MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS OF SPIKING NEURAL NETWORKS

ABDULRAZAK YAHYA SALEH

UNIVERSITI TEKNOLOGI MALAYSIA

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ABDULRAZAK YAHYA SALEH

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To my beloved parents, wife, children, brothers and my sisters

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ABSTRACT

Spiking neural network (SNN) is considered as the third generation of artificial neural networks. Although there are many models of SNN, Evolving Spiking Neural Network (ESNN) is widely used in many recent research works. Among the many important issues that need to be explored in ESNN are determining the optimal pre-synaptic neurons and parameters values for a given data set. Moreover, previous studies have not investigated the performance of the multi-objective approach with ESNN. In this study, the aim is to find the optimal pre-synaptic neurons and parameter values for ESNN simultaneously by proposing several integrations between ESNN and differential evolution (DE). The proposed algorithms applied to address these problems include DE with evolving spiking neural network (DE-ESNN) and DE for parameter tuning with evolving spiking neural network (DEPT-ESNN). This study also utilized the approach of multi-objective (MOO) with ESNN for better learning structure and classification accuracy. Harmony Search (HS) and memetic approach was used to improve the performance of MOO with ESNN. Consequently, Multi-Objective Differential Evolution with Evolving Spiking Neural Network (MODE-ESNN), Harmony Search Multi-Objective Differential Evolution with Evolving Spiking Neural Network (HSMODE-ESNN) and Memetic Harmony Search Multi-Objective Differential Evolution with Evolving Spiking Neural Network (MEHSMODE-ESNN) were applied to improve ESNN structure and accuracy rates. The hybrid methods were tested by using seven benchmark data sets from the machine learning repository. The performance was evaluated using different criteria such as accuracy (ACC), geometric mean (GM), sensitivity (SEN), specificity (SPE), positive predictive value (PPV), negative predictive value (NPV) and average site performance (ASP) using k-fold cross validation. Evaluation analysis shows that the proposed methods demonstrated better classification performance as compared to the standard ESNN especially in the case of imbalanced data sets. The findings revealed that the MEHSMODE-ESNN method statistically outperformed all the other methods using the different data sets and evaluation criteria. It is concluded that multi objective proposed methods have been evinced as the best proposed methods for most of the data sets used in this study. The findings have proven that the proposed algorithms attained the optimal pre-synaptic neurons and parameters values and MOO approach was applicable for the ESNN.

ABSTRAK

Rangkaian Neural Pakuan (SNN) dianggap sebagai generasi ketiga buatan saraf rangkaian.Walaupun terdapat banyak model dari SNN, Rangkaian Neural Pakuan Berevolusi (ESNN) telah digunakan secara meluas di dalam kajian terkini. Antara isu-isu penting yang perlu dikaji di dalam ESNN adalah menentukan bilangan optimal pra-sinaptik neuron dan bilangan parameter bagi data set yang telah diberikan. Selain itu, kajian sebelum ini tidak menekankan prestasi pendekatan pelbagai objektif bersama ESNN. Tujuan utama kajian ini adalah untuk mencari nilai optimum pra-sinaptik neuron dan parameter ESNN secara serentak dengan mencadangkan beberapa integrasi antara ESNN dan Evolusi Pembezaan (DE). Pelbagai algoritma telah dicadangkan iaitu DE bersama Rangkaian Neural Pakuan Berevolusi (DE-ESNN) dan DE bagi penalaan parameter dengan Rangkaian Neural Pakuan Berevolusi (DEPT-ESNN). Kajian ini juga menggunakan pendekatan multi-objektif (MOO) bersama ESNN, bagi menerangkan struktur pembelajaran yang lebih baik dan ketepatan pengelasan. Carian Harmoni (HS) dan pendekatan memetik digunakan untuk meningkatkan prestasi MOO bersama ESNN. Oleh itu, Multi-Objektif Evolusi Pembezaan bersama Rangkaian Neural Pakuan Berevolusi (MODE-ESNN), Carian Harmoni Multi-Objektif Evolusi Pembezaan bersama Rangkaian Neural Pakuan Berevolusi (HSMODE-ESNN) dan Multi-Objektif Evolusi Pembezaan bersandarkan memetik harmoni bersama Rangkaian Neural Pakuan Berevolusi (MEHSMODE-ESNN) digunakan bagi memperbaiki struktur ESNN dan ketetapan kadar. Kaedah hibrid telah diuji dengan menggunakan tujuh penanda aras data set dari repositori pembelajaran mesin. Prestasi kaedah yang dicadangkan telah dinilai menggunakan kriteria yang berbeza seperti ketepatan (ACC), min geometri (GM), kepekaan (SEN), kekhususan (SPE), nilai ramalan positif (PPV), nilai ramalan negatif (NPV) dan tapak purata prestasi (ASP) menggunakan pengesahan silang k kali ganda. Analisis penilaian menunjukkan bahawa kaedah yang dicadangkan menunjukkan prestasi klasifikasi yang lebih baik berbanding dengan standard ESNN terutama dalam kes data set yang tidak seimbang. Penilaian ini mendedahkan bahawa kaedah MEHSMODE-ESNN statistik secara telak mengatasi semua kaedah lain yang menggunakan data set dan kriteria penilaian yang berbeza. Hasil kajian mendapati bahawa MEHSMODE-ESNN yang di cadangkan telah terbukti sebagai kaedah terbaik bagi kebanyakan data set yang digunakan dalam kajian ini. Hasil kajian telah membuktikan bahawa algoritma yang dicadangkan mencapai optimum neuron pra-sinaptik dan parameter nilai dan pendekatan MOO terpakai untuk ESNN.

