ENHANCED HOPFIELD NEURAL NETWORKS WITH ARTIFICIAL IMMUNE SYSTEM ALGORITHM FOR SATISFIABILITY LOGIC PROGRAMMING

MOHD. ASYRAF MANSOR

UNIVERSITI SAINS MALAYSIA

2017

ENHANCED HOPFIELD NEURAL NETWORKS WITH ARTIFICIAL IMMUNE SYSTEM ALGORITHM FOR SATISFIABILITY LOGIC PROGRAMMING

by

MOHD. ASYRAF MANSOR

Thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

August 2017

ACKNOWLEDGEMENT

In the first place, all the praises and thanks to Allah S.W.T, the Almighty for the infinite blessings and giving me strength throughout my research journey.

I would like to record my sincere appreciation to my supervisor, Associate Professor Saratha Sathasivam for her incessant encouragement and professional guidance as well as providing us with mountains of insights for the research. I am very grateful for her patience in answering all my queries so promptly and always being supportive and constructive. I could not have completed this thesis without the immense knowledge and continuous support I have been given.

Also, I would like to thank my parents, Mansor Majin and Jelihah Taha including my siblings for their constant support and comfort during the ups and downs of my research. I am extremely grateful to my parents for their prayers and sacrifices for educating and preparing me for a better future. Indeed, my family members have been my genuine inspiration and motivation to improve my knowledge and soar higher for my future career. In addition, I dedicated this thesis to my family including those in Taha's and Majin's clan.

I am fervently indebted to my research colleague, Mohd Shareduwan Mohd Kasihmuddin who has assisted in the fundamental concept of neural networks and providing millions information about publications. Hence, I am predominantly indebted for his thought-provoking insight throughout this research, but trying to express the enormity of my gratitude would be like trying to divide by zero. Completing this work would have been even more difficult were it not for the support and friendship provided by the other comrades from USM, some of which include Mohamad Asyraf

Mohamad Adnan, Ardiana Amirsom, Faisal Basir, Ainina Redwan, Yushalify Misro, Soffiah Sahubar Ali and Syafiah.

I would like to thank the academic and administrative staffs of the School of Mathematical Sciences (PPSM), USM and IPS, USM for generous provision of facilities and support to complete this research. I am momentously indebted for the excellent and conducive academic atmosphere that is captivating. Special credit to Professor Hailiza Kamrulhaili, Dean of PPSM, USM and Associate Professor Ong Hong Choon, Deputy Dean of PPSM, USM for organizing the seminar and endless academic programs that boost my research horizon.

Finally, I would like to express a token of appreciation to Ministry of Higher Education, Malaysia for the generous financial support I received. The funding was in the form of a scholarship for tertiary education under MyBrain15 and without this funding, the research would not have been possible.

Mohd. Asyraf Mansor

2017

TABLE OF CONTENTS

Acknowledgement ii

Table of Contents iv

List of Tables ix

List of Figures xi

List of Abbreviations xx

List of Symbols xxiv

Abstrak xxvii

Abstract xxix

CHAPTER 1 – INTRODUCTION

1.1 Introduction to Artificial Neural Network 1

1.2 Data Mining in Neural Network 4

1.3 Problem Statement 5

1.4 Research Objectives 7

1.5 Methodology 8

1.6 Scope and Limitations of Research 11

1.7 Organization of Thesis 12

CHAPTER 2 – LITERATURE REVIEW

2.1 Hopfield Neural Network 14

2.2 Logic Programming 17

2.3 Hyperbolic Tangent Activation Function 20

2.4 General Concept of 3-Satisfiability 22

2.5 General Concept of Maximum 3-Satisfiability 24

2.6 Artificial Immune System Algorithm 26

2.7 Exhaustive Search 28

2.8 Genetic Algorithm 29

2.9 Circuit Satisfiability 31

2.10 Data Mining in Hopfield Neural Network 32

2.11 Summary 33

CHAPTER 3 – LOGIC PROGRAMMING IN HOPFIELD NEURAL NETWORK

3.1 The Architecture of Hopfield Neural Network 34

3.2 The Implementation of Discrete Hopfield Neural Network 38

3.3 The Implementation of Hyperbolic Tangent Activation Function 40

3.4 Network Relaxation Approach 41

3.5 Hopfield Content Adressable Memory 42

3.6 Convergence and Dynamics of Hopfield Neural Network 45

3.7 Propositional Logic Programming 47

3.8 Horn Logic Programming in Hopfield Neural Network 48

3.9 Summary 50

CHAPTER 4 – PROPOSED HYBRID HNN MODELS FOR SATISFIABILITY LOGIC PROGRAMMING

4.1 3-Satisfiability Programming in Hopfield Neural Network 51

4.1.1 3-Satisfiability Logical Rule 51

4.1.2 3-Satisfiability Logic Programming Training Phase 53

4.1.3 3-Satisfiability Logic Programming Retrieval Phase 59

4.2 Hybrid Hopfield Neural Network with Enhanced Artficial Immune System Algorithm (HNN-3SATAIS) 62

4.2.1 Standard Model of Artificial Immune System Algorithm 62

4.2.2 Enhanced Artificial Immune System in HNN-3SATAIS 64

4.2.3 Convergence Analysis of Artificial Immune System Algorithm 69

4.3 Hybrid Hopfield Neural Network with Exhaustive Search (HNN-3SATES) 69

4.3.1 Exhaustive search in HNN-3SATES 69

4.3.2 Limitation of Exhaustive Search 71

4.4 Hybrid Hopfield Neural Network with Genetic Algorithm (HNN-3SATGA) 72

4.4.1 Standard Genetic Algorithm 72

4.4.2 Enhanced Genetic Algorithm in HNN-3SATGA 74

4.4.3 Convergence Analysis of Genetic Algorithm 77

4.5 3-Satisfiability Enhanced Reverse Analysis Paradigm (3-SATERAP) 77

4.6 Implementation of HNN-C3SATGA and HNN-C3SATAIS in Circuit Verification 79

4.7 Maximum 3-Satisfiability Logic Programming in Hopfield Neural Network 83

4.7.1 Maximum 3-Satisfiability Logical Rule 83

4.7.2 Implementation of Maximum 3-Satisfiability Logic Programming in Hopfield Neural Network 84

4.8 Summary 88

CHAPTER 5 – SIMULATED RESULTS OF HYBRID HNN MODELS

5.1 Introduction 89

5.2 Performance Evaluation Metrics 89

5.2.1 Root Mean Square Error (RMSE) 90

5.2.2 Mean Absolute Error (MAE) 91

5.2.3 Sum of Squared Error (SSE) 92

5.2.4 Symmetric Mean Absolute Percentage Error (SMAPE) 93

5.2.5 Global Minima Ratio and Ratio of Satisfied Clauses................ 94

5.2.6 Schwarz Bayesian Criterion (SBC) 95

5.2.7 CPU Time 96

5.2.8 Accuracy.. 96

5.3 Simulated Results and Discussions for HNN Models in 3-SAT............ 97

5.4 Simulated Results and Discussions for HNN models in MAX-3SAT 107

5.5 Simulated Results and Discussions for Circuit Verification 115

5.6 Summary.. 119

CHAPTER 6 – PERFORMANCE EVALUATIONS OF HYBRID HNN MODELS IN DATA MINING

6.1 Introduction.. 120

6.2 Real Data Set 121

6.3 Analysis of Hybrid HNN in Training the Real Data Sets.................... 124

6.3.1 Bach choral harmony data set 125

6.3.2 Census Income data set 128

6.3.3 Diabetic Retinopathy Debrecen data set 131

6.3.4 Statlog data set 134

6.3.5 Heart disease data set 137

6.3.6 Indian Liver Patient data set 139

6.3.7 Ionosphere data set.. 142

6.3.8 Japanese Credit Screening data set.................................. 144

6.3.9 MAGIC Gamma Telescope data set 146

6.3.10 PIMA Indians diabetes data set 148

6.3.11 Skillcraft1 master table data set 150

6.3.12 Seismic-bumps data set 152

6.3.13 Spambase data set 155

6.3.14 Steel plates faults data set 158

6.3.15 Thoracic Surgery data set 160

6.4 Analysis of Hybrid HNN Model in Testing the Real Data Sets 162

6.5 Summary 164

CHAPTER 7 – CONCLUSION

7.1 Conclusion and Summary of the Research 165

7.2 Suggestions for Future Research 167

REFERENCES 170

APPENDICES 184

LIST OF PUBLICATIONS

LIST OF TABLES

		Page
Table 2.1	Related Literature on Hopfield Neural Network	16
Table 2.2	Related Literature on Logic Programming	19
Table 2.3	Related Literature on Hyperbolic Tangent Activation Function	21
Table 2.4	Related Literature on 3-Satisfiability	23
Table 2.5	Related Literature on Maximum 3-Satisfiability	25
Table 2.6	Related Literature on Artificial Immune System Algorithm	27
Table 2.7	Related Literature on Exhaustive Search	28
Table 2.8	Related Literature on Genetic Algorithm	30
Table 2.9	Related Literature on Circuit Satisfiability	31
Table 2.10	Related Literature on Data Mining in Hopfield Neural Network	32
Table 4.1	The Truth Table for 3-SAT formula, ϕ	55
Table 4.2	The Clauses and Corresponding Synaptic Weights (Wan Abdullah Method)	57
Table 4.3	The Truth Table for MAX-3SAT formula, ω and the corresponding E_{ω}	85
Table 5.1	Performance Evaluations for HNN-C3SATGA and HNN-C3SATAIS in Circuit Verification	118
Table 6.1	The Description of Real Data Sets	122
Table 6.2	Performance Evaluations for Hybrid Models in Training Bach Choral Hramony Data Set	127
Table 6.3	Performance Evaluations for Hybrid Models in Training Census Income Data Set	130

