Data Mining and Soft Computing

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Summary

1. Introduction to Data Mining and Knowledge Discovery
2. Data Preparation
3. Introduction to Prediction, Classification, Clustering and Association
4. Data Mining - From the Top 10 Algorithms to the New Challenges
5. Introduction to Soft Computing. Focusing our attention in Fuzzy Logic and Evolutionary Computation
6. Soft Computing Techniques in Data Mining: Fuzzy Data Mining and Knowledge Extraction based on Evolutionary Learning
8. Some Advanced Topics I: Classification with Imbalanced Data Sets
9. Some Advanced Topics II: Subgroup Discovery
10. Some advanced Topics III: Data Complexity

Outline

✓ Brief 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
Outline

✓ 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


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
1. Introduction to genetic fuzzy systems

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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. Brief 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. Brief introduction to genetic fuzzy systems

**Brief Introduction**

**Genetic Fuzzy Rule-Based Systems:**

![Diagram of Genetic Fuzzy Rule-Based Systems]

- **DESIGN PROCESS**
  - Genetic Algorithm Based Learning Process
  - Knowledge Base: Data Base + Rule Base
- **Input Interface** → **Fuzzy Rule-Based System** → **Output Interface**

*Environment* | **Computation with Fuzzy Rule-Based Systems** | *Environment*
1. Brief 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*
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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
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**Brief Introduction**

As said, 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
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**Brief Introduction**

- **R1**: IF X1 is High AND X2 is Low THEN Y is Medium
- **R2**: IF X1 is Low AND X2 is Low THEN Y is High

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**Knowledge Base**

- **Rule Base**
- **Data Base**

---

**Input**

**Fuzzification Interface** → **Inference Mechanism** → **Defuzzification Interface** → **Output**

---

**Fuzzy rule-based system**
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Taxonomy of Genetic Fuzzy Systems

Genetic fuzzy systems

- Genetic tuning
  - Genetic tuning of KB parameters
  - Genetic adaptive inference system
- Genetic learning of FRBS components
  - Genetic KB learning
  - Genetic learning of KB components and inference engine parameters
- Genetic adaptive inference engine
  - Genetic adaptive defuzzification methods
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**Taxonomy of Genetic Fuzzy Systems**
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1. Genetic Tuning

Classically:
– performed on a predefined DB definition
– tuning of the membership function shapes by a GA

– tuning of the inference parameters
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1. Brief 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
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1. Brief 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)
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Rule Extraction Process

Genetic Rule Selection

Rule set

RB

Evaluation Module (RB)
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Example of genetic rule selection
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4. Genetic DB Learning

– Learning of the membership function shapes by a GA
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1. Brief 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
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1. Brief 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
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¿Why do we use GAs?

GFSs versus Neural Fuzzy Systems
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¿Why do we use GAs? GFSs versus Neural Fuzzy Systems

Neuro Fuzzy Systems

- The most usual architecture:
  1. Variables
  2. Fuzzification
     (Fuzzy Partition, Data Base)
  3. Rules
  4. Consequents
  5. Defuzzification
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¿Why do we use GAs? GFSs versus Neural Fuzzy Systems

- **ANFIS**: *Adaptive Network based Fuzzy Inference System* (Jyh-Shing Roger Jang, 1993)
  - It uses a fixed number of linguistic labels per variable
  - It only tunes the membership functions

Neuro Fuzzy Systems (ANFIS)

![ANFIS Diagram]

\[
\begin{align*}
Z_1 &= p_1 x + q_1 y + r_1 \\
Z_2 &= p_2 x + q_2 y + r_2 \\
Z &= \frac{w_1 Z_1 + w_2 Z_2}{w_1 + w_2}
\end{align*}
\]
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¿Why do we use GAs? GFSs versus Neural Fuzzy Systems

Limitations of the Neuro Fuzzy Systems

- **Dimensionality problem:** The can manage a small number of variables (the complexity increase geometrically with the number of variables)

- **A necessity:** To know previously the number of labels per variable.

- **Difficulty for learning the rule structure:** Usually, NFS only learn the membership functions and rule consequent coefficients.
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¿Why do we use GAs? GFSs versus Neural Fuzzy Systems

Advantages of the Genetic Fuzzy Systems

- We can code different FS components in a chromosome:
  - Identify relevant inputs
  - Scaling factors
  - Membership functions, shape functions, optimal shape of membership funct., granularity (number of labels per variable)
  - Fuzzy rules, Any inference parameter, ....

We can define different mechanism for managing them (combining genetic operators, coevolution,...)
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¿Why do we use GAs? GFSs versus Neural Fuzzy Systems

Advantages of the Genetic Fuzzy Systems

- We can consider multiple objectives in the learning model (interpretability, precision, ....)
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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)

- Valenzuela-Rendón’s PPSN-I paper (Scatter Mamdani-type KB Learning. Michigan approach)

- Pham and Karaboga’s Journal of Systems Engineering paper (Relational matrix-based FRBS learning. Pittsburgh approach)

- Karr’s AI Expert paper (Mamdani-type Data Base Tuning)

Almost the whole basis of the area were established in the first year!
1. Introduction to genetic fuzzy systems

**Thrift’s GFS:**


– 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
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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
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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
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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 evolution" 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


