Improvement Opportunities in the Design of Multi-Objective Evolutionary Fuzzy Classifiers: Handling Rule Selection and Interpretability-Accuracy Tradeoff

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Abstract— **During design of fuzzy rule based systems/fuzzy classifiers many rules may be applied on input variables to find out the desired output but there are number of possible ways for rule selection. Interpretability and accuracy are two most important features for the design of any fuzzy systems but these two features are generally conflicting in nature i.e. one can be enhanced with reduction of other one. This situation is called "Interpretability-Accuracy Tradeoff". Multi –objective evolutionary algorithms are used to handle such tradeoff to design fuzzy systems. An optimization activity or search problem is known as automatic design of fuzzy rule based system and to complete the optimization activity evolutionary or genetic algorithms are being used. For improvement in the design of any fuzzy systems, it is very necessary to sort out the problem of rule selection in high dimensional data, secondly find out the proper assessment technique for interpretability as there is no global assessment method for interpretability and last but not the least application of multi-objective evolutionary algorithms to deal with I-A tradeoff.**

In this paper, authors would like to analyze the problem of rule selection in high dimensionality, problem of no global assessment techniques for interpretability and handling of interpretability –accuracy tradeoff using multi-objective optimization.

Keywords— **MOEA(Multi-Objective Evolutionary Algorithm), I-A tradeoff(Interpretability Accuracy tradeoff), FRBS(Fuzzy Rule Based Systems) etc.**

I. INTRODUCTION

The very critical research issue in designing fuzzy systems for high dimensional data sets [1] is the exponential growth of rule search space. To handle this issue different routines have been proposed and executed for developing so as to take care of high dimensional information sets interpretable and exact fuzzy frameworks. A strategy named FARC-HD (fluffy affiliation standard base arrangement for high dimensionality) has been proposed and actualized in [2]. This method develops compact and accurate fuzzy rule based classifiers. The structure of fuzzy rule based systems is as shown in Fig 1.

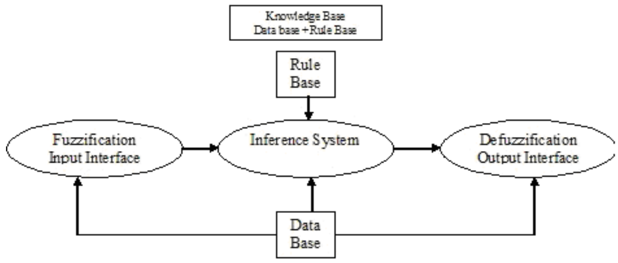

Fig 1: Structure of an FRBS

A method using multi objective evolutionary algorithms has been developed in [3], which carries out the learning of variables, granularities and displacement in fuzzy partitions. All these terms are parts of database during design of any fuzzy systems. In [4] multi objective evolutionary framework has been discussed by handling high dimensional and large data sets. Learning of rule base in multi objective evolutionary framework is performed by selection of reduced number of rules and conditions.

There are two main objectives during design of any fuzzy systems: improvement in the accuracy and interpretability of fuzzy rule based system. These two objectives are generally opposite in nature i.e. increment in one will cause reduction in other as shown in Fig 2.

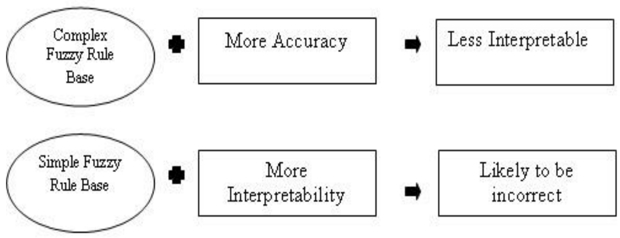

Fig 2: Relation of Fuzzy rule with Accuracy & Interpretability

The problem of high dimensionality of datasets is a major concern during design of any fuzzy system and apart from this interpretability assessment [5] and interpretability-accuracy tradeoff [7, 8] are also main research issues. There is no global assessment method for measurement of interpretability. Also interpretability and accuracy are conflicting in nature. The improvement in one leads to loss in other and this condition is called as I-A tradeoff. With the improvement in interpretability a tuning method for interval type-2 fuzzy systems has been proposed in [9].

A study on the outline of fuzzy classifiers utilizing developmental multi target calculations has been done in [6].

To manage I-A tradeoff multi-objective transformative advancement systems called evolutionary algorithms are being used. In [10] interpretability assessment indexes are developed for multi objective optimization framework.

In this paper, the problem of interpretability assessment and high dimension rule selection are discussed. In section Ii, various interpretability assessment methods are introduced. Section III is about interpretability accuracy tradeoff. In section IV various rule selection methods are discussed. Section V gives an idea about multi objective optimization and section VI is conclusion and future scope.

