# PARAMETER OPTIMIZATION OF EVOLVING SPIKING NEURAL NETWORKS USING IMPROVED FIREFLY ALGORITHM FOR CLASSIFICATION TASKS

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To my beloved mother and father

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# ABSTRACT

Evolving Spiking Neural Network (ESNN) is the third generation of artificial neural network that has been widely used in numerous studies in recent years. However, there are issues of ESSN that need to be improved; one of which is its parameters namely the modulation factor (Mod), similarity factor (Sim) and threshold factor (C) that have to be manually tuned for optimal values that are suitable for any particular problem. The objective of the proposed work is to automatically determine the optimum values of the ESNN parameters for various datasets by integrating the Firefly Algorithm (FA) optimizer into the ESNN training phase and adaptively searching for the best parameter values. In this study, FA has been modified and improved, and was applied to improve the accuracy of ESNN structure and rates of classification accuracy. Five benchmark datasets from University of California, Irvine (UCI) Machine Learning Repository, have been used to measure the effectiveness of the integration model. Performance analysis of the proposed work was conducted by calculating classification accuracy, and compared with other parameter optimisation methods. The results from the experimentation have proven that the proposed algorithms have attained the optimal parameters values for ESNN.

# ABSTRAK

Rangkaian Neural Pakuan Berevolusi (ESNN) adalah rangkaian neural buatan generasi ketiga yang banyak digunakan dalam kajian terkini. Walau bagaimanapun, terdapat permasalahan ESNN yang perlu diselesaikan iaitu salah satunya adalah parameternya iaitu faktor modulasi (Mod), faktor persamaan (Sim) dan faktor ambang (C) yang perlu diubah secara manual untuk nilai optimum yang sesuai bagi setiap permasalahan. Objektif bagi cadangan kerja yang dicadangkan adalah menentukan nilai parameter yang optimum secara automatik untuk parameter ESNN bagi setiap dataset dengan mengintegrasikan pengoptimum Algoritma Kelip-kelip (FA) ke dalam fasa latihan ESNN dan secara adaptif mencari nilai parameter yang paling baik. Dalam kajian ini FA telah diubahsuai dan ditambahbaik serta digunakan untuk meningkatkan ketepatan struktur ESNN dan kadar ketepatan klasifikasi. Lima dataset dari pembelajaran mesin *University of California, Irvine* (UCI) telah digunakan untuk mengukur keberkesanan model integrasi ini. Analisis prestasi kerja yang dicadangkan dilakukan dengan mengira ketepatan klasifikasi dan dibandingkan dengan kaedah pengoptimuman parameter yang lain. Hasil kajian telah membuktikan bahawa algoritma yang dicadangkan telah mencapai nilai parameter optimum untuk ESNN.

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## LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| ANN | - | Artificial Neural Networks |
| deSNN | - | Dynamic Synapse and ESNN |
| ECOS | - | Evolving Connectionist Systems |
| ESNN | - | Evolving Spiking Neural Network |
| FA | - | Firefly Algorithm |
| HH | - | Hodgkin-Huxley model |
| hMM-EDA | - | Heterogeneous Multi-Model Estimation of Distribution Algorithm |
| LSM | - | Liquid State Machine |
| MLP | - | Multilayer Perceptron |
| NHS-ESNN | - | New Hybrid Harmony Search Algorithm with Evolving Spiking Neural Network |
| POC | - | Population Rank Order Coding |
| QiPSO | - | Quantum-inspired Particle Swarm Optimization |
| ROC | - | Rank Order Coding |
| reSNN | - | reservoir-based ESNN |
| SRM | - | Spike Response Model |
| SPAN | - | Spike Pattern Association Neuron |
| vQEA | - | Versatile Quantum-inspired Evolutionary Algorithm |

## LIST OF SYMBOLS

| | | |
|---|---|---|
| Mod | - | Modulation factor |
| Sim | - | Similarity factor |
| C | - | Threshold factor |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Overview

Classification is one of the most commonly encountered processing tasks for decision making. A problem of classification occurs when an object requires to be assigned into a group that are predefined or class based on a number of observed attributes related to that object. Classification problems cover many areas in life such as medical diagnoses, medicine, science, industry, speech recognition and handwritten character recognition. A classifier have proven to be one of the most robust classification system which is ANN. It has the ability to deal with input pattern that are noisy and able to handle continuous data. Thus, demonstrated ANN as an important tool for classification (Mitchell, 1997).

ANN has been inspiration by the dynamics of the human brain. It has motivated the researchers to use the model as a powerful computational tool in solving complex pattern recognition, function estimation, classification problems and complex optimisation problems (Ghosh-Dastidar & Adeli, 2009). In designing and training the ANN structure, parameter defining is necessary; for example, the number of hidden layers and neurons in the layers. Upon specific application, these features have changed. In defining these parameters, there is no general and explicit method. Each time the method of trial and error was used, the computational time has been increased and the method output has not been precise. Over time, researchers have been able to grasp the dynamics of the human brain which has led to the development of more biologically realistic network models. The outcome of this development has pointed towards to the introduction of SNN (Maass, 1997).