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LIST OF ABBREVIATIONS

ACC	-	Accuracy
ANNs	-	Artificial Neural Networks
ASP	-	Average Site Performance
BP	-	Back-Propagation
CM	-	Current method (ESNN)
CPSO	-	Cooperative Particle Swarm Optimization
DE	-	Differential Evolution
DE-ESNN	-	Differential Evolution with Evolving Spiking Neural Network
DEPT-ESNN	-	Differential Evolution for Parameter Tuning with Evolving Spiking Neural Network
DM	-	Decision Making
EAs	-	Evolutionary Algorithms
ErrR	-	Error Rate
ESNN	-	Evolving Spiking Neural Network
FN	-	False Negative
FNR	-	False Negative Rate
FP	-	False Positive
FPR	-	False Positive Rate
GA	-	Genetic Algorithm
GM	-	Geometric Mean
GRF	-	Gaussian Receptive Fields
HM	-	Harmony Memory
HMCR	-	Harmony Memory Considering Rate
HMS	-	Harmony Memory Size
HS	-	Harmony Search algorithm

HSA	-	Harmony Search Algorithm
HSMODE-ESNN	-	Harmony Search Multi objective Differential Evolution with Evolving Spiking Neural Network
LTD	-	Long Term Depression
LTP	-	Long Term Potentiation
MEHSMODE-ESNN	-	Memetic Harmony Search Multi objective Differential Evolution with Evolving Spiking Neural Network
ML	-	Machine Learning
MLP	-	Multilayer Perceptron Network
Mod	-	Modulation Factor
MODE-ESNN	-	Multi objective Differential Evolution with Evolving Spiking Neural Network
MOEAs	-	Multi-objective evolutionary algorithms
MOGA	-	Multi objective genetic algorithm
MOO	-	Multi-Objective Optimization
MuSpiNN	-	Multi-Spiking Neural Network
NPV	-	Negative Predictive Value
NRU	-	No right to use
PAR	-	Pitch Adjusting Rate
PM	-	Proposed Method
PNNs	-	Probabilistic Neural Networks
PPV	-	Positive Predictive Value
PSO	-	Particle Swarm Optimization
QiPSO	-	Quantum-inspired Particle Swarm Optimization
r_{accept}	-	Accepting Rate
SA	-	Simulated Annealing
SEN	-	Sensitivity
SI	-	Swarm Intelligence
Sim	-	Neuron Similarity Value
SNN	-	Spiking Neural Network
SO	-	Single Objective
SOM-AC	-	Self-Organizing Map with modified adaptive coordinates
SPE	-	Specificity
SRM	-	Spike Response Model

STDP	-	Spike Time Dependent Plasticity
SVM	-	Support Vector Machine
SWRNN	-	Spiking Wavelet Radial Basis Neural Network
Threshold	-	Proportion Factor
TN	-	True Negative
TNR	-	True Negative Rate
TP	-	True Positive
TPR	-	True Positive Rate
TS	-	Tabu Search

