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Logic mining in football matches

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ABSTRACT

Sports results forecast has became increasingly popular among the fans nowadays. It made predicting the outcome of a sport's match, a new and interesting challenge. This paper presented a logic mining technique to model the results (Win Draw / Lose) of the football matches played in English Premier League, Spanish La Liga and France Ligue 1. In this research, a method namely *k* satisfiability based reverse analysis method (*k*SATRA) hybridized with Ant Colony Optimization (ACO) was brought forward to obtain the logical relationship among the clubs in these leagues. The logical rule obtained from the football matches was used to categorize the results of future matches. ACO is a population-based and nature-inspired algorithm to decipher several combinatorial optimization problems. *k*SATRA made use of the advantages of Hopfield Neural Network and k Satisfiability representation. The data set used in this study included the data of 6 clubs from each league, which composed of all league matches from year 2014 to 2018. The effectiveness of *k*SATRA with ACO in obtaining logical rule in football matches was tested based on root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and CPU time. Results acquired from the computer simulation showed the robustness of *k*SATRA in exhibiting the performance of the clubs.

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1. INTRODUCTION

Football is a popular sport where two teams consists of eleven players each compete in. In football, a large amount of data can be collected for each player, club, match and season. Many football clubs, coaches and league have begun to gain interest in analysing these data to help assess their players, improve game strategies and even predict match results. Match results prediction of any sports is naturally one of the most obvious objectives in sports analytics. There were many researches on match predictions in football. However, most of those researches were focused on predicting the results in terms of win, loss or draw and final score of goals. For example, Tsakonas et al. [1] proposed soft computing methods to predict the result of a football match in regard to neural networks, fuzzy rules and genetic programming approach. On the other hand, Baio and Blangiardo [2] proposed a Bayesian hierarchical model to predict the final score of a football match. Nunes and Sousa [3] successfully applied data mining techniques to two football data sets and with classification, they created a model which provided better results than a pure probabilistic classifier. Cintia et al. [4] outlined the performance of a football team in a game by 3 network indicators. They observed that these indicators correspond with the teams' success and their approach also outperformed other two models in predicting the outcomes of long-running competitions. Chen et al. [5] proposed a decision tree-based multi-modal data mining framework for soccer goal detection. The experimental results have shown that the integration of data mining and multi-modal processing of video was a feasible approach to effectively extract soccer goal events.

Match results prediction can be a really challenging task due to the sport's stochastic nature. Prediction of match outcomes is done before the game starts so the team managers, coaches and players are able to predict the possibilities of winning, draw or losing the game. In team sports, there are two types of analysis that can be conducted: a) individual and b) team analysis. In terms of analysing team performance, current methods [6,7] are mostly to predict the results or number of goals of a certain match. However, such methods has been reported only for special case or event. The method does not provide the generality of the relationship among clubs in the league. Several methods require unnecessary mathematical complexity such as multiple assumptions that disrupt the actual objective of the method. Unfortunately, these assumption and complexity have been proven to cause overfitting in data mining. In this paper, we will employ the 2 Satisfiability based Reverse Analysis method to induce the best logical rule that shows the trend of results among 6 clubs in 3 different football leagues, namely English Premier League (EPL), Spanish La Liga (SLL) and France Ligue 1 (FL1). Through the relationship among the clubs in the league, the team managers, coaches and players of a certain club will be able to forecast the results of the match by taking the results of another club into consideration. Positive outcome prediction will definitely raise the players' spirit. A negative outcome does not necessarily lower the players' spirit but serve as a guidance for them to play exceptionally cautious and possibly come up with a counter strategy.

Swarm intelligence (SI) inspired by optimization have been widely sought after during the last decade. Ant Colony Optimization (ACO) was proposed as a method to solve hard combinatorial optimization problems [8]. By leaving behind a trail of pheromone, ants are able to locate the shortest trail connecting their nest and the food source. Zhang and Crossley [9] proposed that ACO can be utilized to effectively solve optimization problems and ACO produces optimum solution. Zangari et al. [10] have confirmed that binary ACO can achieve moderate results by using a fair number of fitness evaluation. Wang et al. [11] have also shown that binary ACO is useful and adaptive in remote sensing image classification. ACO can present a superior performance compared to other algorithms in terms of fitness value.

