Edwin Lughofer

Evolving Fuzzy Systems – Methodologies, Advanced Concepts and Applications

Studies in Fuzziness and Soft Computing, Volume 266

Editor-in-Chief

Prof. Janusz Kacprzyk
Systems Research Institute
Polish Academy of Sciences
ul. Newelska 6
01-447 Warsaw
Poland
E-mail: kacprzyk@ibspan.waw.pl

Further volumes of this series can be found on our homepage: springer.com

Vol. 251. George A. Anastassiou
Fuzzy Mathematics: Approximation Theory, 2010
ISBN 978-3-642-11219-5

Vol. 252. Cengiz Kahraman, Mesut Yavuz (Eds.)
Production Engineering and Management under Fuzziness, 2010
ISBN 978-3-642-12051-0

Vol. 253. Badredine Arfi
Linguistic Fuzzy Logic Methods in Social Sciences, 2010
ISBN 978-3-642-13342-8

Vol. 254. Weldon A. Lodwick, Janusz Kacprzyk (Eds.)
Fuzzy Optimization, 2010
ISBN 978-3-642-13934-5

Vol. 255. Zongmin Ma, Li Yan (Eds.)
Soft Computing in XML Data Management, 2010
ISBN 978-3-642-14009-9

Vol. 256. Robert Jeansoulin, Odile Papini, Henri Prade, and Steven Schockaert (Eds.)
Methods for Handling Imperfect Spatial Information, 2010
ISBN 978-3-642-14754-8

Vol. 257. Salvatore Greco, Ricardo Alberto Marques Pereira, Massimo Squillante, Ronald R. Yager, and Janusz Kacprzyk (Eds.)
*Preferences and Decisions,*2010
ISBN 978-3-642-15975-6

Vol. 258. Jorge Casillas and Francisco José Martínez López
Marketing Intelligent Systems Using Soft Computing, 2010
ISBN 978-3-642-15605-2

Vol. 259. Alexander Gegov
Fuzzy Networks for Complex Systems, 2010
ISBN 978-3-642-15599-4

Vol. 260. Jordi Recasens
Indistinguishability Operators, 2010
ISBN 978-3-642-16221-3

Vol. 261. Chris Cornelis, Glad Deschrijver, Mike Nachtegael, Steven Schockaert, and Yun Shi (Eds.)
35 Years of Fuzzy Set Theory, 2010
ISBN 978-3-642-16628-0

Vol. 262. Zsófia Lendek, Thierry Marie Guerra, Robert Babuška, and Bart De Schutter
Stability Analysis and Nonlinear Observer Design Using Takagi-Sugeno Fuzzy Models, 2010
ISBN 978-3-642-16775-1

Vol. 263. Jiuping Xu and Xiaoyang Zhou
Fuzzy-Like Multiple Objective Decision Making, 2010
ISBN 978-3-642-16894-9

Vol. 264. Hak-Keung Lam and Frank Hung-Fat Leung
Stability Analysis of Fuzzy-Model-Based Control Systems, 2011
ISBN 978-3-642-17843-6

Vol. 265. Ronald R. Yager, Janusz Kacprzyk, and Prof. Gleb Beliakov (eds.)
Recent Developments in the Ordered Weighted Averaging Operators: Theory and Practice, 2011
ISBN 978-3-642-17909-9

Vol. 266. Edwin Lughofer
Evolving Fuzzy Systems – Methodologies, Advanced Concepts and Applications, 2011
ISBN 978-3-642-18086-6

Edwin Lughofer

Evolving Fuzzy Systems – Methodologies, Advanced Concepts and Applications

Springer

Author

Dr. Techn. Edwin Lughofer
Fuzzy Logic Laboratorium Linz-Hagenberg
Softwarepark Hagenberg
Hauptstrasse 99
A-4232 Hagenberg
Tel.: +43 (0)7236 / 3343 435
Fax: +43 (0)7236 / 3343 434
http://www.flll.jku.at/people/staff/lughofer.html

ISBN 978-3-642-18086-6 e-ISBN 978-3-642-18087-3

DOI 10.1007/978-3-642-18087-3

Studies in Fuzziness and Soft Computing ISSN 1434-9922

Typeset & Cover Design: Scientific Publishing Services Pvt. Ltd., Chennai, India.