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CHAPTER 1

INTRODUCTION

1.1 Overview

Classification of patterns is vital for several data mining processes. Classification is one of the most commonly obverse processing tasks for a decision support system (Ahmed *et al.*, 2013a). There are many areas in life which need classification such as medical diagnoses, medicine, science, industry, speech recognition and handwritten character recognition. Among feasible classifiers, artificial neural network (ANN) classifiers have proved to be one of the most robust classification systems; their ability to deal with noisy input patterns and to handle both noisy and continuous data demonstrates their use as an important tool for classification (Mitchell and Michell, 1997).

ANNs are amongst the most well-known brain computational models and ANN solves problems that are based on standard algorithmic techniques. ANNs can be utilized in pattern recognition, generalization, perception and non-linear control. Action potentials or spikes are responsible for all communications between neurons; however, individual spikes in ANN models are averaged out over time. All interactions are divided by the mean firing rate of the neurons. Furthermore, they are computationally more powerful than ANNs, which use mean firing rates (Maass and Bishop, 2001).

Due to its effectiveness in ANNs, the sigmoidal neuron model is considered to be one of the best models of the biological neuron. Several vital applications of ANNs have been built by rate modeling, which means a single biological neuron releases action potentials (spikes) as a monotonically increasing function of input-match. From another point of view, explorations of the computational power in single spikes have been undertaken due to the spiking nature of biological neurons. Bohte *et al.* (2002a) prove that more powerful computation can be found through individual spike times rather than sigmoidal activation functions.

Spiking neural networks (SNNs), the third generation of ANNs, play an essential role in biological information processing (Gerstner and Kistler, 2002). Compared with ANNs, which use rate coding for neuronal activity representation, spiking models provide an in-depth description of biological neuronal behavior. More information has been used with the average firing rate for computations with real neurons. Furthermore, instead of rate coding, the difference in firing times may be used (Belatreche *et al.*, 2006).

Although there are many models of SNN, the evolving spiking neural network (ESNN) is used widely in recent research. The ESNN has several advantages (Schliebs *et al.*, 2009c) including being a simple, efficient neural model and trained by a fast one-pass learning algorithm. The evolving nature of the model can be updated whenever new data becomes accessible with no requirement to retrain earlier existing samples. However, the ESNN model is affected by the choice of parameter; the correct selection of parameters allows the network to evolve towards reaching the best structure, thus guaranteeing the best output. For this reason, an optimizer is needed to find the best combination of parameters.

Optimization has been used to enhance the ESNN algorithm. Choosing a good optimization algorithm for real-world applications is necessary, especially for optimal solutions of an ESNN. Evolutionary algorithms (EAs), mainly differential evolution (DE), are common competitors in optimization problems because of the following characteristics: simpler implementation, better performance, very few control parameters and low space complexity (Abbass, 2001; Das and Suganthan, 2011). Therefore, DE is conducted to enhance ESNN algorithms. However, many real-world optimization problems include several contradictory objectives. Rather than single optimization, multi-objective optimization (MOO) can be utilized as a set of optimal solutions to solve these problems. Every MOO solution appears to be a new trade-off between the objectives. The key objective of MOO is to improve ESNN optimal solutions of both structure and classification accuracy. In addition, optimization of both accuracy and complexity leads to generalization.

The MOO approach is preferred to algorithms of traditional learning for a number of reasons. First, as a result of using MOO, a good performance of these learning algorithms can be achieved (Abbass, 2003b). Second, various objectives are taken into consideration in the generation of multiple learning models such as accuracy, complexity (Igel, 2005; Jin, 2006; Jin *et al.*, 2004), interpretability and accuracy (Jin *et al.*, 2005), multiple error measures (Fieldsend and Singh, 2005). Third, it is superior to build learning ensembles to use models that are produced using MOO (Abbass, 2003a; Chandra and Yao, 2004; Jin *et al.*, 2004). The important goal of the MOO algorithm is to find a set of solutions from which the best one is chosen. Based on Tan *et al.* (2001), the ability of EAs to search for optimal solutions gives them the priority to be selected in MOO problems. EAs have the ability to explore different parts of the related algorithm in the optimal set because of the population-based algorithms.

