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Author Index

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Table of Contents

Scroll to the title and select a **Blue** link to open a paper.

Robust Radial Basis Function Networks Based on Least Trimmed Squares-Support Vector Regression 1
Shun-Feng Su, Jin Tsong Jeng, Yue-Shiang Liu, Chen-Chia Chung and Imre J. Rudas

An Extended Numerical Analysis of an Intuitionistic Fuzzy Classifier for Imbalanced Classes 7
Eulalia Szmidt, Janusz Kacprzyk and Marta Kukier

Evolutionary Fuzzy Classifiers for Imbalanced Datasets: An Experimental Comparison 13
Michela Antonelli, Pietro Ducange, Francesco Marcelloni and Armando Segatori

Convergence Analysis of an Elitist Non-homogeneous Genetic Algorithm with Mutation Probability Adjusted by a Fuzzy Controller 19
André G. C. Pereira, Jose A.F. Roveda, Luiz Amorim Carlos, Viviane Simioli Medeiros Campos and Sandra R.M.M. Roveda

A New Granular Particle Swarm Optimization Variant for Granular Optimization Problems 24
Guohua Wu, Witold Pedrycz, Dishan Qiu and Manhao Ma

A Quantum-inspired Evolutionary Algorithm for Fuzzy Classification 29
Waldir Nunes, Marley Vellasco and Ricardo Tanscheit

Dimensions of L-semilinear Spaces over Zerosumfree Semirings 35
Shu Qianyu and Wang Xueping

Quantitative Domains via Fuzzy Sets: Locally order Preserving Functors 41
Su Shuhua, Li Qingguo and Chen Huodi

Reflective Categories of Cut Systems and Fuzzy Sets in Ω-sets 45
Jiří Močkoř

Generating Embedded Type-1 Fuzzy Sets by means of Convex Combination 51
Omar Salazar and Jairo Soriano

Pythagorean Fuzzy Subsets 57
Ronald R. Yager

On Properties of Fuzzy Ideals 62
Flaulles Boone Bergamaschi and Regivan H. N. Santiago

Big Data Granulation Challenges 68
Marcin Kowalski and Dominik Slezak

An evolutionary fuzzy system for the detection of exceptions in subgroup

discovery 74
Cristóbal J. Carmona, Pedro González, María José Del Jesus,Beatriz García-Domingo and Jorge Aguilera

Optimized Feature Selection using Neuroevolution of Augmenting Topologies (NEAT) 80
Soroosh Sohangir, Shahram Rahimi and Bidyut Gupta

Neighborhood Rough Sets based Multi-label Classification 86
Ying Yu, Witold Pedrycz, Duoqian Miao and Hongyun Zhang

Rule Induction Based on Rough Sets from Information Tables Containing Possibilistic Information 91
Michinori Nakata and Hiroshi Sakai

Centroids of Fuzzy Sets When Membership Functions Have Spikes 97
Janet Aisbett and John T. Rickard

Combining Chain-Ladder Claims Reserving with Fuzzy Numbers 102
Jochen Heberle and Anne Thomas

Linguistic Weighted Standard Deviation 108
Minshen Hao and Jerry M. Mendel

A Fuzzy Structuralist View on the Analytical Philosophy of Medicine 114
R. Seising

Compressing the representation of a causal graph 122
C. Puente, E. Garrido, J. A. Olivas and R. Seisdedos

A Public Health Decision Support System Framework Using Approximate Reasoning methods 128
Nick. J. Pizzi

Possibilistic Stackelberg Solutions to Bilevel Linear Programming Problems with Fuzzy Parameters 134
H. Katagiri, K. Kato and T. Uno

Route Planning Problem under Fuzzy Sightseeing Times and Satisfaction Values of Sightseeing Places 140
T. Hasuike, H. Katagiri, H. Tsubaki and H. Tsuda

Channel Coordination in the Supply Chain with the One-shot Decision Theory 146
X. Ma, C. Wang and P. Guo

Operations on Bounded Fuzzy Lattices 151
Ivan Mezzomo, Benjamin Bedregal and Regivan H. N. Santiago

alpha-Ideals of Fuzzy Lattices 157
Ivan Mezzomo, Benjamin Bedregal and Regivan H. N. Santiago

Partial Orders on the Truth Value Algebra of Finite Type-2 Fuzzy Sets 163

John Harding, Carol Walker and Elbert Walker

Fixed Point Theorems in Fuzzy Metric Spaces *169*
Shaban Sedghi

The design of a CUSUM control chart for LR-fuzzy data *171*
Dabuxilatu Wang and Olgierd Hryniewicz

Context Modeling for the Clinical Predictors of Obstructive Sleep Apnea *181*
M. Kwiatkowska, J. Matthews and L. Matthews

A Preliminary Fuzzy Model for Screening Obstructive Sleep Apnea *187*
J. M. Matthews, M. Kwiatkowska and L. R. Matthews

Fuzzy Braunwald–Modified Chest Pain Assessment for Unstable Angina *192*
Angela S. K. Takesaki, Ernesto Araujo, Ricardo Simoes and Reinaldo G. I. Arakaki

Consumption-Investment Problems with the One-Shot Decision Theory *198*
Y. Li, P. Guo

The Karush-Kuhn-Tucker Optimality Conditions for a Class of Fuzzy Optimization problems using strongly generalized derivative *203*
Y. Chalco-Cano, W. A. Lodwick and H. Roman-Flores

Necessary Efficiency is Partitioned into Possible and Necessary Optimalities *209*
M. Inuiguchi

Formal Concept Analysis on Fuzzy Sets *215*
Lili Shen and Dexue Zhang

Toward Reduction of Formal Fuzzy Context *221*
Radim Belohlavek and Jan Konecny

Linear-Algebraic Representation of Generalised Fuzzy Petri Nets *226*
Zbigniew Suraj

Construction Project Risk Assessment Using Combined Fuzzy and FMEA *232*
Amir Mohammadi and Mehdi Tavakolan

A Relationship Hierarchy Structural Fuzzy ANP Model to Explore Development of Marketing Strategic Alliances *238*
Tsuen-Ho Hsu and Jia-Wei Tang

Interval-based Analysis of BOCR (Benefits, Opportunities, Costs and Risks) Models Evaluated by Multiple Experts *244*
K. Krishna Mohan, Marek Z. Reformat, and Witold Pedrycz

A Decision Support System for ICU Readmissions Prevention *251*
Susana M. Vieira, Joao P. Carvalho, Andre S. Fialho, S. R. Reti,S. N. Finkelstein and Joao M.C. Sousa

Acceptability and Difficulties of (Fuzzy) Decision Support Systems in

Clinical Practice *257*
Christian J. Schuh, Jeroen S. de Bruin and Walter Seeling

Optimization of Value-at-Risk Portfolios in Uncertain Lognormal Models *263*
Y. Yoshida

Relative evaluation of criteria for cooperative interval AHP in group decision making *269*
T. Entani

The Contributions of K. Asai and H. Tanaka in Fuzzy Optimization *274*
M. Inuiguchi and W. A. Lodwick

Constructing Dense Fuzzy Systems by Adaptive Scheduling of Optimization Algorithms *280*
Krisztián Balázs and Laszló T. Kóczy

Simulated Annealing-Based Optimization of Fuzzy Models for Magnetic Levitation Systems *286*
Claudia-Adina Dragos, Radu-Emil Precup, Radu-Codrut David, Emil Petriu, Stefan Preitl and Alexandra-Iulia Stinean

Multi-objective Iterative Genetic Approach for Learning Fuzzy Classification Rules with Semantic-based Selection of the Best Rule *292*
Edward C. Hinojosa and Heloisa A. Camargo

Hierarchical Genetic Algorithm for Type-2 Fuzzy Integration Applied to Human Recognition *298*
Daniela Sanchez and Patricia Melin

Dental Classification for Periapical Radiograph based on Multiple Fuzzy Attribute *304*
Martin L. Tangel, Chastine Fatichah, Fei Yan, Janet P. Betancourt,M. Rahmat Widyanto, Fangyan Dong and Kaoru Hirota

Face Recognition based on Fuzzy Probabilistic SOM *310*
Laura Lanzarini, Franco Ronchetti, César Estrebou,Aurelio Fernandez Bariviera and Luciana Lens

Intuitionistic Fuzzy Choquet Integrals and their Application in Modeling Linguistic Quantifiers *315*
Yongming Li and Lu Li

