Pertanika J. Sci. & Technol. 28 (3): 967 - 981 (2020)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Palm Oil Trend Analysis via Logic Mining with Discrete Hopfield Neural Network

Alyaa Alway[1], Nur Ezlin Zamri[1], Mohd Shareduwan Mohd Kasihmuddin[2], Mohd. Asyraf Mansor[1]* and Saratha Sathasivam[2]

[1]School of Distance Education, Universiti Sains Malaysia, 11800, Penang, Malaysia
[2]School of Mathematical Sciences, Universiti Sains Malaysia, 11800, Penang, Malaysia

ABSTRACT

Analyzing commodity prices contributes greatly to traders, economists and analysts in ascertaining the most feasible investment strategies. Limited knowledge about the price trend of the commodities indeed will affect the economy because commodities like palm oil and gold contribute a huge source of income to Malaysia. Therefore, it is important to know the optimal price trend of the commodities before making any investments. Hence, this paper presents a logic mining technique to study the price trend of palm oil with other commodities. This technique employs 2-Satisfiability based Reverse Analysis Method (2-SATRA) consolidated with 2-Satisfiability logic in Discrete Hopfield Neural Network (DHNN2-SAT). All attributes in the data set are represented as a neuron in DHNN which will be programmed based on a 2-SAT logical rule. By utilizing 2-SATRA in DHNN2-SAT, the induced logic is generated from the commodity price data set that explains the trend of commodities price. Following that, the performance evaluation metric; error analysis and accuracy will be calculated based on the induced logic. In this case, the experimental result has shown that the best-induced logic identifies which trend will lead to an increase in the palm oil price with the highest accuracy rate.

Keywords: 2-Satisfiability, Hopfield neural network, logic mining

ARTICLE INFO

Article history:
Received: 18 January 2020
Accepted: 18 March 2020
Published: 16 July 2020

E-mail addresses:
alyaalway@student.usm.my (Alyaa Alway)
ezlinzamri@student.usm.my (Nur Ezlin Zamri)
shareduwan@usm.my (Mohd Shareduwan Mohd Kasihmuddin)
asyrafman@usm.my (Mohd. Asyraf Mansor)
saratha@usm.my (Saratha Sathasivam)
* Corresponding author

INTRODUCTION

In 1870, oil palm was founded as an ornamental plant in Malaysia before being marketed at Tennamaram Estate, Selangor, in 1917 (Nambiappan et al., 2018). Naturally, palm oil is known as the most profitable industrial production. In the early 1960s, palm oil production grew quickly. Due to

ISSN: 0128-7680
e-ISSN: 2231-8526

that, palm oil has been a significant subsection of Malaysia's economy, adding 37.9% of the agricultural industry to domestic product development (Department of Statistics Malaysia, 2019). The global resolution of the palm oil industry has established the palm oil industry in Malaysia as one of the biggest contributors to domestic product growth in the world (Balu et al., 2018). Malaysia is currently the second-largest palm oil producer and exporter after Indonesia (Kushairi et al., 2019). Approximately 20 million tons of crude palm oil is produced annually (Ismail, 2013). Despite being the top producing crops, the subsector for palm oil encounters several difficulties. The difficulties including lower production of palm oil, lower exports, greater demand for palm oil and lower prices of palm oil (Kushairi et al., 2019). Besides that, the rise and fall of commodities price influence the performance of the subsector of the palm oil (Songsiengchai et al., 2020). Bakar (2009) stated that Malaysia currently suffered poor returns in agricultural production and the stagnant commodity prices were escalating. Learning less about the price trend would impact the economy as a whole, as Malaysia still depends on these resources to expand economically. Some researchers (Baruník & Malinska, 2016; Alameer et al., 2019) had reported that understanding the price trend in advance would support the interest group in decisions making (buying or selling). In this scenario, the government should create a countermeasure if the drop in the commodity price is inevitable. Since this has become a major problem that needs to be tackled, therefore, it is crucial to evaluate the palm oil price trend before making any decisions or investments.

