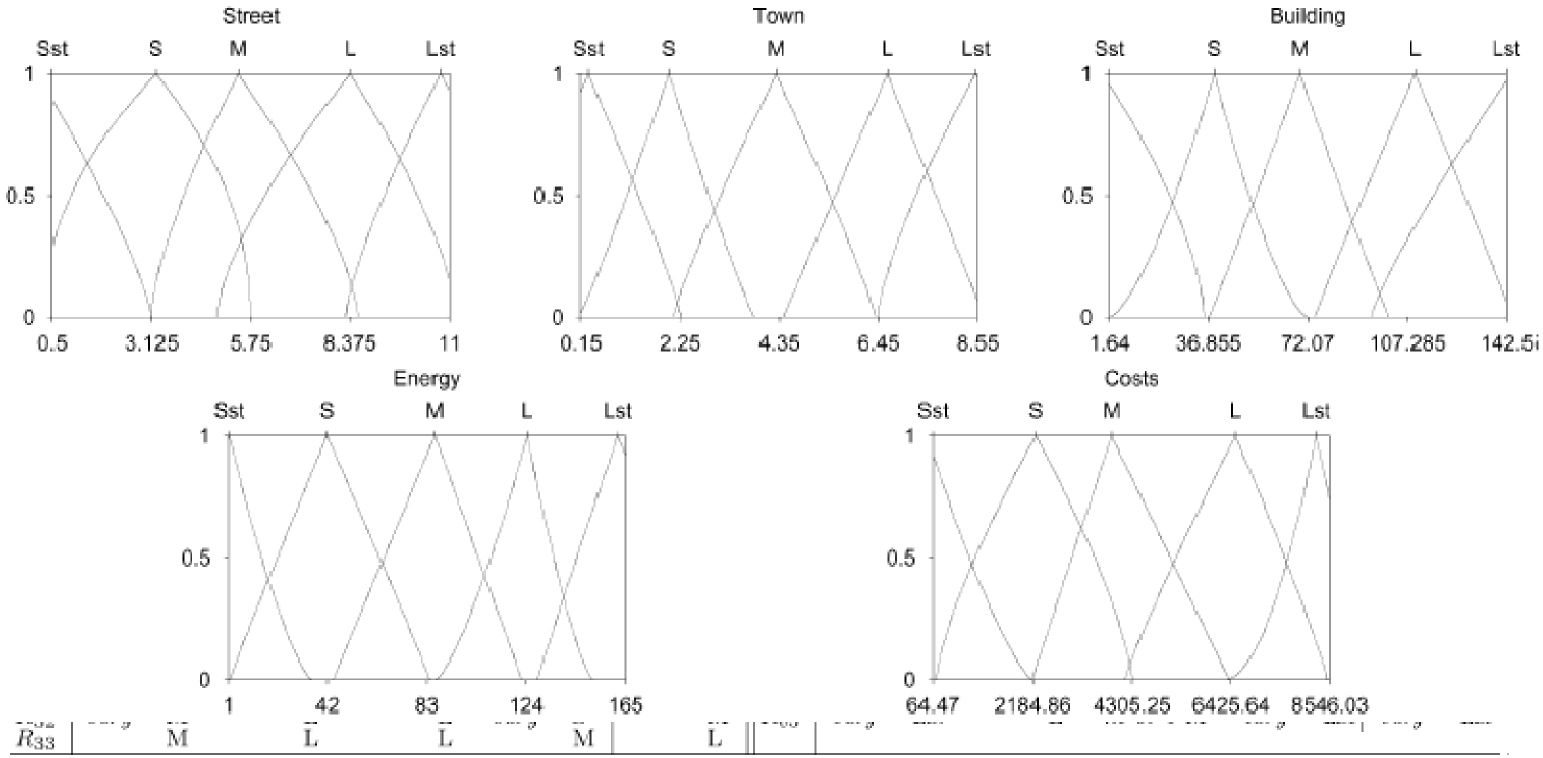
Other fuzzy modeling techniques and GFS:

	Electrical Problem									
	$\bar{x}$				σ_{x_i}			σ_{x_i}		
Method	#R	MSE_{tra}	MSE_{tst}	h:m:s	#R	MSE_{tra}	MSE_{tst}	#R	MSE_{tra}	MSE_{tst}
Nozaki [5]	**532**	**26,705**	**27,710**	**0:00:00**	**0.0**	**764**	**2,906**	—	—	—
Thrift [38]	565.3	31,228	37,579	3:13:25	2.6	1,018	7,279	6.1	**2,110**	**3,609**
Liska [45]	624.9	49,263	56,089	7:13:34	0.1	2,356	4,628	**0.1**	7,522	11,191

2. Evolutionary Tuning of FRBSs

Obtained results for the medium voltage line problem:

Example of one KB derived from the WM+PAL-tun method:



Before tuning: $MSE_{tra/test}$ = 58032 / 55150

After tuning: $MSE_{tra/test}$ = 11395 / 14465

2. Evolutionary Tuning of FRBSs

New coding schemes: 2- and 3-tuples:

IDEA: New fuzzy rule representation model allowing a more flexible definition of the fuzzy sets of the linguistic labels