Moreover, one of the EAs i.e. harmony search (HS) algorithm was utilized to overcome problems of convergence rate at finding the global minimum of DE (Gao *et al.*, 2014; Purnomo and Wee, 2014; Wang and Guo, 2013). Subsequently, backpropagation (BP) was used to speed up convergence known as a memetic approach.

1.2 Problem Background

In SNN, the behavior which is archived in topology is like that of Kohonen's self-organization map and can be used effectively in character recognition (Buonomano and Merzenich, 1999), classifications and dynamic path planning (Yang and Luo, 2004). Consequently, SNNs have been utilized as a vital method for classification. Many types of SNN are used for classification problems. Bohte *et al. (2002a)* proposed a supervised learning algorithm, spike backpropagation

(SpikeProp), using spike-time encoding based on error BP, which is used for solving classification problems. Schrauwen *et al*. (2004) proposed many learning rules to extend SpikeProp for good learning of spike times. Ghosh-Dastidar *et al.* (2009) introduced a multi-SpikeProp for supervised learning of spike patterns in multiple-synapse transmission (Bohte *et al.*, 2002b). Ahmed *et al*. (2013a) proposed and presented several methods for classification problems for an improved SpikeProp by particle swarm optimization (PSO) and angle-driven dependency learning rate. Ahmed *et al*. (2014) mentioned that the most important challenge is to find out efficient learning rules that might take advantage of the specific features of SNNs while keeping the advantageous properties (general-purpose, easy-to-use, available simulators etc.) of traditional connectionist models.

There have been many attempts to improve new models of SNNs. Wysoski *et al*. (2006c) proposed a new model type, ESNN. Recently, a few studies on the hybridization of the ESNN algorithm have been implemented. A novel supervised learning algorithm combined with PSO for this model ESNN has been introduced by Hamed *et al.* (2011a).

The most significant problem facing these recent studies is to determine the optimal number of pre-synaptic neurons for a given data set (Hamed *et al.*, 2011a). The number of pre-synaptic neurons is required before the ESNN structure can be constructed. This problem is similar to identifying the number of hidden nodes in multilayer perceptron (MLP). Based on the work by Hamed (2012), a smaller number of pre-synaptic neurons cause fewer input spikes to be generated and may subsequently affect learning accuracy, while a larger number increases computational time. Evolving processes are difficult to model as there might be no prior knowledge for some parameters (Kasabov, 2003). Figure 1.1 explains the scenario which leads to the problem settled by this research. In Figure 1.1 the challenges of ESNN model and the limitation of existing model are revealed.