Printed on acid-free paper

9 8 7 6 5 4 3 2 1

springer.com

To my wife Ilona

Preface

"Evolving: to develop gradually; to evolve a scheme."
Dictionary.com

In today's industrial systems, economic markets, life and health-care sciences fuzzy systems play an important role in many application scenarios such as system identification, fault detection and diagnosis, quality control, instrumentation and control, decision support systems, visual inspection, psychological modelling, biomedical and bioinformatic systems, financial domains. Fuzzy systems are specific mathematical models aimed at imitating the real natural dependencies, procedures as accurately and as transparent as possible, building upon the concept of fuzzy logic, which was first introduced in 1965 by Lotfi A. Zadeh. The great attraction of fuzzy systems is because they are providing a reliable tradeoff between precise and linguistic modelling and offer a tool for solving complex problems in the real world. Precise modelling aims to achieve high accuracy in model outputs and is supported by the fact that fuzzy systems are universal approximators, i.e. having the potential to identify a model of the system with sufficient accuracy in order to guarantee process-save and correct model feedbacks. On the other hand, in linguistic modelling the main objective is to obtain models with a good interpretable capability, offering insights into the system processes and behaviors in an understandable way. Furthermore, fuzzy systems are able to express 1.) any form of uncertainty implicitly contained in the system as natural fact and 2.) any form of vagueness contained in the knowledge of human beings by a possibilistic point of view.

While during the stone ages in the field of fuzzy systems research (70s and 80s) most of the fuzzy systems relied on (vague) expert knowledge, during the 90s a big shift in the design of these systems towards data-driven aspects could be observed. This development went hand in hand with the technological progress of automated information processing in computers and the increasing amount of data in industrial systems. The extraction of fuzzy systems automatically from data was a cornerstone for omitting time-intensive design phases and discussions with the experts and bringing in more automatization capability. Another major advantage of data-driven fuzzy systems is that they rely on objective data rather than subjective experiences, which may be affected by different moods of the experts or be contradictory. Data-driven fuzzy systems are extracting basic trends and patterns out of the data to gain a deeper understanding of 'what the data says'. As such, they can be seen as an important contribution to both, the *fuzzy (systems)* as well as the *machine learning* and *data mining* community.

In order to account for changing systems dynamics and behaviors as well as new operating conditions and environmental influences, during the last decade (2000 to 2010) a new topic in the field of data-driven design of fuzzy systems emerged, the so-called *evolving fuzzy systems* (EFS). An evolving fuzzy system updates its structural components and parameters on demand based on new process characteristic, system behavior and operating conditions; it also expands its range of influence and evolves new model structures in order to integrate new knowledge (reflected by new incoming data). In this sense, evolving (fuzzy) systems can be seen as an important step towards *computational intelligence*, as the models permanently and automatically learn from changing system states and environmental conditions. *Evolving* should be here not confused with *evolutionary*. An evolutionary approach learns parameters and structures based on genetic operators, but does this by using all the data in an iterative optimization procedure rather than integrating new knowledge permanently on-the-fly. Nowadays, the emerging field of evolving fuzzy systems is reflected by many publications in international conferences and journals such as Fuzzy Sets and Systems, IEEE Transactions on Fuzzy Systems, Evolving Systems, IEEE Transactions on Systems, Man and Cybernetics part B, International Journal of Approximate Reasoning, Applied Soft Computing and many others. In the second half of the last decade, a lot of workshops (EFS '06, GEFS '08, ESDIS '09, EIS '10 and others) and special sessions at different international conferences (FUZZ-IEEE, EUSFLAT, IFSA, IPMU) were organized, mainly by the 'three musketeers' Plamen Angelov, Dimitar Filev and Nik Kasabov, who, along with other researchers, carried out pioneering research work at the beginning of the last decade, resulting in the evolving fuzzy systems approaches such as (alphabetically) *DENFIS* (Kasabov), *eTS* (Angelov and Filev), *FLEXFIS* (author of this book), *SAFIS* (Rong, Sundararajan et al.), *SOFNN* (Leng, McGinnity, Prasad) and *SONFIN* (Juang and Lin). These were completed during the second half of the last decade by approaches such as *EFP* (Wang and Vrbanek), *ePL* (Lima, Gomide, Ballini et al.), *SEIT2FNN* (Juang and Tsao) and others.