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


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
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, ...) → 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 chromosome encodes a different DB definition:
  - 2 (variables) \( \cdot \) 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 \( \cdot \) 3 = 18 real-coded genes
      (binary coding can be used 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
2. Evolutionary Tuning of FRBSs

Genetic tuning of DB and RB using linguistic hedges


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

- Linguistic hedges ($L$) (RB tuning): integer coding

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

\[c_{ij} = 0 \iff \text{‘very’} \]
\[c_{ij} = 1 \iff \text{no hedge} \]
\[c_{ij} = 2 \iff \text{‘more-or-less’} \]
2. Evolutionary Tuning of FRBSs

Initial Data Base

Initial Rule Base

R₁ = IF X is S1 THEN Y is S₂
R₂ = IF X is L₂ THEN Y is M₁
R₃ = IF X is M₂ THEN Y is L₂

Genetic Tuning

Tuned Data Base

Tuned Rule Base

R₁ = IF X is very S₂ THEN Y is very M₂
R₂ = IF X is mol S₁ THEN Y is very M₂
R₃ = IF X is M₁ THEN Y is mol L₂
2. Evolutionary Tuning of FRBSs

Experimental study for the medium voltage line problem:

- Learning method considered: Wang-Mendel

- Tuning method variants:

<table>
<thead>
<tr>
<th>Method</th>
<th>Basic m.f. parameters</th>
<th>$\alpha$ m.f. parameter</th>
<th>Surface structure with linguistic hedges</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-tun</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>A-tun</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>L-tun</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>PA-tun</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>PL-tun</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>AL-tun</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>PAL-tun</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

- 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:


• 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 government 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:

<table>
<thead>
<tr>
<th>Method</th>
<th>#R</th>
<th>(\bar{x})</th>
<th>(\text{MSE}_{\text{tra}})</th>
<th>(\text{MSE}_{\text{tst}})</th>
<th>h:m:s</th>
<th>#R</th>
<th>(\text{MSE}_{\text{tra}})</th>
<th>(\text{MSE}_{\text{tst}})</th>
<th>h:m:s</th>
<th>#R</th>
<th>(\text{MSE}_{\text{tra}})</th>
<th>(\text{MSE}_{\text{tst}})</th>
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</table>

Other fuzzy modeling techniques and GFS:

<table>
<thead>
<tr>
<th>Method</th>
<th>#R</th>
<th>(\bar{x})</th>
<th>(\text{MSE}_{\text{tra}})</th>
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<td></td>
</tr>
</tbody>
</table>

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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: \( \text{MSE}_{\text{tra/test}} = 58032 / 55150 \)
After tuning: \( \text{MSE}_{\text{tra/test}} = 11395 / 14465 \)
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


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 $\alpha_i \in [-0.5, 0.5]$
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 $(S^1_i, \alpha_1, \beta_1)$ AND ... AND $X_n$ IS $(S^n_i, \alpha_n, \beta_n)$ THEN $Y$ IS $(S^y_i, \alpha_y, \beta_y)$
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 → full interpretability (usual fuzzy partitions)
- Genetic 2-tuple/3-tuple DB tuning at rule level → lower interpretability, higher flexibility (like scatter Mamdani FRBSs)
- Genetic 2-tuple/3-tuple DB tuning + rule selection
2. Evolutionary Tuning of FRBSs

Initial Data Base

Initial Rule Base

\[ R_1 = \text{If } X \text{ is } G_1 \text{ THEN } Y \text{ is } P_2 \]
\[ R_2 = \text{If } X \text{ is } P_1 \text{ THEN } Y \text{ is } M_2 \]
\[ R_3 = \text{If } X \text{ is } M_1 \text{ THEN } Y \text{ is } G_2 \]
2. Evolutionary Tuning of FRBSs

Medium voltage electrical network in towns

Genetic 2-tuple tuning + rule selection method:

<table>
<thead>
<tr>
<th>Method</th>
<th>#R</th>
<th>MSE(_{\text{tra}})</th>
<th>(\sigma_{\text{tra}})</th>
<th>t-test</th>
<th>MSE(_{\text{tst}})</th>
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Five labels per linguistic variable
50000 Evaluations per run

5 data partitions 80% - 20%
6 runs per data partition
Averaged results from 30 runs
t-student Test with \(\alpha = 0.05\)
2. Evolutionary Tuning of FRBSs

Obtained results for the low voltage line problem:

Genetic 2-tuple tuning + rule selection method:

<table>
<thead>
<tr>
<th>Method</th>
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<th>$\sigma_{\text{tra}}$</th>
<th>t-test</th>
<th>$\text{MSE}_{\text{tst}}$</th>
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</tbody>
</table>

- 5-fold cross validation $\times$ 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:

After tuning+rule selection: \#R=13; \text{MSE}_{\text{tra/test}} = 187494 / 176581
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:


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

![Diagram showing the relationship between error and complexity for FRBSs, with a focus on a small number of short rules versus a large number of long rules.](image-url)
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:

<table>
<thead>
<tr>
<th>Method</th>
<th>#R</th>
<th>MSE_{tra}</th>
<th>σ_{tra}</th>
<th>t-test</th>
<th>MSE_{tst}</th>
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</tbody>
</table>

- 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

Comparison of the SPEA2acc and classical GA for the medium voltage line problem:

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