II. ASSESMENT OF INTEREPRETABILITY

Interpretability is known by other names like transparency, intelligibility, understandability, readability, comprehensibility etc. it is defined as a property to understand the relevance of something [11].

In [12] two modeling approaches of fuzzy systems has been mentioned, one is linguistic fuzzy modeling (LFM) and different one is precise fuzzy modeling (PFM). In LFM , the fundamental focus is on interpretability and these fuzzy models are developed by means that of linguistic FRBS referred to as Mamdani-type FKBS. In PFM, the main focus is on accuracy and these models are known as Takagi-Sugeno FKBS. To achieve the desired I-A tradeoff, improvement in accuracy in LFM and interpretability improvement in PFM are carried out.

Many classifications for assessment of interpretability are proposed in [13], [14],[15]. In [13], a framework based on the explanation and description has been discussed for quantification of the FRBS interpretability. A study of various constraints on the design of fuzzy system has been done in [14]. In [15] a classification based on high level interpretability and low level interpretability has been discussed. Two completely different versions of interpretability complexness, linguistics and rule base, fuzzy partitions has been targeted in [16].Logical view index (LVI) and Average Fired Rules (AFR) has been proposed for the assessment of interpretability in [17]. Another index for interpretability based on fuzzy ordering has been discussed in [18].

For assessment of interpretability, the parameters from various levels are selected for evolving interpretability indexes and proposed in the classification (Fig 3) under three heads: Knowledge Base Interpretability (KBI), Inference engine Interpretability (IEI) and User Knowledge Base Interpretability (UKBI). Two other subheads Data Base Interpretability (DBI) and Rule Base Interpretability (RBI) are classified under KBI and these classifications are fully compatible with Mamdani type FRBS. For improving the interpretability, many methods are applied like reduction in number of membership functions by merger, reduction in number of rules by rule selection and by applying rule learning procedure.

According to classification mentioned here, improvement in interpretability may be done at the amount of rule base, database, logical thinking method and user cognitive content. When quantification of interpretability of any system is tried, the user understanding level should be taken care because assessment is directly connected to user understandability.

Estimation of the system interpretability with user's prospect, this user interpretability can be used. For different user the interpretability of the system would be different Also, the improvement in the interpretability can be done by training users for specific system.

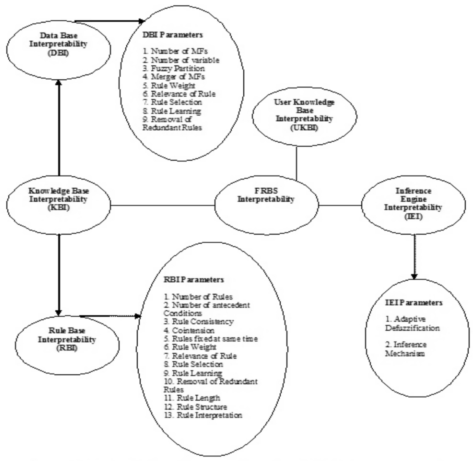

Fig-3 Classification of Interpretability of Fuzzy Rule Base Systems

According to above classification, a current state-of-art in the interpretability assessment is discussed in Table 1, Table 2, Table 3 and Table 4.

Table 1. Year Wise Summary of work carried out for Interpretability according to DBI

Year	Parameters	Authors	Reference
2001	SF, NL, MF	Cordon et. al.	[19]
2001	MFT	Guillaume et. al.	[20]
2004	MFM, FP	Guillaume et. al.	[21]
2005	LH	Cassilas et. al.	[22]
2007	MFT	Alcala et. al.	[23]
2009	MFT	Gacto et. al.	[24]
2009	FOR	Botta et. al.	[25]

2010	MFT	Gacto et. al.	[26]
2011	FP	Alonso et. al.	[27]
2012	MF	G.-Hernandez et.al.	[28]
2012	MFG	Villar et. al.	[29]

Table 2. Year Wise Summary of work carried out for Interpretability according to RBI

Year	Authors	Parameters	Reference
2000	Jin et. al.	FTFRR	[30]
2001	Guillaume et. al.	FRG	[20]
2004	Ishibuchi et. al.	FRG,REM	[31]
2005	Cassilas et. al.	FRR	[22]
2007	Alcala et. al.	FRR	[23]
2007	Alcala et. al.	FRG	[32]
2009	Gacto et. al.	FRS	[24]
2010	Gacto et. al.	FRG	[26]
2011	Mencar et. al.	COI	[33]
2011	Alonso et. al.	FRG	[27]
2012	G.-Hernandez et.al.	FRS	[28]
2012	Villar et. al.	FS	[29]
2012	Marquez et. al.	FRR	[34]