Table 6.4	Performance Evaluations for Hybrid Models in Training Diabetic Retinophaty Debrecen Data Set	133
Table 6.5	Performance evaluations for Hybrid Models in Training Statlog Data Set	136
Table 6.6	Performance Evaluations for Hybrid Models in Training Heart Disease Data Set	138
Table 6.7	Performance Evaluations for Hybrid Models in Training Indian Liver Patient Data Set	141
Table 6.8	Performance Evaluations for Hybrid Models in Training Ionosphere Data Set	143
Table 6.9	Performance Evaluations for Hybrid Models in Training Japanese Credit Screening Data Set	145
Table 6.10	Performance Evaluations for Hybrid Models in Training MAGIC Gamma Telescope Data Set	147
Table 6.11	Performance Evaluations for Hybrid Models in Training PIMA Indians diabetes Data Set	149
Table 6.12	Performance Evaluations for Hybrid Models in Training Skillcraft1 Master Table Data Set	151
Table 6.13	Performance Evaluations for Hybrid Models in Training Seismic-bumps Data Set	154
Table 6.14	Performance Evaluations for Hybrid Models in Training Spambase Data Set	157
Table 6.15	Performance Evaluations for Hybrid Models in Steel Plates Faults Data Set	159
Table 6.16	Performance Evaluations for Hybrid Models in Training Thoracic Surgery Data Set	161
Table 6.17	Performance Evaluations for Hybrid Models in Testing the Data Sets	163
Table B.1	Sample of Thoracic Surgery data sets	201

LIST OF FIGURES

		Page
Figure 1.1	Biological Neural Network Model (Takefuji, 2012)	2
Figure 1.2	The Advancement of ANN in Face Recognition (Levy, 2016)	3
Figure 1.3	The Methodology of Hybrid HNN Networks in 3-SAT, MAX-3SAT, and C3-SAT Logic Programming	9
Figure 1.4	The Methodology of Hybrid HNN models in Logic Mining	10
Figure 3.1	Recurrent Hopfield Neural Network (Swarup and Simi, 2006).	35
Figure 3.2	Simple Topology of Hopfield Neural Network (Sathasivam et al., 2011).	36
Figure 4.1	The Implementation of 3-SAT Logic Programming in Hopfield Neural Network	61
Figure 4.2	Clonal Selection Principle in AIS (Shangce et al., 2007).	63
Figure 4.3	Important Stages in Standard Genetic Algorithm (Gen and Cheng, 2000).	73
Figure 4.4	The Configuration of Circuit Satisfiability (Hamadneh, 2013).	81
Figure 5.1	RMSE Evaluation for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES	98
Figure 5.2	MAE Evaluation for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES	98
Figure 5.3	SSE Evaluation for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES	100
Figure 5.4	SMAPE Evaluation for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES	101
Figure 5.5	Global Minima Ratio Evaluation for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES	103

Figure 5.6	SBC Evaluation for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES	104
Figure 5.7	CPU Time Evaluation for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES	105
Figure 5.8	RMSE Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	107
Figure 5.9	MAE Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	108
Figure 5.10	SSE Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	109
Figure 5.11	SMAPE Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	110
Figure 5.12	SBC Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	111
Figure 5.13	Global Minima Ratio Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	112
Figure 5.14	Ratio of Satisfied Clauses Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	113
Figure 5.15	CPU Time Evaluation of HNN-MAX3SATGA and HNN-MAX3SATAIS	114
Figure A.1	Performance Evaluations of HNN-3SAT Models in Training Bach Choral Data Set	185
Figure A.1(a)	RMSE Evaluation of HNN-3SAT Models in Training Bach Choral Data Set	185
Figure A.1(b)	MAE Evaluation of HNN-3SAT Models in Training Bach Choral Data Set	185
Figure A.1(c)	SSE Evaluation of HNN-3SAT Models in Training Bach Choral Data Set	185
Figure A.1(d)	SMAPE Evaluation of HNN-3SAT Models in Training Bach Choral Data Set	185
Figure A.1(e)	SBC Evaluation of HNN-3SAT Models in Training Bach Choral Data Set	185

Figure A.1(f)	CPU Time Obtained by HNN-3SAT Models in Training Bach Choral Data Set	185
Figure A.2	Performance Evaluations of HNN-3SAT Models in Training Census Income Data Set	186
Figure A.2(a)	RMSE Evaluation of HNN-3SAT Models in Training Census Income Data Set	186
Figure A.2(b)	MAE Evaluation of HNN-3SAT Models in Training Census Income Data Set	186
Figure A.2(c)	SSE Evaluation of HNN-3SAT Models in Training Census Income Data Set	186
Figure A.2(d)	SMAPE Evaluation of HNN-3SAT Models in Training Census Income Data Set	186
Figure A.2(e)	SBC Evaluation of HNN-3SAT Models in Training Census Income Data Set	186
Figure A.2(f)	CPU Time Obtained by HNN-3SAT Models in Training Census Income Data Set	186
Figure A.3	Performance Evaluations of HNN-3SAT Models in Training Diabetic Retinopathy Debrecen Data Set	187
Figure A.3(a)	RMSE Evaluation of HNN-3SAT Models in Training Diabetic Retinopathy Debrecen Data Set	187
Figure A.3(b)	MAE Evaluation of HNN-3SAT Models in Training Diabetic Retinopathy Debrecen Data Set	187
Figure A.3(c)	SSE Evaluation of HNN-3SAT Models in Training Diabetic Retinopathy Debrecen Data Set	187
Figure A.3(d)	SMAPE Evaluation of HNN-3SAT Models in Training Diabetic Retinopathy Debrecen Data Set	187
Figure A.3(e)	SBC Evaluation of HNN-3SAT Models in Training Diabetic Retinopathy Debrecen Data Set	187
Figure A.3(f)	CPU Time Obtained by HNN-3SAT Models in Training Diabetic Retinopathy Debrecen Data Set	187
Figure A.4	Performance Evaluations of HNN-3SAT Models in Training Statlog Data Set	188

Figure A.4(a) RMSE Evaluation of HNN-3SAT Models in Training Statlog Data Set 188

Figure A.4(b) MAE Evaluation of HNN-3SAT Models in Training Statlog Data Set 188

Figure A.4(c) SSE Evaluation of HNN-3SAT Models in Training Statlog Data Set 188

Figure A.4(d) SMAPE Evaluation of HNN-3SAT Models in Training Statlog Data Set 188

Figure A.4(e) SBC Evaluation of HNN-3SAT Models in Training Statlog Data Set 188

Figure A.4(f) CPU Time Obtained by HNN-3SAT Models in Training Statlog Data Set 188

Figure A.5 Performance Evaluations of HNN-3SAT Models in Training Heart Disease Data Set 189

Figure A.5(a) RMSE Evaluation of HNN-3SAT Models in Training Heart Disease Data Set 189

Figure A.5(b) MAE Evaluation of HNN-3SAT Models in Training Heart Disease Data Set 189

Figure A.5(c) SSE Evaluation of HNN-3SAT Models in Training Heart Disease Data Set 189

Figure A.5(d) SMAPE Evaluation of HNN-3SAT Models in Training Heart Disease Data Set 189

Figure A.5(e) SBC Evaluation of HNN-3SAT Models in Training Heart Disease Data Set 189

Figure A.5(f) CPU Time Obtained by HNN-3SAT Models in Training Heart Disease Data Set 189

Figure A.6 Performance Evaluations of HNN-3SAT Models in Training Indian Liver Patient Data Set 190

Figure A.6(a) RMSE Evaluation of HNN-3SAT Models in Training Indian Liver Patient Data Set 190

Figure A.6(b) MAE Evaluation of HNN-3SAT Models in Training Indian Liver Patient Data Set 190

Figure A.6(c)	SSE Evaluation of HNN-3SAT Models in Training Indian Liver Patient Data Set	190
Figure A.6(d)	SMAPE Evaluation of HNN-3SAT Models in Training Indian Liver Patient Data Set	190
Figure A.6(e)	SBC Evaluation of HNN-3SAT Models in Training Indian Liver Patient Data Set	190
Figure A.6(f)	CPU Time Obtained by HNN-3SAT Models in Training Indian Liver Patient Data Set	190
Figure A.7	Performance Evaluations of HNN-3SAT Models in Training Ionosphere Data Set	191
Figure A.7(a)	RMSE Evaluation of HNN-3SAT Models in Training Ionosphere Data Set	191
Figure A.7(b)	MAE Evaluation of HNN-3SAT Models in Training Ionosphere Data Set	191
Figure A.7(c)	SSE Evaluation of HNN-3SAT Models in Training Ionosphere Data Set	191
Figure A.7(d)	SMAPE Evaluation of HNN-3SAT Models in Training Ionosphere Data Set	191
Figure A.7(e)	SBC Evaluation of HNN-3SAT Models in Training Ionosphere Data Set	191
Figure A.7(f)	CPU Time Obtained by HNN-3SAT Models in Training Ionosphere Data Set	191
Figure A.8	Performance Evaluations of HNN-3SAT Models in Training Japan Credit Screening Data Set	192
Figure A.8(a)	RMSE Evaluation of HNN-3SAT Models in Training Japan Credit Screening Data Set	192
Figure A.8(b)	MAE Evaluation of HNN-3SAT Models in Training Japan Credit Screening Data Set	192
Figure A.8(c)	SSE Evaluation of HNN-3SAT Models in Training Japan Credit Screening Data Set	192
Figure A.8(d)	SMAPE Evaluation of HNN-3SAT Models in Training Japan Credit Screening Data Set	192