A Linguistic Quantifier-Based Approach for Skyline Refinement *321*
Katia Abbaci, Allel Hadjali, Ludovic Liétard and Daniel Rocacher

Modeling Linguistic Probabilities and Linguistic Quantifiers Using Interval Type-2 Fuzzy Sets *327*
Mohammad Reza Rajati and Jerry M. Mendel

Some Results of Interval-valued Fuzzy Relational Equations with

sup-conjunctor composition 333
Xiong Qingquan and Wang Xueping

Box Math and KSM: Extending Sherman--Morrison to Functions of Interval Matrices 338
Ralph Kelsey

Interval-Valued Fuzzy Associative Memories Based on Representable Conjunctions with Applications in Prediction 344
Peter Sussner and T Schuster

Determining Beach Closures Necessary to Protect Bull Shark (Carcharhinus leucas) Species (and Bathers): A Fuzzy Rule-Based Model 350
Margaret F. Shipley and J. Brooke Shipley-Lozano

Mining Fuzzy Rules Based on Pattern Trees 356
Xinghua Feng and Xiaodong Liu

A Fuzzy-Genetic System for Rule Extraction from Support Vector Machines 360
Cintia F. F. Carraro, Marley Vellasco and Ricardo Tanscheit

Approximation Properties of Higher Order Takagi-Sugeno Fuzzy Systems 368
Barnabas Bede and Imre J. Rudas

Fuzzy Relational Structures: Learning Alternatives for Fuzzy Modeling 374
Orion Fausto Reyes-Galaviz and Witold Pedrycz

Fuzzy Systems Modeling with Participatory Evolution 380
Yi Ling Liu and Fernando Gomide

Intuitive Decision-Making Using Hyper Similarity Matching 386
Ronald R. Yager and Fred E. Petry

A Similarity Measure with Uncertainty for Incompletely Known Fuzzy Sets 390
Anna Stachowiak and Krzysztof Dyczkowski

Fuzzy Semantic Similarity in Linked Data using Wikipedia Infobox 395
Parisa D. Hossein Zadeh and Marek Z. Reformat

Two Evolutionary Computation Approaches for Active Power Losses Minimization in Smart Grids 401
F. Possemato, G. L. Storti, M. Paschero, A. Rizzi and F. M. F. Mascioli

Optimal Distribution Feeders Configuration for Active Power Losses Minimization by Genetic Algorithms 407
G. L. Storti, F. Possemato, M. Paschero, A. Rizzi and F. M. F. Mascioli

The Design of Fuzzy C-Means Clustering based Neural Networks for Emotion Classification 413
Byoung-Jun Park, Eun-Hye Jang, Sang-Hyeob Kim, Chul Huh and Myoung-Ae Chung

Genetic Optimization of a Fuzzy Control System for Energy Flow

Management in Micro-Grids 418
E. De Santis, A. Rizzi, A. Sadeghian and F. M. F. Mascioli

A new Approach based on Generalized Type-2 Fuzzy Logic for Edge Detection 424
Claudia I. Gonzalez, Juan R. Castro, Gabriela E. Martinez, Patricia Melin and Oscar Castillo

Improved Fuzzy-Based Single-Stroke Character Recognizer 430
Alex Tormási and László T. Kóczy

An approach to improve semantics in Smart Spaces using reactive fuzzy rules 436
Natalia Díaz Rodríguez, Johan Lilius, Manuel Pegalajar Cuéllar and Miguel Delgado Calvo-Flores

Semantic Similarity Measure in Ontology Alignment 442
Valerie Cross, P. Silwal and Xi Chen

Searching optimal product bundles by means of GA-based Engine and Market Basket Analysis 448
C. Birtolo, D. D. Chiara, S. Losito, P. Ritrovato and M. Veniero

Estimating Third Central Moment C3 for Privacy Case under Interval and Fuzzy Uncertainty 454
A. Jalal-Kamali and V. Kreinovich

An Overview of the Upcoming IEEE P-1788 Working Group Document: Standard for Interval Arithmetic 460
R. B. Kearfott

Back to the Future: Advanced Control Techniques Justify–on a New Level–Traditional Education Practices 466
O. Kosheleva, K. Villaverde and S. D. Cabrera

Fuzzy Theory in Cognition, Economic Man and Organization Behavior 471
F. S. Nobre

Towards Intelligent Mining of Public Social Networks' Influence in Society 478
J P. Carvalho, V. C. Pedro and F. Batista

Quality of work and elderly care - Preliminary experiments 484
G. Facchinetti, G. Solinas and T. Pirotti

A Novel Fuzzy Associative Classifier Based on Information Gain and Rule-Covering 490
Yue Ma, Guoqing Chen and Qiang Wei

Theoretical Examination of Clustering Structure in Fuzzy Joint Points Method 496
Gözde Ulutagay

From Clustering to Granular Clustering: A Granular Representation of Data in Pattern Recognition and System Modeling 502
Adam Gacek

Clustering of Web Search Results based on an Iterative Fuzzy C-means Algorithm and Bayesian Information Criterion *507*
C. Cobos, M. Mendoza, E. León, M. Manic, E. Herrera-Viedma

Creating a Natural Language Summary from a Compressed Causal Graph *513*
C. Puente, E. Garrido, J. A. Olivas, R. Seisdedos

Enhancing Knowledge Management Capabilities in Web-based Decision Aids using Fuzzy Prototypes and Data Quality Criteria *519*
Francisco P. Romero, Jose A. Olivas Ismael Caballero, Jesus Serrano-Guerrero and Mauro J. Oruezabal

Likert-Scale Fuzzy Uncertainty from a Traditional Decision Making Viewpoint: It Incorporates Both Subjective Probabilities and Utility Information *525*
J. Lorkowski and V. Kreinovich

Sparse Fuzzy Techniques Improve Machine Learning *531*
R. Sanchez, C. Servin and M. Argaez

Towards Fuzzy Method for Estimating Prediction Accuracy for Discrete Inputs, with Application to Predicting At-Risk Students *536*
X. Wang, M. Ceberio and A. F. G. Contreras

An Overview of Fuzzy–Logic Based Approaches to Ecology: Addressing Uncertainty *540*
F. A. Pouw and M. Kwiatkowska

Ordered Fuzzy Numbers in Financial Stock and Sccounting Problems *546*
W. Kosinski and A. Chwastyk

How to Face the Arab Spring using Fuzzy Logic *552*
G. Facchinetti, G. Mastroleo and G. Ricci

“Beyond GDP”: a Fuzzy Way to Measure the Country Wellbeing *556*
L. Anzilli, G. Facchinetti, G. Mastroleo

Reduction Fuzzy Social Computing for Gross National Income Cross–Country Comparison *561*
E. Araujo

A Granular Recursive Fuzzy Meta-clustering Algorithm for Social Networks *567*
Kishore Rathinavel and Pawan Lingras

Growing Rule-based Fuzzy Model Developed with the Aid of Fuzzy Clustering *573*
W.-D. Kim, S.-K. Oh, K.-S. Seo and W. Pedrycz

How Deep Data Becomes Big Data *579*
Marcin Szczuka and Dominik Slezak

Finding an λ-Representative Subset from Massive Data *585*

Jin Zhang, Qiang Wei and Guoqing Chen

A note on "Solving Fuzzy Linear Programming Problems with Interval Type-2 RHS" *591*
J. C. F. Garcıa and G. Hernandez

Solving Multiobjective Programming Problems With Fuzzy Objective Functions *595*
M. K. Luhandjula

Fuzzy Set Based Multicriteria Decision Making in Power Engineering Problems *599*
G. B. Alves, P. Ya. Ekel, I. V. Kokshenev, R. O. Parreiras, H. S. Schuffner and P. M. N. Souza

A Proposal of a Linguistic Group Decision Model to Support Public Decisions in Brazil *605*
V. B. S. Silva and D. C. Morais

Data Anonymization that Leads to the Most Accurate Estimates of Statistical Characteristics: Fuzzy-Motivated Approach *611*
G. Xiang, S. Ferson, L. Ginzburg, L. Longpre, E. Mayorga and O. Kosheleva

How to Generate Worst-Case Scenarios When Testing Already Deployed Systems Against Unexpected Situations *617*
F. Zapata, R. Pineda and M. Ceberio