Artificial neural network (ANN) learns from the biological nervous system of human beings, for example how information is processed by the brain [12]. Hopfield Neural Network (HNN) is one of the well-known network implemented to solve various optimization problems [13]. HNN shows outstanding learning behaviour. For example, productive learning and retrieval operation. Traditional HNN is susceptible to a few deficiencies [14], so logic programming is embedded to HNN as a single intelligent unit [15].

Logic mining in HNN was proposed by Sathasivam [16] by applying Reverse Analysis method. This method is able to obtain the logical rule among neurons. Mean field theory applied to perform logic programming in HNN has proven to be fruitful in accelerating the computational ability of neuro symbolic integration by Velavan et al. [17]. 2 Satisfiability (2SAT) was discovered to enhance the representation of general SAT itself [18]. This makes 2SAT a suitable approach to represent logical rules in neural network. By considering only 2 literals per clause, the logical complexity in learning the relationship between the variables in real life problem decreases. By hybridizing Reverse Analysis, 2SAT and ACO, a new method, 2 Satisfiability based Reverse Analysis method (2SATRA) with ACO will be utilized to obtain the logical rule of football matches.

2. SATISFIABILITY REPRESENTATION

2 Satisfiability (2SAT) is a logical rule that comprises of only 2 literals per clause. 2SAT is usually expressed as Boolean formulas called Conjunctive Normal Form (CNF) or Krom formulas. 2SAT consists of three components [19]:

a) A set of *x* variables, $v_1, v_2, ..., v_x$
b) A set of literals. A literal can be any variable or a negation of any variable.
c) A set of *y* definite clauses, $C_1, C_2, C_3, ..., C_y$ linked by logical AND ($\wedge$). Each clause comprises of strictly 2 literals joined by just logical OR ($\vee$).

Each of the variable can only take bipolar value of 1 or -1 which represents true or false respectively. Explicit definition of the 2SAT formula P_{2SAT} is given by:

$$P_{2SAT} = \bigwedge_{i=1}^{y} C_i \tag{1}$$

where C_i is a list of clause with 2 variables each,

$$C_i = \bigvee_{i=1}^{y}(m_i, n_i) \tag{2}$$

The main objective of 2SAT representation is to find the consistent interpretation that make formula P_{2SAT} become satisfied [20].

3. ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) is simulated by the behaviour of foraging of real ants [8-21]. Real ants traverse the space surrounding their nest in random when searching for food. The ant will evaluate and carry back some of the food to the nest when it find a food source. When travelling back to the nest, the ant will leave a trace of pheromone on the ground. Density of the pheromone it deposits is decided by the amount and value of the food. Pheromones deposited will lead the other ants to the food source. Through the pheromone trails, the ants are able to find short paths from their nest to the food source [22, 23].

ACO algorithm consists of artificial ants (agents) with distinctive functions and structures. The agents work with each other to accomplish a potential unified behaviour for the system as a whole, creating a vigorous system that has the ability to find high quality solutions for problems with a huge search space. Dorigo and Di Caro [24] proposed this system as a metaheuristic to solve COPs. This metaheuristic has been proven to be vigorous and flexible since it has been put into use successfully to different COPs [25]. The ACO algorithm in learning 2SAT is inspired by Changdar et al. [26]:

Step 1: Initialization. Initialize the state of the bitstring, S_i where $S_i(t) \in [1,-1]$.

Step 2: Fitness evaluation. Calculate the fitness of $S_i(t)$ by using the following equation [27]:

$$f(S_i(t)) = \sum_{i=1}^{NC} C_i \tag{3}$$

where NC is the number of clause in 2SAT and C_i is given as follows

$$C_i = \begin{cases} 1 & True \\ 0 & False \end{cases} \tag{4}$$

Step 3: Pheromone density initialization. Pheromone for each value of candidate group 1 or -1 is represented by a real vector $T_{ij}(1) = (T_{i1}, T_{i2}, ..., T_{iU})$ and $T_{ij}(-1) = (T_{i1}, T_{i2}, ..., T_{iU})$ where each T_{ij} is a random number between [0,1], $i = 1,2,......V;\ j = 1,2,......,U$.