Figure A.8(e)	SBC Evaluation of HNN-3SAT Models in Training Japan Credit Screening Data Set	192
Figure A.8(f)	CPU Time Obtained by HNN-3SAT Models in Training Japan Credit Screening Data Set	192
Figure A.9	Performance Evaluations of HNN-3SAT Models in Training MAGIC Gamma Telescope Data Set	193
Figure A.9(a)	RMSE Evaluation of HNN-3SAT Models in Training MAGIC Gamma Telescope Data Set	193
Figure A.9(b)	MAE Evaluation of HNN-3SAT Models in Training MAGIC Gamma Telescope Data Set	193
Figure A.9(c)	SSE Evaluation of HNN-3SAT Models in Training MAGIC Gamma Telescope Data Set	193
Figure A.9(d)	SMAPE Evaluation of HNN-3SAT Models in Training MAGIC Gamma Telescope Data Set	193
Figure A.9(e)	SBC Evaluation of HNN-3SAT Models in Training MAGIC Gamma Telescope Data Set	193
Figure A.9(f)	CPU Time Obtained by HNN-3SAT Models in Training MAGIC Gamma Telescope Data Set	193
Figure A.10	Performance Evaluations of HNN-3SAT Models in Training PIMA Indians Diabetes Data Set	194
Figure A.10(a)	RMSE Evaluation of HNN-3SAT Models in Training PIMA Indians Diabetes Data Set	194
Figure A.10(b)	MAE Evaluation of HNN-3SAT Models in Training PIMA Indians Diabetes Data Set	194
Figure A.10(c)	SSE Evaluation of HNN-3SAT Models in Training PIMA Indians Diabetes Data Set	194
Figure A.10(d)	SMAPE Evaluation of HNN-3SAT Models in Training PIMA Indians Diabetes Data Set	194
Figure A.10(e)	SBC Evaluation of HNN-3SAT Models in Training PIMA Indians Diabetes Data Set	194
Figure A.10(f)	CPU Time Obtained by HNN-3SAT Models in Training PIMA Indians Diabetes Data Set	194

Figure A.11 Performance Evaluations of HNN-3SAT Models in Training Skillcraft1 Master Table Data Set 195

Figure A.11(a) RMSE Evaluation of HNN-3SAT Models in Training Skillcraft1 Master Table Data Set 195

Figure A.11(b) MAE Evaluation of HNN-3SAT Models in Training Skillcraft1 Master Table Data Set 195

Figure A.11(c) SSE Evaluation of HNN-3SAT Models in Training Skillcraft1 Master Table Data Set 195

Figure A.11(d) SMAPE Evaluation of HNN-3SAT Models in Training Skillcraft1 Master Table Data Set 195

Figure A.11(e) SBC Evaluation of HNN-3SAT Models in Training Skillcraft1 Master Table Data Set 195

Figure A.11(f) CPU Time Obtained by HNN-3SAT Models in Training Skillcraft1 Master Table Data Set 195

Figure A.12 Performance Evaluations of HNN-3SAT Models in Training Seismic-bumps Data Set 196

Figure A.12(a) RMSE Evaluation of HNN-3SAT Models in Training Seismic-bumps Data Set 196

Figure A.12(b) MAE Evaluation of HNN-3SAT Models in Training Seismic-bumps Data Set 196

Figure A.12(c) SSE Evaluation of HNN-3SAT Models in Training Seismic-bumps Data Set 196

Figure A.12(d) SMAPE Evaluation of HNN-3SAT Models in Training Seismic-bumps Data Set 196

Figure A.12(e) SBC Evaluation of HNN-3SAT Models in Training Seismic-bumps Data Set 196

Figure A.12(f) CPU Time Obtained by HNN-3SAT Models in Training Seismic-bumps Data Set 196

Figure A.13 Performance Evaluations of HNN-3SAT Models in Training Spambase Data Set 197

Figure A.13(a) RMSE Evaluation of HNN-3SAT Models in Training Spambase Data Set 197

Figure A.13(b)	MAE Evaluation of HNN-3SAT Models in Training Spambase Data Set	197
Figure A.13(c)	SSE Evaluation of HNN-3SAT Models in Training Spambase Data Set	197
Figure A.13(d)	SMAPE Evaluation of HNN-3SAT Models in Training Spambase Data Set	197
Figure A.13(e)	SBC Evaluation of HNN-3SAT Models in Training Spambase Data Set	197
Figure A.13(f)	CPU Time Obtained by HNN-3SAT Models in Training Spambase Data Set	197
Figure A.14	Performance Evaluations of HNN-3SAT Models in Training Steel Plates Faults Data Set	198
Figure A.14(a)	RMSE Evaluation of HNN-3SAT Models in Training Steel Plates Faults Data Set	198
Figure A.14(b)	MAE Evaluation of HNN-3SAT Models in Training Steel Plates Faults Data Set	198
Figure A.14(c)	SSE Evaluation of HNN-3SAT Models in Training Steel Plates Faults Data Set	198
Figure A.14(d)	SMAPE Evaluation of HNN-3SAT Models in Training Steel Plates Faults Data Set	198
Figure A.14(e)	SBC Evaluation of HNN-3SAT Models in Training Steel Plates Faults Data Set	198
Figure A.14(f)	CPU Time Obtained by HNN-3SAT Models in Training Steel Plates Faults Data Set	198
Figure A.15	Performance Evaluations of HNN-3SAT Models in Training Thoracic Surgery Data Set	199
Figure A.15(a)	RMSE Evaluation of HNN-3SAT Models in Training Thoracic Surgery Data Set	199
Figure A.15(b)	MAE Evaluation of HNN-3SAT Models in Training Thoracic Surgery Data Set	199
Figure A.15(c)	SSE Evaluation of HNN-3SAT Models in Training Thoracic Surgery Data Set	199

Figure A.15(d) SMAPE Evaluation of HNN-3SAT Models in Training Thoracic Surgery Data Set 199

Figure A.15(e) SBC Evaluation of HNN-3SAT Models in Training Thoracic Surgery Data Set 199

Figure A.15(f) CPU Time Obtained by HNN-3SAT Models in Training Thoracic Surgery Data Set 199

LIST OF ABBREVIATIONS

3-SAT	3-Satisfiability
3-SATERAP	3-Satisfiability Reverse Analysis Paradigm
ABM	Agent Based Modelling
ANN	Artificial Neural Network
AI	Artificial Intelligence
AIS	Artificial Immune System
C-3SAT	Circuit 3-Satisfiability
CAM	Content Adressable Memory
CIRCUIT-SAT	Circuit Satisfiability
CNF	Conjunctive Normal Form
COMBMAX	Combination of Neuron
CPU	Central Processing Unit
CSP	Constrained Satisfaction Problem
DNA	Deoxyribonucleic acid
DNF	Disjunctive Normal Form
DPP	David-Putnam Procedure
ES	Exhaustive Search
FCM	Fuzzy C-Means Algorithm
GA	Genetic Algorithm

GASAT	Genetic Algorithm for Satisfiability problem
G-SAT	Greedy Satisfiability
GNN	Graph Neural Network
GS	Greedy Search
HNN	Hopfield Neural Network
HNN-3SATAIS	Hopfield Neural Network with Artificial Immune System Algorithm for 3-Satisfiability
HNN-3SATES	Hopfield Neural Network with Exhaustive Search Algorithm for 3-Satisfiability
HNN-3SATGA	Hopfield Neural Network with Genetic Algorithm for 3-Satisfiability
HNN-C3SATGA	Hopfield Neural Network with Genetic Algorithm for Maximum 3-Satisfiability
HNN-C3SATAIS	Hopfield Neural Network with Artificial Immune System Algorithm for Circuit 3-Satisfiability
HNN-MAX3SATAIS	Hopfield Neural Network with Artificial Immune System Algorithm for Maximum 3-Satisfiability
HNN-MAX3SATGA	Hopfield Neural Network with Genetic Algorithm for Maximum 3-Satisfiability
HTAF	Hyperbolic Tangent Activation Function
IC	Integrated Circuit
IPS	Institut Pengajian Siswazah

KM	K-Means Algorithm
LNS	Large Neighborhood Search
LS	Local Search
MAE	Mean Absolute Error
MASE	Mean Absolute Scaled Error
MeAE	Median Absolute Error
MAX-3SAT	Maximum 3-Satisfiability
MAX-kSAT	Maximum k-Satisfiability
MLP	Multi Layer Perceptron
MSE	Mean Square Error
NC	Noise Clause
NN	Number of Neurons
NP	Non-deterministic polynomial
NT	Number of Transistors
PPSM	Pusat Pengajian Sains Matematik
Q-MAXSAT	Quantified Maximum Satisfiability
Q-SAT	Quantified Satisfiability
RAM	Reverse Analysis
RAM	Random Access Memory
RBE	Rank Based Error
RBFNN	Radial Basis Function Neural Network

RMSE	Root Mean Square Error
SBC	Schwarz Bayesian Criterion
SMAPE	Symmetric Mean Absolute Percentage Error
SSE	Sum of Squared Error
UCI	University of California Irvine
USM	Universiti Sains Malaysia
VLSI	Very Large System Integrated Circuit

LIST OF SYMBOLS

$\vee$	OR
$\wedge$	AND
$\leftarrow$	Implication
$\neg$	Negation
$\top$	True
$\bot$	False
$\exists$	There Exists
$\forall$	For All
ε	Termination Criterion
ψ	Relaxation Rate
W_{ij}	Synaptic weight from unit i to j
h_i	Local Field of neuron connection
sgn	Signum function
S_j	State of unit j
S_i	State of unit i
ξ_i	Threshold of unit i
$E_{lyapnov}$	Lyapunov Energy Function
E	Generalized Lyapunov Energy Function
$E(S^*)$	Generalized Lyapunov Energy Function for the Update in Neuron Activation

E_{min}	Optimized Global Minimum Energy
$\triangle E$	Change in Energy
ϕ	3-SAT formula ϕ
E_{ϕ}	Cost function of E_{ϕ}
NT	Number of Transistor
ρ_k	Total Neuron Excitation
$N_{E_{min}}$	Global Minimum Solutions
P_i	Targeted values
O_i	Observed values
f_{GA}	Fitness function for genetic algorithm
f_{ES}	Fitness function for exhaustive search
$f_{affinity}$	Affinity function for artificial immune system
$D_{optimum}$	The Optimum Logical Rule
$D_{induced}$	The Induced Logical Rule
D_{test}	The Testing Logical Rule
D_{train}	The Training Logical Rule
β	Number of population clone
$affinity_i$	Initial affinity
C_i	Clause to the unit i
NV	Number of variables in 3-SAT formula
NB	Number of mutation

$affinity\ N_i$	Normalized affinity
ω	MAX-3SAT formula
f_{max}	Maximum Fitness
f_i	Measured Fitness
$\tanh(x)$	Hyperbolic tangent activation function
R	Relaxation Rate of neuron
h_i^{new}	New induced local field
h_i	Induced local field
A_N	Clause A
B_N	Clause B
r	Number of satisfied clauses
P_{C3-SAT}	Circuit 3-Satisfiability formula
I_n	Parallel Output Channel
V_n	Parallel Input Channel
U	Interconnectivity between Neurons
NTr	No of Trial
$N_{E_{min}}$	Global Minimum Solutions
$COMBMAX$	Global Minimum Solutions
pa	Number of Free Parameter