Solving Linear Programming Problems with Interval Type-2 Fuzzy Constraints using Interval Optimization *623*
Juan Carlos Figueroa Garcia and German Hernandez

The Negation in the Checklist Paradigm based m_2 Non-Commutative Fuzzy Interval Logic System of Goguen and Gaines *629*
Eunjin Kim

Neural Network with Lower and Upper Type-2 Fuzzy Weights using the Backpropagation Learning Method *637*
Fernando Gaxiola, Patricia Melin and Fevrier Valdez

A Gaussian Process Echo State Networks Model for Time Series Forecasting *643*
Ying Liu, Jun Zhao and Wei Wang

The Linguistic Forecasting of Time Series based on Fuzzy Cognitive Maps *649*
Wei Lu, Jianhua Yang and Xiaodong Liu

Design of Face Recognition Algorithm Realized with Feature Extraction from 2D-LDA and Optimized Polynomial-based RBF NNs *655*
S.-H. Yoo, S.-K. Oh and W. Pedrycz

Optimizing Fuzzy Control of Energy Harvesting Remote Monitoring Systems *661*
A. G. Watts, P. Musilek and L. Wyard-Scott

Non-parametric Interval Forecast Models from Fuzzy Clustering of

Numerical Weather Predictions *667*
A. Zarnani and P. Musilek

The Fuzzy Set of Computer Science *673*
R. Seising

Technology and human sciences: a dialogue to be constructed or a common tread to be rediscovered? *679*
F. A. D'Asaro, V. Perticone, M. E. Tabacchi and S. Termini

Quest for Rigorous Intelligent Tutoring Systems under Uncertainty: Computing with Words and Images *685*
B. Kovalerchuk

Perceptual Computing in Social Networks *691*
John T. Rickard and Ronald R. Yager

Using Tagging in Social Networks to Find Groups of Compatible Users *697*
Marek Z. Reformat and Ronald R. Yager

Fuzzy regular tree expressions *703*
Xiaofeng Huang, Zhiwen Mo and Lan Shu

A comparative analysis of pruning strategies for fuzzy decision trees *709*
Mariana V. Ribeiro, Heloisa A. Camargo and Marcos E. Cintra

Fuzzy Pattern Trees as an Alternative to Rule-based Fuzzy Systems: Knowledge-driven, Data-driven and Hybrid Modeling of Color Yield in Polyester Dyeing *715*
Maryam Nasiri, Thomas Fober, Robin Senge and Eyke Hüllermeier

Identification of Atmospheric Pressure Troughs using Image Processing Techniques *722*
Y. Li, P. Musilek and E. Lozowski

An Image Recognition Approach to Classification of Jewelry Stone Defects *727*
P. Hurtik, M. Burda and I. Perfilieva

Recognition of Distorted Characters Printed on Metal using Fuzzy Logic Methods *733*
V. Novak, P. Hurtık and H. Habiballa

A Very Brief History of Soft Computing: Fuzzy Sets, Artificial Neural Networks and Evolutionary Computation *739*
R. Seising and M. E. Tabacchi

Twenty Years Later: Remarks on a Polemic *745*
E. Trillas

An Algorithm for Routes Recommendation Service Based on the Radio-Frequency Identification Application *748*
Y. Zhao, X. Gao and S. Wu

An Online Fuzzy Decision Support System for Resource Management in Cloud Environments *754*
F. Ramezani, J. Lu and F. Hussain

An Intelligent Recommender System for Personalized Fashion Design *760*
X. Zeng, L. Koehl, L. Wang and Y. Chen

Fuzzy Love Selection by Means of Perceptual Computing *766*
M. M. Korjani and J. M. Mendel

Eliciting Comparative Linguistic Expressions in Group Decision Making *771*
R. M. Rodrıguez, L. Martinez and F. Herrera

Fuzzy Linguistic Multicriteria Morphological Analysis in Scenario Planning *777*
P. J. Villacorta, A. D. Masegosa and M. T. Lamata

Classification of Damages on Jewelry Stones: Preprocessing *783*
I. Perfilieva, P. Hodakova, M. Vajgl and M. Dankova

Comparison of Fuzzy Rules and SVM Approach to the Value Estimation of the Use Case Parameters *789*
J. Štolfa, O. Koběrský, P. Krömer, S. Štolfa, M Kopka and V. Snášel

Facility Location Problems with Fuzzy Demands Based on Parametric Assessment *795*
Pei-Chun Lin, Junzo Watada and Berlin Wu

Using the Fuzzy Sets Theory in the Multimodal Transport Network Problem *801*
Juliana Verga, Ricardo Coelho Silva, Akebo Yamakami and Wesley V. I. Shirabayashi

Solution of a Fuzzy Resource Allocation Problem by Various Evolutionary Approaches *807*
Zsolt Dányádi, Péter Földesi and László T. Kóczy

A Fuzzy Tree Similarity Based Recommendation Approach for Telecom Products *813*
D. Wu, G. Zhang and J. Lu

An Approach for Incremental Maintenance of Approximations in Set-valued Ordered Decision Systems while Updating Criteria Values *819*
C. Luo, L. Lu, T. Li, A. Zeng and H. Chen

A hybrid model for migrating customer segmentation with missing attributes *825*
J. Ma, H. Lin, J. Lu and G. Zhang

Using a Semisupervised Fuzzy Clustering process for Identity Identification in Digital Libraries *831*
Irene Diaz-Valenzuela, Maria J.Martin-Bautista and M. Amparo Vila

Predicting the Outcome of Brace Treatment for Scoliosis Using Conditional Fuzzy Clustering *837*
Eric Chalmers, Witold Pedrycz and Edmond Lou

Applications of Realizable Boolean Matrices in Graph Theory *843*
Feng Sun, Xiao-Bing Qu, Tian-Fei Wang and Xue-Ping Wang

OWAD Operators in Type-2 Fuzzy Ontologies *848*
Jozsef Mezei and Robin Wikström

Psychologists: Are They Logically Fuzzy? *854*
Mark Wierman

Aggregating α-planes for Type-2 Fuzzy Set Matching *860*
L. Livi, H. Tahayori, A. Sadeghian and A. Rizzi

Matching General Type-2 Fuzzy Sets by Comparing the Vertical Slices *866*
A. Rizzi, L. Livi, H. Tahayori and A. Sadeghian

Managing Natural Noise in Collaborative Recommender Systems *872*
R. Y. Toledo, L. M. López and Y. C. Mota

Statistical Fault Localization in Decision Support System Based on Probability Distribution Criterion *878*
P. Hao, Z. Zheng, Y. Gao and Z. Zhang

An Interval Type-2 Neural Fuzzy Inference System (IT2NFIS) with Compensatory Operator *884*
Yang-Yin Lin, Jyh-Yeong Chang and Chin-Teng Lin

Advanced Learning of Fuzzy Cognitive Maps of Waste Management by Bacterial Algorithm *890*
Adrienn Buruzs, Miklós Ferenc Hatwágner, Claudiu Radu Pozna and László T. Kóczy

Networked Fuzzy Belief Rule-Based System for Spatiotemporal Monitoring *896*
Farzad Aminravan, Rehan Sadiq, Mina Hoorfar, Manuel J. Rodriguez, Alex Francisque and Homayoun Najjaran

The Look-up Table Controllers and a Particular Class of Mamdani Fuzzy Controllers Are Equivalent – Implications to Real-World Applications *902*
Dimitar Filev and Hao Ying

Fuzzy systems of Mamdani type in the LU representation *908*
Matthew P. Peterson, Barnabas Bede and Luciano Stefanini

Cybernetic Theory of Informational Modeling of Teacher's Behavior in the Learning Process based on Fuzzy Logic *914*
Shahnaz N. Shahbazova

Towards Retranslation of Fuzzy Values in Computing with Words *922*
Nina Marhamati, Purvag Patel, Elham S. Khorasani and Shahram Rahimi

Computing with Prepositions: Syntax *929*
Lauren M. Stuart, Julia M. Taylor and Victor Raskin

Computing With Prepositions: Fuzzy Semantics *934*
Julia M. Taylor, Victor Raskin and Lauren M. Stuart

Selecting the Best Taste: a Group Decision-making Application to Chocolates Design *939*
N. Agell, G. Sanchez, M. Sanchez and F. Javier Ruiz

Challenges and Open Questions in Soft Consensus Models *944*
F.J. Cabrerizo, F. Chiclana, M.R. Urena and E. Herrera-Viedma