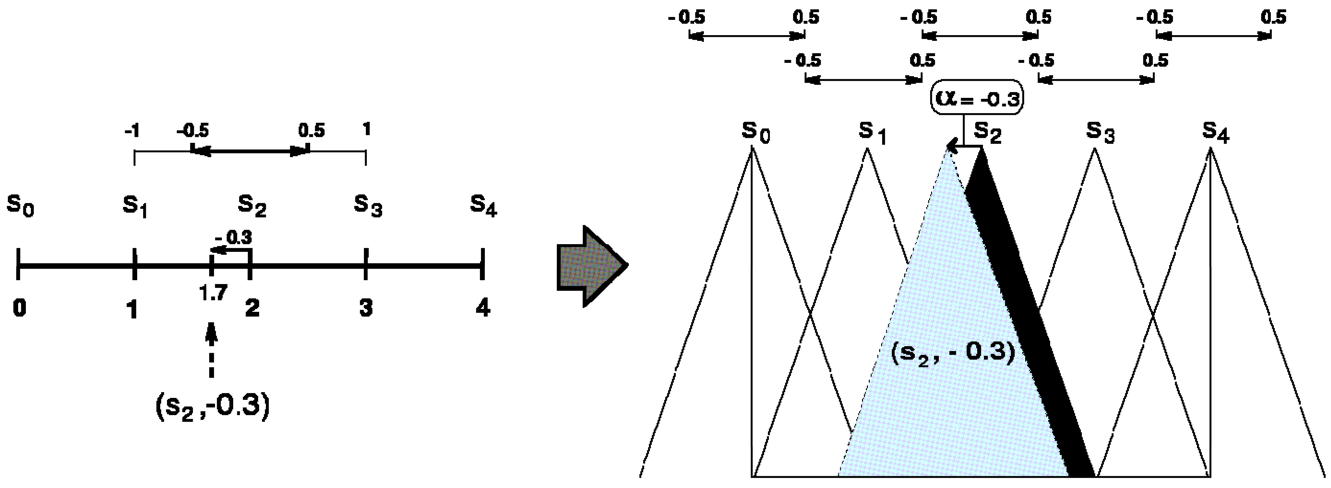
- **R. Alcalá, J. Alcalá-Fdez, F. Herrera, A proposal for the genetic lateral tuning of linguistic fuzzy systems and its interaction with rule selection, IEEE Transactions on Fuzzy Systems 15:4 (2007) 616-635**
- **R. Alcalá, J. Alcalá-Fdez, M.J. Gacto, F. Herrera, Rule base reduction and genetic tuning of fuzzy systems based on the linguistic 3-tuples representation, Soft Computing 11 (5) (2007) 401-419**

2. Evolutionary Tuning of FRBSs

New coding schemes: 2- and 3-tuples

IDEA: New fuzzy rule representation model allowing a more flexible definition of the fuzzy sets of the linguistic labels

– **2-tuples**: label id. **i** and a displacement parameter $\alpha_i \in [-0.5, 0.5]$



a) Simbolic Translation of a label

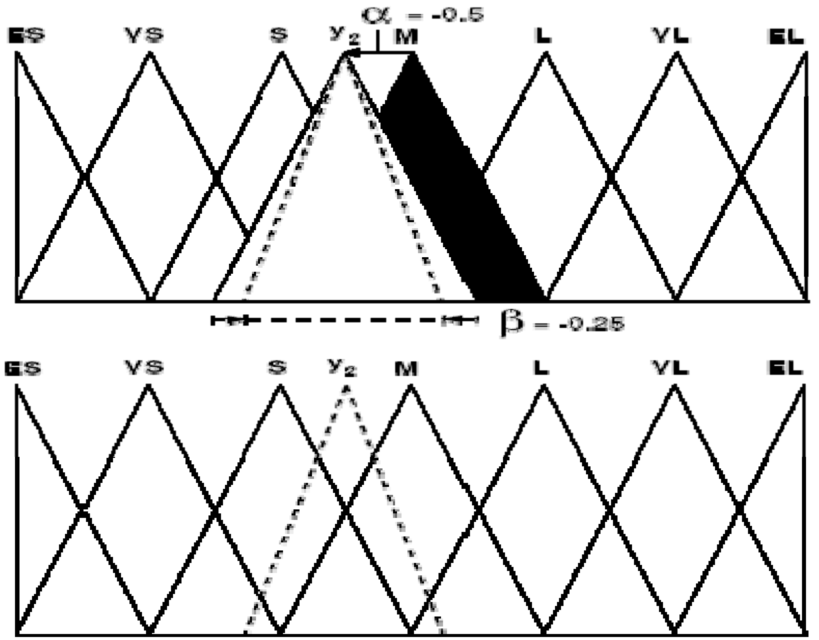
b) Lateral Displacement of a Membership function

– New rule structure:

IF X_1 IS (S^1_i, α_1) AND … AND X_n IS (S^n_i, α_n) THEN Y IS (S^y_i, α_y)

2. Evolutionary Tuning of FRBSs

– **3-tuples**: label id. **i**, a displacement parameter $\alpha_i \in [-0.5,0.5]$, and a width parameter $\beta_i \in [-0.5,0.5]$



– New rule structure:

IF X_1 IS (S^1_i,α_1,β_1) AND … AND X_n IS (S^n_i,α_n,β_n) THEN Y IS (S^y_i,α_y,β_y)

