MODIFIED ANFIS ARCHITECTURE WITH LESS COMPUTATIONAL COMPLEXITIES FOR CLASSIFICATION PROBLEMS

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A thesis submitted in
fulfillment of the requirement for the award of the
Degree of Master of Information Technology

Faculty of Computer Science and Information Technology
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JULY 2018

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

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In the name of Allah, Most Gracious, Most Compassionate.

I praise and thank Allah.

Special thanks for my spiritual leader Pir Muhammad Saddique Qureshi Naqshbandi, my beloved father Ashique Hussain and mother Nadra Baloch.

For dearest,
Mashook Hussain, Kashif Hussain, Waqar Hussain, Adnan Hussain, Abida Talpur, Shumaila Salman, Shabana Kashif, Murk Waqar, Shazia Adnan, Abdul Raheem Solangi.
(Brother, brother, brother, brother, sister, sister, sister, sister, brother-in-law)

For their love, support, enthusiasm, encouragement and motivation.

For my supervisor,
Prof. Madya Dr. Mohd. Najib bin Mohd. Salleh
For his incredible help, patience, understanding and support.

For all postgraduate members, fellow friends and ummah.

This thesis is dedicated to all of you.

ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious, the Most Merciful. I praise and thank to Allah for His blessings uncounted in my life and for His willing, I was able to complete this research successfully. This dissertation would not have been possible without the guidance, help and support of many people contributed and extended their valuable assistance in the preparation and completion of this research. I take this opportunity to express my profound sense of gratitude and respect to all those people.

First and foremost, I would like to express my sincere appreciation to my supervisor, Prof. Madya Dr. Mohd. Najib bin Mohd. Salleh for his guidance and endless supports from the initial to the final level, for his patience, motivation, enthusiasm, and immense knowledge. His feedback, editorial comments and suggestions were also invaluable for writing this thesis. I really appreciate it.

In preparing this research, my gratitude is extended to Universiti Tun Hussein Onn Malaysia (UTHM) for supporting this research under the Postgraduate Incentive Research Grant. I would like to gratefully thank to the Centre for Graduate Studies (CGS) and the Research, Innovation, Commercialization, and Consultancy Office (ORICC) for their hospitality during my study. I also wish to say thank to Faculty of Computer Science and Information Technology Postgraduate friends and staff who had supported my research work in one way or another.

A special thanks to my beloved family, for their continuous prayer, encouragement, love, support, patience, and care whenever I needed during these challenging days. I dedicate this work to all of you. My overwhelming gratitude to all my friends who have been together with me, thanks for love, care, concern, and support. Lastly, it is pleasure to thank all those who have helped either directly or indirectly. Thank you.

ABSTRACT

Adaptive Neuro Fuzzy Inference System (ANFIS) is one of those soft computing techniques that have solved the problems effectively in a wide variety of real-world applications. Even though it has been widely used, ANFIS architecture still has a drawback of computational complexities. The number of rules and its tunable parameters increase exponentially which created the problem of curse of dimensionality. Moreover, the standard architecture has a key drawback because of using grid partitioning and combination of gradient descent (GD) and least square estimation (LSE) which have problem to be likely trapped in local minima. Even though grid partitioning method is very useful to generate better accuracy for ANFIS model, since it generates maximum number of rules by considering all possibilities, but it also increases computational complexity. Since, ANFIS use fuzzy logic, the model accuracy is highly dependent on selecting the appropriate type of membership function. Furthermore, researchers have mainly used metaheuristic algorithms to avoid the problem of local minima in standard learning method. In this study, the experiments have been made to find out best suitable membership function for ANFIS model. Additionally, ANFIS architecture is modified for lessening computational complexities of the ANFIS architecture by reducing the fourth layer and reducing the trainable parameters as well. The proposed ANFIS model is trained by one of the metaheuristics approach instead of standard two pass learning algorithm. The performance of proposed modified ANFIS architecture is validated with the standard ANFIS architecture for solving classification problems. The results show that the proposed modified ANFIS architecture with gaussian membership function and Artificial Bee Colony (ABC) optimization algorithm, on average has achieved classification accuracy of 99.5% with 83% less computational complexity.