Artificial Intelligence (AI) is widely used in agriculture applications (Mekonnen et al., 2020) and planning marketing strategies (Davenport et al., 2020). The common method in extracting the important information about one data set is by using data mining integrated with AI. Nonetheless, several types of research have discovered a more precise model for the extraction of information through integrating Artificial Neural Network (ANN) such as Kasihmuddin et al. (2018) and Kho et al. (2020). Usage of ANN occurring in different disciplines varying from market share to commodity price. The usage of ANN has proven its effectiveness against statistical methods in forecasting commodity prices, especially in energy fuels (Rahman, 2012) and metal prices (Abdullah & Wahid, 2010). The work by Khamis and Wahab (2016) presents that ANN is the best model in forecasting the price of crude palm oil. Moreover, the study conducted by Ramakrishnan et al. (2017) utilizes ANN with other statistical models to examine the effective interplays between commodity prices and the exchange rate for Malaysia. Discrete Hopfield Neural Network (DHNN) is a recurrent ANN that is popularized by Hopfield and Tank (1985) to tackle several problems of constraint optimization. The operation in the DHNN can be described as follows (Nájera et al., 2020): (1) A data is inserted and shared with the input layer. (2) This transmits it to the middle layers that change their status. (3) Choose each neuron that is updated at random. (4) A state of equilibrium is achieved. (5) The pattern of activation is transferred to the output layer. DHNN has a content addressable memory (Liu et al., 2006) and mimics the human brain (Haykin, 1994).

According to Mainzer (2020), most of the general problem-solving methods are successfully represented in a formal logical rule. There is a technical procedure in extracting the information from the logical formulas. It has been shown that logic mining can maps information into the logical form (Kowalski, 1979). Satisfiability (SAT) logic is capable of transforming problems into a mathematical representation. Cook (1971) had introduced a non-deterministic problem known as *k*-SAT logic. Sathasivam et al. (2014) had suggested a higher order of Horn Satisfiability (HORN-SAT) combining different forms of *k*-SAT logic representation because HORN-SAT was considered as a good logical representation as this logic guarantees satisfiable property. Another representation of *k*-SAT logic is 3-Satisfiability (3-SAT) logic. Iverson (1962) stated that any real-life problem could be reduced to 3-SAT to reveal the behavior of the data set. Besides that, in the work of Mansor et al. (2019), they utilized 3-SAT in a new modified Hopfield Neural Network (HNN) called Elliot HNN by implementing an Artificial Immune System (AIS) to solve optimization task. The work by Kasihmuddin et al. (2019) has successfully implemented 2-Satisfiability in logic mining to examine the behavior of real-life data set of students' performances which attained better accuracy than most existing model. In this case, the choice of suitable logical rules to be incorporated into the neural network plays a significant role in logic mining.

Several researchers incorporate DHNN with logic mining because of its effectiveness in solving optimization problems (Abdullah & Sathasivam, 2005). Thus, in our framework, we utilized logic mining with DHNN in investigating the price trend of commodities. As mentioned earlier, it is proven that by using the logic mining technique, we can transform any information into the logical rules. Sathasivam and Abdullah (2011) introduced the incorporation of logic with reverse analysis in DHNN. AN extended work by Kasihmuddin et al. (2018) improved the existing model by implementing 2-Satisfiability based Reverse Analysis Method (2-SATRA) in classifying the condition of the diabetic patient. Furthermore, Mansor et al. (2018) utilized 3-SATRA incorporated with DHNN in evaluating numerous cardiovascular diseases data set. The application of 2-SATRA in Kho et al. (2020) revealed the best logical rule that represented the behavior among the gameplay or objectives in the League of Legends game. 2-SATRA is also known as an efficient logic mining technique to obtain the best-induced logic that reveals the link between the attributes inside a real-life data set. As for our case, the proposed 2-SATRA will discover the logical relationship between palm oil prices with other commodities. Hence, this paper proposed the logic mining technique named 2-SATRA incorporate with DHNN technique to identify the price trend of palm oil.

However, there is no current study that executes logic mining in examining the price trend of the commodities. Most of the current studies only emphasize an individual commodity instead of doing a comparison with other commodities. The contributions of this research presented as follows: (1) To represent commodity price data into 2-SAT logical rules. (2) To implement 2-SATRA with DHNN to extract the information of the commodity price data set. (3) To investigate the relationship between commodity price data set by analyzing the interpretation of induced logic. Therefore, through our findings, we can provide information on which price trend commodity encourages the fluctuation of palm oil prices. The generated induced logic from our mechanism could aid and explain in layman terms for economists and traders of which resources affect our nation's economic growth. The structure of this paper is organized as follows. Section 2 presents a brief description of the materials and methods used such as Boolean satisfiability and Discrete Hopfield Neural Network. Section 3 demonstrates the implementation of 2-SATRA into our proposed model and provides all the information involved. In Section 4, the results from various performance evaluation metrics were discussed in detail and conclusions are finally presented in Section 5.