2. Evolutionary Tuning of FRBSs

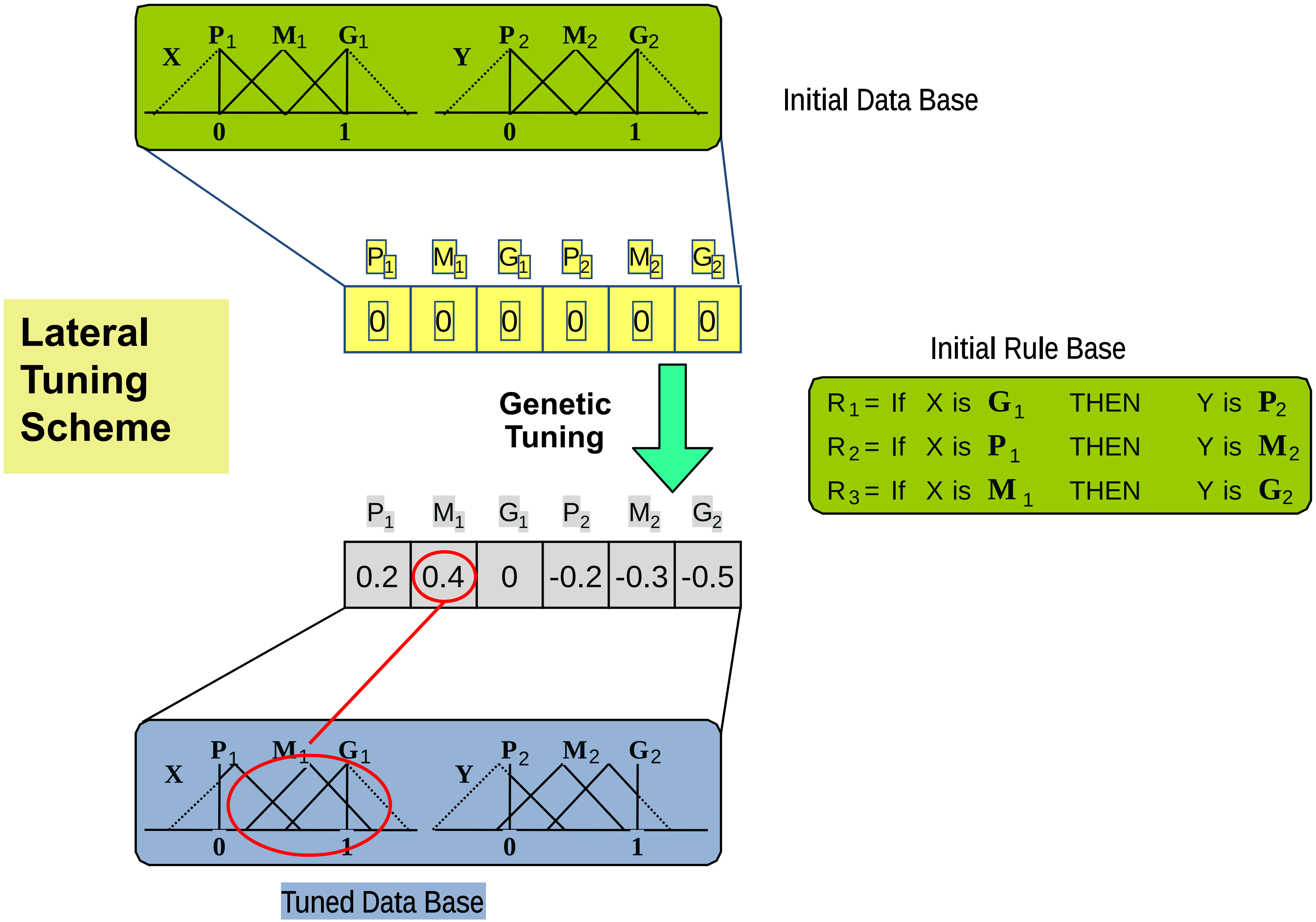
New coding schemes: 2- and 3-tuples

COLATERAL PROBLEM: Both structures decreases the KB learning/tuning large scale problem, since the fuzzy sets are encoded using a lower number of parameters

Existing proposals:

- Genetic 2-tuple/3-tuple DB global tuning: adjustment of the global fuzzy sets $\rightarrow$ full interpretability (usual fuzzy partitions)
- Genetic 2-tuple/3-tuple DB tuning at rule level$\rightarrow$ lower interpretability, higher flexibility (like scatter Mamdani FRBSs)
- Genetic 2-tuple/3-tuple DB tuning + rule selection

2. Evolutionary Tuning of FRBSs



2. Evolutionary Tuning of FRBSs

Medium voltage electrical network in towns

Genetic 2-tuple tuning + rule selection method:

WM	Wang and Mendel Learning Method
S	Rule Selection Method
GL	Global Lateral Tuning
LL	Local Lateral Tuning
T	Classical Genetic Tuning
P A L	Tuning of: Parameters, Domains, and Linguistic Modifiers

Five labels per linguistic variable
50000 Evaluations per run

Method	#R	MSE_{tra}	σ_{tra}	t-test	MSE_{tst}	σ_{tst}	t-test
WM	65	57605	2841	+	57934	4733	+
S	40.8	41086	1322	+	59942	4931	+
T	65	18602	1211	+	22666	3386	+
PAL	65	10545	279	+	13973	1688	+
T+S	41.9	14987	391	+	18973	3772	+
PAL+S	57.4	12851	362	+	16854	1463	+
GL	65	23064	1479	+	25654	2611	+
LL	65	3664	390	*	5858	1798	*
GL+S	49.1	18801	2669	+	22586	3550	+
LL+S	58.0	3821	385	=	6339	2164	=

5 data partitions 80% - 20%
6 runs per data partition
Averaged results from 30 runs
t-student Test with α = 0.05

2. Evolutionary Tuning of FRBSs

Obtained results for the low voltage line problem:

Genetic 2-tuple tuning + rule selection method:

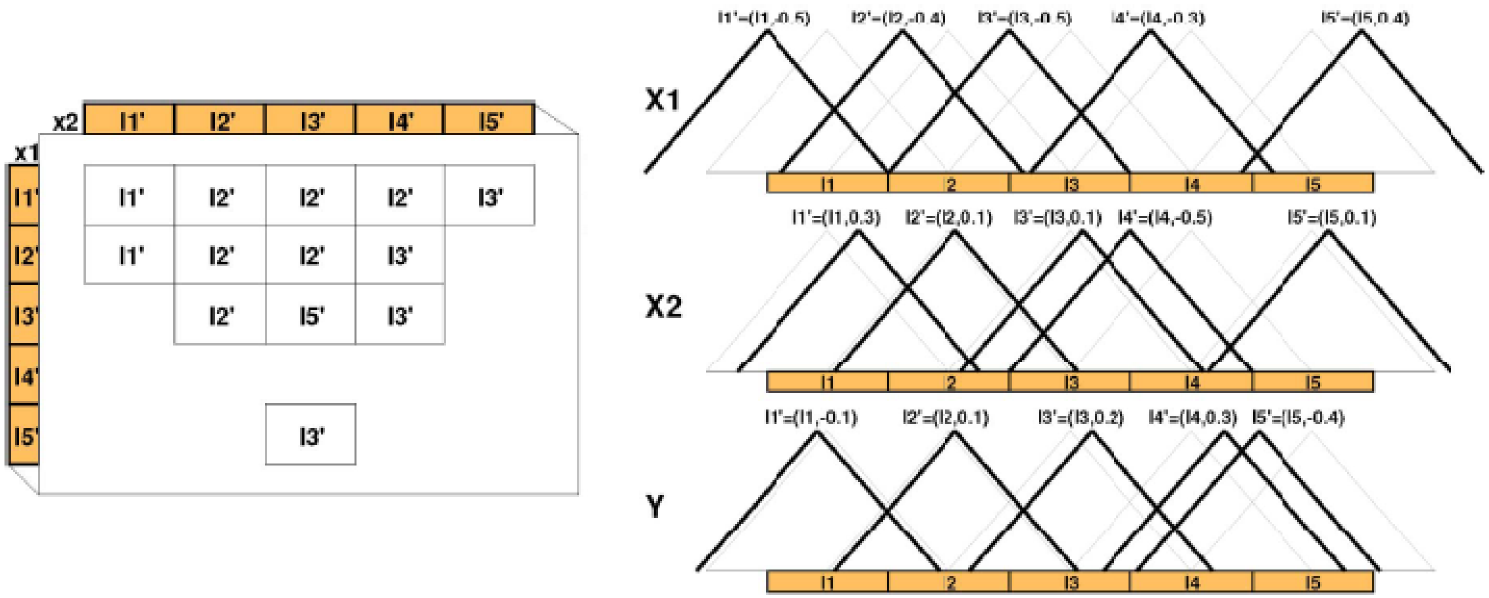
Method	#R	MSE_{tra}	σ_{tra}	t-test	MSE_{tst}	σ_{tst}	t-test
Approaches without tuning							
WM	12.4	234712	32073	+	242147	24473	+
S	10.0	226135	19875	+	241883	19410	+
Approaches with global semantics							
T	12.4	158662	6495	+	221613	29986	+
T+S	8.9	156313	2967	+	193477	49912	=
GL_{dd}	12.4	166674	11480	+	189216	14743	=
GL_{dd}+S	9.0	160081	7316	+	189844	22448	=
Approaches with local semantics							
PAL	12.4	141638	4340	+	189279	19523	=
PAL+S	10.6	145712	5444	+	191922	16987	=
LL_{dd}	12.4	**139189**	3155	⋆	191604	18243	=
LL_{dd}+S	10.5	141446	3444	=	**186746**	15762	⋆

