

**HYBRID ANT COLONY OPTIMIZATION FOR
TWO SATISFIABILITY PROGRAMMING IN
HOPFIELD NEURAL NETWORK**

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**HYBRID ANT COLONY OPTIMIZATION FOR
TWO SATISFIABILITY PROGRAMMING IN
HOPFIELD NEURAL NETWORK**

by

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LIST OF SYMBOLS

| | |
|--------------|--|
| $h(v_i)$ | Alternative Heaviside Step function |
| h_i | Local field |
| θ | Threshold |
| a_i | Unit i Activation |
| W_{ij} | Synaptic Weight from unit i to j |
| S_i | State of the i th Neuron |
| μ | External Field |
| sgn | Signum Function |
| H | Lyapunov Energy |
| \leftarrow | Implication |
| \wedge | Conjunction |
| \vee | Disjunction |
| \neg | Negation |
| $g(x)$ | Activation Function of x |
| R | Relaxation Rate |
| C_i | Clause i |
| P | 2SAT Variant Formula |
| E_P | Cost Function of P |
| H_P | Final Minimum Energy |
| H_P^{min} | Expected Global Minimum Energy |
| Tol | Tolerance Value |
| f_{2SATES} | Fitness Function for Exhaustive Search |

| | |
|-----------------------|--|
| NC | Number of Clause |
| $B(NC,p)$ | Binomial Distribution with NC and Probability of p |
| r | Number of Satisfied Clause |
| f_{2SATGA} | Fitness Function for Genetic Algorithm |
| $f_{2SATACO}$ | Fitness Function for Ant Colony Optimization |
| α | Relative Importance of Pheromone |
| β | Relative Importance of Visibility of Ants |
| ρ | Evaporation Rate |
| P_{learn} | Learning Data Set |
| P_{test} | Testing Data Set |
| P_{best} | Best 2SAT Logic |
| P_i^B | Induced Logic |
| $N_{Success}^{P_i^B}$ | Number of Success P_i^B |
| $N_{Fail}^{P_i^B}$ | Number of Fail P_i^B |
| P_i | Target Value |
| O_i | Observed Value |
| f_{NC} | Total Number of 2SAT Clause |
| t | Number of Trial |
| c | Number of Neuron Combination |
| NN | Number of Neurons |
| Acc_{2SATRA} | Accuracy of 2SATRA |
| Acc_{EM} | Accuracy of Existing Model |

LIST OF ABBREVIATIONS

| | |
|-------------|--|
| 2SAT | 2 Satisfiability |
| 2SATRA | 2 Satisfiability based Reverse Analysis method |
| ABC | Artificial Bee Colony |
| ABM | Agent Based Modeling |
| ACO | Ant Colony Optimization |
| AI | Artificial Intelligence |
| AIS | Artificial Immune System |
| ANN | Artificial Neural Network |
| CAM | Content Addressable Memory |
| CCTV | Clausal Diversification Method and Truth Maintenance |
| CNF | Conjunctive Normal Form |
| CPU | Central Processing Unit |
| DNF | Disjunctive Normal Form |
| EIGA | GA with Exon and Intron |
| ES | Exhaustive Search |
| GA | Genetic Algorithm |
| GPU | Graphics Processing Unit |
| HACO | Hybrid Ant Colony Optimization |
| HNN | Hopfield Neural Network |
| HNN-2SAT | 2 Satisfiability Logic Programming in Hopfield Neural Network |
| HNN-2SATACO | 2 Satisfiability Logic Programming in Hopfield Neural Network by using Ant Colony Optimization |
| HNN-2SATES | 2 Satisfiability Logic Programming in Hopfield Neural Network by using Exhaustive Search |
| HNN-2SATGA | 2 Satisfiability Logic Programming in Hopfield Neural Network by using Genetic Algorithm |
| HNN-ICA | Imperialist Competitive Algorithm with Hopfield Neural Network |
| HTAF | Hyperbolic Activation Function |
| IoV | Internet of Vehicles |
| KHNN | Kernel Hopfield Neural Network |
| k SAT | k Satisfiability |

| | |
|-------------|---|
| MAE | Mean Absolute Error |
| MAJSAT | Majority Satisfiability |
| MAPE | Mean Absolute Percentage Error |
| MAXSAT | Maximum Satisfiability |
| MAX k SAT | Maximum k Satisfiability |
| MCP | McCulloch-Pitts Neuron |
| MFT | Mean Field Theory |
| MINSAT | Minimum Satisfiability |
| PDP | Parallel Distributing Processing |
| RBFNN | Radial Basis Function Neural Network |
| RDCEHNN | Car Evaluation Real Data Set |
| RDCMHNN | Contraceptive Method Choice Real Data Set |
| RDGCHNN | German Credit Real Data Set |
| RDHSHNN | Haberman's Survival Real Data Set |
| RDODHNN | Occupancy Detection Real Data Set |
| RMSE | Root Mean Square Error |
| RNN | Recurrent Neural Network |
| SCC | Strongly Connected Components |
| SCN | Symmetric Connectionist Network |
| SIMT | Single Instruction Multiple Thread |
| SOM | Self Organizing Network |
| SSE | Sum of Square Error |
| TSP | Traveling Salesman Problem |
| UCI | UC Irvine Machine Learning Repository |
| VLSI | Very Large Scale Integration |
| WNN | Wavelet Neural Network |
| IPS | Institut Pengajian Siswazah |
| USM | Universiti Sains Malaysia |