Table 3. Summary of work carried out for Interpretability according to IEI

Year	Authors	Parameters	Reference
2012	Marquez et. al.	AD	[34]

Table 4. Summary of work carried out for Interpretability according to UKBI

Year	Authors	Parameters	Reference
2001	Furuhashi et. al.	CFM	[35]
2010	Alonso et. al.	UPQC	[36]

SF-Scaling Function, MFT-Membership Function Tuning, NL-Number of Labels, MFM- Membership Function Merging, LH-Linguistic Hedges, FOR-Fuzzy Ordering Relations, FP-Fuzzy Partition, MFG-Membership Function Granularity, FRR-Fuzzy Rule Reduction, FRG-Fuzzy Rule Generation, UPQC-User Preference & Quality Criteria, REM-Rule Evaluation Measures, CFM-Concise Fuzzy Model, FTFRR-Fine Training of Fuzzy Rules with Regularization, AD- Adaptive De fuzzification, COI-Coin tension, FRS-Fuzzy Rule Selection, FS-Feature Selection.

III. INTERPRETABILITY–ACCURACY TRADEOFF

Interpretability is primarily centered within the Mamdani Fuzzy Systems (Linguistic Fuzzy modeling) and Accuracy is focused in Takagi-Sugeno-Kang Fuzzy Systems (Precise Fuzzy Modeling). A serious analysis issue in space of developing evolutionary Fuzzy systems is to get several fuzzy systems on the arc of I-A trade-off and out of that conclude anyone having a fine trade off [Fig4].

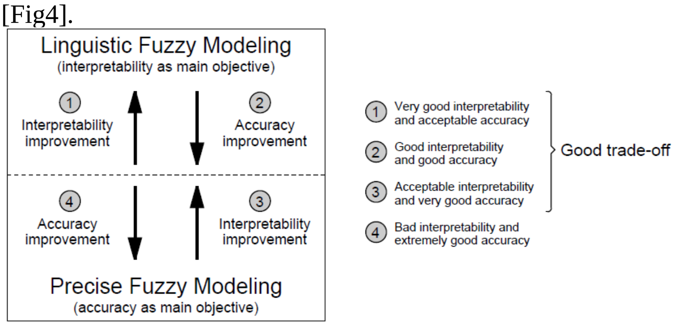

Fig 4. Comparison of two different fuzzy modeling

The improvement in either Interpretability or Accuracy depends upon demand of modeling, some modeling applications rather than focusing individually individual basis} on accuracy or interpretability; need an optimum level of interpretability and accuracy. this can direct to I-A trade off. In [37], a survey on the I-A trade-off has been disbursed in evolutionary Multi-Objective Fuzzy Systems. The essential ideas of evolutionary Multi-Objective Fuzzy Systems has been introduced in this paper.

If complexness of any system is High then the Accuracy of system are going to be High and Interpret ability are going to be Low and If the complexness of any system is Low then the Accuracy of system are going to be Low and Interpretability are going to be High. This condition is understood as I-A exchange. [38] To modify such trade off scenario, multi objective optimization algorithms are used in the fuzzy systems style that is mentioned in different section of this paper.

A classification of assorted problems associated with multi objective optimization, considering I-A trade off has been mentioned in [39].

The two objective primarily based approaches for I-A mistreatment EMO having major focus of feature selection and roughness learning is mentioned in [40] and also the accuracy of classification and range of rules is mentioned in [41].

During Handling I-A tradeoff mistreatment EMO, standardization of membership functions and rule selection may be a important space mentioned in [42-44]. Sum of antecedent conditions and root mean squared error [45], Fine fuzzy partition, and number of antecedent rule [46] are also major focus area for consideration during trade off.

In similar method there square measure such a big amount of classifications like three objectives based mostly approach, High dimensional issues, Ensemble Classifiers, Semantic coin tension, User preference, and context adaptation having completely different focus areas of attributes for managing of I-A trade off in EMO algorithms.

IV. RULE SELECTION

To take care of I-A trade-off, rule generation and selection are main issue throughout design of fuzzy systems. In a fuzzy system with high dimensionality rule base increase invariably as and when inputs are join i.e. rule numbers increase rapidly which results in decrease of interpretability and increase of complexity.

In [47], fuzzy rule selection process is discussed using multi-objective genetic local search. In this, two measures support and confidence have been defined and these measures are basically evaluation measures, which are generally used in the area of data mining.

Reduction within the spatial property of the matter is the main objective of any rule selection for supervised learning method. It means for the design best features must be determined by feature selection algorithm. There are two kinds of algorithms:

Filter rule selection algorithm [48], this algorithm does not use learning algorithm and removes the irrelevant characteristics. Wrapper feature selection algorithm [49], this process evaluates each candidate subset with estimation precision obtained by learning algorithms.