- 5-fold cross validation × 6 runs = 30 runs per algorithm
- T-student test with 95% confidence

2. Evolutionary Tuning of FRBSs

Obtained results for the low voltage line problem:

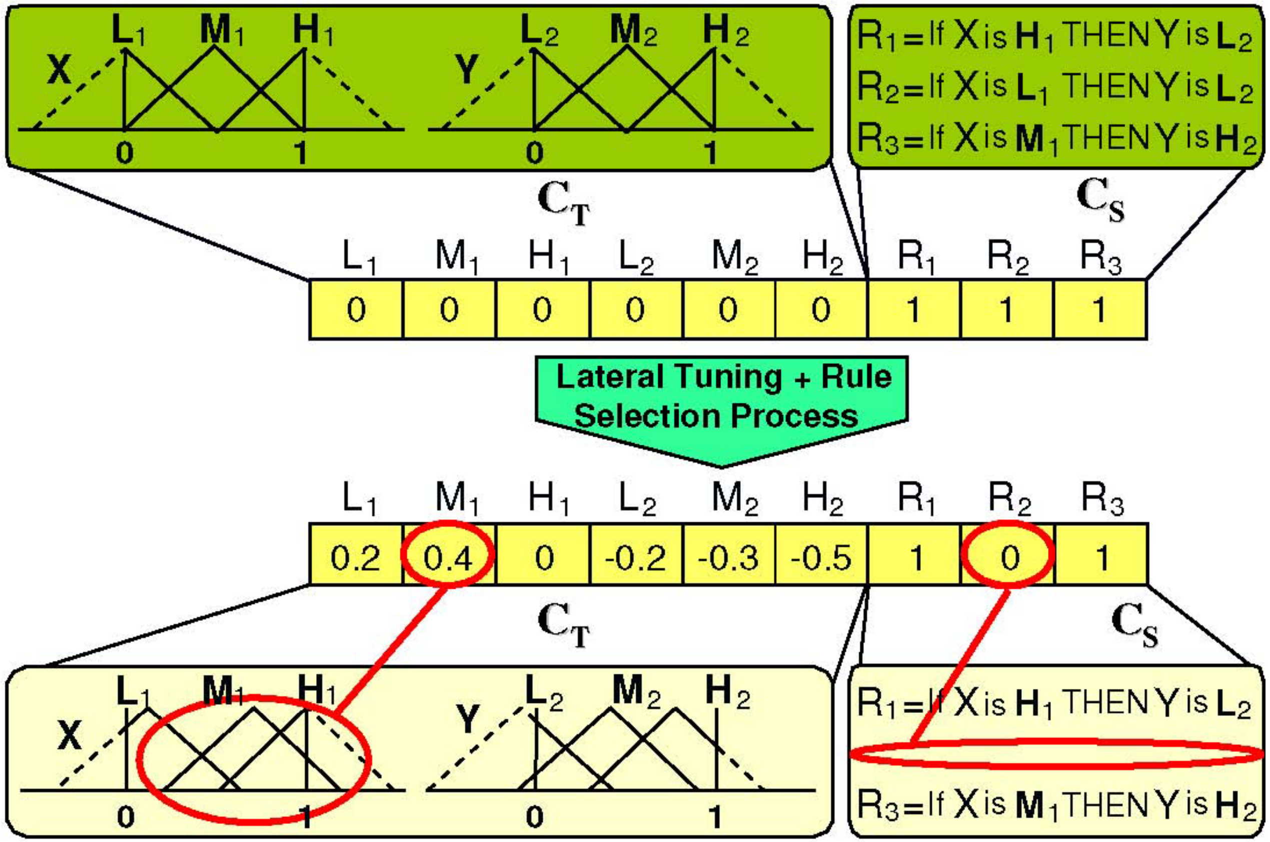
Example of one KB derived from the global tuning method:



	l1'	l2'	l3'	l4'	l5'
l1'	l1'	l2'	l2'	l2'	l3'
l2'	l1'	l2'	l2'	l3'	
l3'		l2'	l5'	l3'	
l4'					
l5'			l3'		

After tuning+rule selection: #R=13; $MSE_{tra/test}$ = 187494 / 176581

2. Evolutionary Tuning of FRBSs



Example of genetic lateral tuning and rule selection

2. Evolutionary Tuning of FRBSs

New Tuning Model: Multi-objective GFS for the interpretability-accuracy trade-off