Fuzzy Reasoning for Medical Diagnosis based on Subjective Attributes and Objective Attributes Alignment *950*
H. Fujita

Fuzzy Granular Principal Curves Algorithm for Large Data Sets *956*
Hongyun Zhang, Witold Pedrycz and Duoqian Miao

A Visualization Method of Third-Order Tensor for Knowledge Extraction from Questionnaire Data *962*
Hiroaki Masai, Tomohiro Yoshikawa and Takeshi Furuhashi

On Soft Measurements and Data Mining Based on Granular Pragmatics, Multi-Valued and Fuzzy Logics *968*
Valery B. Tarassov and Maria N. Svyatkina

Granular Regression *974*
Przemyslaw Grzegorzewski

Outlier Detection Approaches in Fuzzy Regression Models *980*
Chao Wang and Peijun Guo

On Pseudo Gradient Search for Solving Nonlinear Multiregression with the Choquet Integral *986*
Bo Guo, Li Zhang-Westman and Zhenyuan Wang

A Type 2 Fuzzy Multi Agent based System for Scheduling of Steel Production *992*
M. H. Fazel Zarandi and F. Kashani Azad

A New Diamond Shape Architecture based on Multi Agents for Supply Chain in an uncertain Environment *997*
M.H Fazel Zarandi, B.Bahrami, M.Sayad and I.B. Türkşen

A Fuzzy Hybrid Intelligent Agent System for Mitigating Demand Amplification in Supply Chain of Steel Manufacturing *1003*
R. Gamasaee and M.H. Fazel Zarandi

Consensus-based Hierarchical Agglomerative Clustering in the Context of Weak Orders *1010*
J. L. Garcıa-Lapresta and D. Perez-Roman

Aggregating fuzzy implications to measure group consensus *1016*
G. Beliakov, S. James and T. Calvo

New Classes of Threshold Aggregation Functions Based upon the Tsallis q-Exponential *1022*
John T. Rickard and Janet Aisbett

On Consistent Induced Matrix Aggregation Operators *1028*
Daowu Pei, Yuying Shan and Huanzhang Liu

Consistency and Stability in Aggregation Operators with Data Structure *1034*
Daniel Gomez, Javier Montero, J. Tinguaro Rodrıguez and Karina Rojas

Ranking Fuzzy Numbers by Their Left and Right Wingspans *1039*
Li Zhang-Westman and Zhenyuan Wang

The Cardinality of the Set of All Fuzzy Numbers *1045*
Zhenyuan Wang and Li Westman

Type-2 Fuzzy Numbers and Operations by F-transform *1050*
Luciano Stefanini and Laerte Sorini

Statistical Comparison of Type-1 and Type-2 Fuzzy Systems Design with Genetic Algorithms in the Case of Three Tank Water Control *1056*
Leticia Cervantes and Oscar Castillo

Comparison of Fuzzy Controllers for the Water Tank Problem with Type-1 and Type-2 Fuzzy Logic *1062*
Leticia Amador-Angulo, Oscar Castillo and Martha Pulido

Design of Optimal Membership Functions for Fuzzy Controllers of the Water Tank and Inverted Pendulum with PSO Variants *1068*
Resffa Fierro, Oscar Castillo, Fevrier Valdez and Leticia Cervantes

Line-shaped Non-precipitation Echo Detection using Fuzzy Inference System *1074*
Hansoo Lee, Ji Chul Park, Jong Geun Kim and Sungshin Kim

Unifying Fuzzy controller for Indoor Environment Quality *1080*
Miguel Molina-Solana, Maria Ros and Miguel Delgado

Reconstruction of the Environmental Quality Fuzzy Index *1086*
José Arnaldo F. Roveda, Ana Carolina do Amaral Burghi and Sandra R. M. M. Roveda

A Preliminary Approach to Classify Work Descriptions in Construction Projects *1090*
M. Martınez-Rojas, N. Marın and M. A. Vila

Application of Granular Fuzzy Modeling for Abstracting Labour Productivity Knowledge Bases *1096*
A. A. Tsehayae W. Pedrycz and A. Robinson Fayek

Developing a Fuzzy Discrete Event Simulation Framework within a Traditional Simulation Engine *1102*
N. Sadeghi, A. Robinson Fayek and S. P. Mosayebi

Human Motion Recognition through an Adaptive Fuzzy Estimation of Inertial Sensing *1107*
Jesus A. Garcia and Leocundo Aguilar

Internet Service for the Analysis of Enterprise Economics using Time Series Fuzzy Modeling *1113*
I.G. Perfilieva, N.G. Yarushkina, T.V. Afanasieva, and A.A. Romanov

Intelligent Hybrid-Learning Mechanism for IT2 TSK NSFLS2 Composed by REFIL-BP Methods *1119*
Gerardo M. Méndez and M. A. Hernández

A Multi-Stage Expert System for Classification of Pavement Cracking *1125*
H. Zakeri, F. Moghadas Nejad, A. Doostparast Torshizi, M. H. Fazel Zarandi, A. Fahimifar

A new Image Enhancement Method Type-2 Possibilistic C-Mean Approach *1131*
M.H. Fazel Zarandi, M. Zarinbal

Possibilistic C-Means Clustering Using Fuzzy Relations *1137*
M. H. Fazel Zarandi M. Rostam Niakan Kalhori M. F. Jahromi

Enhanced Fuzzy Evidential Reasoning using an Optimization Approach for Water Quality Monitoring *1143*
Farzad Aminravan, Rehan Sadiq, Mina Hoorfar, Manuel Rodriguez and Homayoun Najjaran

A Fuzzy Rule-Based Approach for Water Quality Assessment in the Distribution Network *1149*
Elaheh Aghaarabi, Farzad Aminravan, Rehan Sadiq, Mina Hoorfar, Manuel J. Rodriguez and Homayoun Najjaran

Fuzzy Index for Public Supply Water Quality *1155*
Jose A.F. Roveda, Larissa T. Arashiro, Sandra R.M.M. Roveda and Jessica M. Silverio

Fuzzy Consensus Qualitative Risk Analysis Framework for Building Construction Projects *1160*
A. M. Aboushady, M. M. Marzouk and M. M. G. Elbarkouky

A Hybrid Fuzzy C-Means Clustering-AHP Framework to Select Construction Contractors *1166*
M. M. G. Elbarkouky, A. M. El-Deep and M. M. Marzouk

Fuzzy Dynamic Programming for Optimized Scheduling of Repetitive Construction Projects *1172*
I. Bakry, O. Moselhi, and T. Zayed

Quantitative and Qualitative Risk in EPCM Projects Using Fuzzy Set Theory *1177*
A. Salah and O. Moselhi

Fuzzy Operators for Quality Evaluation in Images Edge Detection *1182*
Felicitas Perez-Ornelas, Olivia Mendoza, Patricia Melin and Juan R. Castro

Fuzzy Logic to Determine Poverty Levels in a Society *1188*
Alberto Ochoa, Saúl González, Fernando Maldonado and Daniel Azpeitia

Ant Colony Optimization for Solving the TSP Symmetric with Parallel Processing *1192*
Fevrier Valdez and Ivan Chaparro

Fuzzy Logic for Dynamic Adaptation in PSO with Multiple Topologies *1197*
Juan Carlos Vazquez and Fevrier Valdez

Difficulties in Choosing a Single Final Classifier from Non-Dominated Solutions in Multiobjective Fuzzy Genetics-Based Machine Learning *1203*
H. Ishibuchi and Y. Nojima

A Design of FCM-based Interval Type-2 Fuzzy Neural Network Classifier with the Aid of PSO *1209*
W.-D. Kim, S.-K. Oh K.-S. Seo and W. Pedrycz

Dual centers Fuzzy Type-2 Clustering *1215*
M. H. Fazel Zarandi, S. MalekMohamadi Golsefid and S. Bastani

Fuzzy Type-2 c-ellipses Clustering *1221*
S. MalekMohamadi Golsefid, M. H. Fazel Zarandi and S. Bastani

A Conceptual Method for Modeling Residential Utility Consumption Using Complex Fuzzy Sets *1227*
J. Ma, R. Wickramasuriya, M. Safari, T. Davies and P. Perez

Why Complex-Valued Fuzzy? Why Complex Values in General? A Computational Explanation *1233*
O. Kosheleva, V. Kreinovich and T. Ngamsantivong