ABSTRAK

Adaptive Neuro Fuzzy Inference System (ANFIS) adalah merupakan salah satu daripada teknik komputeran lembut yang telah menyelesaikan masalah secara efektif dalam pelbagai aplikasi dunia nyata. Meskipun teknik ini telah digunakan secara meluas, seni bina ANFIS masih mempunyai kelemahan komputeran kompleks. Bilangan *rules* dan parameter boleh ubah bertambah secara mendadak mengakibatkan masalah dimensi yang rumit berlaku. Selain itu, seni bina standard mempunyai kelemahan utama kerana menggunakan *grid partitioning* dan gabungan antara *gradient descent (GD)* dan *least square estimation (LSE)* yang mungkin mengakibatkan masalah terperangkap dalam *local minima*. Walaupun teknik *grid partitioning* mampu memberi ketepatan keputusan yang lebih baik, ia menjana bilangan *rules* secara maksimum dan meningkatkan masalah komputeran kompleks. Algoritma GD pula terkenal dengan masalah *local minima*. Memandangkan ANFIS menggunakan *fuzzy logic,* ketepatan model sangat bergantung kepada pemilihan *membership function* yang bersesuaian. Oleh itu, para penyelidik telah menggunakan algoritma *metaheuristic* untuk mengelakkan masalah *local minima*. Justeru itu, kajian ini telah dilakukan untuk mendapatkan nilai *membership function* yang terbaik untuk ANFIS. Di samping itu, lapisan ke empat seni bina ANFIS telah diubahsuai untuk mengurangkan kerumitan ANFIS dan mengurangkan bilangan parameter untuk dilatih. Dalam kajian ini, algoritma *metaheuristic* iaitu *Artificial Bee Colony* (ABC) telah digunakan menggantikan kombinasi GD dan LSE algoritma di dalam ANFIS. Keberkesanan model yang dicadangkan dibandingkan dengan konvensional ANFIS untuk menyelesaikan masalah klasifikasi. Hasil keputusan jelas menunjukkan bahawa model yang dicadangkan secara puratanya telah mencapai ketepatan klasifikasi sebanyak 99.5% beserta pengurangan terhadap masalah komputeran kompleks sebanyak 83%.

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LIST OF SYMBOLS AND ABBREVIATIONS

A_i	-	*i*th fuzzy set of input variable *A* for ANFIS
B_i	-	*i*th fuzzy set of input variable *B* for ANFIS
m	-	Size of training dataset
O_{avg}	-	Average of selected rules' output
O_m^t	-	Target output of *m*th training pair
$Target_i$	-	Target class in the sampled tuple *i*
$Output_i$	-	Output generated by ANFIS against the tuple *i*
f_i	-	Node function for *i*th rule
σ	-	Width parameter of Gaussian type membership function
c	-	Center parameter of Gaussian type membership function
$\prod$	-	Product operator to calculate firing strength of *i*th rule in ANFIS
$O_{1,i}$	-	Output of *i*th node in layer 1 of ANFIS
$O_{2,i}$	-	Output of *i*th node in layer 2 of ANFIS
$O_{3,i}$	-	Output of *i*th node in layer 3 of ANFIS
$O_{4,i}$	-	Output of *i*th node in layer 4 of ANFIS
$O_{5,i}$	-	Output of *i*th node in layer 5 of ANFIS
p_i	-	Consequent parameter of *i*th rule
q_i	-	Consequent parameter of *i*th rule
r_i	-	Consequent parameter of *i*th rule
$\mu_{A_i}(x)$	-	*i*th membership function of input variable *A*
$\mu_{B_i}(x)$	-	*i*th membership function of input variable *B*
$\mu A(x)$	-	Membership degree of *x* in the fuzzy set