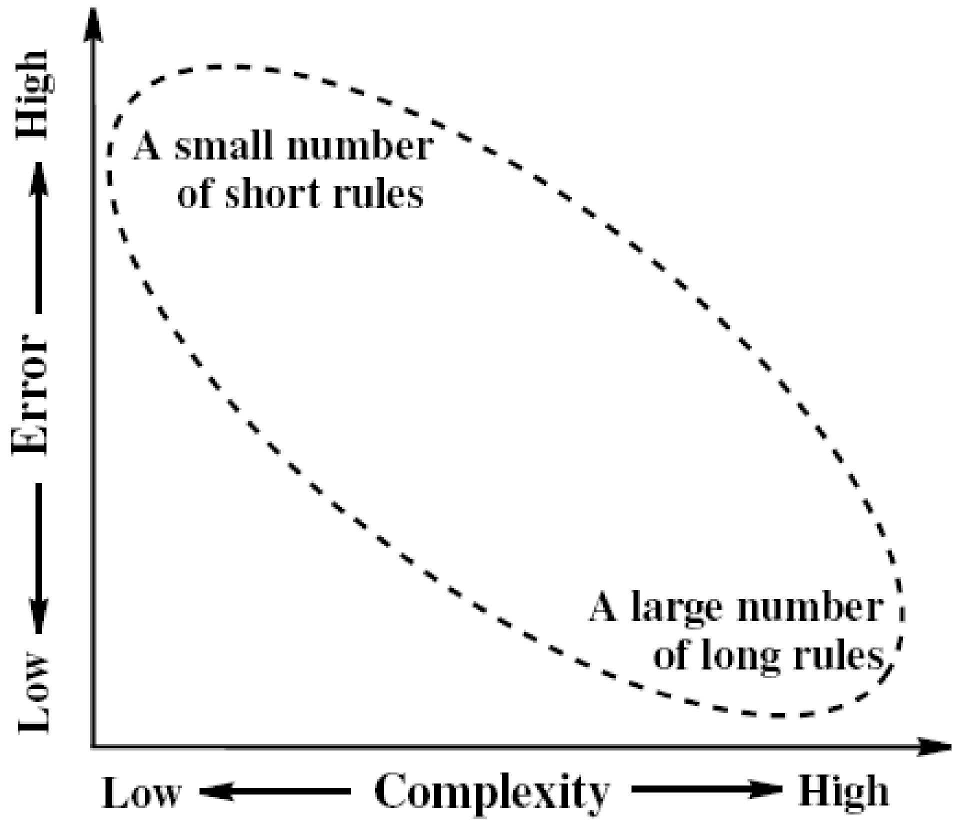
R. Alcalá, J. Alcalá-Fdez, M.J. Gacto, F. Herrera, A multi-objective genetic algorithm for tuning and rule selection to obtain accurate and compact linguistic fuzzy rule-based systems, *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 15:5 (2007) 539–557*,

Multi-objective EAs are powerful tools to generate GFSs but they are based on getting a large, well distributed and spread off, Pareto set of solutions

– The two criteria to optimize in GFSs are accuracy and interpretability. The former is more important than the latter, so many solutions in the Pareto set are not useful

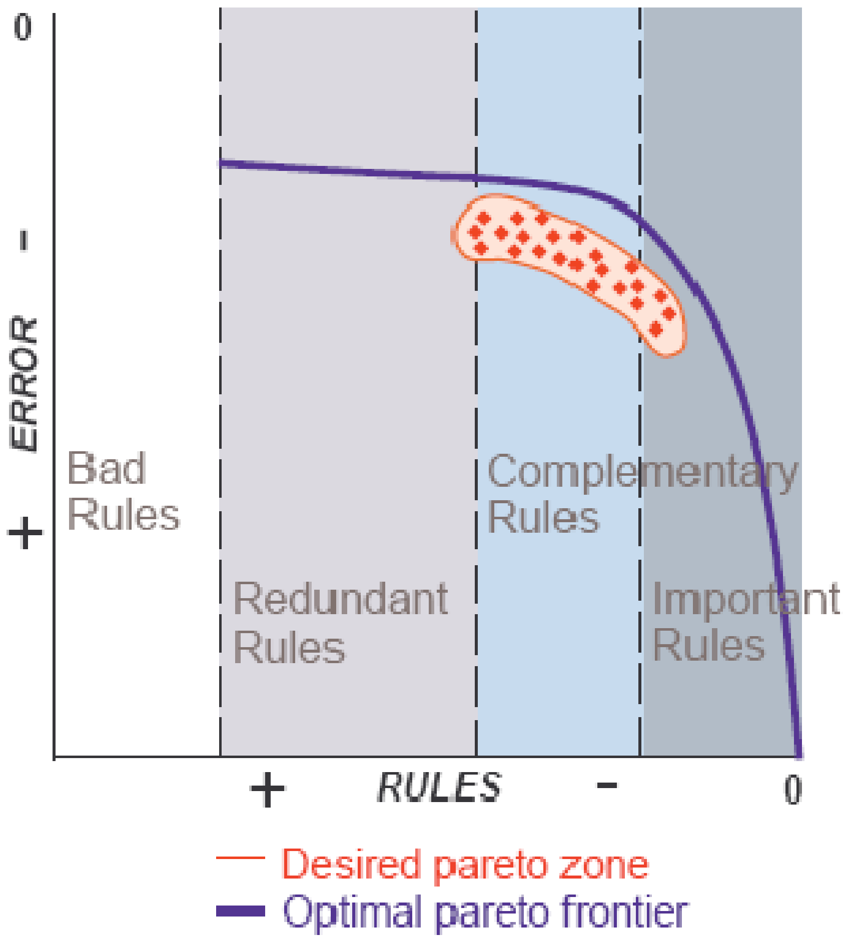
– Solution: Inject knowledge through the MOEA run to bias the algorithm to generate the desired Pareto front part

2. Evolutionary Tuning of FRBSs



2. Evolutionary Tuning of FRBSs

Pareto front classification in an interpretability-accuracy GFSs:



- Bad rules zone: solutions with bad performance rules. Removing them improves the accuracy, so no Pareto solutions are located here
- Redundant rules zone: solutions with irrelevant rules. Removing them does not affect the accuracy and improves the interpretability
- Complementary rules zone: solutions with neither bad nor irrelevant rules. Removing them slightly decreases the accuracy
- Important rules zone: solutions with essential rules. Removing them significantly decreases the accuracy

2. Evolutionary Tuning of FRBSs

Accuracy-oriented modifications performed:

– Restart the genetic population at the middle of the run time, keeping the individual with the highest accuracy as the only one in the external population and generating all the new individuals with the same number of rules it has