Fuzzy in 3-D: Contrasting Complex Fuzzy Sets with Type-2 Fuzzy Sets *1237*
S. Greenfield and F. Chiclana

Predicting Solar Power Output using Complex Fuzzy Logic *1243*
O. Yazdanbaksh, A. Krahn and S. Dick

Fuzzy Logic as a Geometry *1249*
Peter Lawrence Belluce, Antonio Di Nola and Giacomo Lenzi

Query Answering over Fact Bases in Fuzzy Propositional Logic *1252*
Gerald S. Plesniewicz

On Classic-like Fuzzy Modal Logics *1256*
Adriano Alves Dodó, João Marcos and Flaulles Boone Bergamaschi

A System Based on Interval Fuzzy Approach to Predict the Appearance of Pests in Agriculture *1262*
Leonardo Martins Rodrigues, Graçaliz Pereiri Dimuro, Denis Teixeira Franco and José Carlos Fachinello

A Hybrid Method for IT2 TSK Formation based on the Principle of Justifiable Granularity and PSO for Spread Optimization 1268
Mauricio A. Sanchez, Juan Ramon Castro, Felicitas Perez-Ornelas and Oscar Castillo

Algorithm for Interval Linear Programming Involving Interval Constraints 1274
Ibraheem Alolyan

Bipolar Linguistic Summaries: a Novel Fuzzy Querying Driven Approach 1279
M. Dziedzic, J. Kacprzyk and S. Zadrozny

The Conceptual Framework of Fairness in Consensus Reaching Process Under Fuzziness 1285
J. Kacprzyk and D. Gołuńska

A New Measure of Groups Perturbation 1291
M. Krawczak and G. Szkatuła

The K-Modes Method using Possibility and Rough Set Theories 1297
Asma Ammar, Zied Elouedi and Pawan Lingras

Semantic Issues in Game-theoretic Rough Sets 1303
Nouman Azam and Jingtao Yao

Fuzzy Interval Decision-theoretic Rough Sets 1315
Dun Liu, Tianrui Li and Decui Liang

Exchange Rate Prediction Using Fuzzy System Neural Network Approach 1321
A. F.M. Khodadad Khan, Mohammed Anwer and Shipra Banik

A Development of Granular Logic Neural Networks 1327
Mingli Song, Yongbin Wang and Shujuan Wang

Generalized Type-2 Fuzzy Logic in Response Integration of Modular Neural Networks 1331
Gabriela E. Martinez, Olivia Mendoza, Juan Ramon Castro, Patricia Melin and Oscar Castillo

Uncertainty Quantification for Possibilistic/Probabilistic Simulation 1337
Thomas Whalen, Brad Morantz and Murray Cohen

Simultaneous Assessment of Teams in Collaborative Virtual Environments Using Fuzzy Naive Bayes 1343
Ronei Marcosde Moraes and Liliane S. Machado

Towards a Better Understanding of Space-Time Causality: Kolmogorov Complexity and Causality as a Matter of Degree 1349
Vladik Kreinovich and Andres Ortiz

Coreference Detection in XML Metadata 1354
M. Szymczak, S. Zadrozny and G. De Tre

Finite Automata with Imperfect Information as Tools for Accumulating Information *1360*
W. Homenda and W. Pedrycz

A Harmonization Model with Partial Fuzzy Knowledge *1366*
M. Rybnik and W. Homenda

Mining top-k Granular Association Rules for Recommendation *1372*
Fan Min and William Zhu

Multi-objective Cost-sensitive Attribute Reduction *1377*
Bingxin Xu, Huiping Chen, William Zhu and Xiaozhong Zhu

Mean-value-based decision-theoretic shadowed sets *1382*
Xiaofei Deng and Yiyu Yao

Learning Aggregation Weights from 3-tuple Comparison Sets *1388*
Gleb Beliakov, Simon James and Dale Nimmo

Correlations from Conjugate and Dual Intuitionistic Fuzzy Triangular Norms and Conorms *1394*
Renata Reiser, Lidiane Visintin, Ibero Benıtez and Benjamin Bedregal

An Approach for Aggregation of Experts' Qualitative Evaluations by Means of Fuzzy Sets *1400*
Teimuraz V. Tsabadze

Type 1 Fuzzy Sets in Complex Control Applied to Evaluation of Resort Management System *1406*
Elisabeth Rakus-Andersson and Lujiao Tan

Application of Fuzzy Classification and Fuzzy Pattern Recognition for Distributed Production and Global Supply Chain *1412*
Dieter Roller and Erik Engesser

Genetic Optimization of Interval Type-2 Fuzzy Reactive Controllers for Mobile Robots *1418*
Abraham Melendez, Oscar Castillo and Patricia Melin

Nature Inspired Chemical Optimization to Design a Type-2 Fuzzy Controller for a Mobile Robot *1423*
Leslie Astudillo, Patricia Melin and Oscar Castillo

Fuzzy Separation Potential Function Based Flocking Control of Multiple AUVs *1429*
Basant Kumar Sahu, Madan M. Gupta and Bidyadhar Subudhi

Image Classification using Evolving Fuzzy Inference Systems *1435*
Ahmed A. Othman and Hamid R. Tizhoosh

Fuzzy clustering based encoding for Visual Object Classification *1439*
Danilo Dell'Agnello, Gustavo Carneiro, Tat-Jun Chin, Giovanna Castellano and Anna Maria Fanelli

Fuzzy Fractional-Order PID Controller Design using Multi-Objective Optimization 1445
Amir Hajiloo and Wen-Fang Xie

Study on Interval Fuzzy Series Forecasting based on GM(1,1) Model 1451
Xiangyan Zeng and Lan Shu

A Note on Gronwall Type Inequality for Interval Valued Functions 1455
Heriberto Roman-Flores, Yurilev Chalco-Cano and Geraldo N. Silva

An Ostrowski Type Inequality for Interval-valued Functions 1459
Arturo Flores-Franulic, Yurilev Chalco-Cano and Heriberto Roman-Flores

Characterizing Quantum Channels via Wigner-Yanase Skew Information 1463
Zhihua Zhang, Lan Shu, Zhiwen Mo and Jun Zheng

A Supervised Fuzzy Network Analysis for Risk Assessment in Stock Markets: An ANFIS Approach 1470
M.H. Fazel Zarandi, S.Farivar, I.B. Türkşen

Developing Type-2 Fuzzy FCA for Similarity Reasoning in the Semantic Web 1477
H. Safaeipour, M. H. Fazel Zarandi, I. B. Türkşen

Biogas Intelligence - operate Biogas Plants using Neural Network and Fuzzy Logic 1483
Christine Wahmkow, Maximilian Knape and Egon Konnerth

Fuzzy Defect Based Condition Assessment of Concrete Bridges 1489
Sami A. Moufti, Tarek Zayed and Saleh Abu Dabous

Pipeline Risk Assessment Using a Fuzzy Systems Network 1495
Gustavo Perez

An Approach to Issue of Diagnosing Marginal Oil Wells 1499
R.A.Guliyev

Space-time Support System using Simplified Time-Change Fuzzy Set 1502
Xiang Liu, Shibuya Takeshi and Yasunobu Seiji

Optimization of Type-2 Fuzzy Integration in Ensemble Neural Networks for Predicting the US Dolar/MX Pesos Time Series 1508
Martha Pulido, Patricia Melin and Oscar Castillo

Anomaly Detection in Time Series Data using a Fuzzy C-Means Clustering 1513
Hesam Izakian and Witold Pedrycz

Parameters to use a fuzzy rulebase approach to remap gridded spatial data 1519
Jörg Verstraete

An evolutionary fuzzy system for the detection of exceptions in subgroup discovery

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***Abstract*—Subgroup Discovery (SD) is a data mining technique whose main objective is the search for descriptions of subgroups of data that are statistically unusual with respect to a property of interest. General rules describing as many instances as possible are preferred in SD, but this can lead to less accurate descriptions that incorrectly describe some instances. These negative examples can be grouped into exceptions.**

The paper presents a new evolutionary fuzzy system for the detection of exceptions associated to rules previously obtained by a SD algorithm. Considering the initial subgroup and associated exceptions, the aim is to obtain a new description in order to increase the accuracy of the initial subgroup. This algorithm can be applied to the results of any SD algorithm. An experimental study shows the utility of the proposal, which is also applied in a real problem related to concentrating photovoltaic technology, providing useful information to the experts.