During maintaining or raising the system's performance fuzzy rule set reduction strategies attempt to minimize the quantity of rules of a specific FRBS. The improvement in system's accuracy is done by eliminating the conflicting rules that decrease the performance. Further accuracy is not only the major necessity of model, but interpretability also becomes a major aspect. To improve the system's readability reduction in complexity is required i.e. a system with less number of rules requires minor effort in interpretation.

Rule selection is that the most used fuzzy rule set reduction technique that is typically applied as a post process stage once an initial fuzzy rule set has been extracted.

For getting most successful set of fuzzy rules, there are many methods of rule selection with different search algorithms [50], [51]. A method of rule selection is also present based on a relevance factor calculated for each fuzzy rule and then select the most relevant ones.

Such techniques of rule selection can be combined easily with other post processing techniques to get more accurate FRBS. Hence among identical method and considering solely performance criteria, few works have thought-about the rule choice with standardization of membership functions in [52], [53]–[55]. Rules would be extracted providing it's doable to either maintain or maybe improve the system's accuracy. a really attention-grabbing conclusion from a number of these recent works [52], [55] is that each techniques will gift a positive synergy once they square measure combined among a well-designed optimization process.

Sometimes related to our problem big number of rules can be extracted from data mining method. The understanding of the behavior of FRBS having large rule base and high dimensional rules is very difficult. Thus totally different forms of rules will be found during a fuzzy rule set: digressive rules, redundant rules, inaccurate rules and conflictive rules, which perturb the FRBS performance once they exist with others. To face this drawback a genetic rule choice method for getting associate degree optimized set of rules from a previous fuzzy rule set by choosing a number of them will be used. Fig 5 diagrammatically shows this concept. In [56] the foremost classic and 1st contribution during this space is mentioned and in [57] the primary work on multi objective genetic rule selection is represented. Rule choice will be combined with standardization approaches, attempting to urge an honest rule set beside a tuned set of parameters. In [58, 59] two recent proposal that mixes genetic standardization with rule selection has been mentioned.

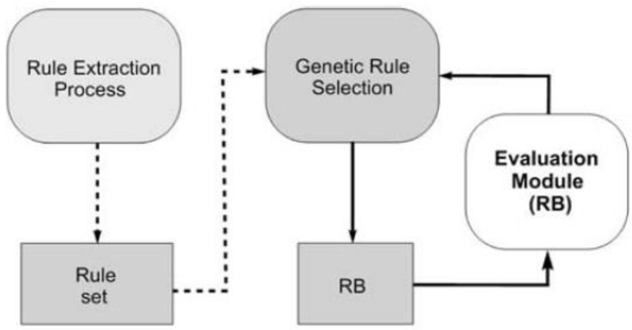

Fig 5: Genetic Rule Selection Process

V. MULTI-OBJECTIVE OPTIMIZATION

To alter the issues associated with multi objective improvement evolutionary algorithms are extremely capable, as a result of evolutionary algorithms consists associate approach supported population to urge multiple solutions in single run. These algorithms also are capable to alter Brobdingnagian unsure and complicated search space.

During design of fuzzy systems, handling of I-A trade off is known as a multi objective optimization drawback. Evolutionary multi objective improvement includes integration of any of the approach like genetic formula [60], evolution ways [61], genetic programming [62] and evolutionary programming [63] to alter multi objective issues.

There are two generations of MOEA, the primary generation having options, fitness sharing and niching incorporated with the rank of Pareto. Non-dominated Sorting Genetic Algorithm (NSGA) [64], Niched Pareto Genetic Algorithm (NPGA) [65], and Multi-Objective Genetic Algorithm (MOGA) [66] are first generation MOEAs.

Second generation MOEA area unit incorporated with the concept of elitism. The tactic of generating a brand new population much is to modify the most effective rule from existing generation to hold forward to subsequent with none alteration. This approach is termed as elitist choice and guarantees that the standard of the output obtained by genetic algorithmic won't be decremented within the next generation.

Few MOEAs of Second generation are Strength Pareto Evolutionary Algorithm (SPEA) [67], Strength Pareto Evolutionary Algorithm 2 (SPEA2) [68], Pareto Achieved

Evolution Strategies (PAES) [69], Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [70], Niched Pareto Genetic Algorithm-II (NPGA-II) [71], Pareto Envelop based Selection Algorithm (PESA) [72], Micro Genetic Algorithm [73].

Multi objective optimization framework

Multi objective Evolutionary Algorithms (MOEA) area unit accustomed to develop fuzzy systems and located efficient in handling the interpretability-accuracy trade-off. The basic concepts of evolutionary multi objective optimization are well discussed in [74]. Few frameworks of MOEA for developing fuzzy systems are developed in [75]. The review related to evolutionary multi objective fuzzy systems is carried out in [76].