– In each MOGA step, the number of chromosomes in the external population considered for the binary tournament is decreased, focusing the selection on the higher accuracy individuals

2. Evolutionary Tuning of FRBSs

Obtained results for the medium voltage line problem:

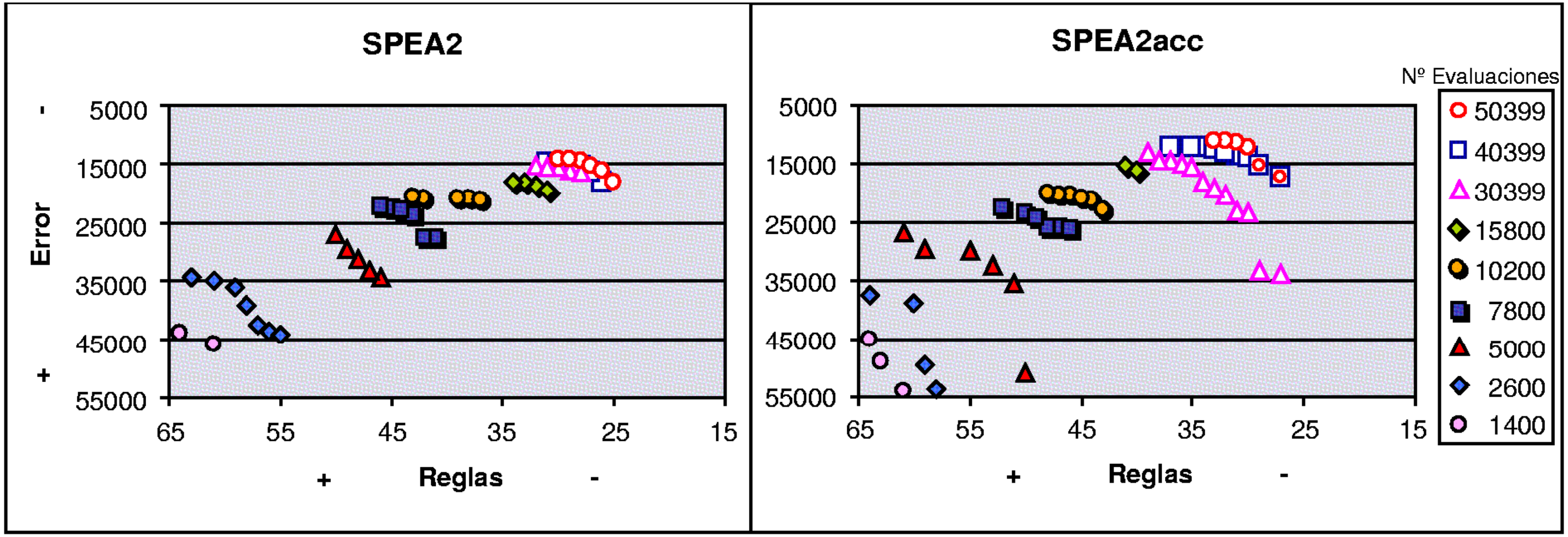
Multi-objective genetic tuning + rule selection method:

Method	#R	MSE_{tra}	σ_{tra}	t-test	MSE_{tst}	σ_{tst}	t-test
WM	65	57605	2841	+	57934	4733	+
WM+T	65	18602	1211	+	22666	3386	+
WM+S	40.8	41086	1322	+	59942	4931	+
WM+TS	41.9	14987	391	+	18973	3772	+
NSGAII	41.0	14488	965	+	18419	3054	+
$NSGAII_{ACC}$	48.1	16321	1636	+	20423	3138	+
SPEA2	**33**	13272	1265	+	17533	3226	+
$SPEA2_{ACC}$	34.5	**11081**	1186	*	**14161**	2191	*

- 5-fold cross validation × 6 runs = 30 runs per algorithm
- T-student test with 95% confidence

2. Evolutionary Tuning of FRBSs

Comparison of the SPEA2 – SPEA2acc convergence:



2. Evolutionary Tuning of FRBSs

STUDY ON SEVERAL ALTERNATIVE APPROACHES AND IMPROVEMENTS

M.J. Gacto, R. Alcalá, F. Herrera, Adaptation and Application of Multi-Objective Evolutionary Algorithms for Rule Reduction and Parameter Tuning of Fuzzy Rule-Based Systems. *Soft Computing 13:5 (2009) 419-436*

2. Evolutionary Tuning of FRBSs

- **To perform the study we have applied six different approaches based on the two most known and successful MOEAs:**
  - **Application of *SPEA2* and *NSGA-II***
  - **Two versions of NSGA-II for finding knees, $NSGA\text{-}II_A$ and $NSGA\text{-}II_U$**
  - **Two extensions for specific application $SPEA2_{Acc}$ and $SPEA2_{Acc2}$**
- **Two objectives are considered: MSE and Number of Rules**
- **Proper operators have to be selected.**
- **The determination of the population size becomes an important issue. Specially in the case of NSGA-II**

2. Evolutionary Tuning of FRBSs

Method	Description
WM	Wang & Mendel algorithm
T	Tuning of Parameters
S	Rule Selection
TS	Tuning & Selection
Application of standard MOEAs for general use	
TS-SPEA2	Tuning & Selection by SPEA2
TS-NSGA-II	Tuning & Selection by NSGA-II
TS-NSGA-II$_A$	Tuning & Selection by NSGA-II$_{angle}$
TS-NSGA-II$_U$	Tuning & Selection by NSGA-II$_{utility}$
Extended MOEAs for specific application	
TS-SPEA2$_{Acc}$	Accuracy-Oriented SPEA2
TS-SPEA2$_{Acc^2}$	Extension of SPEA2$_{Acc}$

2. Evolutionary Tuning of FRBSs

NSGA-II FOR FINDING KNEES

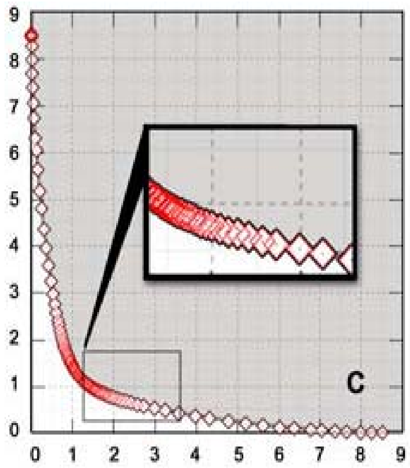
J. Branke, K. Deb, H. Dierolf, and M. Osswald, "Finding Knees in Multi-objective Optimization," Proc. Parallel Problem Solving from Nature Conf. - PPSN VIII, LNCS 3242, (Birmingham, UK, 2004) 722–731.