HIBRID KOLONI SEMUT PENGOPTIMUMAN UNTUK PROGRAM DUA SATISFIABILITY DALAM RANGKAIAN NEURAL HOPFIELD

ABSTRAK

Persembahan logik dengan menggunakan 2 *Satisfiability* atau 2SAT semakin dilihat sebagai peraturan logik yang penting untuk mensintesis banyak aplikasi kehidupan sebenar. Walaupun terdapat ramai penyelidik dalam bidang ini telah mencadangkan penyelesaian kepada 2SAT, hanya sedikit perhatian telah diberi kepada kepentingan dan kelebihan peraturan logik 2SAT. Dengan itu, kajian ini menghipotesiskan bahawa, 2SAT boleh digunakan sebagai peraturan logik dalam sistem pintar. Untuk mengesahkan kenyataan ini, 2 *Satisfiability* telah diintegrasikan dengan rangkaian neural Hopfield (HNN) sebagai unit tunggal. Pembelajaran dalam HNN telah mendapat inspirasi daripada kaedah Wan Abdullah kerana pembelajaran tradisional iaitu pembelajaran secara Hebbian dilihat sebagai tidak cekap apabila berhadapan dengan klausa yang banyak. Oleh kerana bilangan klausa untuk 2SAT boleh meningkat, kecekapan dan keberkesanan fasa pembelajaran dalam HNN juga akan merosot. Algoritma metaheuristik telah diperkenalkan untuk mengurangkan kerumitan pembelajaran HNN. Algoritma metaheuristik yang dicadangkan ialah algoritma pengoptimuman koloni semut (ACO). Algoritma ini akan diintegrasikan dengan model HNN-2SAT sebagai unit tunggal iaitu HNN-2SATACO. Prestasi model akan diuji dengan menggunakan simulasi set data. Dari segi aplikasi kehidupan sebenar, kaedah Analisis Berbalik berasaskan 2 *Satisfiability* (2SATRA) akan dibangunkan untuk melakukan perlombongan logik dalam 5 set data sebenar yang berlatarkan bidang kewangan hingga perubatan. 2SATRA akan menggunakan model HNN-2SAT yang dicadangkan ketika fasa pembelajaran. Prestasi perbandingan menunjukkan HNN-

2SATACO berjaya mengatasi model hibrid HNN-2SAT lain dalam melakukan simulasi set data dan set data sebenar.

HYBRID ANT COLONY OPTIMIZATION FOR TWO SATISFIABILITY PROGRAMMING IN HOPFIELD NEURAL NETWORK

ABSTRACT

The representation of 2 Satisfiability problem or 2SAT is increasingly viewed as a significant logical rule in order to synthesize many real life applications. Although there were many researchers proposed the solution of 2SAT, little attention has been paid to the significance of the 2SAT logical rule itself. It can be hypothesized that 2SAT property can be used as a logical rule in the intelligent system. To verify this claim, 2 Satisfiability logic programming was embedded to Hopfield neural network (HNN) as a single unit. Learning in HNN will be inspired by Wan Abdullah method since the conventional Hebbian learning is inefficient when dealing with large number of constraints. As the number of 2SAT clauses increased, the efficiency and effectiveness of the learning phase in HNN deteriorates. Swarm intelligence metaheuristic algorithm has been introduced to reduce the learning complexity of the network. The newly proposed metaheuristic algorithm was enhanced ant colony optimization (ACO) algorithm. This algorithm will combine with HNN-2SAT model as single unit namely HNN-2SATACO. The performance of the model will be tested by using simulated data set. In terms of real life application, the newly improved 2 Satisfiability based Reverse Analysis Method (2SATRA) will be implemented to do logic mining in 5 different real life data sets ranging from finance to medical field. 2SATRA will implement the proposed hybrid HNN-2SAT model during learning phase. The performance comparison indicates that most of the time, HNN-2SATACO outperformed other hybrid HNN-2SAT models in doing simulated and real data set.

CHAPTER 1

INTRODUCTION

1.1 Introduction to Neural Network

Neural networks, artificial intelligence and deep learning are robust machine learning-based techniques utilized to solve many real world problems. Artificial intelligence aims at creating computers or machines as intelligent as human beings. Hence, neural networks which is inspired from the natural neural network of human nervous system is one of the popular research area in artificial intelligence.

1.1.1 Introduction to Artificial Intelligence

Neural networks are mathematical models inspired by biological processes of the human brain (Agatonovic-Kustrin and Beresford, 2000). The human brain computes in an entirely different way from digital computer. Human brain has capability to organize its structural constituents, known as neurons or nerve cells. In biological neural networks, information (synapse) was stored and transferred among neurons in different topologies and architecture (See Figure 1.1). Neurons “fire” (input) signals through axon (output) when defined threshold exceeded. A fundamental issue in neural network is how the information is encoded in and retrieved from the neural system. This issue leads to the development of artificial intelligence (AI). The field of AI is a pursuit to understand intelligent entities. Schalkoff (1990) concisely defined AI as “a field of study that seeks to explain and emulate intelligent behaviour in terms of computational process”. Different from other field of studies, AI emphasized on building intelligent entities as well as understanding them (Russell and Norvig, 1995). In that sense, AI encompasses a huge subarea such as perception and logical reasoning to specific task. The popular tasks that associated with AI are playing chess, proving mathematical

theorem, diagnosing diseases. Neural symbolic is one of the popular field in AI. Neural symbolic combines the advantages of parallelism in neural network and symbolism in knowledge representation (Garcez et al., 2012).

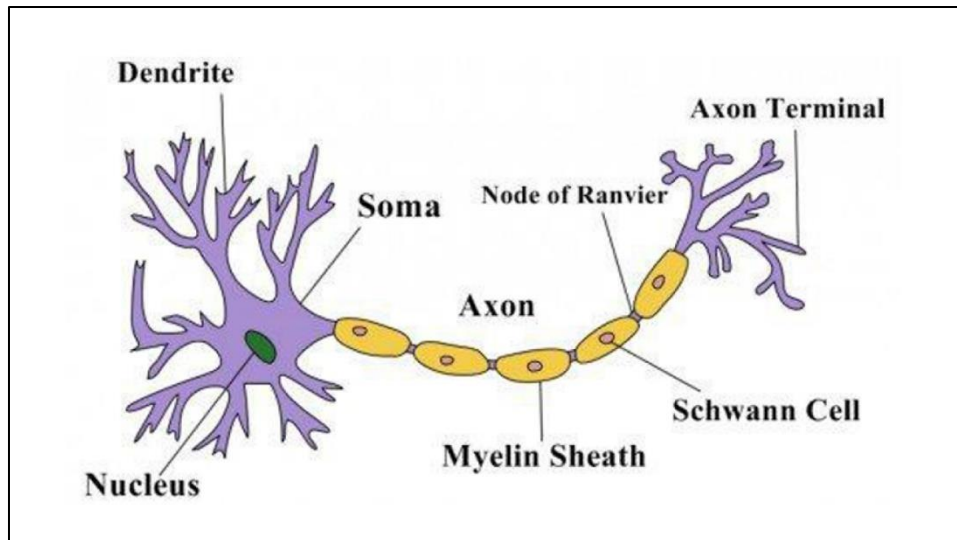


Figure 1.1 A Structure of Biological Neuron (Rojas, 2013)

1.1.2 Introduction to Artificial Neural Network

In AI research, artificial neural network (ANN) plays an important role in knowledge and data extraction. ANN is designed to simulate the way human process information. There are also commonly referred as parallel distributing processing (PDP) models or simply neural nets. ANN gather their knowledge by revealing patterns and relationships among data during training (Rojas, 2013). ANN is very useful in computer simulation in order to illustrate the usefulness of certain technique to solve optimization problem such as pattern recognition, classification, data compression and constrained optimization problem. For instance, ANN is applicable to find the desired output based on embedded input in the system. ANN comprised interconnected group of neurons that use a mathematical model for information processing based on multiple connectionist approach to computation. ANN continue to receive attention from various researchers

in order to analyse non linear problems (Hopfield and Tank, 1985; Moody and Darken, 1989).