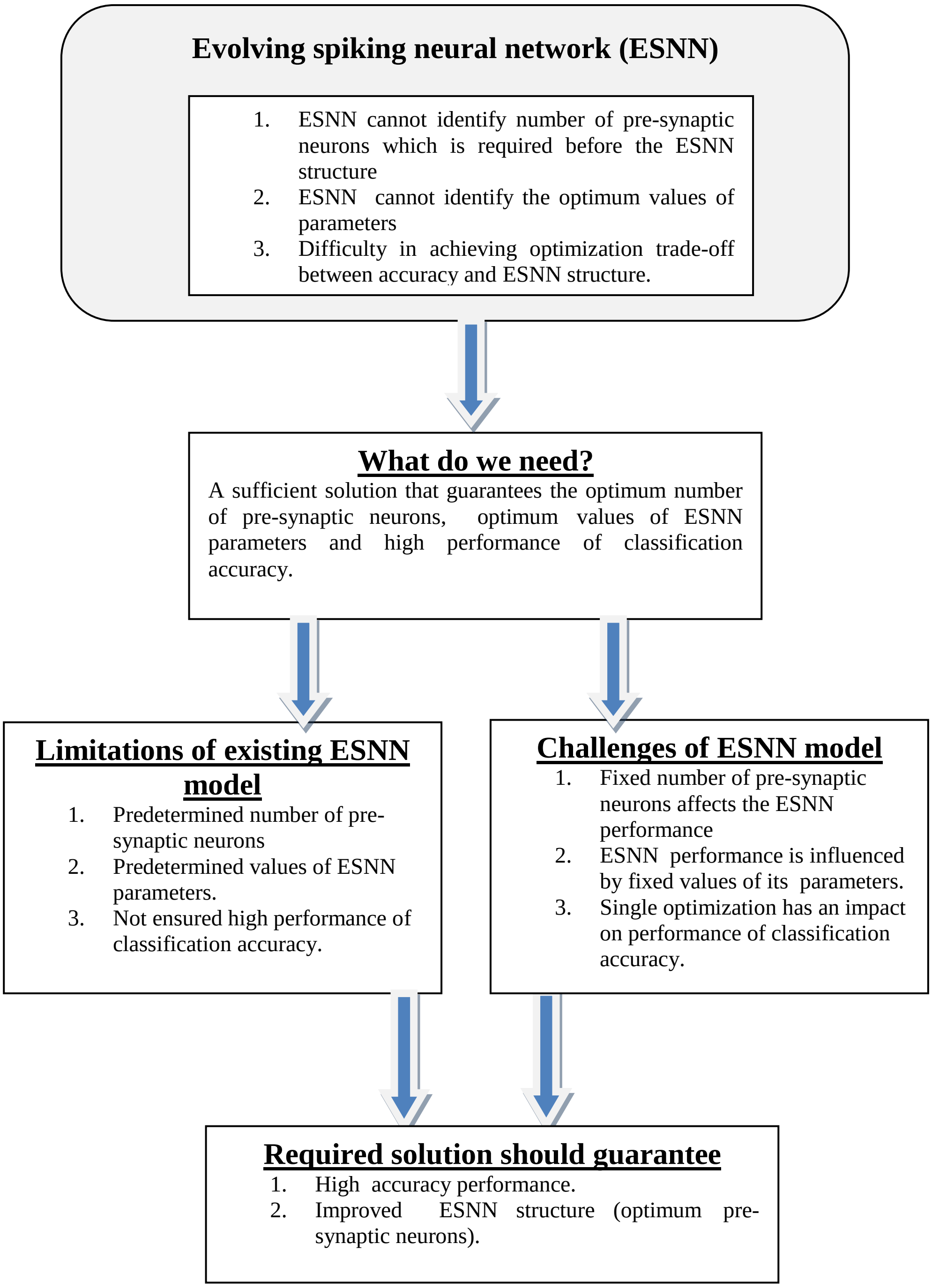

Figure 1.1 Scenario guides to the research problem

The scenario shown in Figure 1.1 draws attention to the most important requirements that should be taken into consideration during the design of the solution.

According to Watts (2009), the automatic selection of evolving connectionist systems (ECOS) training parameters would be a significant advantage. Therefore, it would be interesting to choose an optimization technique to carry out this parameter adaptation. Among the various optimization techniques, EAs have been used to solve learning problems when applied to the ESNN model. The significance of using EAs is their ability to adapt to a varying environment (Fernandez Caballero *et al.*, 2010); that is why it is a common optimizer in many classification models such as ANNs (da Silva *et al.*, 2010; Mineu *et al.*, 2010), wavelet neural networks (Dheeba and Selvi, 2012) and support vector machine (SVM) (Zhou *et al.*, 2007). To capitalize on the particular advantage of DE, it can be an attractive method to optimize pre-synaptic neurons and to find trade-off solutions to overcome the problems of MOO.

A few studies have evaluated multi-objective evolutionary algorithm (MOEAs) methods with SNN such as multi-objective genetic algorithm (MOGA) with SpikeProp and showed that this algorithm performs well (Jin *et al.*, 2007a). As Yee and Teo suggested in (2013) multi-objective techniques could generate better solutions in SNNs. Therefore, this research improved new hybrid methods with other types of SNNs, for example ESNN with MOEAs such as multi-objective differential evolution with evolving spiking neural network (MODE-ESNN), harmony search multi-objective differential evolution with evolving spiking neural network (HSMODE-ESNN) and memetic harmony search multi-objective differential evolution with evolving spiking neural network (MEHSMODE-ESNN). The proposed methods aim to create a trade-off between the structures of ESNN and the accuracy of testing data of ESNN.