RANGKAIAN NEURAL HOPFIELD YANG DIPERTINGKATKAN DENGAN ALGORITMA SISTEM IMUN BUATAN UNTUK PENGATURCARAAN LOGIK SATISFIABILITI

ABSTRAK

Kepesatan dalam masalah 3-Satisfiabiliti (3-SAT) telah menghasilkan banyak kajian yang berpaksikan kepada bidang logik dan perlombongan data. Dalam kajian ini, kaedah hibrid baharu dalam pengaturcaraan logik iaitu peraturan logik 3-SAT sebagai alat pengiraan akan dibentangkan. Oleh itu, sistem kepintaran yang tuntas dengan mengintegrasikan rangkaian neural Hopfield dan teknik metaheuristik akan dibangunkan bagi mengekstrak maklumat tersembunyi bagi set data dalam bentuk peraturan logik 3-Satisfiabiliti. Rangkaian hibrid dipanggil HNN-3SATAIS telah dicadangkan dengan mengasimilasikan rangkaian neural Hopfield dengan algoritma sistem imun buatan (AIS) sebagai medium latihan dalam melakukan pengaturcaraan logik 3-Satisfiabiliti. Prestasi rangkaian yang telah dicadangkan, HNN-3SATAIS telah dibandingkan dengan rangkaian neural Hopfield dengan algoritma genetik yang diubahsuai (HNN-3SATGA) dan algoritma carian lengkap dengan rangkaian neural Hopfield (HNN-3SATES) sebagai satu rangkaian tunggal. Secara teorinya, teknik hibrid HNN-3SATAIS dijangka akan mengurangkan kerumitan rangkaian kerana terdapatnya mekanisme pencarian yang lebih sistematik. Tambahan pula, HNN-3SATAIS adalah satu kaedah lebih mantap di mana algoritma metaheuristik akan membantu proses pencarian dan mendorong kepada penyelesaian global yang lebih layak. Kemampuan teknik-teknik hibrid ini telah diuji dengan menggunakan set data simulasi dan set data sebenar. Perisian Dev-C ++ Versi 5.11 untuk Windows 10 telah digunakan sebagai platform untuk latihan, simulasi dan pengesahan prestasi rangkaian yang telah

dicadangkan. Oleh itu, penilaian model pengkomputeran hibrid telah dijalankan secara eksperimen dengan menggunakan data 3-SAT rawak dan 15 set data sebenar yang diarkibkan dari laman sesawang pembelajaran mesin UCI. 15 set data sebenar dengan saiz yang berbeza dipilih daripada bidang yang berbeza seperti bidang kewangan, astronomi dan data set penyakit kronik. Dalam kajian ini, paradigma analisis berbalik berasaskan 3-Satisfiabiliti (3-SATERAP) telah diperkenalkan bagi mengekstrak peraturan logik terbaik daripada set data yang tertentu. Kemantapan HNN-3SATES, HNN-3SATGA dan HNN-3SATAIS yang diintegrasikan dengan kaedah 3-SATERAP dalam menghasilkan peraturan logik yang terbaik daripada 15 set data UCI telah dinilai dari RMSE, MAE, SSE, SMAPE, SBC dan tempoh CPU. Menurut hasil eksperimen, HNN-3SATAIS mempunyai prestasi yang lebih baik berbanding HNN-3SATES dan HNN-3SATGA dalam pengaturcaraan logik 3-SAT. Selain itu, masalah pengesanan litar satisfiabiliti (Circuit-SAT) dengan menggunakan kaedah yang dicadangkan, HNN-C3SATAIS dan HNN-C3SATGA telah juga dibincangkan dengan lengkap. Seterusnya, teknik hibrid telah diuji bagi menyelesaikan kes satisfiabiliti yang sukar seperti masalah maksimum 3-Satisfiabiliti (MAX-3SAT). Maka, HNN-MAX3SATAIS mempunyai prestasi yang lebih baik daripada HNN-MAX3SATGA dari segi indikator penilaian prestasi. Kesimpulannya, kajian yang dibentangkan di dalam tesis ini mampu menyelesaikan pelbagai masalah satisfiabiliti. Oleh itu, rangkaian hibrid yang telah dicadangkan boleh digunakan sebagai alat perlombongan data dalam bidang-bidang lain seperti transformasi ekonomi, masalah dalam sains sosial, pengurusan pelancongan, sains komputer dan sebagainya.

ENHANCED HOPFIELD NEURAL NETWORKS WITH ARTIFICIAL IMMUNE SYSTEM ALGORITHM FOR SATISFIABILITY LOGIC PROGRAMMING

ABSTRACT

The emergence of 3-Satisfiability (3-SAT) problem has produced a prolific number of works devoted to the field of logic and data mining. In this study, a new hybrid method in doing logic programming by incorporating 3-SAT logical rules as a computational tool will be presented. Hence, a robust intelligence system that integrates the Hopfield neural network and metaheuristic paradigm is constructed to extract the data set hidden knowledge in the form of 3-Satisfiability logical rule. A hybrid network called HNN-3SATAIS is proposed by assimilating the Hopfield neural network with the enhanced artificial immune system (AIS) algorithm as a training tool in doing 3-Satisfiability logic programming. The performance of the proposed network, HNN-3SATAIS is compared with a modified genetic algorithm with Hopfield neural network (HNN-3SATGA) and the exhaustive search with Hopfield neural network (HNN-3SATES). Theoretically, the proposed HNN-3SATAIS technique is expected to reduce the complexity of the network due to the systematic searching mechanism. In addition, HNN-3SATAIS is a robust method since the metaheuristic algorithm will boost the searching process that will drive to more feasible global solutions. The performances of the hybrid techniques were tested by using simulated and real data set. Dev-C++ Version 5.11 for Windows 10 was used as a platform for training, simulating and validating the performances of the proposed network. Hence, the appraisal of hybrid computational models was conducted experimentally by using the randomized 3-SAT instances and 15 real data sets archived from the UCI machine learning repository. 15 real data sets of different sizes are selected from different fields, ranging from the finances, astronomy to the vigilant diseases data sets. In this research, 3-Satisfiability enhanced reverse analysis paradigm (3-SATERAP) is introduced as a tool to extract the logical rule from the real life data sets. The robustness of the HNN-3SATES, HNN-3SATGA and HNN-3SATAIS integrated with 3-SATERAP in extracting the best logical rule of 15 UCI data sets were evaluated in terms of RMSE, MAE, SSE, SMAPE, SBC and CPU Time. It can be observed from the experimental results, HNN-3SATAIS outperforms the other counterparts, HNN-3SATES and HNN-3SATGA in doing 3-SAT logic programming. In addition, verification of the circuit satisfiability (Circuit-SAT) by using the proposed methods, HNN-C3SATAIS and HNN-C3SATGA are discussed in detail. Then, the proposed techniques were tested to withstand the vilest case satisfiability such as maximum 3-satisfiability (MAX-3SAT). In this case, the HNN-MAX3SATAIS outclasses HNN-MAX3SATGA in terms of the performance evaluation metrics. To sum up, the work presented in this thesis is able to counter the variety of the satisfiability problem. Hence, the hybrid network can be applied as a data mining tool in other fields such as economic transformation, social sciences problems, tourism management, computer sciences and so forth.

CHAPTER 1

INTRODUCTION

1.1 Introduction to Artificial Neural Network

Artificial neural network is a staple computational field that produces a prolific amount of research. It is a staple mathematical model, inspired by the way of the biological nervous system such as the brain process information (Hopfield, 1982; Park et al., 1993; Zhu and Yan, 1997). One of the goals of the neural network or specifically called as artificial neural network (ANN) was to comprehend and outline the functional characteristics and computational power of the brain when it performs cognitive processes such as concept cognition, sensorial perception, concept association, and learning. Hence, the artificial neural network can be defined as an intelligent system that impersonates the mechanism of human intelligence (Strong, 2016). In fact, neural networks have been popularized as a computational tool. Historically, the work on the ANN basically focused on the work of trying to model the neuron as a computational model. The earliest model of a neuron was crafted by physiologists McCulloch and Walter Pitts (McCulloch and Pitts, 1943). The model they created had two inputs and a single output. McCulloch and Pitts (1943) proposed that a neuron would not be activated if only one of the inputs was active. The weights for each input were symmetric, and the output was binary. Until the inputs summed up to a certain threshold level, the output was stable. The McCulloch and Pitts neuron has become the pioneer in the development of the other variants of ANN. Strictly speaking, most of the ANN model is inspired by the biological neurons (Basheer and Hajmeer, 2000; Wasserman, 1989). Theoretically, the ANNs consist a set of interconnected entities called nodes or units that usually operates in parallel (Takefuji, 2012). Figure 1.1 depicts the biological neural network that became the building block of numerous artificial neural network up to today. There are many types of neural networks such as the Hopfield