MATERIALS AND METHOD

Boolean Satisfiability (SAT)

Generally, Boolean satisfiability or satisfiability (SAT) is defined as logical rule with conjunction of clauses which consists of disjunction of literals with each literals or variables can be either true or false. There are three components of the fundamental SAT logical rule presented as follows (Kasihmuddin et al., 2017):

1. SAT formula comprises of a set of q literals or variables, $\left(x_1,...,x_q\right)$ within each clause. Note that l_i only complies with bipolar representation of $\{-1,1\}$ and all the variables are connected by logical operator $OR\left(\vee\right)$.
2. Literals or variables can represent the variable itself, M or the negation of the variable, $\neg M$.
3. Comprises of a set of k different clauses, $\left(C_1,C_2,C_3,...,C_k\right)$ where each distinct clauses contains q literals and will be connected by logical operator $AND\left(\wedge\right)$.

In other notation, this work comprises limited number of literals, which is two ($q = 2$), namely as; 2-Satisfiability (2-SAT) logical rule, A_{2-SAT}. The general formulation of A_{2-SAT} is shown in Equation 1:

$$A_{2-SAT}=\wedge_{i=1}^{k}C_i \quad (1)$$

where $C_i=\vee_{j=1}^{2}(x_{ij},y_{ij})$ and k represents the number clauses denoted by Conjunctive Normal Form (CNF) formula. Further explanation of three cases of A_{2-SAT} is presented as follows, where according to Equation 2:

$$A_{2-SAT}=(U\vee\neg V)\wedge(W\vee X)\wedge(\neg Y\vee\neg Z) \quad (2)$$

Case 1. Satisfiable when $(U, V, W, X, Y, Z) = (1,-1,1,1,-1,-1)$ which concludes that A_{2-SAT} is true when $A_{2-SAT} = 1$.
Case 2. Unsatisfiable when $(U, V, W, X, Y, Z) = (-1,1,1,1,-1,-1)$ in resulting $A_{2-SAT} = -1$.
Case 3. Equation 2 achieved the full inconsistency when $(U, V, W, X, Y, Z) = (-1,1,-1,-1,1,1)$.
This work will utilize the symbolic representation of A_{2-SAT} into our framework of 2-SAT and DHNN to represent the commodity price data set and implement reverse analysis to unveil the price trend of palm oil in Malaysia from the year 2008-2019. There is no recent research in integrating A_{2-SAT} with reverse analysis in order to investigate the relationship of related commodities such as gold, crude petroleum and timber with the inconsistent price of palm oil in Malaysia which plays a major role to our economic growth as the second largest palm oil exporter in the world.

2-Satisfiability in Discrete Hopfield Neural Network (DHNN)

Over the years, HNN has become one of the leading neural networks utilized by many researchers and neural networkers due to its structure flexibility and variability to act as an extensive network to solve optimization tasks. Initially, HNN was introduced by Hopfield and Tank in 1985, where HNN acted as a platform to solve multiple NP problems. HNN is a fully connected recurrent neural network without self-feedback. The utilization of HNN varies in terms of application versatility, from; obesity detection (Nájera et al., 2020), stability analysis (Shen et al., 2020), face recognition (Swapna et al., 2020) and financial forecasting (Del Ángel, 2020). This work is focusing on implementing A_{2-SAT} to represent the commodity price data set, therefore, the mechanism of discrete HNN (DHNN) is favourable as it is an auto associative memory network which could interpret functions of a memory to a neural network model (Shevchuk, 2016). The general DHNN characteristics utilized in this work are the input and output patterns are in discrete vector, specifically in bipolar state $\{-1,1\}$ (Kasihmuddin et al., 2017). Other than that, each neuron connection or synaptic weights are depicted as $W_{ij}^{(2)}$ where DHNN has symmetrical weights therefore it has zero diagonal elements with no self-connections between the neurons, $W_{ij}^{(2)} = W_{ji}^{(2)}$. Note that, the synaptic weights are calculated by using Abdullah method (1993). The fundamental neurons update formulated in DHNN is shown as follows (Equation 3):

$$S_i = \begin{cases} 1 & , if \sum_j W_{ij} S_j \geq \phi \\ -1 & , Otherwise \end{cases} \quad (3)$$