SNN are the third generation of neural network model. The model uses spikes as a substitute and analyses the pulse coded information (Gerstner, 2001; Gerstner et al., 1993; Gerstner & van Hemmen, 1994; N. Kasabov, 2008; Maass, 1997). Additionally, when SNN is compared with ANN, SNN models provide more in-depth descriptions of the behaviour of biological neurons. Moreover, more addition information is used for the computations of the firing rate between real neurons. The rate coding which ANN used to represent the neuronal activity is less preferred compared to SNN, which used the difference in firing times.

Even though SNN has many models, ESNN is one of the SNN which uses more of the research to do with neural networks. The reasons are that ESNN is simple with an efficient model of neurons and is trained with a fast one-pass learning algorithm (Hamed, 2012). ESNN's evolved model nature can be updated when new data is accessible with no regards to retraining the earlier existing samples.

In contrast, according to Hamed (2012), ESNN architecture - which has been discussed first in Wysoski et al. (2006) and as a further extension of evolving connectionist systems (ECOS) method extended by Kasabov (1998) where the output of the network is influenced by the correct combination of parameters. This allows the network to reach the best outcome. Therefore, in order to find the best combination of parameters, an optimiser is needed.

Optimization has been used to optimize ESNN parameters. There are three ESNN parameter values: (1) modulation factor (Mod), (2) threshold factor (C) and (3) similarity value (Sim). Selecting a better optimization algorithm is necessary to solve the real-world applications, especially for optimal parameter values for ESNN. Meta-heuristic algorithms, mainly FA, are common competitors in optimization problems because of the following characteristics: adaptive applicability, simpler implementation, efficiently solving complex problems. Therefore, FA is conducted to optimize ESNN parameters.

FA is one of the promising meta-heuristic algorithms that have been developed by Yang (2008) and can be utilized for solving optimization problems. FA solving uses a stochastic way and local search for a set of solutions which balances the exploration and exploitation of the search processes. The key objective of FA is to improve ESNN optimal solutions for parameter values and classification accuracy.

## 1.2 Problem Background

The research conducted by Maass (1999) and Schrauwen and Van Campenhout (2006) has shown SNN as being auspicious in simulating the information processed inside the human brain than sigmoid representations and analog neural networks. These has been directed SNN toward as vital method for classification. There are many classification problems that have used many types of SNN. Several studies done by Bohte et al. (2002a) such as supervised learning algorithm, spike backpropagation (SpikeProp), and spike-time encoding based on error BP has been used for solving classification problems.

In Schrauwen et al. (2004), various learning rules to extend SpikeProp for good learning of spike times has been proposed. Consequently, Improved SpikeProp with particle swarm optimization (PSO) and angle-driven dependency learning rate has been presented for different methods for classification problems (Ahmed et al., 2013a). Even though much research in to SNN has been done, there is still a need to further the research to find out the most effective methods for optimising the parameters. One attempts is by Wysoski et al, (2006c), which proposed a new and improved model of SNN which is the ESNN.

Recent studies on the hybridization of the ESNN algorithm have been implemented. ESNN has been combined with PSO as a novel supervised learning algorithm proposed by Hamed et al. (2011a). ESNN has shown that it is an efficient neural model trained using fast one-pass learning and that the abilities of the model can be updated whenever new samples are accessible without retraining (Schliebs et al., 2009). Despite that, ESNN is affected by the selection of parameters, in which case the right selection of parameters will allow the network to develop towards a more effective structure. In Hamed et al. (2011) studies, it is determined that to achieve the number of optimal pre-synaptics neurons for a given dataset is the most significant problem. Another work from Hamed (2012), lower number of input spikes generated is caused by a fewer number of pre-synaptic neurons. This can affect learning accuracy, but with a larger number, this also increases the computational time. Kasabov (2003) mentioned that the evolving processes are difficult to model as there might be no prior knowledge for some parameters.

Watt (2009) has pointed that a significant advantages would have been achieved to train parameters with the automatic selection of ECOS. Therefore, for the right parameter combination to be found, an optimiser is required (Saleh et al., 2014). There are several research studies that have been done in relation to the optimisation parameters of ESNN such as the Versatile Quantum-inspired Evolutionary Algorithm (vQEA) with ESNN (Schliebs, Platel, et al., 2009), Quantum-inspired Particle Swarm Optimisation (QiPSO) with ESNN by Hamed *et al.*, (2009), and Evolutionary Algorithms (EA) with ESNN proposed by Saleh et al. (2014). According to Schliebs et al. (2009), from the analysis of the research results, the average accuracy achieved is constantly above 80%. On the other hand, in ESNN-QiPSO research, it was reported that from the analysis of the results, the average accuracy achieved is more than 90% when compared to ESNN only. Furthermore, the integrated ESNN-EA also reported that the average accuracy achieved is more than 90%.