The aim of this book is to provide a round picture of the whole emerging field of evolving fuzzy systems within a consistent and comprehensive monograph. The first part will demonstrate the most important evolving fuzzy systems approaches developed during the last decade (as mentioned above), including a description of the most essential learning and parameter optimization steps used in these. Applications in the third part of the book will underline the necessity of evolving fuzzy systems in today's industrial systems and life sciences, including *on-line system identification,*

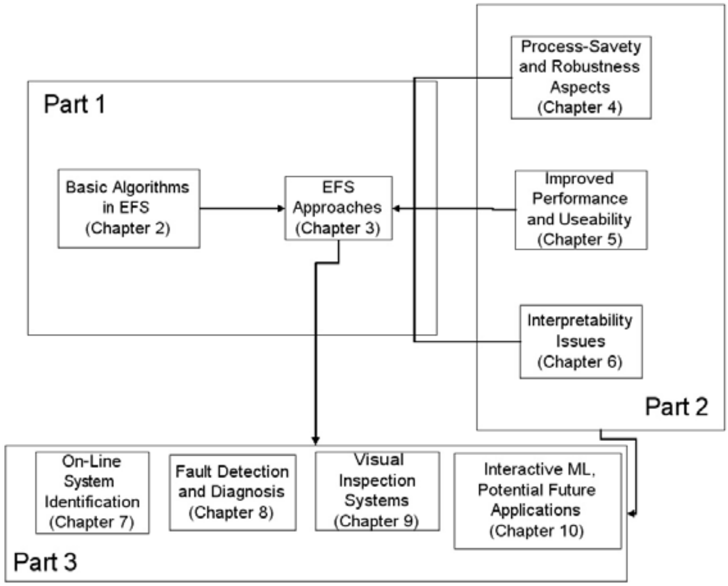

Fig. 0.1 Overview of the content in this book

fault detection in multi-channel measurement systems, visual inspection scenarios, perception-based texture analysis, bioinformatics, enhanced human-machine interaction and many more. The second part of the book deals with advanced concepts and novel aspects which were in large parts just partially handled in EFS approaches and can be seen as promising directions for improving *process safety, predictive quality, user-friendliness* and *interpretability* as well as *understandability* of evolving fuzzy systems. The epilogue concludes the book with *achieved issues, open problems* and *future challenges*, which may serve as inspiration and motivation for all (evolving) fuzzy systems researchers to enrich this newly emerging field with their ideas, point of views, further developments etc. A global view on the content of the book and the connections between the different parts and chapter are shown in Figure 0.1.

The book has not particularly been written in a mathematical theorem/proof style, but more in a way where ideas, concepts and algorithms are highlighted by numerous figures, tables, examples and applications together with their explanations. The book looks to be read not only from the field of fuzzy sets and systems research, but also from the machine learning, data mining, system identification and control community as well as attracting technicians from engineering and industrial practice.

Linz, October 2010 Edwin Lughofer

Acknowledgements

First of all, special thanks are dedicated to my wife Ilona, who showed great patience and tolerance during the writing period of this book, which lasted about 2 and 1/2 years and was proceeded in large parts during weekends and free time. Special thanks are also dedicated to my whole family and friends for supporting me morally and to all of my colleagues in our research department for providing me with inspirations, hints and discussions about the book. Further special thanks go to Günther Frizberg who brought me to the topic of on-line adaptation of data-driven models in 2000/2001 within the scope of an European project, which can be seen as my research starting point, Erich Peter Klement who acted as supervisor during my PhD on Evolving Fuzzy Models (2001-2005), supported by Eyke Hüllermeier who provided me with many useful inspirations and hints during the preparation of the thesis and beyond. Special thanks are also dedicated to Anne Margery for proof-reading and improving the English language of the whole monography, Janusz Kacprzyk for establishing the contract with Springer Verlag Heidelberg and Christian Eitzinger, the project coordinator of two European research projects (2005-2010) where I was involved as key researcher of our university and who supported the concept of on-line learning of fuzzy systems in various work-packages and application scenarios.

Furthermore, I would like to acknowledge the following persons (alphabetically according to family names) with whom I had intensive contacts and collaborations in several joint publications, projects (proposals), organizations of special sessions/issues and workshops, research visits as well as discussions and exchanging of ideas during the last years:

Plamen Angelov, Frank Bauer, Ulrich Bodenhofer, Janos Botzheim, Abdelhamid Bouchachia, Hendrik van Brussel, Oscar Cordon, Antonio Dourado, Mario Drobics, Hajrudin Efendic, Dimitar Filev, Veniero Giglio, Fernando Gomide, Carlos Guardiola, Christoph Hametner, Wolfgang Heidl, Frank Hoffmann, Eyke Hüllermeier, Richard Jacobs, Stefan Jakubek, Nik Kasabov, Uzay Kaymak, Stefan Kindermann, Frank Klawonn, Thomas Krieger, Wolfgang Märzinger, Bernhard Moser, Robert Murphy, Thomas Natschläger, Kurt Niehl, Marnix Nuttin, Witold Pedrycz, Daniel Sanchez, Davy Sannen, Moamar Sayed-Mouchaweh, Michael Scherrer, Holger Schöner, Rudolf Seising, James Edward Smith, Muhammad Atif Tahir, Stefan Thumfart, Bogdan Trawinski, Krzysztof Trawinski, Gancho Vachkov, Karin Wiesauer, Xiaowei Zhou.