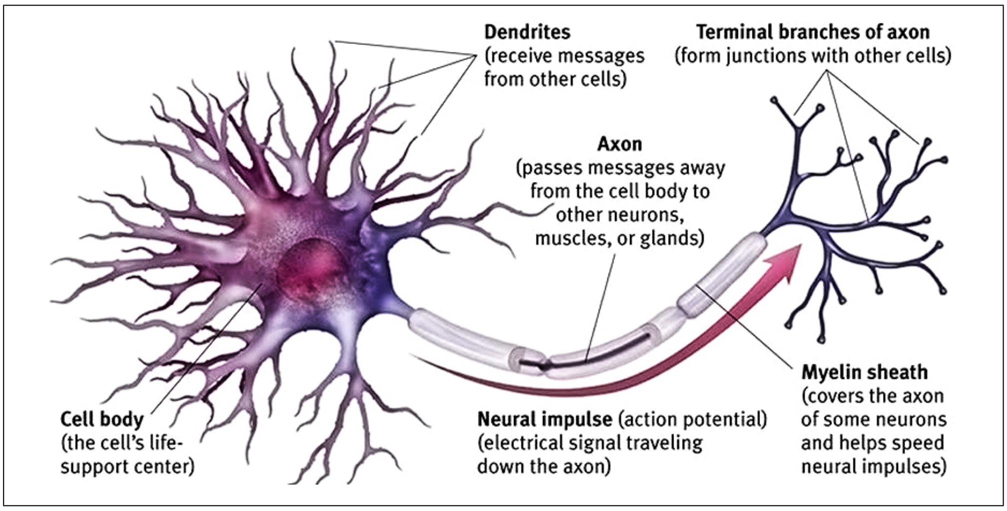

Figure 1.1: Biological Neural Network Model (Takefuji, 2012)

neural network (HNN) presented by Hopfield and Tank (1985). The state-of-the-art neural network model is the HNN. According to Hopfield (1982), HNN is a recurrent and synaptic connection pattern, whereby there is a Lyapunov function for the activity dynamics. The process of association and information retrieval is simulated by the dynamical behavior of a highly interconnected system of non-linear circuit elements with collective computational abilities. Park et al. (1993) asserted that the HNN can be applied to tackle the electric power system problem. Pursuing that, Cheng et al. (1996) implemented the HNN in medical image segmentation. By the same token, Sathasivam (2009) introduced the implementation of HNN in the logic programming. Additionally, Velavan et al. (2016) proposed the HNN incorporated with mean field theory to solve higher-order logic programming. Thus, the developments in HNN are still mushrooming due to the flexibility of the HNN to be assimilated with other ANN and machine learning techniques. The rapid development of ANN has produced an array of neural network models that can be applied in numerous real life problems. One of the recent development in the artificial neural network is a deep convolutional neural network that deploys the deep learning algorithms. The development of this artificial neural network is still new in the artificial intelligence field. Guo et al. (2016) proposed the implementation of deep learning in image classification and human pose estimation. Basically, the implementation of deep neural network revolves around the computer vision (Bengio, 2009), automatic age estimation (Dong et al., 2016) and so forth. The advancement of ANN can be seen in the development of the features in the smartphone. Figure 1.2 demonstrates the example of neural network embedded in the system for the face recognition in iPhone 6 Plus. Basically, the network will detect the

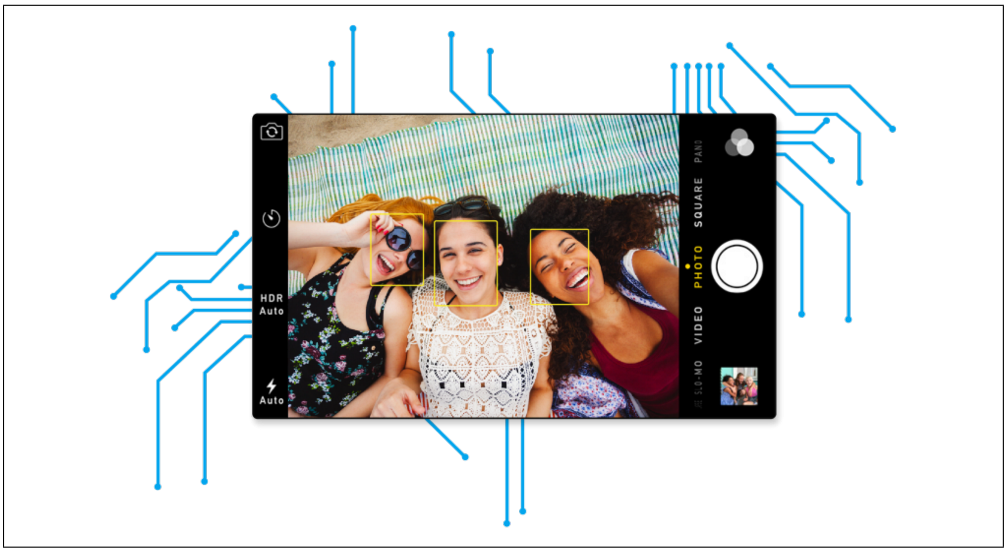

Figure 1.2: The Advancement of ANN in Face Recognition (Levy, 2016)

correct face or pattern by looking at the databases entrenched to the system. Thus, the data mining in neural network plays an important role to many real life applications.

1.2 Data Mining in Neural Network

Recent studies on data mining have been mushrooming especially with the emergence of ANN and machine learning that can foster the process. Hence, the data mining practitioners are assimilating the multidisciplinary knowledge such as mathematics, artificial intelligence, machine learning and statistics in order to establish an ideal data mining technique. The competencies of the data mining have benefited numerous fields such as improving the disease diagnosis based on the medical record, predicting the finance trend, propelling the tourism industries, weather prediction and so on. In theory, data mining is defined as the extraction of some significant information from any databases. In layman terms, data mining can be defined as finding the underlying information according to the behavior of databases or data sets. Similarly, the core impetus of data mining is to extract some information that will provide insight about a particular database. Kamruzzaman and Sarkar (2011) asserted that knowledge discovery in databases refers to the process of automated extraction of hidden, previously unknown and potentially useful information from large databases. Equally important, Sawale and Gupta (2013) proposed the data mining system for climatology forecasting by implementing the ANN with backpropagation rule. Henceforth, Wan Abdullah and Sathasivam (2005) inaugurated the logic mining in HNN by extracting the logical rule of a particular database via reverse analysis method. Pursuing that, Sathasivam and Wan Abdullah (2011) has addressed the implementation of Conjunctive Normal Form (CNF) clause as the logical rule in knowledge extraction from real life data set. Sathasivam et al. (2014) introduced the reverse analysis for higher order HNN in determining the optimum Horn logical rule entrenched in a particular data entry. Hence, data mining in neural network can be improved to cater different problems.

1.3 Problem Statement

The main drawback of a simple propositional logic is the limitation in representing the attributes in a particular data set. Furthermore, a better logical rule is needed to extract the hidden information in the data sets. Hence, the 3-SAT logic is proposed to induce the real life data sets in a more precise way. The 3-SAT form was chosen due to the flexibility of the logical problem to be entrenched in the logic programming. Thus, the 3-SAT problem which is considered as non-horn clauses is embedded into our logic programming. Additionally, 3-SAT programming will be encoded into the hybrid HNN as a single computational model. Moreover, the 3-SAT programming is expected to provide our network with sufficient symbolic instructions in order to foster the training and retrieval phase in the hybrid HNN. The drawback of the standard reverse analysis method is the difficulties to unearth the relationship of the real data sets. As a result, 3-Satisfiability enhanced reverse analysis paradigm (3-SATERAP) is formulated in order to extract a solid logical rule from the attributes of real life data sets. The attributes of the real data sets can be represented as the neurons in the 3-SAT formula in a systematic manner. The proposed knowledge extraction method has the flexibility to create many possibilities of 3-SAT logical rules according to the behavior of the real data sets. Therefore, the proposed data extraction method can be applied to tackle the problem with high complexity such as data sets with a huge number of instances. The Hopfield neural network is not symbolic and requires another computing system to assist the process. Henceforth, 3-SAT logic programming is incorporated in Hopfield neural network to give the symbolic form to the existing network. In this thesis, the enhanced AIS algorithm is proposed to improve the performance of HNN. The proposed hybrid HNN will overcome the circumstances associated with standalone non-symbolic HNN. However, there is still a problem in checking clause satisfaction during the training phase. The network tends to deteriorate the solutions and requires more iterations to achieve the convergence. In order to address the problem, the meta-heuristics are proposed to foster the training process in doing logic programming. The metaheuristic algorithm is usually robust because only focusing on selected searching space in generating the correct interpretations. In fact, the optimization operator will accelerate the process of generating the optimal output. In this case, HNN-3SATAIS, HNN-3SATGA, and HNN-3SATES are formulated to address the problem in training the network. Another problem with the standard HNN is when the complexity of the system increases exponentially with the instances. Moreover, the computation burden for the network will become higher. Some enhanced metaheuristic methods are introduced to search for feasible solutions in more systematic search spaces. Hence, HNN-3SATAIS and HNN-3SATGA are formulated based on a modification of the previous metaheuristic. In order to develop a computational model, the model should be able to counter the worst case problem. In this study, HNN-MAX3SATGA and HNN-MAX3SATAIS are expected to be able to do MAX-3SAT programming. So, the proposed hybrid model must be able to be the tool to solve various real life satisfiability problem. One of the notable problems is the circuit verification problem.

1.4 Research Objectives

The thesis is centered on the performance analysis of the hybrid HNN model in 3-SAT programming. The objectives of the thesis are:

1. To derive a brand new non-horn logic programming paradigm based on 3-SAT logic programming embedded in the Hopfield neural network (HNN).

2. To compare the performance of hybrid Hopfield neural network with enhanced artificial immune system algorithm (HNN-3SATAIS), modified genetic algorithm (HNN-3SATGA) and exhaustive search (HNN-3SATES) in doing 3-SAT logic programming.

3. To develop a knowledge extraction technique called 3-Satisfiability enhanced reverse analysis paradigm (3-SATERAP) to explain and unearth the behaviour real data sets. The performance analysis of 3-SATERAP with HNN-3SATAIS, HNN-3SATGA, and HNN-3SATES will be validated by using real data sets.