Step 4: Visibility density initialization. Visibility density for each value of candidate group 1 or -1 is represented by a real vector $\eta_{ij}(1) = (\eta_{i1}, \eta_{i2}, ..., \eta_{iU})$ and $\eta_{ij}(-1) = (\eta_{i1}, \eta_{i2}, ..., \eta_{iU})$ where each η_{ij} is a random number between [0,1], $i = 1,2,......V;\ j = 1,2,......,\ U$.

Step 5: Ant's searching phase. The movement probability of the ant "k" ($k = 1,2,......,M$) is defined as follow:

$$p_{ij}^{k}(-1) = \frac{\left[T_{ij}(-1)\right]^{\alpha} . \left[\eta_{ij}(-1)\right]^{\beta}}{\left[T_{ij}(-1)\right]^{\alpha} . \left[\eta_{ij}(-1)\right]^{\beta} + \left[T_{ij}(1)\right]^{\alpha} . \left[\eta_{ij}(1)\right]^{\beta}} \tag{5}$$

where α $(\alpha > 0)$ is the relative importance of the pheromone and β $(\beta > 0)$ is the relative importance of the visibility of the ants. Hence the complementary of the movement is written as follows:

$$p_{ij}^{k}(1) = 1 - p_{ij}^{k}(-1) \tag{6}$$

where p_{ij}^{k} is the probability of movement from the bit "i" to the state "j" at time t.

Step 6: Evaporation. The decrement of pheromone is based on the following equation:

$$T_{ij}\left(-1\right)\left(t+1\right)=\left(1-\rho\right)T_{ij}\left(-1\right)\left(t\right)+\Delta T_{ij}^{best} \tag{7}$$

$$T_{ij}\left(1\right)\left(t+1\right)=\left(1-\rho\right)T_{ij}\left(1\right)\left(t\right)+\Delta T_{ij}^{best} \tag{8}$$

$$\Delta T_{ij}^{best}=\frac{1}{f\left(S_i^{best}\right)} \tag{9}$$

where ρ is the coefficient representing evaporation rate and $\rho\in\left[0,1\right]$, $f(S_i^{best})$ is the number of clause for 2SAT.
Step 7: Refinement. Calculate the fitness of the solution $f(S_i)$ by using (3). The optimal solution found so far will be recorded as $S_i^*(t+1)$. If $S_i^*(t+1)$ is superior than $S_i^*(t)$, then $S_i^*(t)$ is replaced by $S_i^*(t+1)$. Pheromone density will be updated by using (5). If $f(S_i)\neq NC$, repeat Step 4 to Step 8 until pre-determined trial, *Trial* is achieved.

4. LOGIC PROGRAMMING IN HOPFIELD NEURAL NETWORK

Neural network is able to model complex relationships between inputs and outputs also to look for patterns in data. Pattern recognition and function estimation are the reasons why neural networks are utilized in data mining [28]. Several other reseachers [29-31] have also employed neural network in extracting critical relationship among the data. HNN is one of the most commonly used neural network models. It is a simple neural network model that has feedback connections. HNN systematically stores patterns as a content addressable memory (CAM) [32]. HNN is a network of *N* interconnected neurons where the output and input of each neuron is connected. The connection weight from neuron *i* to *j* is denoted by w_{ij}. In HNN, $w_{ij}=w_{ji}$ (symmetric networks) and $w_{ii}=w_{jj}=0$ (no self-feedback connections). Let S_i be the state or output of the *i* th unit, θ is the pre-defined threshold of unit *i*. For bipolar networks, S_i is either +1 or -1. General updating rule in HNN is given by:

$$S_i=\begin{cases}1 & if\ \sum_j w_{ij}S_j>\theta_i\\ -1 & Otherwise\end{cases} \tag{10}$$

The local field of the network is given by:

$$h_i(t)=\sum_j w_{ij}^{(2)}S_j+w_i^{(1)} \tag{11}$$

The updating rule will be:

$$S_i\left(t+1\right)=\operatorname{sgn}\left[h_i\left(t\right)\right] \tag{12}$$

The final state of neurons will be examined by using Lyapunov or energy function:

$$H_{P_{2SAT}}=-\frac{1}{2}\sum_i\sum_j w_{ij}^{(2)}S_iS_j-\sum_i w_i^{(1)}S_i \tag{13}$$

The final energy of HNN is always decreasing with the dynamics. 2SAT in HNN is abbreviated as HNN-2SAT model.