There are several integrations between Evolutionary Algorithm (EA) and Swarm Intelligence (SI) methods with ESNN that have been conducted such as QiPSO (Hamed *et al.*, 2009), vQEA (Schliebs et al., 2009), Heterogeneous Multi-Model Estimation of Distribution Algorithm (hMM-EDA) (Schliebs et al., 2010) and new hybrid harmony search algorithm with evolving spiking neural network (NHS-ESNN) (Saleh et al., 2017). However, for example, Genetic Algorithms (GA) have some drawbacks such as the fixed value of the parameters, competing for conventions and premature convergence problems (Kim et al., 2005; Sahab et al., 2005).

The research studies above have shown good performance when integrating EA with ESNN. However, to challenge these research studies in order to get more effective optimisation and to improve ESNN performance, FA integrated with ESNN is proposed. Although FA is a relatively new meta-heuristic algorithm, its effectiveness and advantages have been applied in various applications such as classification and clustering (Rajini, 2012). Subsequently, a comprehensive performance study of FA with a comparison to another 11 different algorithms has also been conducted. The study showed that clustering can be solved using FA efficiently (Senthilnath et al., 2011). According to Banati and Bajaj (2011), FA has shown consistency and performs better in finding the optimal value for feature selection. Several studies conducted by Abshouri *et al*. (2011) and Farahani *et al.* (2011) have evaluated FA in relation to optimisation in dynamic environments has shown that FA is very efficient. Therefore, this research integrates FA with ESNN to find the optimal parameters value of ESNN and improve the classification accuracy of ESNN.

The problem faced in this research is if the proposed integration method of ESNN and FA is beneficial for learning improvement and for use as a new and effective ESNN parameter optimiser. In the latest study in neural networks, ESNN has received a lot of attention since ESNN offers several advantages over other neural networks model such as perceptron and multilayer perceptron (MLP) (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). Despite that, due to the ineffectiveness of model optimisation and parameter selection strategies such as MLP with PSO (Çam et al., 2015; Kawam & Mansour, 2012), the integration of ESNN with FA has been proposed in this study.

Mod, Sim and C are ESNN parameters used in the learning process of the ESNN algorithm. Currently, these parameters are currently set by hand. Therefore, to produce automated parameter selection is quite challenging (Kasabov, 2012; Kita, 2011; Pears et al., 2013; Yu et al., 2014). The parameter optimisation in ESNN is crucial as it ensures the best classification output (Hamed, 2012).

Nevertheless, it is supposed that there is ‘no free lunch theorem’ as no specific algorithm can achieve optimal performance for specific problems (Wolpert and Macready 1997). These study will explore further in to improving the FA for classification enhancement. On the other hand, it is the superiority of FA compared to other optimisation algorithms such as PSO and GA to consider, which includes being much more convenient to implement and better performance with a low number of parameters and being less complex in space (Fister et al., 2013) that has inspired research in to utilising this integration.

## 1.3 Research Aim

This research aims to enhance the learning of Evolving Spiking Neural Networks (ESNN) with the Firefly Algorithm as a new and effective ESNN parameter optimizer.

## 1.4 Research Questions

The following are the research questions used to address the goal of the research:

i. How to develop an integrated model of Evolving Spiking Neural Network (ESNN) and Firefly Algorithm (FA) for learning improvement?
ii. How to improve Firefly Algorithm as parameter optimizer to optimize ESNN's parameters?
iii. What are the estimation of parameters range for ESNN?

## 1.5 Research Objectives

The objectives of this study are:

i. To develop an integrated model of Evolving Spiking Neural Network (ESNN) and Firefly Algorithm (FA) for learning improvement.
ii. To improve Firefly Algorithm (FA) as parameter optimizer to optimize ESNN's parameters
iii. To estimate the optimal parameter range for ESNN.

## 1.6 Research Scope

The scope of this research is as follow:

i. The benchmark dataset used for evaluating the proposed methods are Iris, Wisconsin Breast Cancer, Pima Indians Diabetes, Heart and Wine dataset taken from UCI Machine Learning
ii. The proposed architecture ESNN-FA focuses on the optimization of the three parameters of ESNN namely modulation factor (Mod), proportion factor (C) and similarity factor (Sim) for learning improvement.
iii. The performance of the proposed methods is tested based on the classification accuracy.

## 1.7 Significance of Research

This research study is conducted to enhance the ESNN learning algorithm by using FA as a new and effective parameter optimiser. The performance of FA as a parameter optimiser for enhancing ESNN training has been investigated using ESNN-FA integration. Furthermore, the integration of the ESNN structure with FA will be developed.

## 1.8 Thesis Organization

This thesis contains five chapters and is briefly discussed below:

Chapter 2, the literature review, this chapter provides an overview of SNN, ESNN and the meta-heuristic algorithm that are used in this study. The components of SNN, which are encoding methods, neuron models and learning are introduced. ESNN’s principles and their applications are also reviewed.

Chapter 3, this chapter illustrates the research methodology in this study. The methodology is presented in flow chart diagram with brief explanation on each step being utilized. The integrated model of ESNN-FA where FA acts as an optimizer of ESNN parameters is explained.

Chapter 4, this chapter presents the results of this study. Analysis and comparative study of the results to evaluate the performance of the proposed methods are also discussed here.

Chapter 5, conclusions and the future research are discussed in this chapter. The contributions and the results of this study also highlighted in this chapter.

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