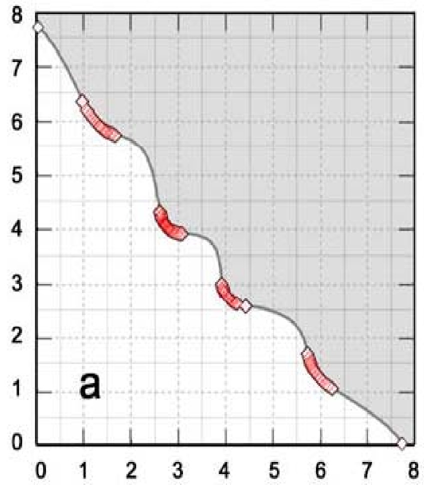
- **A variation of NSGAII in order to find knees in the Pareto front by replacing the crowding measure by either an angle-based measure or an utility-based measure**

Two different approaches

Angle Based Approach

Utility Based Approach





- **In our case, a knee could represent the best compromise between accuracy and number of rules.**

2. Evolutionary Tuning of FRBSs

Extension of $SPEA2_{Acc}$ ($SPEA2_{Acc2}$)

A New Crossover Operator for the Rule Part

- **Objective:** to improve the search with a more intelligent operator replacing the HUX crossover in $SPEA2_{ACC}$
- **Once BLX is applied a normalized euclidean distance is calculated between the centric point of the MFs used by each rule of the offpring and each parent**
- **The closer parent determines if this rule is selected or not for this offpring**
- **Whit this crossover operator, mutation can be particularly used to remove rules**

2. Evolutionary Tuning of FRBSs

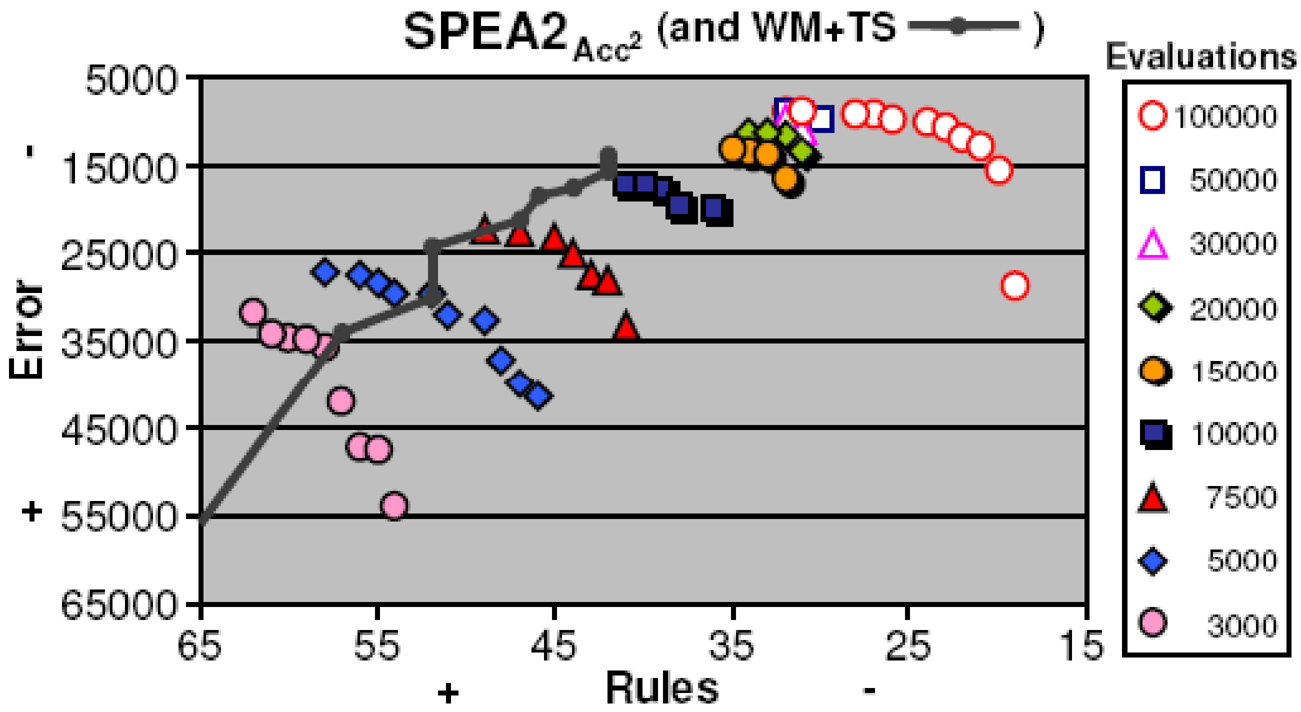
Obtained results for the medium voltage line problem:

Method	#R	MSE_{tra}	σ_{tra}	t	MSE_{tst}	σ_{tst}	t
100,000 evaluations							
WM	**65.0**	**57605**	**2841**	+	**57934**	**4733**	**+**
T	**65.0**	**17020**	**1893**	**+**	**21027**	**4225**	**+**
S	**40.9**	**41158**	**1167**	**+**	**42988**	**4441**	**+**
TS	**41.3**	**13387**	**1153**	**+**	**17784**	**3344**	**+**
TS-SPEA2	**28.9**	**11630**	**1283**	+	**15387**	**3108**	**+**
TS-NSGA-II	**31.4**	**11826**	**1354**	**+**	**16047**	**4070**	**+**
TS-NSGA-II_A	**29.7**	**11798**	**1615**	**+**	**16156**	**4091**	**+**
TS-NSGA-II_U	**30.7**	**11954**	**1768**	**+**	**15879**	**4866**	**+**
TS-$SPEA2_{Acc}$	**32.3**	**10714**	**1392**	=	**14252**	**3181**	=
TS-$SPEA2_{Acc2}$	**29.8**	**10325**	**1121**	*	**13935**	**2759**	*