5. 2 SATISFIABILITY BASED REVERSE ANALYSIS METHOD (2SATRA)

Logic mining will execute efficiently if the most favourable HNN-2SAT model is used. The neurons (attributes) is represented in bipolar form {-1,1}. By acquiring the synaptic weight between 2 neurons, 2SATRA might be able to reveal the level of their connectedness. Therefore, Wan Abdullah's method [15] is utilized in the learning phase of 2SATRA to figure out the accurate synaptic weight between the two neurons. By considering both neurons C and D where $S_C \in \{-1,1\}$ and $S_D \in \{-1,1\}$, the possible 2SAT clause with its corresponding synaptic weight are summarized in Table 1.

Table 1. Possible 2SAT Logic with Its Corresponding Synaptic Weight

Synaptic Weight	$P_1 = C \vee D$	$P_2 = \neg C \vee D$	$P_3 = C \vee \neg D$	$P_4 = \neg C \vee \neg D$
W_C	0.25	-0.25	0.25	-0.25
W_D	0.25	0.25	0.25	-0.25
W_{CD}	-0.25	0.25	-0.25	-0.25

As an example, given that neuron *C* and *D* shows 1 and -1 respectively, P_3 will be selected as the clause representation of the data set. In accordance with the nature of the neuron, 2SATRA will convert all the data sets into 2SAT logic. The Figure 1 shows the implementation of 2SATRA.

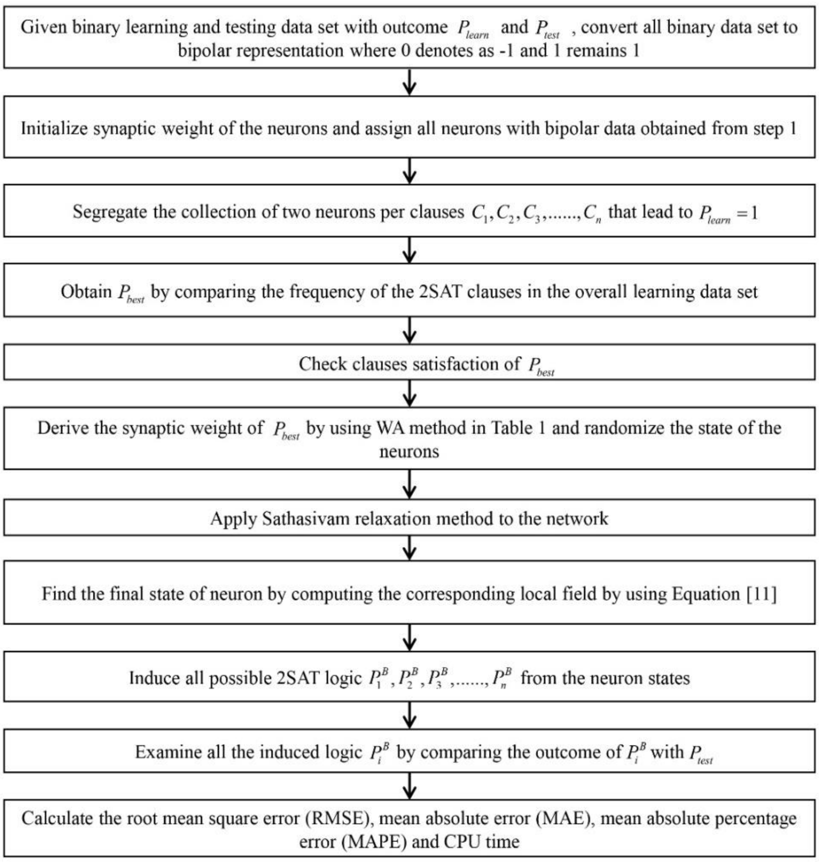

Figure 1. Algorithm of implementation of 2SATRA

In learning data set, {Win / Draw, Lose} will be converted into bipolar representation {1,-1} respectively. Each football club will be represented in terms of neuron in 2SATRA. Hence, there will be a total of six neurons being considered in this data set. The respective football club and neuron is summarized in Table 2.

