NEW EVOLVING FUZZY SYSTEM ALGORITHMS USING DYNAMIC CONSTRAINT

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by

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TABLE OF CONTENTS

CHAPTER 3- METHODOLOGY

CHAPTER 4 – RESULTS AND DISCUSSION

CHAPTER 5 – CASE STUDY: RECURSIVE CONSTRUCTION OF OUTPUT-CONTEXT FUZZY SYSTEMS FOR THE CONDITION MONITORING OF ELECTRICAL HOTSPOTS BASED ON INFRARED THERMOGRAPHY

CHAPTER 6 - CONCLUSIONS AND FUTURE WORK

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Acc.	Accuracy
ANN	Artificial Neural Network
ASTM	American Society for Testing and Materials
AUC	Area Under Curve
APE	Average Percentage Error
BNR	Balanced Number of Rule
CLIP	Categorical Learning-Induced Partitioning
CI	Computational Intelligence
ECSFS	Evolving-Construction Scheme for Fuzzy Systems
EER	Error-Evolving Rate
EFS	Evolving Fuzzy System
EIG	Evolving Information Granule
eFSM	Evolving Neural-Fuzzy Semantic Memory
EOCFS	Evolving Output-Context Fuzzy System
ESFS	Evolving Structural Fuzzy System
FCM	Fuzzy C-Means
FIG	Fuzzy Information Granule
FRBS	Fuzzy Rule Base System
FST	Fuzzy Set Theory
GrC	Granular Computing
GFRBS	Granular Fuzzy Rule-Based System
IRT	Infrared Thermography
JG	Justifiable Granularity

LFM	Linguistic Fuzzy Modeling
LPA	Localized Parameter Adaptation
LSM	Least Square Method
MF	Membership Function
MLP	Multi-Layer Perceptron
MPG	Miles Per Gallon
MSE	Mean Square Error
MSB	Main Switch Board
NR	Number of Rules
NFS	Neural Fuzzy System
OAIG	Optimal Allocation of Information Granularity
PFM	Precise Fuzzy Modeling
RCFS	Recursive Construction of Fuzzy System
RCFS	Recursively Constructed Fuzzy System
RGB	Red, Blue and Green
RMSE	Root of MSE
RPE	Rational Partition Error
RSA	Rule Selection Algorithm
SaFIN	Self-Adaptive Fuzzy Inference Network
SC	Semantic Cointention
SM	Similarity Measure
SONFIN	Self-Constructing Neural Fuzzy Inference Network
SSE	Sum of Square Error
SSEM	Simplified Structure Evolving Method
SVM	Support Vector Machine

TFIG	Theory of Fuzzy Information Granule
UoD	Universe of Discourse
VSANF	Variable Selection Algorithm for the Neuro-fuzzy

LIST OF SYMBOLS

$[\boldsymbol{x}, d]_i$	Evidence of the ith Training Data where $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$ is an input vector, and d is the corresponding output
i	ith Training Data Where $i = \{1, 2, \ldots, N\}$
n	Number of Features (Inputs)
N	Number of Training Data
x_p	pth input feature
r	A Rule
t	An Evolving Stage
$R^{t,r}$	rth IF-THEN Mamdani-type Fuzzy Rule at tth Evolving Stage Where $r = 1,2, \ldots, R^t$
R^t	Number of Rules at tth Evolving Stage and $\{r = 1,2, \ldots, R^t\}$
μ	Gaussian Membership Function
c	Center of the Linguistic Levels
σ	Width (or variance) of the Linguistic Levels
α	Minimum Membership Value or Distinguishability Factor for UoD
$C^{t,(r)}$	rth Consequent Part at tth Evolving Stage
$c^{t,(r)}$	Center of the rth Consequent Part at tth Evolving Stage
$\sigma^{t,(r)}$	Width (or variance) of the rth Consequent Part at tth Evolving Stage
$A_p^{t,(r)}$	rth Antecedent Part at tth Evolving Stage Associated with the pth Input Variable
$c_p^{t,(r)}$ or $c_p^{t,(r)}(x_p)$	Center of the rth Antecedent Part at tth Evolving Stage Associated with the pth Input Variable
$\sigma_p^{t,(r)}$ or $\sigma_p^{t,(r)}(x_p)$	Width (or variance) of the rth Antecedent Part at tth

	Evolving Stage Associated with the pth Input Variable
$E(t)$	Error Function at tth Evolving Stage Using SSE, MSE or RMSE
$E(t-1)$	Error Function at $(t-1)$th Evolving Stage Using SSE, MSE or RMSE
E_{global}	global threshold error
E	Error, Without Considering Any Stage
E_i	Error for i Training Data Where $i = \{1, 2, \dots, N\}$
$o(\boldsymbol{x_i})$	Model's output of the ith Training Data
d_{des_i} or d_i	Desired Output of the ith Training Data
c_{1p}	Center of the First Antecedent Part (A_{1p}) (used in SAFIN)
σ_{1p}	Width of the First Antecedent Part (A_{1p}) (used in SAFIN)
Q	Optimization Factor
y_i	Desired Output data Where $i = \{1, 2, \dots, N\}$
$T_i(y_i)$	Granular Output of y_i
$\hat{y}_i$	Model Output Where $i = \{1, 2, \dots, N\}$
Δw	Gradient Vector
w_{new}	New Gradient Point
w_{old}	Current Gradient Point
η	Iteration Rate
u_j	Output Parameter with Rule Weight
Ω	An Information Granule
D	Experimental Evidence (data) where $D = \boldsymbol{x} = \{x_1, x_2, \dots, x_N\}$ (used in Pedrycz et al. (2013))
card Ω	Cardinality of Ω