I. INTRODUCTION

SD [1]–[3] is a supervised induction technique which obtains descriptive rules through the use of supervised learning. The aim is to find interesting rules regarding a property of interest, in the sense that they provide unknown information, confirm information known by intuition or give extraordinary knowledge for experts. Knowledge extracted should be simple to be useful for experts, and sometimes the search for simplicity in SD algorithms can lead to a reduction of precision if general rules with negative examples are obtained.

The detection of these negative examples and their description using rules with exceptions [4] can improve the knowledge extracted on the property of interest. The modified subgroups including exceptions would not only improve the accuracy of SD rules but also offer novel and valuable knowledge to the experts.

SD task usually implies the optimisation of different quality measures related to precision, simplicity and interest aspects of SD descriptions, which are generally represented as rules and sometimes as fuzzy rules. Evolutionary algorithms are general propose search methods which have shown good behaviour for rule learning processes and multi-objective problems. The hybridization between multiobjective evolutionary algorithms and fuzzy systems is known as multiobjective fuzzy systems [5] and it has been successfully applied to SD task citeDghm07,Bdghm06.

This paper presents a new post-processing algorithm based on an evolutionary multi-objective fuzzy system for the detection of exceptions in subgroups. This proposal searches with a multiobjective approach for exceptions within subgroups previously obtained by any SD algorithm. In short the process is the following: exceptions composed of a small number of examples described by the subgroup corresponding to the opposite value of the target variable are detected for each initial SD rule. Then, it is obtained a new modified subgroup describing the initial subgroup and its exceptions.The performance of the algorithm is verified through an experimental study, and a case study related to the description of the behaviour of a kind of concentrating photovoltaic module is presented.

The paper is organised as follows: In Section II, the main concepts used in this paper are described. An algorithm for the detection of exceptions associated to SD rules is presented in Section III. In Section IV the experimental study can be observed, and Section V shows the case study. Finally, concluding remarks are outlined in Section VI.

II. RELATED WORK

A. Subgroup discovery

The concept of SD was initially introduced by Kloesgen [1] and Wrobel [2]. It has been defined as [6]:

"In subgroup discovery, we assume we are given a so-called population of individuals and a property of those individuals we are interested in. The task of subgroup discovery is then to discover the subgroups of the population that are statistically "most interesting", i.e., are as large as possible and have the most unusual statistical (distributional) characteristics with respect to the property of interest."

The main objective of the SD task is to extract descriptive knowledge concerning a property of interest ($TargetVar$) from the data [7]. The knowledge is represented by patterns that may characterise the data represented in such a way that domain experts can understand them. Thus, in SD it is not necessary to obtain complete but rather partial relations usually represented as rules:

$$R : Cond \rightarrow TargetVar \tag{1}$$

One of the most important aspects in a SD algorithm is the quality measures used to analyse the interest of the subgroups obtained. Throughout the literature, a wide range of quality measures have been employed, which can be divided into different groups depending on their main objective [3]: complexity, generality, precision, and interest.

Proposals for SD can be classified in extensions of classification algorithms (such as EXPLORA [1], MIDOS [2] or CN2-SD [8]), extensions of association algorithms (as APRIORI-SD [9] or SD-MAP [10]) and evolutionary fuzzy systems (EFSs) (SDIGA [11], MESDIF [12] or NMEEF-SD [13]). EFSs have demonstrated their ability to extract SD descriptions and specially NMEEF-SD is a robust EFS which obtains better results obtaining simple, accurate and interpretable SD fuzzy rules with respect to different complex real-world problems in a large number of applications. See [3] for an overview of SD algorithms, quality measures and applications.

B. Exception rule mining

An exception can be defined as something different from most of the rest [14]. Exception rule mining was introduced by Hussain et al. in [4] as the extraction of rules with low support and high confidence. The problem is that most data mining methods are focused on obtaining general rules with high support and confidence, which are considered as interesting. However, rules with low support could provide interesting and extraordinary knowledge to the experts.

Two different approaches can be distinguished when searching for exception rules [4]: directed (or subjective), which obtains a set of exception rules each of which contradicts to a user-specified belief; and undirected (or objective), which obtains a set of pairs of an exception rule and a general rule.

Applied to the results of any SD algorithm, the detection of undirect exceptions could lead to an improvement in the precision and description because small areas within subgroups with negative examples, i.e. incorrectly-described examples, are discovered and described.

III. A MULTI-OBJECTIVE EVOLUTIONARY FUZZY SYSTEM FOR DETECTION OF EXCEPTIONS IN SUBGROUPS

This section presents a post-processing algorithm for the detection of exceptions in SD. The main idea is the following: small areas formed by examples with the opposite value of the target variable of the initial subgroup are searched for. They describe exceptions to the knowledge represented by the subgroup. Next, with the initial subgroup and its exceptions, a new rule is obtained where precision and description are improved. This process is repeated for each SD rule.

This concept is graphically explained below. A subgroup for the target value *o* is represented in Fig. 1 as a grey circle. This subgroup covers all the examples of the value *o* of the target variable, also covering some examples of the other value of the target variable (value *x*), but the knowledge representation is simple and valuable for experts. However, these negative examples (shown in a dark grey) are exceptions of the subgroup.

The proposal is an multi-objective fuzzy system [5], [15] which is able to work in fuzzy and/or crisp domains obtaining

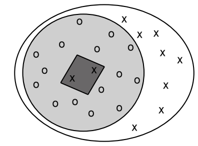

Fig. 1. Detection of exceptions within a subgroup

modified subgroups which are formed by initial subgroups and their exceptions. Specifically, this algorithm will obtain crisp modified subgroups if the initial subgroups are crisp and fuzzy subgroups if they are fuzzy. The main features of the proposal are presented below.

A. Individual representation

An integer representation model with as many genes as variables contained in the original data set without considering the target variable is used. It works with categorical and/or continuous variables depending on whether the initial subgroup rules are crisp or fuzzy rules.

In domains with continuous variables different SD algorithms use fuzzy logic to manage these continuous features without a previous discretisation. In this situation the proposal considers continuous variables as linguistic ones, and the fuzzy sets corresponding to the linguistic labels are those defined by the SD algorithm used previously.

Codification is performed according to the "*Chromosome = Rule*" approach [15], where only the antecedent is represented in the chromosome. The value of the target variable for the individuals is considered to be the opposite value of the initial subgroup. If we consider the rule $IF\ x_1 = Medium\ AND\ x_3 = Low\ THEN\ TargetVar$ as a previously obtained fuzzy SD rule, the exception associated to the subgroup maintains the values of the attributes of the initial subgroup. In this way, the exception $IF\ x_1 = Medium\ AND\ x_3 = Low\ AND\ x_5 = Medium$ $THEN\ \overline{TargetVar}$ will be more specific than the initial subgroup.

Individual representation in crisp rules is also performed with "*Chromosome = Rule* approach. The set of possible features for these rules are both categorical or continuous, but discretised previously in the last case.

B. Multi-objective evolutionary algorithm approach

Algorithm starts with a set of i subgroups obtained by any SD algorithm ($S_R = \{R_1,\ R_2, \ldots,\ R_i\}$) represented with the following type of rule:

$$R_i : IF\ Cond_i\ THEN\ TargetVar \quad (2)$$

The algorithm searches for small sets of examples within the space delimited by the antecedent of a rule that possess a value for the target variable different to the one established in the consequent of the subgroup, This search is performed through a multi-objective evolutionary algorithm with the NSGA-II approach [16], according to a two-step process:

1) *Detection of group of exceptions associated with each subgroup*. These exceptions are more specific than the initial subgroup (each one is composed by the same variables as the subgroup in addition to others) but corresponding to the opposite value of the target variable of the subgroup.
2) *Generation of the modified subgroups*. A new subgroup formed by the initial one and the exceptions of the previous step is obtained:

$$R'_i : IF\ Cond_i\ AND\ \overline{Exc_i}\ THEN\ TargetVar \quad (3)$$

where Exc_i represents conditions for associated exceptions to the rule R_i (without the common variables).