Table 2. Respective Football Club and Neuron

Neuron	EPL	SSL	FL1
A	Arsenal (*Ar*)	Barcelona (*Ba*)	PSG (*Psg*)
B	Chelsea (*Ch*)	Sevilla (*Se*)	Lyon (*Ly*)
C	Liverpool (*Li*)	Real Madrid (*Rm*)	Monaco (*Mo*)
D	Man. City (*Mc*)	Atletico Madrid (*Am*)	Nantes (*Na*)
E	Man. United (*Mu*)	Valencia (*Va*)	Marseille (*Ma*)
F	Tottenham Hotspurs (*Sp*)	Villareal (*Vi*)	Toulouse (*To*)

In this paper, HNN will be incorporated with ACO in doing 2SAT based Reverse Analysis method (HNN-2SATACO). The proposed model will be compared with the existing model, HNN-2SATES [33]. All outputs that exceed the threshold CPU time, which is 24 hours will be excluded. Both HNN-2SAT models will be implemented in Dev C++ Version 5.11 on a computer equipped with Intel Core i7 2.5GHz processor and 8GB RAM using Windows 8.1. All HNN-2SAT program executions run 100 trials with 100 combination of neurons to reduce statistical error [34].

6. PERFORMANCE EVALUATION

In order to evaluate the efficiency of all HNN-2SAT models, a total of four performance evaluation metrics, namely root mean square error, mean absolute error, mean absolute percentage error and CPU time will be analysed.

6.1. Root Mean Square Error

Root mean square error (RMSE) is normally used to compute the differences between target value and the actual observed value of the model. The equation for RMSE is defined as [35, 36]

$$RMSE = \sum_{i=1}^{n} \sqrt{\frac{1}{n}(f_{NC} - f_i)^2} \tag{14}$$

Where f_{NC} is the total number of 2SAT clauses, f_i is the fitness of the solution in HNN-2SAT model and n is the number of iteration before $f_i = f_{NC}$. The best HNN-2SAT model will have the smallest value of *RMSE*.

6.2. Mean Absolute Error

Mean absolute error (MAE) is the mean of the absolute values of the errors. The error is derived from each difference of $f_{NC} - f_i$. MAE is defined by the following equation [37].

$$MAE = \sum_{i=1}^{n} \frac{1}{n} |f_{NC} - f_i| \tag{15}$$

Where f_{NC} is the total number of 2SAT clauses, f_i is the fitness of the solution in HNN-2SAT model and n is the number of iteration before $f_i = f_{NC}$. Similar to *RMSE*, the least value of *MAE* indicates the best HNN-2SAT model.

6.3. Mean Absolute Percentage Error

Mean absolute percentage error (MAPE) is the mean of the absolute values of the errors in percentage terms. MAPE is a measure of accuracy in the percentage form. MAPE can be expressed as [19]

$$MAPE = \sum_{i=1}^{n} \frac{100}{n} \frac{|f_{NC} - f_i|}{|f_i|} \tag{16}$$

The theory of *MAPE* is very simple, however, it has a crucial flaw. *MAPE* cannot be used if the observed value is zero as it will lead to division by zero. The best HNN-2SAT model will have the lowest percentage of *MAPE*.

6.4. Computational Time

CPU time is defined as the time required by a particular HNN-2SAT model to finish one execution. CPU time denotes the stability and competency of the HNN-2SAT models. Each simulations will be run on identical processor to cancel off the effect of bad sector and memory build-up. Equation of the CPU time is given by [38]

$$CPU\_Time = Learning\_Time + Retrieval\_Time \tag{17}$$

A good HNN-2SAT model will be able to lessen the computation time in the learning phase. Hence, the best HNN-2SAT model will have the shortest CPU time.