4. To compare the performance of HNN-MAX3SATAIS and HNN-MAX3SATGA in doing MAX-3SAT logic programming.

5. To compare the capability of HNN-C3SATGA and HNN-C3SATAIS in doing circuit verification.

1.5 Methodology

In this thesis, a hybrid Hopfield neural network in 3-SAT logic programming is established with the metaheuristic technique such as exhaustive search (ES), modified genetic algorithm (GA), and enhanced artificial immune system (AIS) algorithm. Since the previous data mining technique revolves around the Horn logical rule, the advantages of the 3-SAT form are used to map the real data sets. In this research, a data extraction paradigm, namely 3-Satisfiability enhanced reverse analysis (3-SATERAP) method is developed to address the weakness of the previous techniques. The proposed knowledge extraction technique will unearth the relationship entrenched between the attributes by taking into account the 3-SAT logical rule. Hence, the solid logical rule extracted by 3-SATERAP will be used to explain the hidden behavior of the real data sets. In this research, the effectiveness of our hybrid computing paradigm, namely HNN-3SATAIS, HNN-3SATGA, and HNN-3SATES to do 3-SAT logic programming will be compared. The proposed algorithms are expected to withstand vigorous training and the complexity. The computing paradigms will be tested by using simulated data set and real data set. The Dev-C++ Version 5.11 for Windows 10 is used as the platform of training, simulating and validating for our hybrid network. For the simulated data sets, the HNN-3SATAIS, HNN-3SATGA and HNN-3SATES will train the randomized 3-SAT logical rule. Then, a knowledge extraction method, 3-SATERAP is proposed in order to extract the optimum logical rule from 15 data sets obtained from UCI machine learning repository. In addition, the ability of hybrid HNN models in MAX-3SAT logic programming and C-3SAT in circuit verification will also investigated by using simulated data set. In this research, the HNN-3SATAIS, HNN-3SATGA, HNN-3SATES, HNN-MAX3SATAIS, HNN-MAX3SATGA, HNN-

C3SATGA, and HNN-C3SATAIS will be appraised in term of performance evaluation metrics. The goodness of fit or error evaluations involved are root mean square error (RMSE), mean absolute error (MAE), sum of squared error (SSE) and symmetric mean absolute percentage error (SMAPE). The performance evaluations such as Schwarz Bayesian Criterion (SBC), global minima ratio, ratio of satisfied clauses, accuracy and CPU time are vital in determining the robustness and effectiveness of the hybrid model. The methodologies for this research are summarized in Figure 1.3 and Figure 1.4.

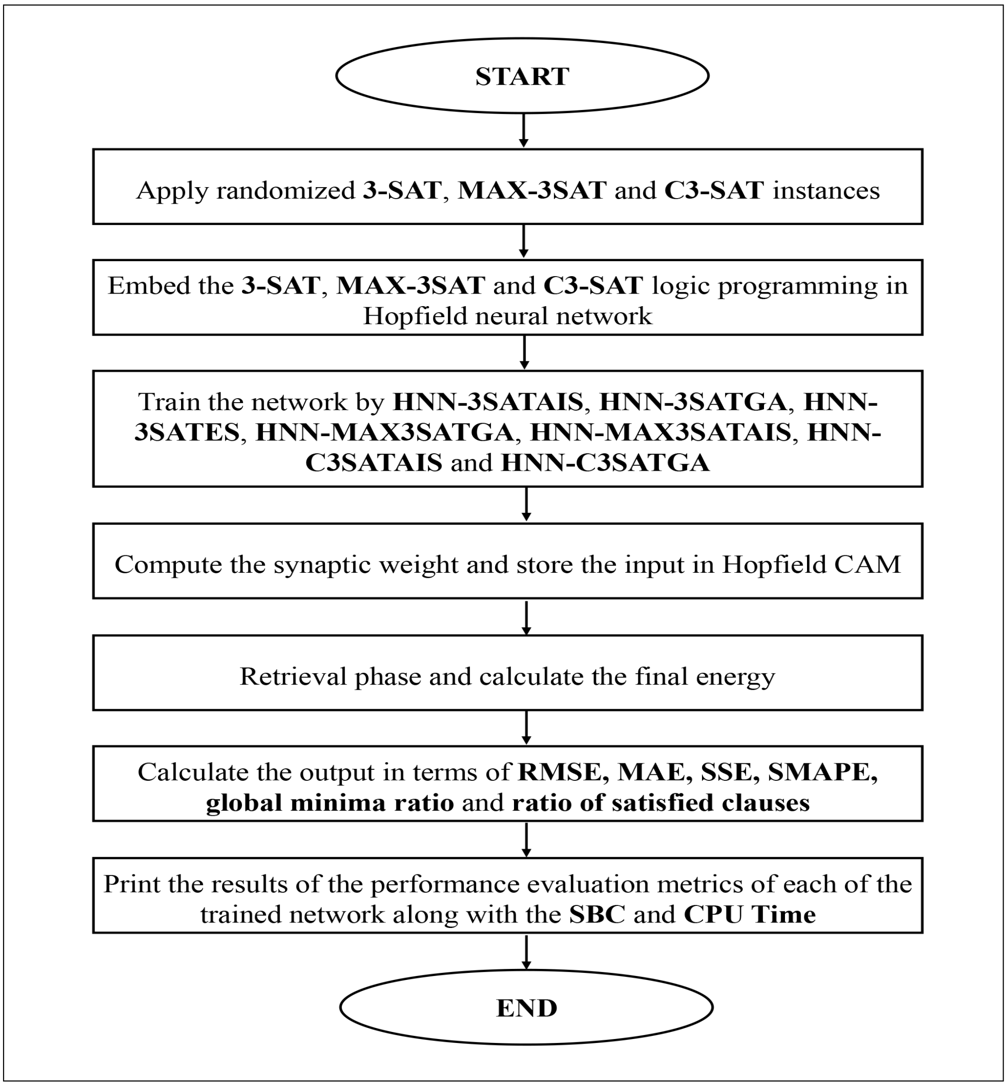

Figure 1.3: The Methodology of Hybrid HNN Networks in 3-SAT, MAX-3SAT, and C3-SAT Logic Programming

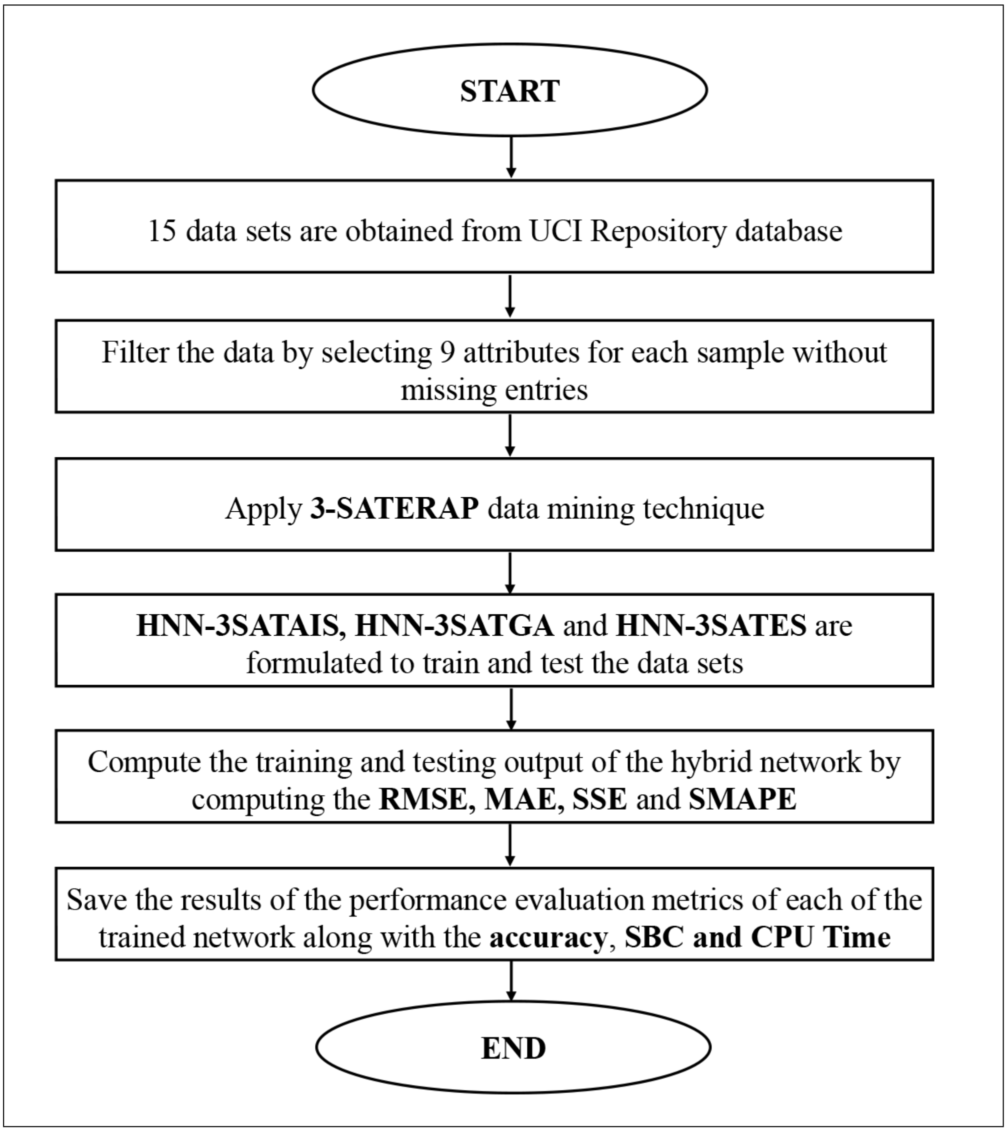

Figure 1.4: The Methodology of Hybrid HNN models in Logic Mining

1.6 Scope and Limitations of Research

The logical semantics in our research only revolves around propositional logic such as 3-SAT and MAX-3SAT problem to be entrenched into our non-symbolic hybrid Hopfield systems. Other variants of logic such as predicate logic cannot be deployed in the proposed models because it only complies with propositional logic. Hence, more modifications are necessary to do the predicate logic programming due to more complex operators. On the other hand, logic programming with complicated constraints will require a massive change in the method developed by Wan Abdullah (1991) and Sathasivam and Wan Abdullah (2011). The data mining technique is deployed in this research, namely 3-Satisfiability enhanced reverse analysis method (3-SATERAP) has only capability to classify the bipolar data sets. Hence, the model deals with 3-dimensional decision problems with only bipolar decisions. However, the ternary decision cannot be done by the proposed method. On the other hand, the technique cannot cope with the data set containing missing values. The logical rule will become convoluted when the missing data being replaced with random values. In the simulated data set, we limit the investigation until $NN = 180$ during the simulation of HNN-3SATAIS, HNN-3SATGA and HNN-3SATES for simplicity. The networks require more computation time if we increase the complexity of the problem. On the other hand, the real data set deployed is limited into 15 data sets obtained from UCI data set repository. Hence, the 15 data sets will provide the network with the different levels of training and testing that is crucial in assessing the performance of the hybrid networks. The selection complies with the work of Hamadneh (2013) and Pwasong and Sathasivam (2016). Although the capacity of discrete HNN is still satisfactory for our research, the problem will arise when dealing with a more complex datum. The discrete HNN is sufficient in the research due to the ability of the network to blend with the other training algorithms. This is because the HNN can be considered the building block for the elegant neural network available in the market nowadays. Moreover, the circuit design (C-3SAT) simulation is limited until 90 transistor for simplicity.