Note that S_j is the state of unit j and ϕ is the predetermined threshold value of unit *i*. The structure of local field formulated by Abdullah (1993) complies with DHNN which cater a case of higher order of neurons connections as shown in Equation 4 with updating rule presented in Equation 5 presented as follows:

$$h_i(t) = \sum_{j=1, i \neq j}^{N} W_{ij}^{(2)} S_j + W_i^{(1)} \tag{4}$$

$$S_i(t+1) = sgn[h_i(t)] \tag{5}$$

Note that $W_{ij}^{(2)}$ is the second order synaptic weight where else $W_i^{(1)}$ is the first order synaptic weight. The sgn is a signum function to squash the output of neurons, where in this case, we utilized Hyperbolic Tangent Activation Function (HTAF) (Mansor & Sathasivam, 2016).

The utilization of Lyapunov energy function to affirm the stability of DHNN (Sathasivam & Abdullah, 2010) in generating the optimized induced logic, $A_i^{induced}$ is formulated in Equation 6 and Galán-Marín & Muñoz-Pérez (2001) also emphasized on the dynamics of Hopfield network must be determined by the energy theorem mechanism stated as follows:

$$H_{A_{2-SAT}} = -\frac{1}{2} \sum_{i=1, i \neq j}^{N} \sum_{j=1, i \neq j}^{N} W_{ij}^{(2)} S_i S_j - \sum_{i=1}^{N} W_i^{(1)} S_j \tag{6}$$

Energy Theorem: *In a Hopfield neural network, any changes by the updating rule in Equation 6 in the components of the results in a decrease in the Lyapunov energy function.*

DHNN provides a central memory feature or content addressable memory to store synaptic weights in a matrix form and best logic, A_{best} to be later retrieved in the testing phase. The significance of implementing DHNN with A_{2-SAT} is the extensive yet straightforward framework that could generate a plausible induced logic which explicitly emphasizes the price trend of palm oil. From the produced $A_i^{induced}$, we could ascertain which commodity affects the rise and fall of palm oil price. Currently, there is no work in incorporating DHNN with $A_i^{induced}$ in order to investigate the influence of palm oil with respect to other significant commodities.

Implementation of DHNN2-SATRA Model

Each commodity can be interpreted as a neuron in DHNN and integrated based on A_{2-SAT}. Therefore, the implementation of DHNN2-SAT in Reverse Analysis Method is called 2-Satisfiability based Reverse Analysis Method (2-SATRA). The research done by Sathasivam and Abdullah (2011) had shown that they had succeeded in inducing all possible logical rules that explained the behavior of one data set by proposing a reverse analysis method. After that, Kasihmuddin et al. (2018) had revised the traditional method resulting to 2-SATRA so that more logical rules and learning methods could be applied to reliably generalize the behavior of the data set. Further to this, 2-SATRA is an effective logic mining tool to find best-induced logic from the commodity price data set that explains the behavior of the data set which in this case is the trend of palm oil price. The flow of this experiment can be seen in the Figure 1. All simulations were measured in two parts; training stage and testing stage. Root mean square error (RMSE) and mean absolute error (MAE) would be calculated in the training stage to test the performance of DHNN2-SAT model. The formulation of RMSE, MAE and accuracy are as follows (Equation 7 & 8):

$$RMSE = \sum_{i=1}^{n} \sqrt{\frac{1}{n}(\rho - o)} \tag{7}$$

$$MAE = \sum_{i=1}^{n} \frac{1}{n} |\rho - o| \tag{8}$$

where ρ is the total number of clauses in A_{2-SAT}, o is the number of satisfied clauses in A_{2-SAT} and n is the number of iteration before $\rho = o$. The lowest value of RMSE and MAE indicates the best performance DHNN2-SAT model. In the testing stage, accuracy (α) will be computed to investigate the capability of 2-SATRA in our DHNN2-SAT model. We describe α formulation as follows (Equation 9):

$$\alpha = \frac{A_i^{induced}}{N_{A_{test}}} \times 100\% \tag{9}$$

where $A_i^{induced}$ is the induced logic and $N_{A_{test}}$ is the number of testing data. By computing α, the best induced logic is attained that explains the behavior of the commodity data set.