7. RESULTS AND ANALYSIS

A total of 4 performance evaluation namely RMSE, MAE, MAPE and CPU time were analysed to determine the effectiveness, precision and steadiness of HNN-2SAT in doing 2SATRA. *NC* is defined as the total number of clause and 1 clause has 2 neurons (attributes). Figure 2, Figure 3, Figure 4 and Figure 5 showed the results of RMSE, MAE, MAPE and CPU time respectively for HNN-2SATES and HNN-2SATACO of all 3 leagues. In this execution, 92 data points have been embedded to 2SATRA as learning data and 60 as testing data. 6 clubs of each league were chosen and learning phase for all HNN models will be conducted with different number of *NC*.

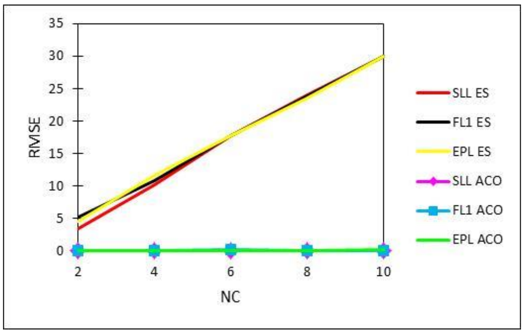

Figure 2. RMSE for HNN-2SAT models

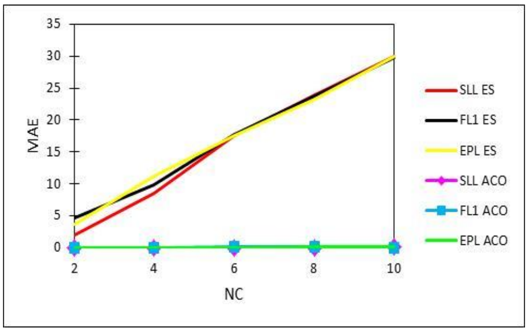

Figure 3. MAE for HNN-2SAT models

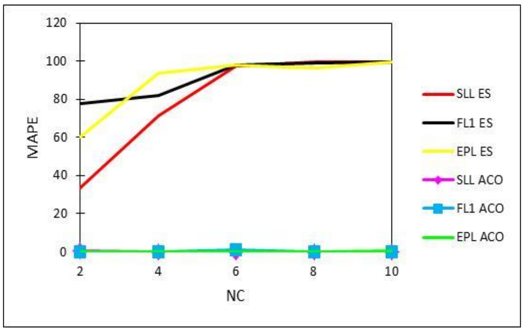

Figure 4. MAPE for HNN-2SAT models

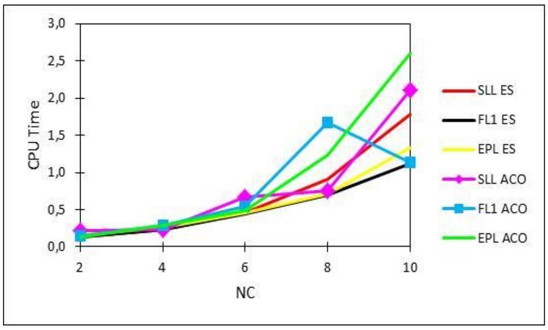

Figure 5. CPU Time for HNN-2SAT models

Based on Figure 2, Figure 3 and Figure 4, HNN-2SATACO had significantly lower value of RMSE, MAE and MAPE compared to HNN-2SATES. Learning phase of 2SATRA in HNN-2SATES was trapped in trial and error state and lead to RMSE, MAE and MAPE accumulation. On the contrary, the effect of interaction between the ants and pheromone density helped HNN-2SATACO to diversify candidate solution in search space. Any non-fit solution after pheromone evaporation will be improved further by pheromone density initialization. Two layered optimization mechanism of pheromone initialization and pheromone evaporation reduced the deviation error of the network and results in minimal RMSE, MAE and MAPE. Additionally, the learning error for 2SATRA in both HNN-2SATACO and HNN-2SATES increased as the number of clause increased. 2SATRA achieved maximum value of RMSE, MAE and MAPE when *NC*=10. As the number 2SAT inconsistencies increased, the probability of getting all satisfied clause decreased dramatically. This was due to the high number of iterations required to satisfy high number of clauses during the learning phase. Based on Figure 5, HNN-2SATACO required a short CPU time to complete a single execution.