The algorithm uses adapted expressions for sensitivity [1] and confidence [11] measures to evaluate exceptions and to direct the learning process:

- **Sensitivity** that measures the proportion of actual positives which are correctly identified.

$$Sens(Exc) = \frac{TP}{TP + FN} = \frac{n(\overline{TargetVar} \cdot Cond)}{n(\overline{TargetVar})} \quad (4)$$

where $n(\overline{TargetVar})$ are the examples with the opposite value to the target variable of the initial subgroup, and $n(\overline{TargetVar} \cdot Cond)$ are the examples covered by the exception with the opposite value of the target variable to that of the subgroup.

- **Fuzzy/crisp confidence** that measures the proportion of examples which are correctly identified with respect to the opposite value of the target variable.

$$FCnf(Exc) = \frac{\sum\limits_{E^k \in E / E^k \in \overline{TargetVar}} APC(E^k, Exc)}{\sum\limits_{E^k \in E} APC(E^k, Exc)} \quad (5)$$

where $E = \{E^k = (e_1^k, e_2^k, \ldots, e_v^k), TargetVar^k)\ /k = 1, \ldots,\ N,\ TargetVar^k\ \in\ T\}$ is a set of examples, e_v is the number of variables for the example, $TargetVar^k$ is the value of the target variable for the example E^k (i.e., the target variable for this example), APC is the degree of compatibility between an example and the antecedent part of an exception rule. In crisp domains the degree of compatibility for an example and the antecedent part of the rule is 1 or 0.

The Pareto front obtained at the end of the evolutionary process contains all different exceptions which reach a confidence threshold, and so only exceptions with high precision values and describing specific areas with incorrectly-described examples are obtained.

C. Genetic operators

The evolutionary post-processing algorithm includes tournament selection and multi-point crossover operators [17], in addition to specific operators:

- *Oriented initialisation*. It is generated a population of individuals which contain the same values as the initial subgroup, together with new values for the remaining attributes. To do so, part of the population is generated with biased individuals and the rest are generated randomly. The values of the variables taking part in the initial subgroup are directly copied in the new individuals of the population. The remaining values are generated in the following way: the values of 75% of the individuals are generated considering that a maximum of 90% of the variables can take part in the rule; for the rest (25%) the values are generated randomly. These random individuals always have a value in all the variables.
- *Oriented mutation*. It is derived from standard mutation [17] but the values of the variables of the initial subgroup can not be modified. Furthermore, the mutation of a variable which does not form part of the initial subgroup does not imply its removal in the chromosome; i.e. a possible value is assigned to the variable which is different to the actual one, but never 0.
- *Oriented re-initialisation based on coverage*. The algorithm uses a modification of the operator defined for NMEEF-SD [13]. In the original operator, a verification is made before generating the population for the next generation, to see whether the Pareto evolves or not. If it does not evolve, all non-repeated individuals of the Pareto are introduced into the population of the next generation and the remaining individuals to complete de population are generated to cover examples of the data set not covered by the Pareto. Modification is that the generated individuals must be a specification of the initial subgroup, and all individuals keep the same values of the initial subgroup. New individuals generated are associated to examples not covered by the Pareto because an uncovered example is selected randomly and the values of the individual are codified with respect to this example.
- *Stop condition*. The evolutionary process ends when the algorithm reaches a number of evaluations. It returns the non-repeated individuals of the Pareto front which reach a confidence threshold. These individuals (exceptions) are associated to the correspondent initial subgroup.
- *Generation of subgroups with exceptions*. Once the evolutionary algorithm has been executed for each initial subgroup and their exceptions are obtained, subgroups with exceptions are generated. It is done by combining the initial subgroups with their associated exceptions. It is important to remark that the number of modified subgroups is the same as the initial ones.

IV. Experimental study

The experimentation was undertaken with data sets from KEEL [18], [19] repository[1]. Their properties are presented in Table I, including number of variables (n_v), discrete variables (n_{vD}), continuous variables (n_{vC}) and examples (N). To estimate quality measures on new data, 10 fold-cross validation

[1]http://www.keel.es

procedure is employed and 3 executions are considered for non-deterministic algorithms.

TABLE I
PROPERTIES OF THE DATA SETS USED FROM THE KEEL REPOSITORY

♯	$Name$	n_v	n_{vD}	n_{vC}	N
1	Australian	14	8	6	690
2	Crx	15	12	3	690
3	Heart	13	6	7	270
4	Hepatitis	19	13	6	155
5	Mammographic	5	5	0	961
6	Monk-2	6	6	0	432
7	Housevotes	16	16	0	435
8	Saheart	9	4	5	462
9	Tic-tac-toe	9	9	0	958
10	Titanic	3	0	3	2201
11	Wisconsin	9	9	0	699

To show the advantages given by the evolutionary post-processing algorithm, two SD algorithms are employed to obtain the initial subgroups: NMEEF-SD [13] and Apriori-SD [9]. Then is applied the evolutionary proposal in order to extract exceptions for them. The evaluation of the subgroups with exceptions is performed with adapted expressions for the quality measures of significance (SIG) [1], unusualness (UNU) [20], sensitivity (SEN) [1] and confidence (CNF) [21].

- Significance of a subgroup with exceptions (R'):

$$Sign'(R'_i) = 2 \cdot \sum_{k=1}^{n_c} (TP_{R'_i})_k \cdot log \frac{(TP_{R'_i})_k}{((TP+FN)_{R_i})_k \cdot \frac{((TP+FP)_{R'_i})_k}{N}} \tag{6}$$

  where $TP_{R'_i} = TP_{R_i} - FP_{Exc_i}$, TP_{R_i} are the number of correctly-described examples of the rule, FP_{Exc_i} are the number of incorrectly-described examples for the set of associated exceptions to the rule, $(TP + FN)_{R_i}$ are the number of examples for values of the target variable, $(TP + FP)_{R'_i} = (TP + FP)_{R_i} - (TP + FP)_{Exc_i}$, $(TP + FP)_{R_i}$ are the number of examples covered by the rule and $(TP + FP)_{Exc_i}$ are the examples covered by the set of associated exceptions to the initial rule.
- Unusualness of a subgroup with exceptions:

$$Unus'(R'_i) = \left(\frac{TP_{R'_i}}{(TP+FP)_{R'_i}} - \frac{(TP+FN)_{R_i}}{N} \right) \cdot \frac{(TP+FP)_{R'_i}}{N} \tag{7}$$

- Sensitivity for a subgroup with exceptions:

$$Sens'(R'_i) = \frac{TP_{R'_i}}{(TP+FN)_{R_i}} \tag{8}$$

- Fuzzy confidence of a subgroup with exceptions:

$$FCnf'(R'_i) = \frac{\sum_{E^k \in E / E^k \in TargetVar} APC(E^k, R'_i)}{\sum_{E^k \in E} APC(E^k, R'_i)} \tag{9}$$

  where $APC(E^k, R'_i) = APC(E^k, R_i) - APC(E^k, Exc_i)$.

The average results of the SD algorithms and the same algorithms with the post-processing algorithm are presented in Table II, where n_r represents the number of subgroups, and n_v represents the average of variables for each subgroup. For reasons of brevity, the paper only includes the average results and results of statistical tests.

TABLE II
RESULTS OBTAINED FOR THE ALGORITHMS

$Algorithm$	n_r	n_v	SIG	UNU	SEN	CNF
Apriori-SD	5.42	2.18	3.337	0.067	**0.508**	0.616
Apriori-SD+Exceptions	5.42	5.78	**3.554**	**0.076**	0.487	**0.638**
NMEEF-SD	4.41	2.52	5.154	0.119	**0.846**	0.809
NMEEF-SD+Exceptions	4.41	6.93	**5.924**	**0.131**	0.821	**0.842**

For statistical analysis the Wilconxon signed-rank test [22] is selected with level of confidence $\alpha = 0.05$ in the experiments. In Table III the results of the Wilcoxon test for each quality measure can be observed with the correspondent $p - val$, and the result of the $Hypothesis$. The results obtained show significant differences in the majority of the quality measures and algorithms with the use of the new post-processing approach.