w_i	-	Firing strength of *i*th rule in ANFIS
$\bar{w}_i$	-	Normalized firing strength of *i*th rule in ANFIS
n	-	Input
m	-	Number of membership function per input
m^n	-	Number of rules in ANFIS system
LB	-	Lower bound
UB	-	Upper bound
ANFIS	-	Adaptive Neuro-Fuzzy Inference System
ABC	-	Artificial Bee Colony
ANN	-	Artificial Neural Network
SVM	-	Support Vector Machine
NFS	-	Neuro Fuzzy Systems
AC	-	Ant Colony
PSO	-	Particle Swarm Optimization
FA		Firefly Algorithm
CSO	-	Cuckoo Search Algorithm
GA	-	Genetic Algorithm
FL	-	Fuzzy Logic
MF	-	Membership Function
GD	-	Gradient Descent
LSE	-	Least Squares Estimator
FCM	-	Fuzzy C Mean
SC	-	Subtractive Clustering
PSO	-	Particle Swarm Optimization
GP	-	Genetic Programming
MCN	-	Maximum Cycle Numbers
K-Map	-	Karnaugh map
aABC	-	Adaptive and Hybrid Artificial Bee Colony
MBA	-	Mine Blast Algorithm
AMBA	-	Accelerated Mine Blast Algorithm
IMBA	-	Improved Mine Blast Algorithm
AI	-	Artificial Intelligence
MSE	-	Mean Squared Error

RMSE	-	Root Mean Square Error
UCI	-	University of California Irvine
UCIMLR	-	University of California Irvine Machine Learning Repository
GP	-	Grid Partitioning
BP	-	Backpropagation
FIS	-	Fuzzy Inference System

LIST OF PUBLICATIONS

Conference:

(i) Noureen Talpur, Mohd Najib Mohd Salleh, and K. Hussain. "Adaptive Neuro-Fuzzy Inference System: Overview, Strengths, Limitations, and Solutions", The Second International Conference on Data Mining and Big Data (DMBD'2017), JR Hakata City, Japan. (Published)

(ii) Noureen Talpur, Mohd Najib Mohd Salleh, and K. Hussain. "An investigation of membership functions on performance of ANFIS for solving classification problems", INTERNATIONAL RESEARCH AND INNOVATION SUMMIT (IRIS'2017), Malacca, Malaysia. (Published)

(iii) Mohd Najib Mohd Salleh, Norlida Hassan, Kashif Hussain, Noureen Talpur. "Modified Adaptive Neuro-Fuzzy Inference System Trained by Scoutless Artificial Bee Colony", Future of Information and Communication Conference (FICC) 2018, Singapore. (Accepted).

CHAPTER 1

INTRODUCTION

1.1 Research Background

The recent advances in artificial intelligence and soft computing techniques have opened new avenues for researchers to explore their applications. These machine learning techniques consist of several intelligent computing paradigms, including Artificial Neural Networks (ANN), Support Vector Machine (SVM), decision tree, Neuro-Fuzzy Systems (NFS), which have been successfully employed to model various real-world problems (Buragohain & Mahanta, 2008). These problems include engineering, finance, geology and bio-sciences. Because of successful interventions, many researchers are constantly working on training speed of these techniques.

Among the other soft computing techniques mentioned above, ANFIS is an efficient combination of ANN and fuzzy logic for modeling highly non-linear, complex, and dynamic systems. It is used to mine the rules, during its training process, for a system in which building rules manually is almost impossible (Aghbashlo *et* al., 2016). ANFIS is capable of handling data with uncertainty and noise. It has been proved that, with proper number of rules, an ANFIS system is able to approximate every circumstance. This is the reason, ANFIS systems are widely used and play the advantage of good applicability since they can be interpreted as non-linear modeling and conventional linear techniques for state estimation and control (Liu *et al.*, 2013). However, despite its efficiency in modeling non-linear functions with significant accuracy, the standard learning process is difficult and involves interleaving the optimization of the parameters of antecedent and conclusion parts. Training antecedent part is more difficult than consequent part because it is based on gradient computation which is computationally expensive as well as prone to falling in local optimum (Behmanesh *et al.*, 2014).