This was a result of HNN-2SATACO accentuated on fitness improvement in every iteration. Significantly small error also reduced the CPU time for HNN-2SATACO to complete the learning phase. Conjointly, at *NC*=8 and *NC*=10, HNN-2SATES was observed to have shorter computation time compared to HNN-2SATACO. This was due to HNN-2SATES required less iteration before the network reached relaxation phase. Sathasivam relaxation method [38] was able to lessen neuron oscillation that would prolong the CPU time and hence achieve sub-optimal induced logic, P_i^B. During learning phase, P_i^B induced by 2SATRA managed to accomplish an accuracy of 88% (EPL), 90% (SLL) and 91% (FL1). This was because the character of neuron in HNN, rather than oscillating, the neurons had always converged to minimum energy. The results in this paper was not being compared to other existing methods because the approaches were different and incomparable. For example, Huang and Chang [39] managed to achieve an accuracy of 76.9%. However, the research was done on predicting the winner and loser of the match while this paper was considering the relationship among the clubs in the league. The best induced logic, P_{best} and inconsistent interpretation, $P_{inconsistent}$ for each football league are summarized in Table 3.

Table 3. Best Induced Logic and Inconsistent Interpretation

League	Best induced logic, P_{best}	Inconsistent interpretation, $P_{inconsistent}$
EPL	$(Ar \vee Ch) \wedge (Li \vee Mc) \wedge (Mu \vee Sp)$	$(\neg Ar \wedge \neg Ch) \vee (\neg Li \wedge \neg Mc) \vee (\neg Mu \wedge \neg Sp)$
SLL	$(Ba \vee Se) \wedge (Rm \vee Am) \wedge (Va \vee Vi)$	$(\neg Ba \wedge \neg Se) \vee (\neg Rm \wedge \neg Am) \vee (\neg Va \wedge \neg Vi)$
FL1	$(Psg \vee Ly) \wedge (Mo \vee Na) \wedge (Ma \vee To)$	$(\neg Psg \wedge \neg Ly) \vee (\neg Mo \wedge \neg Na) \vee (\neg Ma \wedge \neg To)$

According to Table 3, the relationship among the football clubs is shown. A list of key findings are summarized in Table 4.

Table 4. Key Findings from Induced Logic

League	Key Findings
EPL	In any match week, if Arsenal, Liverpool and Manchester United lost their matches, the rest of the clubs such as Chelsea, Manchester City and Tottenham Hotspurs will have more player options during that week. With that advantage, club such as Chelsea has the privilege to send their second best team. The implication of the logical rule gives more training time to Chelsea's first team and focus on more important matches. This will reduce the number of injuries faced by the club.
SLL	When Barcelona, Real Madrid and Valencia won or draw in their matches in any match week, Sevilla, Atletico Madrid and Villareal will have to send their best team to try and secure a win. As the logical rule implies that Sevilla, Atletico Madrid and Villareal might lose if Barcelona, Real Madrid and Valencia won or draw in a certain match week. For example, the best players of Sevilla will have to be in great condition and concentrate on the match that week.
FL1	If clubs like Lyon, Monaco and Toulouse lost in a certain match week, the opponents of PSG, Monaco and Marseille could take advantage of it by sending their best players knowing that there's a possibility for club like PSG to send their second best team for that week. The logical rule gives precious information not only to the 6 clubs included in this research but also to their opponents in any match week.

The results has shown that 2SATRA has decent potential to obtain logical rule that classifies the results of win draw or lose for a football match. The induced logic can help the football club managers and coaches in deciding the strategies and players that they should play in a certain matchup. Football analysts could also use the induced logic to provide expert discussion during a football game.

8. CONCLUSION

In this research, 2SATRA is shown to be a brilliant relationship extraction system to model the results of football matches. The effectiveness of 2SATRA in doing logic mining is examined by using 3 data sets from 3 different leagues. The results acquired shows that 2SATRA has decent potential to obtain optimal logic from learned data set. ACO also outperforms ES in extracting the relationship among the football clubs in the league. Future research could be done by utilizing other logical rule such as randomized *k*SAT where *k*

>2 or integrating other metaheuristic algorithm such as Particle Swarm Optimization and Artificial Immune System to accelerate the process of learning phase of 2SATRA.

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