TABLE III
WILCOXON TEST FOR THE COMPARISON OF
APRIORI-SD/NMEEF-SD+EXCEPTIONS VS. APRIORI-SD/NMEEF-SD

$Algorithm$		$p - val$	$Hypothesis$
Apriori-SD	SIG	0.173	Non-rejected
	UNU	0.018	Rejected by Apriori-SD+Exceptions
	SEN	0.011	Rejected by Apriori-SD
	CNF	0.038	Rejected by Apriori-SD+Exceptions
NMEEF-SD	SIG	0.005	Rejected by NMEEF-SD+Exceptions
	UNU	0.009	Rejected by NMEEF-SD+Exceptions
	SEN	0.008	Rejected by NMEEF-SD
	CNF	0.003	Rejected by NMEEF-SD+Exceptions

As can be observed in Table II and Table III, the results after applying the post-processing algorithm improve those obtained by the SD algorithms. In sensitivity, small reductions of the values of the original algorithms in comparison with the results of this proposal are obtained in all the experiments. Due to the fact that this quality measure quantifies the ratio of examples per target variable covered, the ideal values would be the same as the initial subgroups, i.e. it is impossible to improve the results of this quality measure because modified subgroups measure only the examples for the target value of the original subgroup. With respect to the remaining quality measures, the use of exceptions increments precision and interest of the initial subgroups.

V. CASE STUDY: CONCENTRATING PHOTOVOLTAIC TECHNOLOGY, PERFORMANCE AND CHARACTERISATION

Concentrating Photovoltaic (CPV) Technology is an alternative to the conventional Photovoltaic for the electric generation. CPV technology is based on using concentrated sunlight to produce electricity in a cheaper way by means of High Efficiency Multijunction solar cells, specifically designed for this type of technology. The efficiency of this type of solar cells has experienced a fast evolution, from 32.6% in 2000 to 43.5% in 2012 [23] and has a very strong potential of increasing along next years.

Despite of these expectations, several obstacles to develop CPV technology currently still remain, as the lack of CPV normalisation and standardisation, the lack of knowledge of the influence of the meteorological parameters on the performance of High Efficiency Multijunction Solar Cells, or the development of complex regression models for their performance. So, it is necessary to deepen in the study and knowledge of CPV technology.

The most interesting parameter to analyse in CPV is the Maximum Module Power (P_m) and so the study is focused in this variable. It is known that the P_m is highly influenced by atmospheric conditions, but it is needed to know what happens with the combination of real atmospheric conditions. This knowledge can be very useful to predict the energy production in a determined period of time.

IDEA group researchers have designed an Automatic Test & Measurement System which is able to measure simultaneously P_m of the CPV modules and outdoor atmospheric conditions. Data are registered each 5 minutes and include:

- *Target variable*: max Module Power $P_m \epsilon [0, 150]$ (W),
- ambient temperature $T_{amb} \epsilon [-3, 50]$ (°C),
- direct normal irradiance $DNI \epsilon [143, 1034]$ (W/m^2),
- wind speed $W_s \epsilon [0, 30]$ (m/s),
- incident global irradiance $G \epsilon [290, 1410]$ (W/m^2) and
- spectral irradiance distribution of the incident global irradiance, described through average photon energy (APE) values, $APE \epsilon [1.6, 1.95]$.

Measures are taken at University of Jaen from June 2009 to November 2012 (Fig.2). The data set for the CPV solar module analysed in this section has 28182 examples.

Fig. 2. Solar tracker at High Technical School at University of Jaén

The P_m values of the kind of solar module under study have been discretised in four different intervals according their interest: I1: [7.5, 64.5], I2:]64.5, 93], I3:]93, 121.5] and I4:]121.5, 150]. Table IV presents the initial subgroups obtained by NMEEF-SD, the exceptions discovered and the modified subgroups. NMEEF-SD obtains subgroups describing general knowledge about three of the four values for the target variable (the low number of samples corresponding to the fourth interval, prevents the extraction of knowledge for this value).

Table V presents the results with respect to the quality measures analysed. The initial subgroups have a good confidence since the majority of examples are well described. However exceptions cover new examples that were previously incorrectly described. In brief, rules with exception are relevant and interesting taking into account high values for confidence, unusualness, sensitivity and significance. Moreover, subgroups with exceptions give new information to experts for specific situations within different P_m intervals.

TABLE V
RESULTS OBTAINED IN *Concentrating Photovoltaic Module* DATA SET

Rule	*SIGN*	*UNUS*	*SENS*	*CONF*
R_1	2790.523	0.049	0.796	0.786
R'_1	**2793.111**	0.049	0.796	**0.788**
R_2	4092.492	0.095	0.942	0.811
R'_2	**4095.232**	0.095	0.942	**0.812**
R_3	2462.399	0.095	**0.974**	0.696
R'_3	**3091.127**	**0.110**	0.973	**0.720**
Without exceptions	3115.138	0.080	**0.904**	0.764
With exceptions	**3326.490**	**0.085**	0.903	**0.773**

IDEA group researchers establish that:

- Consequent I1 (interval 1) covers the performance of the CPV module at sunrise, sunset and strong cloudy days. Usually under these conditions the P_m of the CPV module must be low, but presents a relevant exception. In opposition to conventional PV, in CPV technology the influence of the ambient temperature (T_{amb}) in the P_m always has been considered negligible. In this case, for a medium Direct Normal Irradiance value (DNI) the P_m of the module increases if the ambient temperature is low.
- Consequent I2 (interval 2) covers the performance of the module during moderate sunny and cloudy days. This subgroup has three exceptions, explaining that if espectral irradiance distribution, APE, is low (sunny days) and ambient temperature is high, the P_m does not belong to the interval 1. In this sense, CPV performance is similar to that of the conventional PV.
- Consequent I3 (interval 3) covers the performance of the module during a sunny day. In this subgroup, it is possible to extract relevant information concerning APE variable. This parameter (not considered in conventional PV technology) could be a crucial to explain the performance of the CPV module as a consequence of the special solar cells used. In this case, exception shows that high values of APE improve the performance of the CPV module.

The last result induces to analyse in more detail the influence of the APE in the performance of the CPV module. APE values offer information about the spectral distribution of the irradiance collected by the CPV module and it is very useful to analyse the fitting of the spectral response of the solar cells.

VI. CONCLUSIONS

A new post-processing multi-objective EFS to improve the subgroups obtained by any SD algorithm is presented in this paper. The aim is the detection of exceptions with two objectives: on the one hand, to describe new small spaces in the data with unusual behaviour within subgroups; and on the other hand, to increase the accuracy of the subgroups by detecting and describing samples within the unusual subgroups which can be interesting for the experts.

TABLE IV
INITIAL SUBGROUPS STUDIED (OBTAINED BY NMEEF-SD), EXCEPTIONS AND SUBGROUPS WITH EXCEPTIONS OBTAINED FOR THE *CPV* DATA SET

Initial Subgroup	Exceptions ($Exc_i = Exc^1_{R_i} \vee \ldots \vee Exc^{n_i}_{R_i}$)	Modified Subgroup
R_1:IF DNI=Low THEN P_m=I1	Exc$^1_{R_1}$: G=High $\wedge$ W_s=Very Low $\wedge$ T_{amb}=Low	R'_1:IF DNI=Low $\wedge$ $\overline{Exc_{R1}}$ THEN P_m=I1
R_2:IF DNI=Med THEN P_m=I2	Exc$^1_{R_2}$: APE=Very Low $\wedge$ G=Low Exc$^2_{R_2}$: APE=Low $\wedge$ T_{amb}=High Exc$^3_{R_2}$: APE=Very Low	R'_2:IF DNI=Med $\wedge$ $\overline{Exc_{R2}}$ THEN P_m=I2
R_3:IF G=High THEN P_m=I3	Exc$^1_{R_3}$: W_s=Extremely Low $\wedge$ DNI=Med Exc$^2_{R_3}$: DNI=Med Exc$^3_{R_3}$: T_{amb}=High $\wedge$ DNI=Med Exc$^4_{R_3}$: W_s=Very Low $\wedge$ T_{amb}=High $\wedge$ DNI=Med Exc$^5_{R_3}$: APE=Very High $\wedge$ DNI=Med	R'_3:IF G=High $\wedge$ $\overline{Exc_{R3}}$ THEN P_m=I3

An experimental study, supported by statistical tests, shows that the algorithm improves the results obtained by a previous SD algorithm (confidence and sensitivity). Furthermore, not only the quality measures used in the evolutionary process are improved but also other quality measures considered in the SD task. Moreover, the algorithm can be applied to real-world problems where experts need to obtain information to improve the analysis and description. For the CPV module problem, SD fuzzy rules with exceptions obtained give new knowledge related to relationships among atmospherical conditions when the CPV provides a certain Pm. Both SD rules and exceptions improve the knowledge about the behaviour of CPV modules.

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