Contents

Part III: Applications

Abbreviations

A/D	Analog/Digital
ANFIS	Adaptive Neuro-Fuzzy Inference System
APE	Average Percent Error
AR	Auto-Regressive
ARMA	Auto-Regressive Moving Average
CART	Classification and Regression Trees
CBS	Center- and Border-Based Selection
CD	Compact Disc
COG	Center of Gravity
COM	Center of Maximum
CV	Cross-Validation
DBSCAN	Density Based Spatial Clustering of Applications with Noise
DDM	Dynamic Data Mining
DENFIS	Dynamic Evolving Neural Fuzzy-Inference System
D-FNN	Dynamic Fuzzy Neural Network
DNA	Deoxyribonucleic Acid
DVD	Digital Versatile Disc
EBF	Ellipsoidal Basis Function
ECM	Evolving Clustering Method
ECMc	Evolving Clustering Method with constraints
ECU	Engine Control Unit
EEG	Electroencephalography
EFC	Evolving Fuzzy Classifier
EFP	Evolving Fuzzy Predictor
EFS	Evolving Fuzzy System
EFuNN	Evolving Fuzzy Neural Network
ELS	Extended Least Squares
EM	Expectation-Maximization (algorithm)
ENFRN	Evolving Neuro-Fuzzy Recurrent Network
EGR	Exhaust Gas Recirculation

ePCA	Evolving Principal Component Analysis
ePL	Evolving Participatory Learning
eTS	Evolving Takagi-Sugeno fuzzy systems
eTS+	Evolving Takagi-Sugeno fuzzy systems from Data Streams
eVQ	Evolving Vector Quantization
eVQ-Class	Evolving Vector Quantization for Classification
FC	Fault Correction
FCM	Fuzzy C-Means
FD	Fault Detection
FI	Fault Isolation
FLEXFIS	Flexible Fuzzy Inference Systems
FLEXFIS-MOD	Flexible Fuzzy Inference Systems using Modified Version of eVQ
FLEXFIS-Class	Flexible Fuzzy Inference Systems for Classification
FLL	Fuzzy Lazy Learning
FMCLUST	Fuzzy Model Clustering
fMRI	functional Magnetic Resonance Imaging
FOU	Footprint of Uncertainty
FW	Feature Weighting
FWLS	Fuzzily Weighted Least Squares (solution)
GAP-RBF	Growing And Pruning Radial Basis Function Network
GCV	Generalized Cross-Validation
GD-FNN	Generalized Dynamic Fuzzy Neural Network
GLVQ	Generalized Learning Vector Quantization
GSVD	Generalized Singular Value Decomposition
GTLS	Generalized Total Least Squares
GUI	Graphical User Interface
HAL	Hybrid Active Learning
HIEM	Human-Inspired Evolving Machines/Models
ICF	Incremental Classifier Fusion
IDC	Incremental direct cluster-based fusion
IFAC	International Federation of Automatic Control
ILVQ	Incremental Learning Vector Quantization
IML	Interactive Machine Learning
iPCA	Incremental Principal Component Analysis
KDD	Knowledge Discovery in Databases
LM	Levenberg-Marquardt (optimization method)
LOESS	Locally Weighted Scatterplot Smoothing
LOFO	Leave-One-Feature-Out (weighting strategy)
LS	Least Squares (solution)
LVQ	Learning Vector Quantization
MAE	Mean Absolute Error
MF	Membership Function
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output