1.2 History of Neural Network

The first mathematical model of a neural network is attributed to McCulloch and Pitts. In 1943, Warren S. McCulloch, a neuroscientist, and Walter Pitts, a logician, published “A logical calculus of the ideas immanent in nervous activity” (McCulloch and Pitts, 1943). Based on the paper, McCulloch and Pitts tried to understand how the brain could produce highly complex patterns by using many basic cells that are connected together. These basic brain cells are defined as neurons, and McCulloch and Pitts gave a highly simplified model of a neuron in their paper. Later, McCulloch and Pitts model of a neuron has made an important contribution to the development of ANN. Another important idea was put forward in 1949 by Donald Hebb, who suggested that a group of neurons could reverberate in different patterns. He formulated a learning strategy commonly referred to as the Hebbian Rule (Hebb, 1949) which suggests that a cell’s efficiency in emitting a neuron to another cell rise with consistent repetitions. This was the first time a model of dynamic memory had been used by neuropsychologist. Hebb’s Rule and a few other theories help us to understand the capabilities of the nets and they could be simulated on contemporary computers. During the 1950’s traditional computing began, it left research of ANN in the dark and full with limitations. Despite that, there are studies continued research on ANN. In 1954, Marvin Minsky wrote a doctorate thesis, Theory of Neural-Analog Reinforcement Systems and its Application to the Brain-Model Problem, which was concerned with research into ANN (Minsky, 1954). He also published a scientific paper entitled, “Steps Toward Artificial Intelligence” which was the one of the first papers to discuss AI in detail

(Minsky, 1961). The paper also consists of a large component on what nowadays is defined as neural networks. In 1982, John Hopfield of Caltech presented a paper to the scientific community in which he stated that the approach to AI should not be to purely imitate the human brain. The approach instead used its concepts to build machines that could solve dynamic problems. He showed what the capabilities of such networks are and how they actually work. His vast knowledge of mathematical analysis convinced scientists and researchers at the National Academy of Sciences to renew interest in the research of AI and neural networks. His ideas gave birth to a new era of neural networks that over time became known as the Hopfield Model (Hopfield, 1982). Throughout 1990's and the technological era, research and development on artificial neural networks are advancing rapidly all over the world. Biological neurons itself is living proof that neural networks do in actual fact work. Nowadays, the "real" challenge lies in finding ways to electronically implement the principals of neural network technology. Electronics companies are working on three types of neuro-chips namely, digital, analog and optical. The neuro-chips are incorporated with ANN design makes the future of ANN technology looks very promising. ANN technologies are now capable of predicting natural disasters such as landslides (Dou et al., 2018) and floods (Falah et al., 2019).

1.3 Significance of Research & Problem Statement

Several intelligence system has been developed in order to imitate how the actual brain work. This means that a closest way to represent the way of human thinking is by mapping the biological human thought process with a set of rules and logic. These set of rules and logics must behave in the dynamic manner where the rules can be changed according to the behaviour of the perceived knowledge. In the real world,

mapping human thought and learning through computer simulation can be done by the usage of symbolized programming. Each of the learning and connection will be assigned with predetermined symbol and states. All the assigned symbol will be mapped based on dynamic logical rules. The main drawback of the models proposed by Wan Abdullah (1992), Sathasivam and Wan Abdullah (2008) and Hamadneh et al. (2012a) are the usage of logical rule that mapped the important knowledge. All the mentioned researchers only focus on Horn programming in HNN which in many real life application failed to represent the perceived knowledge. This phenomenon motivated the development of a new set of logical rule namely 2 Satisfiability programming. This new non-horn logic integrated with HNN is expected to represent knowledge in a preferable scheme. One of the significant drawback of the conventional method possessed as asserted by Sathasivam and Wan Abdullah (2008) is the efficiency of the learning phase. In order to derive the correct cost function efficiently, the network is obligated to find the consistent interpretation based on the embedded logical rule. The task of finding consistent interpretation will be much convoluted as the number of clause increase. Conventional method that is exhaustive search method is proven to consume more iterations and ultimately will cause unnecessary output oscillations. The lack of efficiency reduces the capability of the network to generalize large data sets. Kasihmuddin (2017) integrated genetic algorithm to HNN during the learning phase. However, there's a drawback where during the earlier generation, non-fit chromosomes acquire more iteration to develop its fitness before effective crossover can take place. Hence, lead to error accumulation and higher standard deviation error. This drawback prompted this research to search other intelligent methods to find consistent interpretation during learning phase with minimal error. In this thesis, the learning phase of HNN will be inspired by swarm based intelligence. The metaheuristic algorithm

namely ant colony optimization will address the problems of local solution during learning phase. The proposed hybrid network is able to complete the learning phase of HNN within acceptable time range. The interaction between the ants and pheromone density helps to diversify candidate solution in search space. Hence, will be able to minimize the learning error. The state of the art HNN proposed by Hopfield (1982) has several weaknesses in terms of output optimization. The main weakness of this network is the learning rule applied to solve combinatorial problem. Conventionally, HNN utilized Hebbian learning (Földiák,1990) to find the corresponding synaptic weight. Hebbian learning was proven to be ineffective when the number of constraints are enlarged. In order to reduce the wrong synaptic weight stored as content addressable memory, Wan Abdullah method will be introduced to the network. Efficiency of Wan Abdullah method helps to increase the capacity of HNN in finding the global solution. In another development, output optimization during retrieval phase is fundamental in order to find the optimal result. The usage of Hyperbolic activation function during output optimization can reduce the possible local minima (Nawi, 2014). Sathasivam relaxation method introduces the neuron relaxation to recreate the efficient transfer of information among neurons (Sathasivam, 2010). All the mentioned optimization techniques will be applied to newly proposed hybrid model. Reverse analysis method proposed by Sathasivam and Wan Abdullah (2008) is able to induced the individual logical rule from the data sets. In this model, synaptic weight from the data will be derived based on Wan Abdullah method. The induced logical rule will be measured based on support and confidence with predetermined threshold. This method is not able to generalize the whole logical behaviour of the data set since the model only extract logical rule among the individual neurons. In other word, the extracted logical rule only applies for specific group of neurons. This drawback excites the model to take into

account the global induced logic. Global induced logic is able to generalize the whole data sets in a single 2 Satisfiability logic. In this thesis, improved 2 Satisfiability based reverse analysis method will be proposed to do five real life applications.