- 5-fold cross validation × 6 runs = 30 runs per algorithm
- T-student test with 95% confidence

2. Evolutionary Tuning of FRBSs

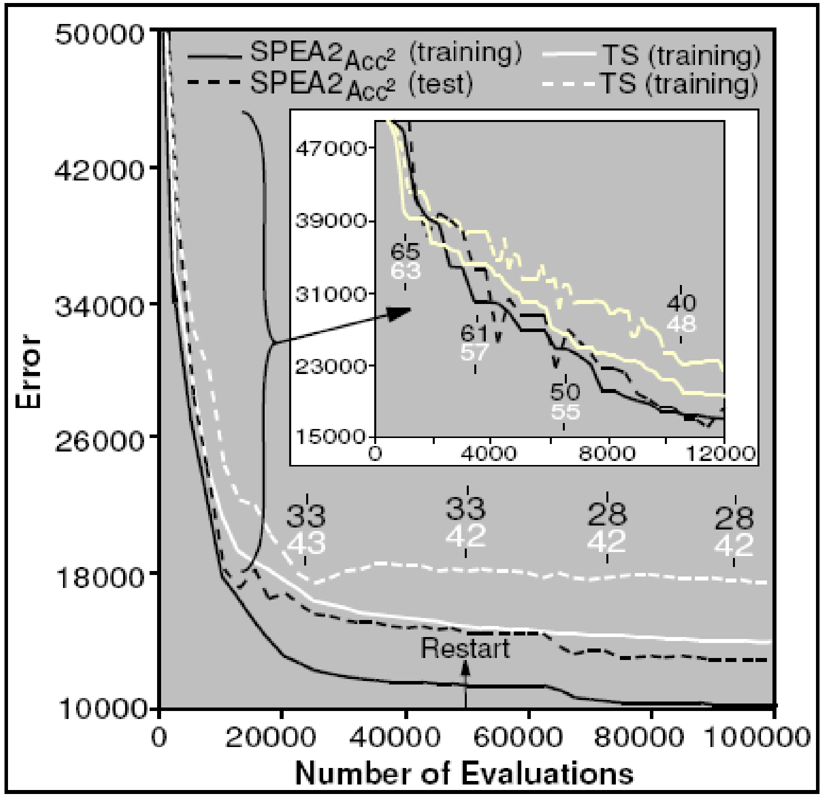
Comparison of the SPEA2acc² and classical GA for for the medium voltage line problem:

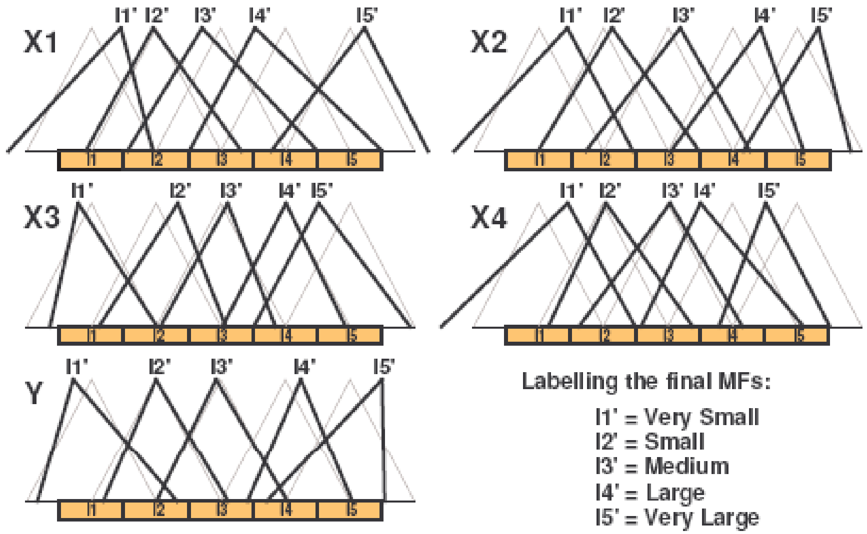


2. Evolutionary Tuning of FRBSs

Multiobjective Tuning and Rule Selection

Convergence and an example model





#R: 28 *MSE-tra: 8232* *MSE-tst: 14670*

X1	X2	X3	X4	Y
l1'	l1'	l1'	l1'	l1'
l1'	l1'	l1'	l2'	l2'
l2'	l1'	l1'	l1'	l1'
l2'	l1'	l1'	l2'	l2'
l2'	l1'	l2'	l2'	l2'
l2'	l2'	l2'	l1'	l2'
l2'	l3'	l3'	l1'	l3'
l3'	l2'	l1'	l1'	l1'
l3'	l2'	l1'	l2'	l2'

X1	X2	X3	X4	Y
l3'	l2'	l1'	l3'	l2'
l3'	l2'	l2'	l3'	l3'
l3'	l3'	l2'	l2'	l2'
l3'	l3'	l3'	l2'	l3'
l3'	l4'	l3'	l3'	l3'
l4'	l2'	l2'	l2'	l2'
l4'	l3'	l2'	l1'	l2'
l4'	l3'	l2'	l3'	l3'
l4'	l3'	l2'	l4'	l3'

X1	X2	X3	X4	Y
l4'	l3'	l3'	l2'	l3'
l4'	l3'	l3'	l3'	l4'
l4'	l4'	l3'	l2'	l3'
l4'	l4'	l4'	l2'	l4'
l4'	l4'	l4'	l4'	l5'
l4'	l5'	l4'	l2'	l3'
l4'	l5'	l5'	l3'	l5'
l5'	l2'	l2'	l5'	l4'
l5'	l2'	l3'	l2'	l3'
l5'	l4'	l3'	l5'	l5'

2. Evolutionary Tuning of FRBSs

Future Studies:

- To develop appropriate MOEAs for getting a pareto with a better trade-off between precision and interpretability, improving the precision.
- To design interpretability measures for including them into the MOEAs objectives.

Outline

- ✓Brief Introduction to Genetic Fuzzy Systems
- ✓Genetic Tuning Methods: Basic and Advanced Approaches
- ✓Genetic Fuzzy Systems Application to HVAC Problems
- ✓GFSs: Current Trends and Prospects
- ✓Concluding Remarks