1.3 Problem Statement

Issue 1: Recently, ESNNs have attracted extensive research attention because of the multiple advantages they offer compared to others models (Batllori *et al.*, 2011; Kasabov, 2012; Kasabov *et al.*, 2014; Mohemmed *et al.*, 2013; Murli *et al.*, 2014; Nuntalid *et al.*, 2011a; Schliebs and Kasabov, 2013). Among the many real issues that need to be explored in ESNN, determining the optimal number of pre-synaptic neurons for a given data set is the most important one (Hamed, 2012; Kasabov *et al.*, 2014). The number of pre-synaptic neurons is required before the ESNN structure can be constructed. This problem is similar to identifying the number of hidden nodes in MLP. Fewer pre-synaptic neurons cause the generation of fewer input spikes, which may subsequently affect learning accuracy, while more pre-synaptic neurons increase computational time. Additionally, each of the methods has a number of parameters which are currently set by hand, based on performance with the training data set. Therefore, the automation of the process of parameter selection is another challenge (Kasabov, 2012; Kita, 2011; Pears *et al.*, 2013; Yu *et al.*, 2014).

Issue 2: Another real issue of the ESNN is achieving an optimized balance between accuracy and the network structure. Several integrations between EAs and Swarm Intelligence (SI) strategies with ESNN have been performed such as: (Hamed *et al.*, 2009a; Schliebs *et al.*, 2009b; Schliebs *et al.*, 2010a). However, GA has some shortcomings such as more predefined parameters, competing conventions and premature convergence problem (Kim *et al.,* 2005; Sahab *et al.,* 2005). Nevertheless, no specific algorithm can achieve the best performance for particular problems as supposed to the 'no free lunch theorem' (Wolpert and Macready, 1997). On the other hand, the many advantages of DE compared to PSO and GA, which include being much simpler to implement, much better performance, very few control parameters and low space complexity (Abbass, 2001; Das and Suganthan, 2011) motivate research in utilizing this hybridization

Therefore, in this thesis, all the hybrid proposed methods: differential evolution with evolving spiking neural network (DE-ESNN), differential evolution for parameter tuning with evolving spiking neural network (DEPT-ESNN), multi objective differential evolution with evolving spiking neural network (MODE-ESNN), harmony search multi objective differential evolution with evolving spiking neural network (HSMODE-ESNN) and memetic harmony search multi objective differential evolution with evolving spiking neural network (MEHSMODE-ESNN) are presented.

Based on the above issues which are mentioned in section 1.3, the main research question is

Are the proposed hybrid methods between ESNN and different meta-heuristic and MOEAs which include DE-ESNN, DEPT-ESNN, MODE-ESNN, HSMODE-ESNN and MEHSMODE-ESNN, beneficial for evolving learning of ESNN in terms of structure (pre-synaptic neurons) and accuracy?

Thus, the following issues need to be addressed:

1. How to optimize both the structure of ESNN (the pre-synaptic neurons) using the proposed method (DE-ESNN) and ESNN parameters using the proposed method (DEPT-ESNN) ?
2. How to improve a multi objective method to optimize ESNN's pre-synaptic neurons as well as the parameters simultaneously using MODE-ESNN ?
3. How effective is harmony search (HS) and memetic technique in enhancing the multi objective method (MODE-ESNN) using HSMODE-ESNN and MEHSMODE-ESNN?
4. Would the classification accuracy and other classification performance measures be improved when all the previous proposed methods are implemented ?

1.4 Research Aim

This research aims to enhance hybrid learning of evolving spiking neural network (ESNN) with the proposed methods to obtain simple (the lowest number of pre-synaptic neurons) and accurate ESNN model.

1.5 Research Objectives

In order to find the answers to the above questions, the objectives of this study have been identified as:

1. To enhance evolving spiking neural network (ESNN) learning by proposing hybrid methods using a differential evolution (DE) algorithm to optimize the pre-synaptic neurons and the parameters of ESNN.
2. To improve a multi-objective hybrid method of multi objective differential evolution with evolving spiking neural network(MODE-ESNN) to optimize the pre-synaptic neuron as well as the parameters simultaneously.
3. To enhance the proposed hybrid methods using HS and memetic techniques.