1.4 Research Objectives

This thesis is centered on using symbolic learning in HNN. Ultimately, the goal of the research is to produce systematic knowledge acquisition by using nature inspired method and logic programming in neural network. Two important areas in the proposed model are optimization and validation. On the optimization side, effort is directed towards building learning network that are efficient and effective. On the validation front, the proposed model must be able to function correctly in doing real life applications. The objectives of this thesis are as follows:

1. To hybridize 2 Satisfiability logic programming with HNN. In order to do so, 2 Satisfiability programming will be proposed in HNN. 2 Satisfiability logic will be the primary logical rule that determine the nature of the HNN.
2. To integrate nature inspired metaheuristic algorithm during learning phase of HNN. The newly improved metaheuristic algorithm namely improved ant colony optimization will enhance the learning capability of the hybrid model.
3. To apply logic mining technique via 2 Satisfiability based Reverse Analysis method in doing 5 real data sets. 2 Satisfiability based Reverse Analysis method is a new logic mining technique that can generalize the logical rule of the data sets. The proposed method will be integrated with the proposed hybrid HNN model.

1.5 Methodology

The action plan for this research are established based on the following foundations.

1.5.1 Research philosophy

The hybrid model formulated in this thesis will be able to perform effectively and efficiently compared to the current model proposed by Wan Abdullah (1992), Sathasivam (2006), Hamadneh (2013), Velavan et al. (2016) and Kasihmuddin (2017). The proposed hybrid model in this thesis is expected to be a benchmark tool to generalize the behaviour of the data.

1.5.2 Research approach

The hybrid network is formulated by embedding 2 Satisfiability logical rule in HNN. A newly improved metaheuristic namely ant colony optimization will be implemented during the learning phase of HNN. 2 Satisfiability programming embedded in HNN with improved learning models will function as a single unit. The learning method will be compared with the existing learning methods which are exhaustive search and genetic algorithm method. This hybrid model will be integrated in newly improved 2 Satisfiability Reverse Analysis method in doing logic mining. The capability of the induced logic in 2 Satisfiability Reverse Analysis method will be compared with other existing models.

1.5.3 Research strategy

The hybrid model will be tested by using simulated data set and real data sets. Both data sets will be conducted in Dev C++ Version 5.11 on Windows 8.1 with Intel Core i7 2.5GHz processor and 8GB RAM. For simulated data set, the data employed during the experiment are based on random neuron state generator. In this regard, Dev

C++ will generate the neuron state randomly during learning and retrieval phase in order to minimize the possible biasness. On the other hand, 5 real data sets obtained from UCI machine learning repository in order to test the ability of the proposed hybrid model. UCI machine learning data set is a benchmark for all neural network practitioner to test their proposed network. Type of real data sets obtained from the website were ranging from finance, health issue, voting system, psychology and technology development. The various type of data set will enhance the confidence of the proposed hybrid model in doing real life applications. All experiments will be conducted in the similar device to avoid biasness during experiment.

1.5.4 Research evaluation

The performance of hybrid model during experiment will be assessed by using various performance evaluation criteria. Each hybrid model will be evaluated based on conventional error evaluation such as root mean square error, mean absolute error, sum of squared error and mean absolute percentage error. All the mentioned errors describe the behaviour of the hybrid model in various perspectives. Global minima ratio will be used to test the effectiveness of the HNN model during the retrieval phase. Finally, CPU time generalize the time performance for all hybrid models in completing a single program execution. The methodology of this thesis can be visualized in Figure 1.2.