VI. Conclusion and Future Scope

There are two major issues in developing the fuzzy systems High dimensionality of data sets and interpretability accuracy trade-off. This paper proposes various assessment techniques of interpretability. To deal with the interpretability-accuracy trade-off Evolutionary multi objective optimization is used. Multiple fuzzy systems may be generated with completely different trade-off values of interpretability and accuracy parameters.

In future the authors will be interested in developing the fuzzy systems dealing with high dimensional data sets in evolutionary multi objective optimization environment. Interpretability improvement and trade-off management would get on the prime concern. the development in search capability of evolutionary multi objective improvement algorithms would even be a replacement analysis line significantly in high dimensionality drawback.

References

[1] Y. Jin, "Fuzzy modeling of high dimensional systems: complexity reduction and interpretability improvement", IEEE Transactions on Fuzzy Systems, vol. 8, no. 2, pp. 212-221, 2000.

[2] J. A.-Fdez, R. Alcala, F. Herrera, "A fuzzy association rule based classification model for high dimensional problems with genetic rule selection and lateral tuning", IEEE Transactions on Fuzzy Systems, vol. 19, no. 5, pp. 857-872, 2011.

[3] M. J. Gacto, R. Alcala, F. Herrera, "Handling high dimensional regression problems by means of an efficient multiobjective evolutionary algorithm", 9th International Conference on Intelligent System Design and Applications, pp. 109-114, 2009.

[4] M. Antonelli, P. Ducange, F. Marcelloni, "A new approach to handle high dimensional and large data sets in multiobjective evolutionary fuzzy systems", 2011 IEEE International Conference on Fuzzy Systems, pp. 1286-1293, 2011.

[5] P. K. Shukla, S. P. Tripathi, "On the design of interpretable evolutionary fuzzy systems (I-EFS) with improved accuracy", 2012 International Conference on Computing Sciences, pp. 11-14, 2012.

[6] Praveen Kumar Dwivedi, Surya Prakash Tripathi, 'A survey on the Design of Fuzzy Classifiers Using Multi-Objective Evolutionary Algorithms', International Journal of Science & Research (IJSR), Vol. 4 issue 5, pp. 1103-1107, May 2015.

[7] P K Shukla, S. P. Tripathi, "A survey on interpretability-accuracy trade-off in evolutionary fuzzy systems", 2011 5th International Confer-ence on Genetic and Evolutionary Computing, Taiwan, Xiamen, pp. 97-101, 2011.

[8] P. K. Shukla, S. P. Tripathi "A review on the Interpretability- Accura-cy Trade-Off in Evolutionary Multiobjective Fuzzy Systems (EMOFS)", Information, vol. 3, no. 3, pp. 256-277, 2012.

[9] P. K. Shukla, S. P. Tripathi, "A new approach for tuning interval type-2 fuzzy knowledge bases using genetic algorithms", Journal of Uncertainity Analysis and Applications, vol. 2, no. 1, pp. 1-15, 2014

[10] R. Cannone, J. M. Alonso, L. Magdalena, An empirical study on in-terpretability indexes through Multiobjective evolutionary algo-rithms, Springer-Verlag, Berlin, Heidelberg, Germany, pp. 83-90, 2011.

[11] Alonso, JM, Magdalena, L: Special issue on interpretable fuzzy systems. Inform. Sci. 181, 4331–4339 (2011)

[12] Cassilas, J, Cordon, O, Herrera, F, Magdalena, L: Interpretability improvements to find the balance interpretabilityaccuracy in fuzzy modeling: an overview. In: Cassilas, J, Cordon, O, Herrera, F, Magdalena, L (eds.) Interpretability Issues in Fuzzy Modeling, Studies in Fuzziness and Soft Computing, pp. 3–22. Springer, Heidelberg (2003)

[13] Alonso, J. M., Magdalena, L., Rodriguez, G. G.: Looking for a good fuzzy system interpretability index: an experimental approach. International Journal of Approximate Reasoning. 51, 115-134 (2009)

[14] Mencar, C., Fanelli, A. M.: Interpretability constraints for fuzzy information granulation. Information Sciences. 178, 4585-4618 (2008)

[15] Zhou, M., Gan, J. Q., Low level interpretability and high level interpretability: a unifiedview of data-driven interpretable fuzzy system modeling. Fuzzy Sets and Systems. 159 (23), 3091-3131 (2008)

[16] Gacto, M. J., Alcala, R., Herrera, F.: Interpretability of linguistic fuzzy rule-based systems:an overview of interpretability measures. Information Sciences. 181, 4340-4360(2011)

[17] Cannone, R., Alonso, J. M., Magdalena, L.: An empirical study on interpretability indexes through Multiobjective evolutionary algorithms. WILF2011, LNAI 6857, 131-138 (2011)