In this paper, a real-life data set of Malaysia's commodities price with 7 types of commodities would be exerted in the established 2-SATRA. The commodities price ranged from the year 2009 until 2018. The real data set use multivariate data. A total of 120 data were adopted where 60% of the data was training data while the rest was for testing data (Kho et al., 2020). Seven attributes were used in A_{2-SAT} logical rule and by using permutation, different combinations of the clause were obtained so that the highest accuracy could be attained. The information of the data set is presented in Table 1. The computational simulation was conducted on Dev C++ Version 5.11 for Windows 10 in 4GB RAM with Intel Core i3. The same device would be used throughout the simulation to avoid any biases. Table 2 shows all the parameters involved in DHNN2-SAT.

RESULT AND DISCUSSION

This work exhibits an extensive network to predict the price trend of palm oil by entrenching A_{2-SAT} with DHNN. The role of A_{2-SAT} is to generalize the trend of the commodity price data set through a comprehensive logical system that could be utilized in explaining the trend in layman representation. DHNN2-SAT with the aid of reverse

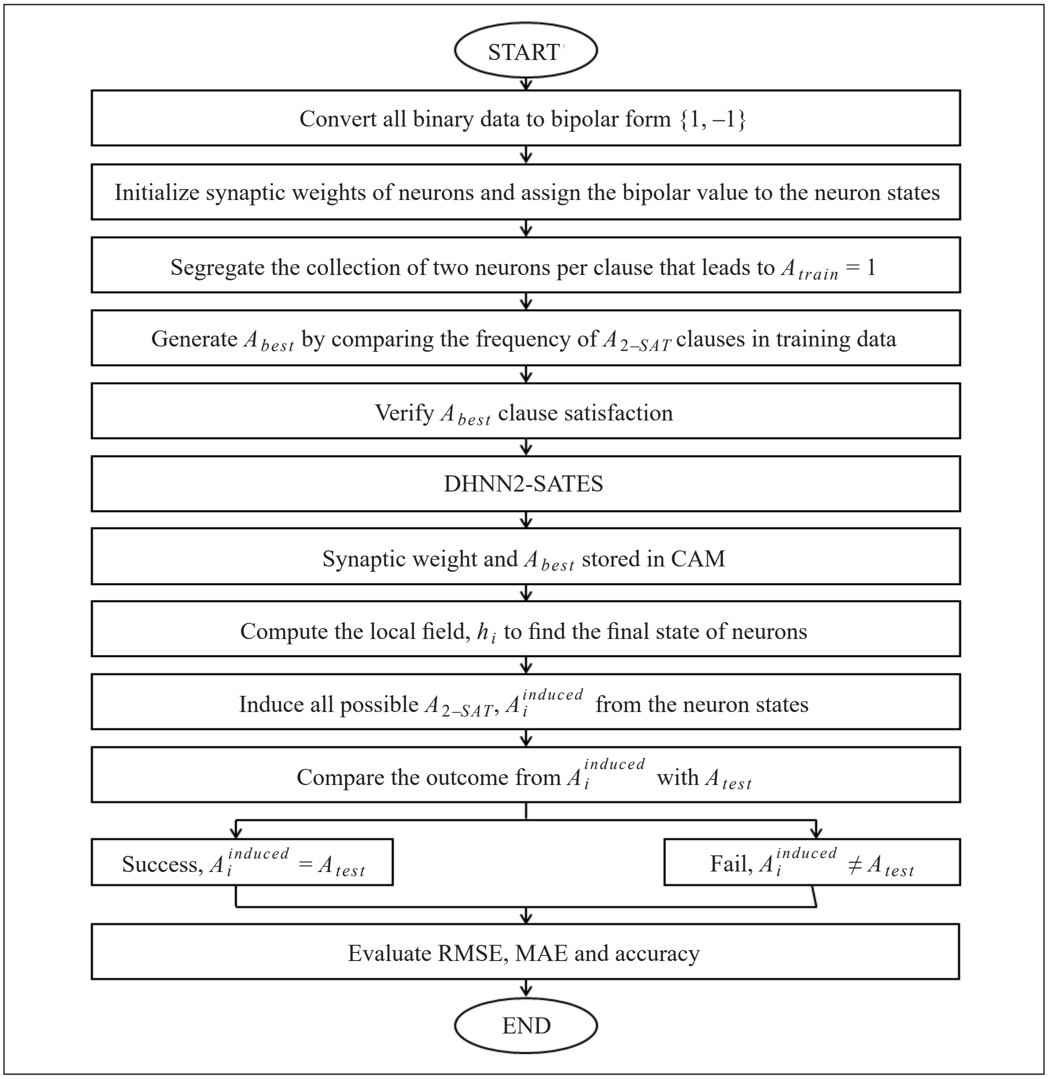

Figure 1. Implementation of DHNN2-SATRA

Table 1
List of commodities

Attributes	Name of Commodities	Source
A	Palm oil	Malaysian Palm Oil Board (2019)
B	Cocoa bean	Malaysian Cocoa Board (2019)
C	Gold	GoldBroker (2019)
D	Crude petroleum	CEIC (2018)
E	Black & white pepper	CEIC (2018)
F	Timber	Malaysia Timber Industry Board (2019)
G	Latex	Malaysian Rubber Board (2019)

Table 2
List of parameters in DHNN2-SAT (Sathasivam et al., 2013)

Parameter	Parameter value
Number of trial	100
Neuron combination	100
Tolerance value	0.001

analysis method, generated induced logic to display explicit manner of which commodities is held accountable for the rise and fall of palm oil price. Table 3 demonstrates the value of RMSE and MAE computed in the training stage for different number of neurons (*NN*). Table 4 exhibits the lists of induced logic after permutating the attributes in commodities data. In Table 4, 9 sets were obtained and determined by permutation, where the different set of induced logic produced different values of accuracy. The optimized induced logic was selected from the induced logic with the highest accuracy.