1.7 Organization of Thesis

The remaining parts of the thesis are organized as follows. Chapter 2 presents the notable literature that became the building blocks of our research. The related literature involved are the fundamental concept of HNN, logic programming, activation function, 3-SAT, MAX-3SAT, ES algorithm, GA, AIS algorithm, circuit verification, and data mining in HNN. Then, Chapter 3 emphasizes on the existing model of Horn logic programming in HNN. The chapter begins with a comprehensive overview and architecture of the HNN, followed by the concept of Hyperbolic tangent activation function that accelerates the HNN. The Hopfield content addressable memory and convergence dynamic are also highlighted. In addition, the logic programming techniques are discussed in this chapter. The proposed algorithms and contributions set the tone for Chapter 4. This chapter starts with the implementation of 3-SAT logic programming in HNN. Specifically, the algorithm for the implementation of ES, enhanced GA and enhanced AIS are discussed in details. In this chapter, HNN-3SATGA and HNN-3SATAIS are introduced to be compared with the state of the art model, HNN-3SATES. Besides, the other counterpart of 3-SAT problems that involved is the MAX-3SAT. In this section, HNN-MAX3SATAIS and HNN-MAX3SATGA are discussed. The implementation of HNN-C3SATAIS and HNN-C3SATGA in circuit verification is also highlighted. In order to extract the logical rule to be applied in data mining, the

3-Satisfiability enhanced reverse analysis paradigm (3-SATERAP) method is also introduced. Chapter 5 reveals the simulated results for HNN-3SATAIS, HNN-3SATGA and HNN-3SATES based on the performance evaluation metrics such as RMSE, MAE, SSE, SMAPE, SBC, global minima ratio, and CPU Time. In addition, the simulated results of HNN-MAX3SATAIS, HNN-MAX3SATGA, HNN-C3SATAIS, and HNN-C3SATGA are also discussed. Chapter 6 validates the effectiveness and robustness of HNN-3SATES, HNN-3SATGA, and HNN-3SATAIS in training and testing 15 real data sets from UCI repository. The training and testing errors can be used to signify the performances of our model. To sum up, Chapter 7 concludes the thesis by summarizing the findings in relations to the motivations and objectives fulfilled in this work and outlining some suggestions for the future direction of our work. Lastly, additional details are deferred to the appendices.

CHAPTER 2

LITERATURE REVIEW

This chapter provides the fundamental overview of the HNN, logic programming, 3-SAT, MAX-3SAT, AIS algorithm, ES, GA, circuit satisfiability and data mining in HNN. These domains are the building blocks of this research. Thus, the important works of literature of these domains are discussed in detail.

2.1 Hopfield Neural Network

The emergence of HNN has produced a prolific amount of research since four decades ago. Firstly, HNN was proposed by John Hopfield, a scientist from the University of California, Berkeley in 1982. Hopfield (1982) proposed an associative computational model that made a tremendous breakthrough in the AI field. Pursuing that, the HNN was implemented to the optimization and constraint satisfaction problems (Gao and Liu, 2009; Hopfield and Tank, 1985; Liang, 1996; Mańdziuk, 2000). Since then, tremendous modification and improvements have been applied to the HNN architecture to solve any optimization problems. In theory, the HNN comprises of a simple recurrent network that has an efficient associative memory and resembled the biological brain. For instance, Wen et al. (2009) proposed that the HNN is one major neural network specialized and crafted for solving constraint optimization or mathematical programming problems. The main benefit of HNN is that its structure can be realized on an electronic circuit, possibly on a very large-scale integration circuit, for an on-line solver with a parallel-distributed process. The structure of HNN utilizes three common methods, penalty functions, Lagrange multipliers, and primal and dual methods to construct an energy function (Pinkas, 1991). Moreover, the HNN minimizes Lyapunov energy by utilizing the physical Ising spin of the neuron states. On top of that, the network produced global output by minimizing the network energy. Pinkas (1991) and Wan Abdullah (1992) described a bi-directional mapping between logic and energy function of symmetric neural network. Besides, both methods are the building blocks for a corresponding logic program. Due to the effectiveness of energy changes in HNN, several researchers have combined the idea of logic programming with HNN. Several standard models were developed by Sathasivam and Wan Abdullah (2011) and Kasihmuddin and Sathasivam (2016). The work by Velavan et al. (2016) portrays the flexibility of HNN to amalgamate with the accelerating algorithm such as Mean Field theory. On the other hand, recent work by Zhang et al. (2017) emphasizes on the classification by using Hopfield associative memories. The work reported the welding quality of Chernoff face image had been successfully classified even though under abnormal welding conditions.

In this research, the HNN is hybridized with robust metaheuristic paradigms such as ES, GA, and AIS algorithm as a network respectively. The newly hybrid HNN networks called HNN-3SATAIS, HNN-3SATGA, and HNN-3SATAIS will serve as computing network in logic programming. The selection of HNN is not only due to the capability to blend with other networks but more primarily due to the power of CAM that resembles the biological intelligence system. Furthermore, the related works on HNN are shown in Table 2.1.

Table 2.1: Related Literature on Hopfield Neural Network

Author	Method	Summary and Findings
Hopfield (1984)	The computational network based on a stochastic model of McCulloch-Pitts neurons.	Thus, the computational power of HNN was inaugurated by taking into account the content addressable memories and the stochastic properties of the primitive McCulloch-Pitts neuron.
Pinkas (1991)	Energy function of HNN.	The work described a bi-directional mapping between propositional logic and energy function of a symmetric neural network.
Wan Abdullah (1993)	Higher order HNN for Horn logic program.	The HNN has minimized the logical inconsistencies in the interpretation of the logic program. Logical contents were obtained by the synaptic strength computed of the network.
Joya et al. (2002)	The dynamic of discrete HNN for optimization.	The proposed discrete HNN was proven in the avoidance of tremendous local minima solutions obtained after the computation.
Wen et al. (2009)	HNN in mathematical programming problem.	The work pinpointed the computational ability of HNN in doing mathematical programming such as VLSI simulation.
Sathasivam and Wan Abdullah (2011)	Logic mining by using discrete HNN.	The logic mining can be done by extracting the information entrenched in the Horn clauses.
Sathasivam and Fen (2013)	Logic programming in the HNN by agent based modelling.	The values of global minima ratio and Hamming distance provide solid evidence of the effectiveness of logic programming in HNN by using agent based modelling.
Zhou et al. (2015)	Bipolar auto-associative memory model in discrete HNN.	The external input patterns were memorized accurately, stable, robust and more generalized by learning through a discrete recurrent neural network compared to the existing methods.
Velavan et al. (2016)	Discrete HNN with mean field theory paradigm.	The results have been proven in accelerating the computational ability of the existing mean field theory. The mean field theory with HNN outperforms the standalone mean field network when being simulated by Agent Based Modelling (ABM).
Bansal and Dixit (2016)	The pattern recalling as content addressable memories by HNN and genetic algorithm.	This work proves that the HNN can be blended with the other metaheuristic algorithms to accelerate the computation and memory.

2.2 Logic Programming

Generally, logic program is an important concept in HNN. In general, logic programming has emerged as an essential field to model some real life problem. According to Kowalski (1979), the logic program provides a genuine and flexible way for problem-solving. Hence, logic program is easier to understand and verify compared with neural network which is a black-box model. Thus, logic program will provide neural network with symbolic instructions. As was mentioned, logic programming can be seen as a problem in combinatorial optimization and thus it can be carried out on a neural network. The HNN model proposed by Hopfield (1982) is a standard model for associative memory and widely incorporated with logic programming. In addition, logic program can be applied in HNN. Pinkas (1991) and Wan Abdullah (1992) defined a bi-directional mapping between propositional logic formulas and energy functions of symmetric neural networks. Both methods are concerned in finding whether the solutions complying with the logic program. Hence, both researchers are interested with Hopfield network. The findings are crucial in applying logic program in HNN. The activation function and McCulloch-Pitts function usually applied in logic programming. Besides that, both approaches can handle non-monotonicity of logic. Pinkas (1991) introduced preferred interpretation concept than Wan Abdullah (1992) in handling non-monotonicity. Kowalski and Sergot (1984) describe the motivation behind logic programming is the idea suits for both logic and computation. Basically, the idea of logic and computing has been emerging since the yesteryears inspired by the Turing machine (Petzold, 2008). Computing involves some computational modes such as programming, databases, and artificial intelligence. Specifically, Lloyd (2012) asserts the logic programming as an array of axioms, clauses or rules that blend together to form literals. Inevitably, the logic programming has emerged as a platform for knowledge extraction and data mining. In fact, the earliest was the propositional logic programming that being done by using Horn clauses. The most direct case of logic programming is when information is disclosed by means of Horn clauses and deduction is carried out by backward reasoning embedded in solution (Robinson, 1965). But logic programming can also be understood more generally such as, to include negation failure (Clark, 1978) or set construction (Miller and Nadathur, 1986). A logic program consists of Horn clauses and is activated by an initial statement. The propositional logic programming emphasizes on the propositional logic formula used to describe the relations. Since, the logical knowledge is symbolic, the logic act as the programming instructions. Hence, a propositional logic program consists of a set of logic clauses. Recent work by Riguzzi et al. (2017) proposes probablistic logic programming under distribution semantics. In this thesis, a brand new logic programming called 3-SAT logic programming is proposed as a core knowledge instructions to be embedded to the hybrid HNN. Thus, 3-SAT logic programming is different from the previous works due to the capability to solve the constraint optimization problem and the power of logic knowledge to be used in data mining. Hence, the 3-SAT logic programming will serve as a building block for the newly proposed 3-SATERAP to be used as a classification approach. Additionally. the 3-SAT logic program will be utilized to map and unearth the relationship between the attributes in the real data set. Moreover, Table 2.2 summarizes the related literatures and developments on logic programming.