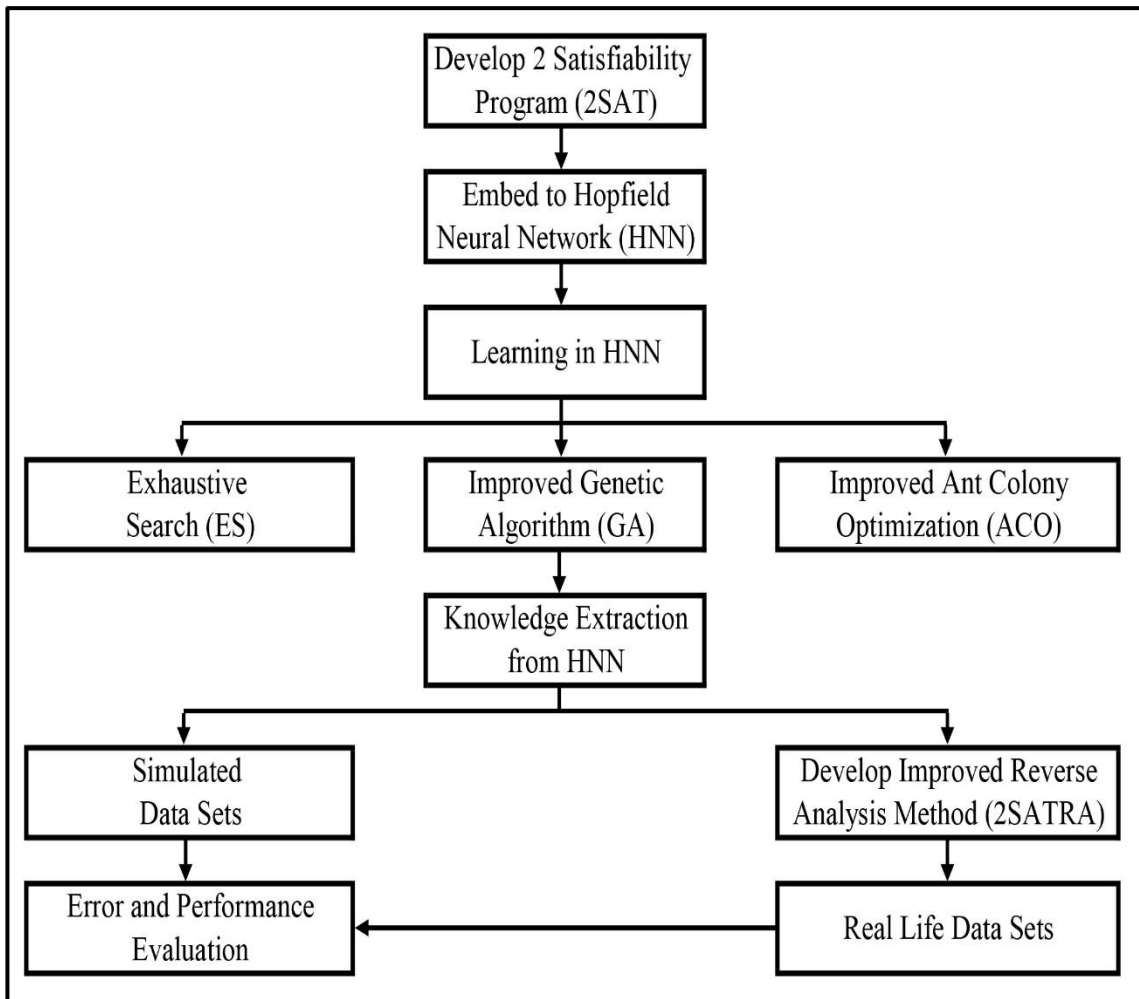


Figure 1.2 Research Methodology Flowchart

1.6 Limitations and Scope of Research

Some of the data set consist of missing values. Strategies such as data deletion and adding any value to the missing data set (Wohlrab and Fürnkranz, 2009) will reduce the quality of the learning in HNN. The proposed logic mining has a limitation when dealing with ternary states (containing more than two neuron state) since the cost function proposed by Wan Abdullah (1992) only consider bipolar neurons. On another note, the proposed hybrid network only considers propositional logic programming. The proposed hybrid network unable to embed other variant of logic such as predicate logic or fuzzy logic. This is due to the nature of HNN proposed by Pinkas (1991) that only

consider symmetric connectionist network. On the other hand, HNN has low storage capacity since the synaptic weight matrix grow indefinitely as the size of the constraints increased.

1.7 Organization of Thesis

Chapter 1 introduces the history of neural network and artificial intelligence. Significance of research and problem statement is also discussed in this chapter. Research objectives and methodology of research are also explained in this chapter. In Chapter 2, literature review on logic programming in neural network will be discussed in detail. In this review, various studies of Hopfield Neural Network with different architecture and application will be explored. In terms of Satisfiability development, this thesis will review the advancement of Satisfiability representation and their significance. Furthermore, the development of metaheuristic algorithm and its possible application in neural network will be discussed. Finally, studies on data mining in neural network with its current potential in logic mining also will be comprehensively reviewed. Chapter 3 demonstrates the theoretical part of logic programming in Hopfield Neural Network. After discussing logic programming, the concept of Hopfield Neural Network as an intelligent model and implementation of Wan Abdullah method will be discussed. This chapter also discuss output optimization via activation function and relaxation method in Hopfield Neural Network. Convergence of logic programming in Hopfield Neural Network will be analysed. Chapter 4 explore a new established hybrid network by implementing Ant Colony Optimization and Genetic Algorithm during learning phase of Hopfield Neural Network. Conventional learning method which is exhaustive search method will be described in detail. All the proposed hybrid network will utilize 2SAT logical rule. Finally, the proposed hybrid network will be used to do

logic mining in improved 2 Satisfiability based Reverse Analysis. Chapter 5 demonstrates the performance analysis of all hybrid model in doing simulated data sets. Wide range of model performance measurement such as root mean square error, mean absolute error, sum of squared error, mean absolute percentage error, global minima ratio and CPU time will be explained in detail. Consequently, simulated result for all proposed hybrid network will be presented and discussed. Chapter 6 illustrates the implementation of improved 2 Satisfiability based Reverse Analysis method in doing 5 different data sets. The mentioned data sets are German credit data set, Car evaluation data set, Contraceptive method choice data set, Haberman's survival data set and Occupation detection data set. The improved 2 Satisfiability based Reverse Analysis method is a tool to extract the logical rule that explain the behaviour of the data set. This logic mining tool will be integrated with the proposed model and the performance of the proposed model will be evaluated. Chapter 7 concludes the research work with summary of finding and future works.

CHAPTER 2

LITERATURE REVIEW

Previous chapter discussed the introduction to artificial intelligence and artificial neural network. In this chapter, important studies on Hopfield neural network, logic programming, Boolean satisfiability, genetic algorithm, ant colony optimization and data mining in neural network will be reviewed.

2.1 Introduction

In this chapter, a vivid discussion of various artificial intelligence perspectives will be the main focus. This review embraces six important domains that contribute to the proposed hybrid network. First, the idea of discrete Hopfield Neural Network in representing various constrained optimization problem will be pointed out. From the recurrent neural network point of view, several important research will be pointed out to show the beneficial feature of Hopfield neural network. Second, review on logic programming as a symbolic tool for problem mapping will be discussed in detail. Third, the advancement of Boolean Satisfiability as a problem representation will be reviewed. In this section, the significance of 2 Satisfiability and its counterparts will be pointed out. Fourth, the review on genetic algorithm as a popular solver to many optimization problems will be discussed conceptually. This review also aligned possible hybridizations with neural network in solving various optimization problems. Fifth, the relevance of using ant colony optimization in solving combinatorial problem will be supported by various reviewed research. Similar to genetic algorithm, the review also aligned possible hybridizations with neural network in solving various optimization problems. Finally, various studies on data mining in neural network to extract

meaningful information from the data set. This review will provide several studies on data mining and the possible hybridization to ANN.

Previous researchers such as Sathasivam and Wan Abdullah (2008) and Hamadneh et al. (2012) have failed to represent the perceived knowledge in many real life application by focusing on only Horn programming. Therefore, the purpose of this study is to develop a new set of logical rule named 2 Satisfiability programming in expectation to represent knowledge in a preferable scheme. The conventional method lacked in efficiency to find consistent interpretation when the number of clause increased has not been elucidated by Sathasivam and Wan Abdullah (2008). Hence, the goal of this research is to integrate Ant Colony Optimization during the learning phase of HNN. The proposed hybrid network is expected to address the problems of local solution during learning phase and minimize the learning error. Reverse based analysis method proposed by Sathasivam and Wan Abdullah (2008) only extract logical rule among the individual neurons. Therefore, the purpose of this study is to apply logic mining technique via the improved 2 Satisfiability based reverse analysis method. The new method is expected to generalize the whole data sets in a single 2 Satisfiability logic.