As depicted in Table 3, we can conclude that the best performance of the DHNN2-SAT model was reported at *NN* = 9 as it yields the least value of RMSE and MAE. The value of errors would be increased as the *NN* increased. This is because of our local searching technique only effective when it incorporates a low value of *NN*. Some researchers (Kasihmuddin et al., 2018; Mansor et al., 2018) suggest increasing the number of neurons to increase the accuracy of 2-SATRA. Nevertheless, the higher value of both errors; RMSE and MAE will be achieved as we increase the *NN* due to DHNN2-SAT requires more iteration to obtain the satisfying interpretation of 2-SAT. The best induced logic represented as $A_5^{induced}$, depicts the commodities of affecting the price trend of palm oil with the highest accuracy. The distinction between this work with other approaches is the utilization of permutation attributes in DHNN2-SAT. The role of attributes permutation is to increase the possibility and verify the network's accuracy by employing a different arrangement of the commodities that contribute to A_{2-SAT}. The attributes permutation showed different generated $A_i^{induced}$ with varies accuracy which we could magnify that the optimized induced logic was selected by observing the highest accuracy attained. Worth mentioning that, the formulated induced logical rule that explains the trend of palm oil prices is considered optimal because the expected global minima ratio is always approximately 1 (Kasihmuddin et al., 2017).

Throughout our findings of $A_5^{induced}$, the extracted information predicts the price of gold influence the price of palm oil. In this case, when the price of gold increases, the price of palm oil will also increase. This finding has a good agreement with the work of Cashin et al. (1999) which indicated that the palm oil price was correlated with gold. On the other hand, the palm oil price would affect others commodities price. The price of cocoa bean, crude petroleum, and latex increased as the palm oil price increases. Hence, the extracted

Table 3
Performance Evaluation of 2-SATRA in Training Stage

NN	RMSE	MAE
9	1.1905	0.8326
18	3.459	2.7523
27	7.4095	6.4491
36	10.8389	10.1037
45	14.3233	13.7653
54	17.5107	17.1898
63	20.727	20.5647
72	23.781	23.6072
81	26.827	26.7267
90	29.8942	29.8518