Even though ANFIS incorporates advantages of neural network and fuzzy logic, and overcomes shortcomings of both the techniques, Su (2011) contended that learning of ANFIS is a difficult task. Moreover, training the parameters of the ANFIS model is one of the main issues encountered when the model is applied to the real-world problems. There is a need for effective methods for tuning the membership functions to minimize the output error measure or maximize performance index. Due to that many have proposed improved approaches, but mostly implement revision and selection for input-output data, and do not resolve the problem (Liu *et al.*, 2013; Su, 2011). To cope with this, many researchers have proposed different learning strategies that include derivative free training via metaheuristic algorithms, clustering input-output data, and even modifying the structure of ANFIS architecture.

1.2 Motivation

ANFIS has achieved more popularity among other machine learning techniques because it combines the advantages of learning ability of neural network and reasoning ability of fuzzy logic. ANFIS architecture has been implemented to solve many highly non-linear complex real-world problems with high accuracy. Since tuning of ANFIS parameters can be termed as optimization problem, many researchers have proposed ANFIS training methods based on metaheuristic algorithms. Those algorithms include Ant Colony (AC), Particle Swarm Optimization (PSO), Firefly Algorithm (FFA), Cuckoo Search Algorithm (CSA), Genetic Algorithm (GA), Artificial Bee Colony (ABC). Most of such ANFIS learning techniques proposed by different researchers are employing metaheuristic algorithms for tuning membership function parameters and least square methods for updating linear consequent parameters. Moreover, the models based on ANFIS are often designed for data with less number of dimensions or with few inputs. ANFIS becomes computationally expensive when the number of dimensions increases significantly. In this case, the number of rules explodes exponentially and so do the parameters to be tuned. There is a need of an efficient technique to train ANFIS computationally less expensive even when there is a large number of inputs. The architecture of ANFIS can also be modified in order to lessen its computations for generating rules and producing accurate output. This research will modify the architecture of ANFIS in order to lessen computational complexity. The consequent layer contains the most number of parameters, which is equal to the number of inputs plus one times the number of rules $[(\text{inputs} + 1) \times \text{number of rules}]$. Additionally, the proposed modified ANFIS architecture will be trained by one of the metaheuristic approach which is artificial bee colony (ABC). Furthermore, the accuracy of ANFIS depends on how its membership function parameters are tuned. Therefore, this research will try different types of membership functions and tune these parameters so that ANFIS generates maximum accurate output.

1.3 Problem Statement

In recent years, neuro-fuzzy systems have been widely implemented which combine the advantages of both techniques, as well as overcome the drawbacks of each one individually. Considering the robustness on the results generated by ANFIS, it has been implemented in wide variety of applications including rule-base control systems, classification tasks and pattern matching.

Even though ANFIS has produced better results as compare to other machine learning techniques but, the model has a major drawback of computational complexities because of grid partitioning. Grid partitioning approach divides data space into grids based on the number of memberships function per input. The number of rules and its tunable parameters increase exponentially when the number of inputs for the underlying system is significantly large. Thus, large number of inputs not only effects to the transparency of the model, but also increases the computational complexity. Generally, ANFIS model is suitable for data with less than 6 number of inputs.

Moreover, the standard two pass learning process of ANFIS involves gradient based learning which is computationally expensive and prone to fall in local minima. The systems designed in literature generally have few inputs and ANFIS models with large inputs have not been implemented due to curse of dimensionality. To cope with this, many researchers have used metaheuristic algorithms to tune parameters of

ANFIS. There has been limited studies found out regarding the modification of ANFIS architecture in order to reduce its complexity.

1.4 Objectives of the study

This study embarks on the following objectives:

(i) To propose a modified ANFIS architecture with efficient training mechanism and appropriate type of membership functions in order to reduce the computational complexity to achieve the better output for ANFIS model.

(ii) To modify the ANFIS architecture according to (i) with artificial bee colony (ABC) as training algorithm and apply the best membership function to achieve reasonable accuracy while implemented on small to large dimensional classification problems.

(iii) To evaluate the performance of modified ANFIS architecture in objective (ii) with the standard ANFIS architecture in terms of MSE, percentage of accuracy, number of trainable parameters and number of epochs.