ML	Machine Learning
MM	Multi Model (architecture)
MRAN	Minimal Resource Allocation Network
MSE	Mean Squared Error
MTS	Mamdani-Takagi-Sugeno (fuzzy system)
MV	Machine Vision
MVEG	Motor Vehicle Emission Group
ND	Noise Detection
NDEI	Non-Dimensional Error Index
NEFCLASS	Neuro-Fuzzy Classification
NF	Neuro-Fuzzy
NIR	Near-InfraRed
NOx	Nitrogen Oxides
NP-hard	Non-deterministic Polynomial-time hard
OFW	On-line Feature Weighting
PAC	Process Analytical Chemistry
PCA	Principal Component Analysis
PCFR	Principal Component Fuzzy Regression
PCR	Principal Component Regression
PI	ProportionalIntegral (Controller)
PID	ProportionalIntegralDerivative (Controller)
PL	Participatory Learning
PLS	Partial Least Squares
PRESS	Predicted REsidual Sums of Squares
QCL	Quantum Cascade Laser
RAN	Resource Allocation Network
RBCLS	Rule-Based Constraint Least Squares
RBF	Radial Basis Function
RBFN	Radial Basis Function Network
RBS	Ribosome Binding Site
RENO	Regularized Numerical Optimization (of Fuzzy Systems)
RFWLS	Recursive Fuzzily Weighted Least Squares
RLM	Recursive Levenberg-Marquardt
RLS	Recursive Least Squares
RMSE	Root Mean Squared Error
ROFWLS	Recursive Orthogonal Fuzzily Weighted Least Squares
ROI	Range of Influence (clusters, rules)
ROI	Region of Interest (objects)
ROLS	Recursive Orthogonal Least Squares
RS	Random Selection
RWLS	Recursive Weighted Least Squares
SAFIS	Sequential Adaptive Fuzzy Inference System
SEIT2FNN	Self-Evolving Interval Type-2 Fuzzy Neural Network
SISO	Single Input Single Output
SM	Single Model (architecture)

SOFNN	Self-Organizing Fuzzy Neural Network
SONFIN	Self-constructing Neural Fuzzy Inference Network
SparseFIS	Sparse Fuzzy Inference Systems
SD	Steepest Descent
SVD	Singular Value Decomposition
SVM(s)	Support Vector Machines
S^3VM	Semi-Supervised Support Vector Machines
SVR	Support Vector Regression
TLS	Total Least Squares
TS	Takagi-Sugeno
TSK	Takagi-Sugeno-Kang
TSVM	Transductive Support Vector Machines
UCI	University of California Irvine (Machine Learning Repository)
VQ	Vector Quantization
WEKA	Waikato Environment for Knowledge Analysis
WLS	Weighted Least Squares (solution)
WTLS	Weighted Total Least Squares

Mathematical Symbols

Here we give an overview of mathematical symbols used repetitively in this book and having the same meaning in all the chapters. The definition of further used symbols, dedicated to and only appearing in combination with specific approaches, methods and algorithms, are given in the text.

N	Number of training samples (seen so far)
p	Dimensionality of the learning problem = the number of input features/variables
$\mathbf{x}$	One (current) data sample, containing p input variables
$\mathbf{x}(k)$ or $\mathbf{x}_k$	The kth data sample in a sequence of samples
$\{x_1, ..., x_p\}$	Input variables/features
y	Measured output/target value for regression problems
$\hat{y}$	Estimated output/target value for regression problems
$\hat{y}_i$	Estimated output/target value from the ith rule in a fuzzy system
m	Polynomial degree of the consequent function, regression model
r, reg	Regressors
X or R	Regression matrix
P	Inverse Hessian matrix
Jac	Jacobian matrix
C	Number of rules, clusters
Φ	Set of parameters (in fuzzy systems)
Φ_{lin}	Set of linear parameters
Φ_{nonlin}	Set of non-linear parameters
$\mathbf{c}_i$	Center vector of the ith rule, cluster
$\boldsymbol{\sigma}_i$	Ranges of influence/widths vector of the ith rule, cluster
cov_{ij}	Covariance between features x_i and x_j
Σ	Covariance matrix

win	Indicates the index of the winning rule, cluster (nearest to sample $\mathbf{x}$)
$\{\mu_{i1}, ..., \mu_{ip}\}$	Antecedent fuzzy sets of the ith rule (for p inputs)
$\mu_i(\mathbf{x})$	Membership/Activation degree of the ith rule for the current sample $\mathbf{x}$
$\Psi_i(\mathbf{x})$	Normalized membership degree of the ith rule for the current sample $\mathbf{x}$
l_i	Consequent function, singleton (class label) in the ith rule
$\{w_{i0}, ..., w_{ip}\}$	Linear weights in the consequent function of the ith rule
L_r	Real class label of a data sample in classification problems
L	Output class label for classification problems (from a fuzzy classifier)
L_i	Output class label of the ith rule (cluster)
K	Number of classes in classification problems
$conf_{ij}$	Confidence of the ith rule in the jth class
$conf_i$	Confidence of the ith rule to its output class label
$conf$	Overall confidence of the fuzzy classifier to its output class label
Small Greek letters	Various thresholds, parameters in the learning algorithms