[18] Botta, A., Lazzerini, B., Marcelloni, F., Stefanescu, D. C.: Context adaptation of fuzzysystems through a multi-objective evolutionary approach based on a novel interpretabilityindex. Soft Computing. 13 (5), 437-449 (2008)

[19] Cordón, O., Herrera, F., Magdalena, L., Villar P.: A genetic learning process for the scaling factors granularity and contexts of the fuzzy rule-based system data base. Information Science. 136, 85–107 (2001)

[20] Guillaume, S., Designing fuzzy inference systems from data: an interpretabilityoriented review. IEEE Transactions on Fuzzy Systems. 9, 426–443 (2001)

[21] Guillaume, S., Charnomordic, B.: Generating an interpretable family of fuzzy partitions from data. IEEE Transactions on Fuzzy Systems. 12, 324–335 (2004)

[22] Casillas, J., Cordón, O., del Jesus, M. J., Herrera, F.: Genetic tuning of fuzzy rule deep structures preserving interpretability and its interaction with fuzzy rule set reduction. IEEE Transactions on Fuzzy Systems. 13, 13–29 (2005)

[23] Alcalá, R., Alcalá-Fdez, J., Herrera, F.: A proposal for the genetic lateral tuning of linguistic fuzzy systems and its interaction with rule selection. IEEE Transactions on Fuzzy Systems. 15, 616–635 (2007)

[24] Gacto, M. J., Alcala, R., Herrera, F.: Adaptation and application of multi-objective evolutionary algorithms for rule reduction and parameter tuning of fuzzy rule based systems. Soft Computing. 13, 419-436 (2009)

[25] Botta, A., Lazzerini, B., Marcelloni, F., Stefanescu, D.C.: Context adaptation of fuzzy systems through a multi-objective evolutionary approach based on a novel interpretability index. Soft Computing. 13, 437-449 (2009)

[26] Gacto, M. J., Alcalá, R., Herrera, F.: Integration of an index to preserve the semantic interpretability in the multi-objective evolutionary rule selection and tuning of linguistic fuzzy systems. IEEE Transactions on Fuzzy Systems. 18, 515–531 (2010)

[27] Alonso, J. M., Magdalena, L.: HILK++: an interpretability-guided fuzzy modelingmethodology for learning readable and comprehensible fuzzy rule-based classifiers, Soft Computing. 15 (10), 1959-1980 (2011)

[28] G.-Hernandez, M., S.-Palmero, G. I., F.-Apricio, M. J.: Complexity reduction and interpretabilityimprovement for fuzzy rule systems based on simple interpretability measures and indices by bi-objective evolutionary rule selection. Soft Computing. 16 (3), 451-470 (2012)

[29] Villar, P., Fernandez, A., Carrasco, R. A., Herrera, F., Feature selection and granularity learning in genetic fuzzy rule based classification systems for imbalanced data sets.International Journal of Uncertainty, Fuzziness and Knowledge Based Systems. 20 (3), 369-397 (2012)

[30] Jin, Y.: Fuzzy modeling of high dimensional systems: complexity reduction and interpretability improvement. IEEE Transactions on Fuzzy Systems. 8(2), 212-221 (2000) Evolutionary Multi-Objective Fuzzy Knowledge Base Systems 479

[31] Ishibuchi, H., Yamamoto, T.: Fuzzy rule selection by multi-objective genetic local search algorithms and rule evaluation measures in data mining. Fuzzy Sets and Systems. 141, 59-88 (2004) Evolutionary Multi-Objective Fuzzy Knowledge Base Systems 481

[32] Alcalá, R., Alcalá-Fdez, J., Herrera, F., Otero, J., Genetic learning of accurate and compact fuzzy rule based systems based on the 2-tuples linguistic representation. International Journal of Approximate Reasoning. 44, 45–64 (2007)

[33] Mencar, C., Castiello, C., Cannone, R., Fanelli, A. M.: Interpretability assessment of fuzzy knowledge bases: a cointension based approach. International Journal of Approximate Reasoning. 52, 501-518 (2011).

[34] Marquez, A. A., Marquez, F. A., Peregrin, A.: A mechanism to improve the interpretability of linguistic fuzzy systems with adaptive defuzzification based on the use of a multi-objective evolutionary algorithms. International Journal of Computational Intelligence Systems. 5(2), 297-321 (2012)

[35] Furuhashi, T., Suzuki, T., On interpretability of fuzzy models based on conciseness measure, In Proc: IEEE International Conference on Fuzzy Systems (FUZZIEEE'01), 284–287 (2001) Evolutionary Multi-Objective Fuzzy Knowledge Base Systems 483

[36] Alonso, J. M., Magdalena, L., Combining user's preference and quality criteria into a new index for guiding the design of fuzzy systems with a good interpretabilityaccuracy trade-off, In Proc: IEEE World Congress on Computational Intelligence 961–968 (2010)

[37] Praveen Kumar Shukla, Surya Prakash Tripathi, "A review on the interpretability-accuracy trade-off in evolutionary multi-objective fuzzy systems (EMOFS)", Information, Vol. 3, Issue 3, pp. 256-277, 2012.