2.2 Discrete Hopfield Neural Network

In the past decades, Hopfield neural network or abbreviated as HNN have been widely developed in solving various constraint optimization problem (Hopfield, 1982; Hopfield and Tank, 1985). Since HNN endured rapid development in term of architecture, it will be fruitful to review the progress of HNN with time. Research studies on the capability of neurons in HNN made a momentous contribution that leads to solution of various optimization problem such as travelling salesman problem and

linear programming problem (Hopfield, 1982; Hopfield and Tank, 1985; Tank and Hopfield, 1986). The proposed HNN by Hopfield and Tank created two different perspectives. First, input fed to the neuron of HNN must produce the desired output by letting the synaptic weight to change according to a certain learning rule (Zurada, 1992). In other perspective, given an optimization problem with a calculated cost function, HNN will be designed so that the minimum energy will have the same point to the previously proposed cost function (Joya et al., 2002). Assimilation between both perspectives lead to various enhanced HNN model in doing classification and pattern recognition problems (Cabeza et al., 2016; Duan et al., 2016; Hsu, 2012a; Pajares et al., 2010). Wan Abdullah (1992) proposed higher order HNN in order to minimize logical inconsistency of logic program. The calculated synaptic weight will be the building block of content addressable memory (CAM) of HNN (Sathasivam et al., 2011). The whole mentioned process displaced the traditional Hebbian learning since both Wan Abdullah method and Hebbian rule will arrive to the same CAM configuration (Sathasivam, 2011). During learning phase of HNN, the proposed HNN model required to find the correct interpretation for Horn clause that corresponds to zero cost function. This architecture inspired numerous researchers to enhance the capability of logic programming in HNN. Work of Sathasivam and Fen (2013) implemented logic programming in HNN by implementing agent based modeling (ABM). Implementation of ABM created the flexibility of HNN in dealing with higher order Horn programming. Alzaeemi et al. (2017) proposed hybrid kernel HNN (KHNN) in doing Non-Horn programming (3SAT). The results obtained certified that KHNN always converges to the optimal solution and maintains more than 99% global minima ratio. Table 2.1 shows list of important studies for discrete HNN.

Table 2.1 List of Important Studies in HNN

| Author(s) | Details of the Studies | Summary and Findings |
|--------------------------|---|---|
| Hopfield (1982) | HNN with emergent collective computational abilities. | The proposed network successfully shows the similarity of the artificial neuron modelling to actual brain modelling. |
| Hopfield and Tank (1985) | Nonlinear analog response of the neuron and energy analysis in HNN. | The proposed network is able to solve travelling salesman problem effectively. |
| Wan Abdullah (1993) | HNN model that minimize logical inconsistency of logic program. | The proposed network is able to create a new learning rule in deriving synaptic weight of Horn clause. The new rule has a good agreement to Hebbian learning. |
| Zhu and Yan (1997) | New approach for detection of brain tumor boundaries. The process acquires the beneficial feature of HNN energy analysis. | The proposed network shows the effectiveness of HNN minimum energy in magnetic resonance imaging data analysis. |
| Joya et al. (2002) | The effect of incoherence in energy function, error due to discrete problem, local minima and convergence analysis. | The study pointed out some modification in HNN to make it very effective in tackling some optimization problem such as diophantine equation, Hamiltonian cycle and k -colorability problem. |
| García and Moreno (2004) | Kernel machine by utilizing auto associative memory of HNN. | The proposed Kernel HNN was reported to acquire better memory capacity and noise tolerance. |
| Wen et al. (2009) | Improved HNN in solving circuit and VLSI problem. | The result from the simulation shows the computational efficiency of discrete HNN in solving VLSI problem. |
| Frolov et al. (2010) | Boolean factor based on the ability of HNN to create attractor. | The study has proved that specific condition in HNN training lead to global spurious attractors. |
| Akhmet et al. (2011) | Extensive analysis on Lyapunov energy in HNN. | The study has demonstrated the usage of Lyapunov function has guaranteed, unique and stable global neuron states. |
| Sathasivam et al. (2011) | Comparison between HNN and Radial basis function in doing logic programming. | The comparison proves that logic programming can be done in HNN. |

Continuation of Table 2.1; List of Important Studies in HNN

| | | |
|------------------------------------|---|--|
| Mansor and Sathasivam (2016) | 3 Satisfiability (3SAT) programming in HNN. | The developed 3SAT logical rule achieved almost 100% accuracy and able to sustain high number of neurons. |
| Sathasivam and Wan Abdullah (2011) | Reverse Analysis method as a logic mining tool in HNN. | Reverse Analysis method is able to induce logical rule with various logical strength. The proposed method has a good agreement with statistical analysis. |
| Hsu (2012b) | Fuzzy HNN as a clustering mechanism in electroencephalogram analysis. | The developed Fuzzy HNN achieved promising results for stationary and non stationary electroencephalogram classification. |
| Sathasivam and Fen (2013) | Agent Based Modeling (ABM) for logic programming in HNN. | The developed method is able to show the flexibility, efficiency and effectiveness of logic programming in doing HNN. |
| Pwasong et al. (2015) | Enhanced auto associative memories in HNN. | The proposed Hyperbolic activation function is able to optimize the output of HNN. |
| Zhou et al. (2015) | Enhanced auto associative memories in HNN. | The proposed method has been proven to store more important pattern and the network tend to converge to correct output. |
| Mansor et al. (2016) | Accelerating feature of hyperbolic tangent activation function and bipolar activation function when doing logic programming in HNN. | The proposed activation function is able to reduce neuron oscillation and increase the computational ability of the network. |
| Velavan et al. (2016) | Mean Field Theory (MFT) algorithm to replace unstable induced local field in HNN. | The proposed network outperformed the conventional HNN proposed by Sathasivam (2008) and Sathasivam and Fen (2013). |
| Kasihmuddin et. al (2018a) | Maximum k -Satisfiability (MAX- k SAT) programming in HNN. | The work showed solid performance of HNN in doing MAX- k SAT programming compared to the exiting method Kernel Hopfield neural network. |
| Jayashree and Kumar (2019) | Genetic optimized HNN (GHNN) to predict diabetic related features. | The research showed that GHNN was capable of classifying the diabetic abnormality features efficiently with highest accuracy up to 99.85% with minimum error rate. |