Table 4
Performance evaluation of 2-SATRA in testing stage

Sets	Induced Logic, $A_i^{induced}$	Accuracy (%)
1	$A_1^{induced} = (D \vee B) \wedge (\neg F \vee G) \wedge (E \vee C)$	72
2	$A_2^{induced} = (D \vee B) \wedge (G \vee C) \wedge (E \vee \neg F)$	60
3	$A_3^{induced} = (B \vee D) \wedge (G \vee C) \wedge (E \vee \neg F)$	60
4	$A_4^{induced} = (B \vee C) \wedge (D \vee \neg E) \wedge (\neg F \vee G)$	66
5	$A_5^{induced} = (B \vee C) \wedge (D \vee \neg E) \wedge (\neg F \vee G)$	75
6	$A_6^{induced} = (G \vee B) \wedge (C \vee D) \wedge (\neg E \vee \neg F)$	66
7	$A_7^{induced} = (\neg D \vee E) \wedge (F \vee G) \wedge (\neg B \vee C)$	72
8	$A_8^{induced} = (\neg F \vee \neg G) \wedge (B \vee C) \wedge (D \vee E)$	66
9	$A_9^{induced} = (D \vee \neg E) \wedge (\neg F \vee G) \wedge (B \vee C)$	75

logical rule is successfully identifying the key components that contribute to the palm oil price trend. Another interesting perspective, the optimal logical rule reported that the price of palm oil would stabilize if the price of the crude oil returned to the threshold price. The price of latex was observed to influence the price of palm Oil. According to Udomraksasakul and Rungreunganun (2018), the price of latex has reached a new low since 2010 and this pattern can be observed in the price of palm oil. In this case, regression analysis such as Weijermars and Sun (2018) and Kasihmuddin et al. (2017) are required to confirm the claim made by logical rule. The price of pepper and timber shows an inverse correlation relative to palm oil where the price of pepper and timber will reduce when the price of palm oil increases. The proposed method is incomparable with the existing work such as Cortez et al. (2018) and Li et al. (2019) because these studies only emphasized on the price trend of palm oil without considering the performance of other commodities. In this case, the value of accuracy is sufficient to validate the performance of 2-SATRA. However, the generated induced logic is still significant to predict the trend of the commodities for the other subsequent year, by entrenching new set of the data entries. The limitation of this work is we only consider the price trend instead of the actual price for commodities. Hence, the increase and decrease of the palm oil price were denoted by 1 and -1 respectively.

Other than that, A_{2-SAT} in this work, depicts the decreasing price trend in palm oil. Hence, alteration of A_{2-SAT} formulation in DHNN2-SAT is required to comply with $A_i^{induced} = -1$. This perspective requires the utilization of other non-Satisfiable formula such as maximum *k*-SAT (MAX*k*-SAT). Ultimately, the induced logic can help the traders, analysts, economist and strategists in deciding the most feasible investment strategies. Investors could also utilize the induced logic to provide an expert discussion regarding on stock market and their potential profit. Industrial players and policymakers can benefit from the generated induced logic to improve the developments of national economic growth.

CONCLUSION

In a nutshell, this paper carries out several important processes to finally obtained a beneficial result that shows which commodities affect the increase in palm oil price. First, A_{2-SAT} is incorporated in DHNN (DHNN2-SAT) as a single logic mining. Every attribute in the commodity price data set is represented in terms of DHNN2-SAT. After that, the training stage in DHNN2-SAT will be intensified by using the local searching technique. Next, this process is extended by integrating DHNN2-SAT with 2-SATRA that operates as a logic mining tool to conclude the logical rule of the commodity price data set. As a consequence, this paper will generate the best induced logic based on the highest accuracy attained to emphasize the behavior of the data set which concluded all objectives presented in this experiment have been successfully achieved. The outcome of this experiment establishes the desired price trend for palm oil with the highest accuracy. In the future, our research can be improved by using different types of searching techniques such as genetic algorithm, imperialist competitive algorithm, artificial immune system, and ant colony optimization. The effectiveness of these searching techniques is different and has its advantages. Furthermore, this research can also explore different logical rule such as Maximum Satisfiability (MAX*k*-SAT) by considering $A_{train} = -1$.

ACKNOWLEDGEMENT

This research was funded by Fundamental Research Grant Scheme (FRGS), Ministry of Education Malaysia, grant number 203/PJJAUH/6711751.

REFERENCES

Abdullah, R., & Wahid, M. B. (2010). *World palm oil supply, demand, price and prospects: Focus on Malaysian and Indonesian palm oil industry.* Kajang, Malaysia: Malaysian Palm Oil Board Press.

Abdullah, W. A. T. W. & Sathasivam, S. (2005, December 1-3). Logic mining using neural networks. In *Proceedings of the International Conference on Intelligent Systems* (pp. 1-6). Kuala Lumpur, Malaysia.