[38] P.K. Shukla, S.P. Tripathi, "A survey on interpretability –accuracy trade-off in evolutionary fuzzy systems", IEEE fifth International Conference on Genetic and Evolutionary Computing, 2011.

[39] P.K.Shukla, S.P. Tripathi, "Interpretability issues in evolutionary multi-objective fuzzy knowledge base systems", Seventh International Conference on Bio-Inspired Computing: Theories and Applications, Advances in Intelligent Systems and Computing, Springer India 2013.

[40] Cordon, O., Herrera, F., del Jesus, M. J., Villar, P.: "A multi-objective genetic algorithm for feature selection and granularity learning in fuzzy rule based classification systems". In Proc:. of 9th IFSA World Congress 2001. 1253-1258 (2001)

[41] Ishibuchi, H., Nojima, Y.: "Accuracy-complexity trade-off algorithms by multi objective rule selection", In Proc:.2005 Workshop on Computational Intelligence in Data Mining, 39-48 (2005)

[42] Gacto, M. J., Alcala, R., Herrera, F.: "Adaptation and application of multi-objective evolutionary algorithms for rule reduction and parameter tuning of fuzzy rule based systems", Soft Computing. 13, 419-436 (2009)

[43] Di Nuovo, A. G., Catania, V.: "Linguistic modifiers to improve the accuracy – interpretability trade-off in multi-objective genetic design of fuzzy rule based classifier systems"9th International Conference on Intelligent Systems Design and Applications, 128-133 (2009)

[44] Alcala, R., Nojima, Y., Herrera, F., Ishibuchi, H.: "Multi-objective genetic fuzzy rule selection of single granularity –based fuzzy classification rules and its interaction with lateral tuning of membership functions", Soft Computing. 15(12), 2303-2318 (2011)

[45] Cococcioni, M., Ducange, P., Lazzerini, B., Marcelloni, F.: "A pareto based multi objective evolutionary approach to the identification of mamdani fuzzy systems", Soft Computing. 11, 1013-1031 (2007)

[46] Ishibuchi, H., Nakashima, Y., Nojima, Y.: "Effects of fine fuzzy partitions on the generalization ability of evolutionary multi-objective fuzzy rule based classifiers", In Proc: of FUZZ-IEEE, 1-8 (2010)

[47] H. Ishibuchi and T. Yamamoto, " Fuzzy rule selection by multi – objective genetic local search algorithms and rule evaluation measures in data mining", Fuzzy Sets & Systems, Vol. 141, No. 1, pp. 59-80, Jan 2004.

[48] R. Kohavi and G. H. John. Wrappers for feature subsetselection. Anijicial Intelligence, 97:273-324, 1997.

[49] H. Liu and H. Motoda. Feature selection for knowledge discovery and data mining. Kluwer Academic Publishers,1998.

[50] H. Ishibuchi, K. Nozaki, N. Yamamoto, and H. Tanaka, "Selecting fuzzy if–then rules for classification problems using genetic algorithms," IEEE Trans. Fuzzy Syst., vol. 3, no. 3, pp. 260–270, Aug. 1995.

[51] F. Herrera, M. Lozano, and J. L. Verdegay, "A learning process for fuzzy control rules using genetic algorithms," Fuzzy Sets Syst., vol. 100, pp. 143– 158, 1998.

[52] M. J. Gacto, R. Alcal´a, and F. Herrera, "Adaptation and application of multi-objective evolutionary algorithms for rule reduction and parameter tuning of fuzzy rule-based systems," Soft Comput., vol. 13, no. 5, pp 419–436, 2009.

[53] R. Alcal´a, J. Alcal´a-Fdez, and F. Herrera, "A proposal for the genetic lateral tuning of linguistic fuzzy systems and its interaction with rule selection," IEEE Trans. Fuzzy Syst., vol. 15, no. 4, pp. 616–635, Aug. 2007.

[54] R. Alcal´a, J. Alcal´a-Fdez, M. J. Gacto, and F. Herrera, "Rule base reduction and genetic tuning of fuzzy systems based on the linguistic 3-tuples representation," Soft Comput., vol. 11, no. 5, pp. 401–419, 2007.