2.3 Logic Programming

Logic programming began in the early 1970 as a foundation to many applications such as AI. The credit for introduction of logic programming goes mainly to Kowalski (1978). During early stage, Kowalski was led to the fundamental idea that logic can be used as a programming language. The ability to extract the knowledge from the logic programming makes ANN is very suitable to develop AI system (Lloyd, 2012). This leads to various methods to integrate symbolic with connectionist AI. This combination has been a major works by Utgoff (1989) where he developed an algorithm that integrates decision tree and perceptron. Blair et al. (1999) showed intimate relationship between logic programming and dynamical system related to self-similarity and chaos. This perspective provoked more researcher to combine logic programming with other intelligent system. The assimilation also was developed by various researchers (Gallant, 1988; Pomerleau, 1991) and successfully created a system that can produce high and low level decisions. Towell and Shavlik (1994) insert a set of symbolic rules into a feedforward network. The network is then refined by using standard learning algorithm with specific set of learning data. The refined network is utilized to classify the raw data. While researchers in traditional symbolic AI concentrate in the development of powerful knowledge representation, Pinkas (1995) were concentrating on powerful learning mechanism. He described any symbolic system requires interpreter to process the information expressed in the representation that is unfortunately absent in many connectionist network. Pinkas considered symmetric connectionist network (SCN) that includes HNN, Boltzman machine, harmony theory and mean field theory. In addition, he described SCN can learn representations of propositional logic by examining the truth assignments that satisfy the formula. The reason why he selected SCNs is because the symmetric networks were

characterized by energy function which make it easier to specify the network's behaviour. In addition, SCN is able to capture the information embedded in logic formula for vital procedural control. Wan Abdullah (1992) proposed a method to find optimal synaptic weight. He showed the dynamical change in synaptic weight when a system learns from the logical rules. Each of the variable in the logic will be represented as neurons. Synaptic weight of the logical rules can be found by comparing the cost function (inconsistencies minimization of logical assignments) with Hopfield energy function. The synaptic weight obtained by using Wan Abdullah method has similar knowledge content as conventional Hebbian learning (Sathasivam and Wan Abdullah, 2008). Sathasivam and Wan Abdullah (2008) showed Wan Abdullah method outperform conventional hebbian learning rule when dealing with larger number of neurons. Both researchers introduced Horn logic as a symbolic representation in HNN. The advancement of logic programming in HNN is not limited to normal logic only. In other development, Sathasivam (2012a) proposed a fuzzy logic in HNN by implementing Fuzzy C-Mean clustering to the neuron state before retrieval phase of HNN can take place. The retrieved neuron states from this model will be computed by using Lyapunov energy function. This study helps user to grade continuous value from the logic programming before it can be learned by HNN. The other side of the coin, Hamadneh et al. (2012a) introduced Horn logic programming in Radial basis function neural network or RBFNN. The proposed RBFNN proposed propositional logic programming with single step operator. His RBFNN model is able to do other variant of logic such as Circuit logic, 3 Satisfiability and knowledge based system. Table 2.2 shows list of important studies for logic programming in neural network.

Table 2.2 List of Important Studies in Logic Programming

| Author(s) | Detail of the Studies | Summary and Findings |
|------------------------------------|---|--|
| Kowalski (1978) | Logical synthesis in programming. | This method helps user or program to interpret problem by using logical language. |
| Utgoff (1989) | Algorithm that integrates decision tree and perceptron. | The findings lead to a simpler way to represent knowledge and decision making system. |
| Pomerleau (1991) | Autonomous system in neural network. | The proposed method reveal the efficiency of neural network in making decision. |
| Pinkas (1991) | Efficient mapping symbolic system by using symmetric connectionist network (SCN). | The developed connectionist network is capable of representing and learning propositional knowledge. |
| Wan Abdullah (1992) | New method to find synaptic weight of Horn programming in Hopfield Neural network. The developed model utilized Horn clauses. | Proposed logic programming emphasized on finding the correct synaptic weight by comparing the cost function and energy function of Hopfield neural network. |
| Pitz and Shavlik (1995) | Set of symbolic rules into feedforward neural network. | Developed symbolic rules in neural network is able to make a better generalization in Chess sub problem and four world problems from the Human Genome Project. |
| Sathasivam and Wan Abdullah (2007) | Final energy analysis by Horn programming in Hopfield neural network. | The result obtained shows the flatness of final energy in doing Horn programming. More than 95% of solution achieve global minima energy. |
| Sathasivam (2010) | Sathasivam relaxation method for logic programming in Hopfield neural network. | The proposed relaxation method improves the neuron state of Hopfield neural network in doing Horn programming. |
| Hamadneh et al. (2012a) | Logic programming in RBFNN. | The result obtained from the experiment proves that RBFNN can act as an intelligent system in Horn programming. Several metaheuristic method such as genetic algorithm may optimize the learning phase of the network. |
| Sathasivam and Velavan (2014) | Mean field theory for higher order logic programming in HNN. | The result obtained from the experiment proves that Boltzmann machine and hyperbolic activation function can reduce neuron oscillation when higher order logic has been considered. |

Continuation of Table 2.2; List of Important Studies in Logic Programming

| | | |
|------------------------|--|--|
| Manhaeve et al. (2018) | DeepProbLog, a probabilistic logic programming language that incorporates deep learning by means of neural predicates. | Result obtained has shown the capability of DeepProbLog in combined symbolic and subsymbolic reasoning, program induction and probabilistic logic programming. |
| Chen et al. (2019) | Logic rules embedded into recurrent neural networks. | The result has shown that the logic rules were able to present prior knowledge from different domains and the proposed embedding approach worked well on a variety of tasks. |