Table 2.2: Related Literature on Logic Programming

Author	**Method**	**Summary and Findings**
Pinkas (1991)	Propositional logic programming in symmetric connectionist model.	The propositional logic was transformed into the energy equation for optimization deployed by the symmetric connectionist model. HNN is a symmetric connectionist model due to the symmetric weights.
Wan Abdullah (1992)	Logic programming implemented on a neural network.	The work had developed a state-of-the-art model of logic programming on the HNN. Hence, the method of computing the connections strength has been outlined from the logic program. This work provides a better insight of synaptic strengths computation for the discrete HNN.
Hölldobler et al. (1999)	Logic program by recurrent neural network.	The recurrent neural network was proven to work effectively with the logic program. Hence, the logic program has provided the semantics or instructions to the non-symbolic recurrent neural network.
Sathasivam (2010)	Enhanced logic programming in HNN.	The performance of the logic programming in HNN was consistently good in term of the global minima ratio, Hamming distance, fitness energy landscape and computational time even though the number of neurons increases.
Hamadneh et al. (2014)	Satisfiability logic programming.	The satisfiability logic programming was carried out in radial basis function neural network (RBFNN). The findings showed a good agreement with the HNN. However, the implementation of RBFNN requires a single operator problem.
Sathasivam (2015)	The logic programming in HNN by using acceleration technique.	The robustness of logic programming in HNN was accelerated by using the modified Hyperbolic tangent activation function (HTAF). Hence, the mechanism could benefit the computation of more complex problems.
Velavan et al. (2016)	The Horn logic programming using mean field theory with HNN.	The hybrid mean field theory with HNN has proven to work with the higher order horn logic programming in terms of global convergence.

2.3 Hyperbolic Tangent Activation Function

Generally, the activation functions are widely utilized to transform the activation level of a unit (neuron) into an output signal in a particular neural network (Karlik and Olgac, 2011). In layman's term, it is also known as the transfer function or squashing function due to the capability to squash the permissible amplitude range of output signal to some finite value. In this research, the Hyperbolic tangent activation function (HTAF) is applied to the system due to the effectiveness in accelerating logic programming in HNN for the Horn clauses (Sathasivam, 2015). Hence, the HTAF is expected to work well with 3-SAT logic programming. The process of training and getting the global solutions for 3-SAT will become tedious and more expensive due to the complexity. Hence, a post optimization paradigm is proposed to counter the circumstances due to the complexity of the network during the process of doing logic programming in Hopfield network. Obviously, the default activation function incorporated as the accelerator of 3-SAT logic programming will set the tone of the research. Therefore, the desired output can be generated systematically when doing the logic programming in Hopfield network. Theoretically, it will lead to produce global solutions. In addition, it will assist the Hopfield's content addressable memories to recall the correct global states. In essence, the HTAF is explained in the work of (Karlik and Olgac, 2011) as the ratio between the Hyperbolic sine and Hyperbolic cosine functions expanded as the ratio of half-difference and half-sum of two exponential functions. Next, the HTAF is essential to optimize the output of the network. In theory, the HTAF is a differentiable function and produced a bounded output (Mathias and Rech, 2012). These properties are essential to maintain non-linearity in neuron's state classification. The important literatures on the HTAF are highlighted in Table 2.3.

Table 2.3: Related Literature on Hyperbolic Tangent Activation Function

Author	**Method**	**Summary and Findings**
Mathias and Rech (2012)	HTAF in three-dimensional HNN.	The HTAF outperformed the piecewise function in modelling the three-dimensional HNN based on performance evaluation metrics. The capability of HTAF in accelerating the HNN has improved the computational power of HNN.
Sibi et al. (2013)	HTAF for backpropagation neural network.	The HTAF was proven as one of the best activation function to be applied in the neural network. It was supported by the magnitude of error obtained at the last Epoch during training for Mushroom data set. The HTAF has enhanced the conventional backpropagation newtork.
Zamanlooy and Mirhassani (2014)	HTAF for VLSI implementation.	It was proven that the VLSI implementation can be done with the HTAF as the transfer function. The simulated results portrayed the compatibility of the activation in digital networks.
Sathasivam and Velavan (2014)	HTAF for higher order Hopfield network.	The HTAF outperformed the McCulloch-Pitts function in terms of global minima ratio, complexity, CPU Time and Hamming distance for higher order Hopfield network. Both activation functions are integrated with Boltzmann machine and HNN.
Pwasong and Sathasivam (2015)	HTAF as an accelerator for reverse analysis paradigm.	The hyperbolic tangent activation function had proven the effectiveness in accelerating the data mining process. In this work, the hyperbolic tangent activation function had accelerated the reverse analysis paradigm even though encountering higher complexity.
da Silva et al. (2017)	Enhanced HTAF for associative memories mapping.	Associative memories mapping has been improved tremendously with the assistance of HTAF that squashes the input effectively. Thus, the results have a good agreement with the computation time obtained by the standalone Hopfield associative memories.

2.4 General Concept of 3-Satisfiability

The work on 3-SAT is still mushrooming even though it can be classified as a classical NP hard problem (Johnson, 1989). Basically, 3-Satisfiability (3-SAT) problem is a mapping problem from a logic programming in 3-CNF to truth values. In theory, 3-SAT can be defined as a formula in a conjunctive normal form with a collection of clauses where each comprises strictly 3 literals per clause (Kutzkov, 2007). Therefore, a 3-SAT paradigm can allow two choices for the value of each variable, which are 1 or -1. In addition, the 3-SAT problem is an example of a non-deterministic problem and constraint satisfaction problem (CSP). Therefore, solving the CSP problem such as 3-SAT is a notoriously expensive due to the complexity.There are limitless of ways to solve 3-SAT problem ranging from exact to the approximation algorithm. Bünz and Lamm (2017) studied the implementation of Graph neural network (GNN) in 3-SAT as a classifier in 3 randomized data sets. However, the result obtained was encouraging with the accuracy in a range of 65% to 71% in terms of training error. In this thesis, the idea of incorporating 3-SAT logic programming is inspired by the Horn logic programming proposed by Sathasivam (2010). The 3-SAT logic will be encoded to the non-symbolic HNN as the main language of knowledge to the system. Apart from that, 3-SAT serves as a constraint optimization problem that requires some approximation algorithm such as metahueristic paradigms as the training method. Overall, 3-SAT logical rule is utilized as a logical representation to study the behaviour of the data sets and serve as a classification method in data mining. The HNN-3SATAIS, HNN-3SATGA, and HNN-3SATES will train the 3-SAT problem before being retrived by the CAM in HNN. The other notable works on 3-SAT are dicussed in Table 2.4.

Table 2.4: Related Literature on 3-Satisfiability

Author	Method	Summary and Findings
Johnson (1989)	A neural network method to the 3-SAT problem.	The inaugural work of solving 3-SAT by using neural network approach proved the hardness of the problem. The work outlined the similarity of 3-SAT and the circuit problem.
Freeman (1996)	Solving a hard 3-SAT problem with David-Putnam procedure (DPP).	The DPP solved the under constrained and over constrained 3-SAT problem. The DPP is a primitive exact method in solving the hard 3-SAT problem under certain constraints.
Brueggemann and Kern (2004)	Deterministic local search for 3-SAT.	The deterministic local search works effectively in solving the 3-SAT problem.
Dahllöf et al. (2005)	Counting models for 3-SAT formula.	The counting model proposed for 3-SAT formula outperforms the conventional model.
Sathasivam and Abdullah (2010)	Satisfiability logic on Little Hopfield network.	The satisfiability aspect in terms of CNF logic was proposed on Little Hopfield network. The results were encouraging based on the Hamming distance and global minima ratio obtained after the simulation.
Hamadneh et al. (2014)	Satisfiability of logic programming based on RBFNN.	The satisfiability problem presented in the form of logic programming in RBFNN. The logic programming deals with a single operator and a small number of clauses only.
Aiman and Asrar (2015)	Solving the 3-SAT problem by binary GA.	The effectiveness of the binary GA in solving the 3-SAT problem was compared with the local search approach. The binary GA was reported as a good method in improving the solutions even though searching spaces are evolving.
Hen and Spedalieri (2016)	Quantum annealing approach in solving constrained optimization problem.	The work highlighted the feasibility of quantum annealing approach in solving the satisfiability problem. The quantum annealing method was applied to accelerate the process of solving the 3-SAT.
Doerr et al. (2016)	Time complexity of randomized satisfiable k-CNF formula.	The analysis of the time complexity for randomized 3-CNF or 3-SAT formula is described. Thus, the time complexity is influenced by the number of clauses involved in the computation of 3-SAT formula.

2.5 General Concept of Maximum 3-Satisfiability

Since a few decades ago, Boolean satisfiability has emerged from a classical problem into a bunch of various hard problems. Hence, MAX-3SAT is a counterpart of classical Boolean satisfiability that has captured the attention of many researchers in the optimization field (Berg and Järvisalo, 2015; Layeb, 2012). Specifically, the MAX-3SAT can be delineated as the maximum number of satisfied clauses achieved by any complete assignment. Maximum 3-Satisfiability (MAX-3SAT) is a notable counterpart of the 3-SAT problem, denoted in Conjunctive Normal Form (CNF) form (Layeb et al., 2010). Zhang (2004) asserted the Max-3SAT problem as the generalized and difficult form of decision problem whereby not the entire constraints are satisfiable. Even though the MAX-3SAT ought to be harder than the normal 3-SAT problem, both are demarcated as a NP-complete problem. This has been demonstrated by Cook (1971), Goemans and Williamson (1994) and Zhou (2016). In this research, the MAX-3SAT is addressed as the logical rule for the logic programming. The selection of MAX-3SAT logic programming was made in order to authenticate the proposed hybrid HNN in dealing with harder satisfiability logic. Hence, HNN-MAX3SATAIS and HNN-MAX3SATGA are formulated to be simulated by using the randomized MAX-3SAT instances. The capability of our proposed models in doing MAX-3SAT logic programming will be investigated by using different complexity of the neurons. So, the related works of MAX-3SAT are shown in Table 2.5.