[55] J. Casillas, O. Cord´on, M. J. del Jesus, and F. Herrera, "Genetic tuning of fuzzy rule deep structures preserving interpretability and its nteraction with fuzzy rule set reduction," IEEE Trans. Fuzzy Syst., vol. 13, no. 1, pp. 13–29, Feb. 2005.

[56] Ishibuchi H, Nozaki K, Yamamoto N, Tanaka H (1995) Selection fuzzy IF-THEN rules for classification problems usinggenetic algorithms. IEEE Trans Fuzzy Syst 3(3): 260–270

[57] Ishibuchi H, Murata T, Turksen IB (1997) Single-objective andtwo-objective genetic algorithms for selecting linguistic rules for pattern classification problems. Fuzzy Sets Syst 8(2):135–150

[58] Alcala´ R, Gacto MJ, Herrera F, Alcala´-Fdez J (2007a) A multiobjective genetic algorithm for tuning and rule selection to obtain accurate and compact linguistic fuzzy rule-based systems. Int J Uncertain Fuzziness Knowl Based Syst 15(5):521–537

[59] Casillas J, Cordo´n O, del Jesus MJ, Herrera F (2005) Genetic tuning of fuzzy rule deep structures preserving interpretability for linguistic modeling. IEEE Trans Fuzzy Syst 13(1):13–29

[60] Goldberg, D.E.: "Genetic algorithms in search optimization and machine learning", Addison Wesley Publishing Company Reading Massachusetts (1989)

[61] Schwefel, H.-P.: "Evolution and optimization seeking", John Wiley & Sons. Newyork, (1995)

[62] Koza, J. R: "Genetic programming on the programming of computers by means of natural selection", The MIT Press, Cambridge, Massachusetts (1992)

[63] Fogel, L. J.: "Artificial Intelligence through simulated evolution", John Wiley, New York (1966)

[64] Srinivas, N., Deb, K.: "Multiobjective optimization using non-dominated sorting in genetic algorithms", Evolutionary Computation. 2(3). 221-248 (1994)

[65] Horn, J., Nafpliotis, N., Goldberg, D.E.: "A niched pareto genetic algorithm for multiobjective optimization", In Proc.: Ist IEEE Conference on Evolutionary Computation. IEEE World Congress on Computational Intelligence. 1, 82-87 (1994)

[66] Fonseca, C. M., Fleming, P. J.: "Genetic algorithms for multiobjective optimization: formulation, discussion and generalization", In proc.: 5th International Conference on Genetic Algorithms. 416-423 (1993)

[67] Zitzler, E., Thiele, L.: "Multi objective evolutionary algorithms: a comparative case study and the strength pareto approach", IEEE Transactions on Evolutionary Computation. 3 (4), 257-271 (1999)

[68] Zitzler, E., Laumanns, M., Thiele, L.: "SPEA2: Improving the strength pareto evolutionary algorithms", Technical Report 103. Computer

Engineering & Networks Laboratory (TIK). Swiss Federal Institute of Technology (ETH). Zurich, Switzerland (2001)
[69] Knowles, J. D., Corne, D. W.: "Approximating the non- dominated front using the pareto achieved evolution strategy", Evolutionary Computation. 8(2), 149-172 (2000)
[70] Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: "A fast and elitist multiobjective genetic algorithm: NSGA II", IEEE Transactions on Evolutionary Computation. 6 (2), 182-197 (2002)
[71] Erickson, M., Mayer, A., Horn, J.: "The niched pareto genetic algorithms applied to the design of ground water remediation system", Ist International Conference on Evolutionary Multi Criteria Optimization. 681-695, Springer-Verlag, LNCS No. 1993 (2001)
[72] Corne, D. W., Knowles, J. D., Oates, M. J.: "The pareto envelop based selection algorithm for multi-objective optimization", In Proc: VI Conference of Parallel Problem Solving from Nature. Paris, France, Springer LNCS 1917, 839-848 (2000)
[73] Coello, C. A. C., Pulido, G. T.: "A micro genetic algorithm for Multi objective optimization", In: proc. First International Conference on Evolutionary Multi-Criteria Optimization, pp. 126-140, LNCS 1993 (2001)
[74] K. Deb, Multiobjective optimization using evolutionary algorithms, John Wiley & Sons, Chichester, UK, 2001.
[75] H. Ishibuchi, Y. Nojima, I. Kuwajima 'Evolutionary Multiobjective design of fuzzy rule based classifiers', Studies in Computational Intelli-gence, vol. 115, pp. 641-685, 2008.
[76] F. Fazzolari, R. Alcala, Y. Nojima, H. Ishibuchi, F. Herrera, "A re-view of the application of Multiobjective evolutionary fuzzy systems: current state and further directions", IEEE Transactions on Fuzzy Sys-tems, vol. 21, no. 1, pp. 45-65, 2012.