2.4 Boolean Satisfiability

The primary goal of complexity theory is to classify and represent computational problems according to their problem feature (Luna et al., 2016). Challenges that were faced by researcher is some fragments of propositional logic which allow few efficient reasoning method (Khardon and Roth, 1996). Davis and Putnam (1960) is of the view that support logical reasoning and has proposed a method to solve Satisfiability problem (SAT). SAT has been a foundation to various challenging problem because SAT provides logical transition from problems to mathematical reasoning. The proposed method helps researcher to develop more SAT solver (Eén and Sörensson, 2003; Hamadi et al., 2008). Since SAT problem consist of various type of optimization problem, Cook (1971) proposed a non-deterministic problem namely kSAT problem. The feature of kSAT leads to the development of 2 Satisfiability problem or 2SAT. 2SAT attracted many researchers from various field of studies because 2SAT has a simpler problem presentation (Bollobás et al., 2001; Fürer and Kasiviswanathan, 2007). After the emergent of 2SAT representation, several research assimilates the 2SAT logical rule to real life simulation. Formann and Wagner (1991) proposed a packing problem by using 2SAT representation. 2SAT representation helps the system to

automate the production of labelling for groundwater maps. In terms of data clustering, 2SAT was reported to minimize the largest distance between two data point (Ramnath, 2004). This 2SAT hybrid model increase the performance of the cluster by reducing suboptimal solution during clustering. Miyashiro and Matsui (2005) presented a hybrid technique which coupled 2SAT representation with equitable home-away assignment for a given timetable of a round-robin tournament. Hybrid model with 2SAT successfully reduce the number of break during the tournament thus increase the efficiency of the scheduling problem. Batenburg and Kusters (2009) demonstrates the hybrid 2SAT to solve Nanogram program. Their model employs two type of paradigms which is pattern reconstruction (empty grid) and 2SAT reasoning. Even though there were many studies demonstrate the effectiveness of 2SAT in representing real life problem, no innovation has been made to embed 2SAT logical rule inside AI. The current work only revolves in Satisfiable logic because higher order satisfiable logic can be reduced to lower order logic (Sathasivam, 2012). Table 2.3 shows list of important reviews on SAT problem.

Table 2.3 List of Important Studies in SAT Problem

| Author(s) | Detail of the Studies | Summary and Findings |
|-------------------------|---|---|
| Davis and Putnam (1960) | Complete method to solve SAT problem. | The proposed method is able to solve SAT effectively and became the eye opener to many researcher to develop improved SAT solver. |
| Cook (1971) | NP problem based on Boolean Satisfiability. | The developed problem leads to restricted 2SAT problem. |
| Garey et al. (1976) | Maximum satisfiability problem as a new satisfiability problem. | The proposed problem proved that maximum satisfiability problem (MAXSAT) is NP problem. |
| Aspvall et al. (1979) | Strongly connected components (SCC) to solve 2SAT. | The proposed method is able to find consistent interpretation for small number of 2SAT variable. |
| Kohli et al. (1994) | Minimum satisfiability problem (MINSAT). | The proposed satisfiability problem created a new variant in satisfiability problem and was proven NP problem. |

Continuation of Table 2.3; List of Important Studies in SAT Problem

| | | |
|--------------------------------|--|---|
| Mansor et al. (2017) | Artificial Immune System (AIS) integrated HNN to do MAX3SAT. | The result demonstrates the effectiveness of AIS in finding consistent interpretation in MAX3SAT. |
| Escalada-Imaz and Manya (1994) | Satisfiability aspect of Horn formulae. | The information obtained was particularly helpful when validating rule based system. |
| Bailey et al. (2001) | Majority satisfiability (MAJSAT) as a new variant of 2 Satisfiability problem. | The newly developed MAJSAT provide a new perspective in representing some NP and probabilistic class problem. |
| Sathasivam (2012b) | Deduction and induction for Horn Programming | The proposed method reduce logical redundancy during learning phase. |
| Hamadneh et al. (2012a) | HornSAT programming in RBFNN. | The result obtained from the experiment proves that RBFNN can act as an intelligent system in Horn programming. |
| Sathasivam et al. (2014) | Higher order Horn formulae in representing logic programming. | The proposed Horn formulae provides a new perspective in representing logic programming with different orders. |
| Hamadneh (2013) | Higher order HornSAT in RBFNN. | The result obtained demonstrate the usage of higher order logic in representing real data set. Full learning of HornSAT is required to increase the chance of finding optimal solution. |
| Luo et al. (2015) | New form of weighted MAXSAT. | The result demonstrate the effectiveness of SLS algorithm to solve weighted maximum satisfiability problem. |
| Kasihmuddin et al. (2017) | Artificial Bee Colony (ABC) integrated HNN to do 2SAT. | The result shows that ABC is more robust than exhaustive search in performing random 2SAT logic programming. |
| Chu et al. (2019) | New SLS algorithm for MAXSAT called CCABMS. | Result showed that the proposed algorithm performed better than its state-of-the-art SLS competitors on a large number of industrial MAXSAT instances. |

2.5 Genetic Algorithm

Originally, genetic algorithm (GA) conceived from the biological evolution of natural selection, survival of the fittest which was proposed by Darwin and firstly used

by Holland (1975). GA is an adaptive metaheuristic method based on improvement of chromosomes (Kumar et al., 2010). Worth mentioning that chromosomes in GA is defined as solution of the problem. GA utilized the probabilistic search algorithm by using chromosome to find near optimal solution (with minimum bias) to various optimization problem. Since chromosomes (solution) in GA are always improving in every generation (Hoque et al., 2007), there were many efforts by researchers to solve real life problem by using GA. Gong and Yang (2001) proposed GA for stereo image processing. The image is represented in terms of constraint assignments and solved by GA. Yasuda and Takai (2001) had applied GA for sensor-based mobile robot path planning with simulated obstacle. The proposed GA method is able to find near optimal orientation in shorter period of time. In another development, GA has been applied to job shop scheduling problem. Madureira et al. (2002) showed the feasibility of GA in dynamic job scheduling. However, there were many recent studies were conducted to solve variety of scheduling problem by using GA (Chang and Liu, 2015; De Giovanni and Pezzella, 2010; Lu et al., 2015; Wu et al., 2017). SAT problems have been progressively solved by using GA. Since there were many real life problems that can be transform to SAT representation, solving SAT by using GA is considered fruitful and relevant. Harmeling (2000), Popov (2013), Zhang et al. (2015) and Li and Zhang (2016) developed a GA to solve SAT problem. The developed GA implemented selection, crossover and mutation operators to solve 3SAT problem. Fitness evaluation by the proposed technique is based on number of satisfied clause in a particular SAT problem. These techniques displayed reasonable outcome in terms of complexity and stability of the solution. Aiman and Asrar (2015) proposed GA in solving 3SAT. The proposed GA has been compared with exhaustive search method (ES). In this study, GA outperformed ES when the number of variable in 3SAT increased. The study was considered