1.6 Research Scope

To accomplish the above objectives, the scope of this study is restricted to the following:

1. Data sets on both binary and multi class classification problems are essential for evaluating the proposed methods Appendicitis, Iris, Hepatitis, Ionosphere, Liver, Haberman and Pima heart.
2. Focus is on the proposed methods of DE-ESNN, DEPT-ESNN, MODE-ESNN, HSMODE-ESNN and MEHSMODE-ESNN for learning, which includes training and testing in classification problems.
3. Performance is tested based on structure (number of pre-synaptic neurons), classification accuracy (ACC), geometric mean (GM), sensitivity (SEN), specificity (SPE), positive predictive value (PPV), negative predictive value (NPV) and average site performance (ASP).
4. The programs are customized, improved and applied to the learning of ESNN using Microsoft Visual C++ 10.0 and Matlab.

1.7 Research Methodology Overview

This study consists of five phases: research planning, data set preparation, research design, implementation and analysis. Research planning is the key to success in guiding the research direction. Additionally, algorithm performance depends on data set nature. The data sets were used as inputs the for the proposed methods in research design and implementation of the process enhancement. The proposed algorithms were trained, tested and validated using quantitative measurements to classification problems. Finally, statistical test analysis was applied. Figure 1.2 shows the research methodology of the study.

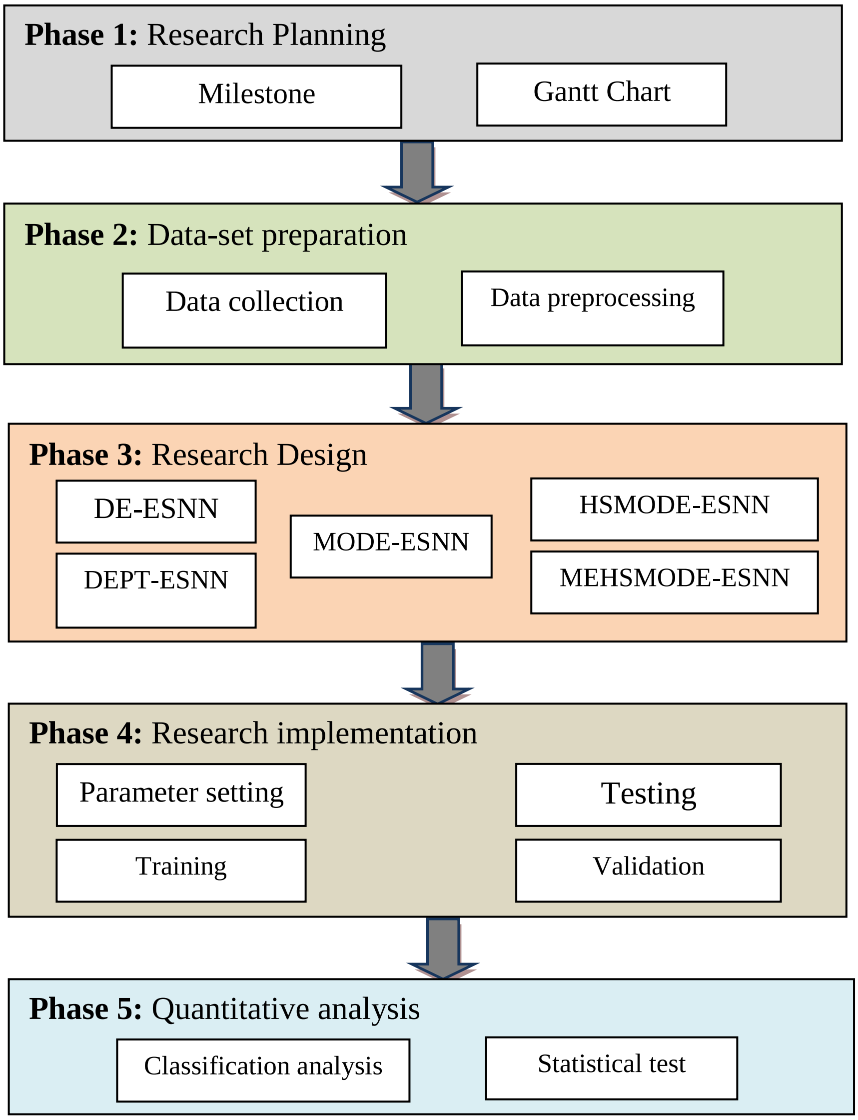

Figure 1.2 Flow of research methodology phases

1.8 Summary of Research Contributions

The contributions of the study can be summarized in the next points, as also illustrated in Figure 1.3:

1. Hybrid method known as DE-ESNN used for optimizing the pre-synaptic neurons.
2. Hybrid method known as DEPT-ESNN used to optimize the parameters (Mod, Sim, Threshold) in ESNN.
3. Multi-objective method known as MODE-ESNN used to optimize the pre-synaptic. neurons and the parameters simultaneously.
4. Hybrid methods known as HSMODE-ESNN used to enhance the MODE-ESNN method.
5. Hybrid methods known as MEHSMODE-ESNN used to enhance the MODE-ESNN method.

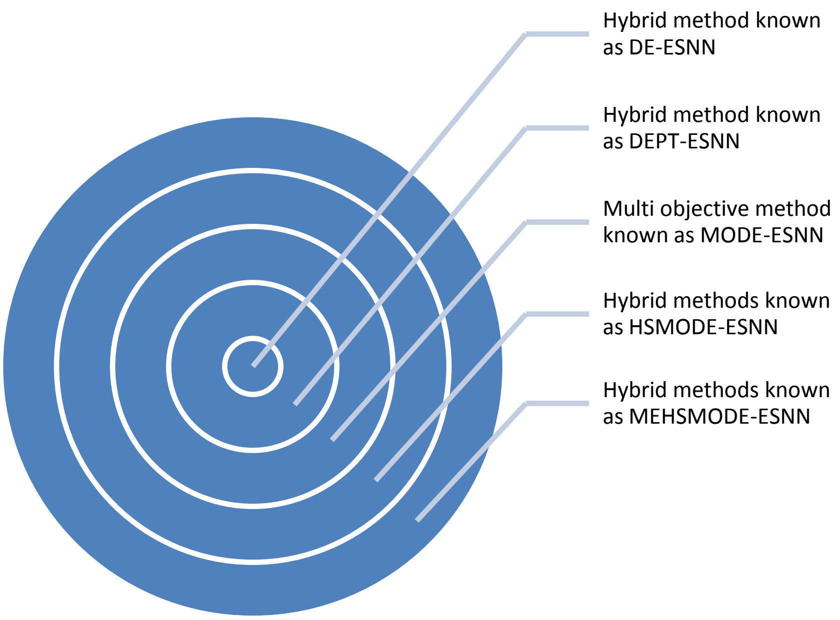

Figure 1.3 Summary of research contributions

1.9 Thesis Outline

This thesis contains seven chapters, including the introduction chapter. The second chapter describes the background and the earlier work in the field of SNNs, evolving spiking neural network and MOEAs. The third chapter describes the research methodology for the work. The fourth and fifth chapters present the proposed methods used in this study and their algorithmic and results details. Finally, the last two chapters present the performance evaluation, discussion, conclusion and future extensions of the study.

Chapter 2, Literature Review, introduces a general overview of the literature review of this study. Fundamental concepts of SNNs, ESNN and EAs that are used in this thesis and MO optimization are introduced.

Chapter 3, Research Methodology, illustrates the methodology used in this study. The research methodology is presented as a flow chart diagram that explains briefly how each step is utilized.

Chapter 4, Hybrid Proposed Methods, explains in detail how EAs can optimize the ESNN model for classification. Furthermore, this chapter describes the implementation of the algorithms which are used. Moreover, the results based on performance measures are illustrated for all proposed methods. Last but not least, statistical analysis is carried out.

Chapter 5, MOO Proposed Methods, describes how multi-objective algorithms can optimize the ESNN model for classification. Additionally, this chapter explains the implementation of MOO algorithms that are used. Moreover, the results based on performance measures are illustrated for all proposed methods. Finally, statistical analysis is carried out.

Chapter 6, Comparative study of the proposed methods, implements the results based on performance measures and illustrates the comparative analysis among all proposed methods. Moreover, a comparison is conducted with various classifiers and data mining algorithms. Last but not least, statistical analysis is carried out.

Chapter 7, Conclusion and Future Work, winds up the study and highlights the contributions and findings of the research work. In addition, Chapter 7 provides recommendations and suggestions and for future work. Finally , a summary is reported for the whole study.

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