1.5 Scope of the Study

This research is scoped at:

This study is limited to an investigation of types and shapes of membership functions of ANFIS architecture to produce maximum accuracy for highly dimensional data. Furthermore, this research also focuses on modifying ANFIS architecture from five layers to four in order to reduce the complexity of the architecture and apply artificial bee colony (ABC) to optimize and train the proposed ANFIS model parameters to solve the problem of local minima. This research is intended to solve the classification problems with the dataset having small to large number of dimensions taken from University California Irvine Machine Learning Repository (UCIMLR) (David & Christopher, 2007).

The proposed approach will be validated by comparing results with standard ANFIS model and modified ANFIS model with the performance measurement criteria of MSE, percentage of accuracy, number of trainable parameters and number of epochs.

1.6 Expected Outcome

As, any application of ANFIS demands expert knowledge of fuzzy logic, therefore, ANFIS structure requires better choice of membership functions. This does not only influence the efficiency of ANFIS-based model, but also the computational cost. Hence, this research discovered the best suitable membership functions for ANFIS architecture to implement for classification problems. Additionally, the standard ANFIS model contains five layers and apply gradient based learning that increase the computational complexities of the ANFIS model when the number of inputs become large. Therefore, this study proposed modified ANFIS architecture with four layers and ABC algorithm that can be implemented for the problems with the small to large number of inputs.

1.7 Thesis Organization

This research thesis comprises of five chapters including Introduction and Conclusion chapters. The followings are synopsis of each chapter.

Chapter 1: *Introduction*. Apart from providing an outline of the thesis, this chapter contains an overview of the research background, problem to be solved, objectives to achieve, scope, aim, and outcome of the study.

Chapter 2: *Literature Review*. This chapter explains basic ANFIS architecture and learning mechanism, applications and reviews some of the work on soft-computing techniques that has already been applied by researchers while solving problems related to achieve more accuracy. After reviewing literature, a critical analysis has been explained in terms of gaps and limitation on existing architecture of ANFIS.

Chapter 3: *Research Methodology***.** This chapter discusses the research methodology used to carry out the study systematically. First, existing work on ANFIS training and optimization has been analyzed and by observing the gap analysis the proposed methodology is presented to explain what phases and steps will be taken in this research to achieve the objectives as an outcome.

Chapter 4: *Results and Analysis.* Different shapes of membership functions have been employed to ANFIS's architecture to find out the best membership function for ANFIS models. The proposed modified ANFIS model with ABC optimization algorithm have been evaluated with standard ANFIS model while training in terms of proficiency of achieving high accuracy with less computational complexity. The performance evaluation was carried out based on MSE, accuracy, total number of parameters and number of epochs.

Chapter 5: *Conclusion and Future work*. The contributions of the proposed modified ANFIS's architecture are summarized, and the recommendations are given for further continuation of work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Artificial Neural Network (ANN) is used to compile a programming structure that behaves like biological neurons; which is made up of interconnected artificial neurons. ANN architecture consists of three layers; (i) input layer, (ii) hidden layer, and (iii) output layer (Venkatesan *et al.*, 2013). To avoid any uncertainty in decisions of neural networks; a fuzzy logic module was used as a decision-making tool. Unlike binary logic that can either be True or False (0 or 1), fuzzy logic provides an attractive solution to the real-world challenges by introducing the concept of values that can be partially true and partially false to handle the imprecision and uncertainty. Because of the concept of fuzzy if-then rules, set theory and reasoning ability; fuzzy inference systems are popular computing paradigms. The three main parts in a fuzzy system are, (i) fuzzification, (ii) inference, (iii) de-fuzzification (Abdulshahed *et al.*, 2014). Despite the fact that it is extremely convenient to express the information as an arrangement of if-then rules, there is no systematic way to make this conversion (Jovanovic *et al.*, 2004). However, ANFIS, as the name suggests, it is an adaptive network with the combination of neural network and fuzzy logic. This relationship eliminates the limitations of both techniques by combining the advantages of both techniques. To train and update parameters; ANFIS applies the hybrid learning algorithm which is a combination of least-square method and gradient descent method to identify the parameters of FIS (Walia *et al.*, 2015).

This chapter is organized in the following order: Section 2.2 defines the fundamentals and working structure of neural network and fuzzy logic. In Section 2.3,

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