Abdullah, W. A. T. W. (1993). The logic of neural networks. *Physics Letters A*, *176*(3-4), 202-206.

Alameer, Z., Elaziz, M. A., Ewees, A. A., Ye, H., & Jianhua, Z. (2019). Forecasting gold price fluctuations using improved multilayer perceptron neural network and whale optimization algorithm. *Resources Policy*, *61*, 250-260.

Bakar, B. B. (2009, September 27-28). The Malaysian agricultural industry in the new millennium: Issues and challenges. In *International Conference on Malaysia: Malaysia in Global Perspective* (pp. 337-356). Cairo University, Egypt.

Balu, N., Azman, I., Hashim, N., Ismail, I., Shahari, D. N., & Idris, N. A. N. (2018). Malaysia: 100 years of resilient palm oil economic performance. *Journal of Oil Palm Research*, *30*(1), 13-25.

Baruník, J., & Malinska, B. (2016). Forecasting the term structure of crude oil futures prices with neural networks. *Applied Energy*, *164*, 366-379.

Cashin, P. A., McDermott, C. J., & Scott, A. M. (1999). *The myth of comoving commodity prices.* Washington, DC: International Monetary Fund.

CEIC. (2018). *Malaysia exports: By selected commodities*. Retrieved January 01, 2020, from https://www.ceicdata.com/en/malaysia/exports-by-selected-commodities.

Cook, S. A. (1971, May 3-5). The complexity of theorem-proving procedures. In *Proceedings of the third annual ACM symposium on Theory of computing* (pp. 151-158). Shaker Heights, Ohio.

Cortez, C. T., Saydam, S., Coulton, J., & Sammut, C. (2018). Alternative techniques for forecasting mineral commodity prices. *International Journal of Mining Science and Technology*, *28*(2), 309-322.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24-42.

Del Ángel, R. G. (2020). Financial time series forecasting using Artificial Neural Networks. *Revista Mexicana de Economía y Finanzas Nueva Época REMEF*, *15*, 105-122.

Department of Statistics Malaysia. (2019). *Selected agricultural indicators.* Retrieved January 01, 2020, from https://www.dosm.gov.my.

Galán-Marín, G., & Muñoz-Pérez, J. (2001). Design and analysis of maximum Hopfield networks. *IEEE Transactions on Neural Networks, 12*(2), 329-339.

GoldBroker. (2019). *Gold price in Malaysian Ringgit - Malaysia*. Retrieved January 01, 2020, from https://www.goldbroker.com/charts/gold-price/myr.

Haykin, S. (1994). *Neural networks: A comprehensive foundation*. Upper Saddle River, NJ: Prentice Hall PTR.

Hopfield, J. J. & Tank, D.W. (1985). Neural computation of decisions in optimization problems. *Biological Cybernetics*, *52*(3), 141-152.

Ismail, A. (2013). The effect of labour shortage in the supply and demand of palm oil in Malaysia. *Oil Palm Industry Economic Journal, 13*(2), 15-26.

Iverson, K. E. (1962, May 1-3). A programming language. In *Proceedings of the spring joint computer conference* (pp. 345-351). San Francisco, California.

Kasihmuddin, M. S. M., Mansor, M. A., & Sathasivam, S. (2017). Hybrid genetic algorithm in the Hopfield network for logic satisfiability problem. *Pertanika Journal of Science and Technology*, *25*(1), 139-152.

Kasihmuddin, M. S. M., Mansor, M. A., & Sathasivam, S. (2018). Satisfiability based reverse analysis method in diabetes detection. In *AIP Conference Proceedings* (Vol. 1974, No. 1, p. 020020). Melville, NY: AIP Publishing LLC.

Kasihmuddin, M. S. M., Mansor, M. A., & Sathasivam, S. (2019, December). Students' performance via satisfiability reverse analysis method with Hopfield Neural Network. In *AIP Conference Proceedings* (Vol. 2184, No. 1, p. 060035). Melville, NY: AIP Publishing LLC.

Khamis, A., & Wahab, A. (2016). Comparative study on predicting crude palm oil prices using regression and neural network models. *International Journal of Science and Technology, 5*(3), 88-94.

Kho, L. C., Kasihmuddin, M. S. M., Mansor, M., & Sathasivam, S. (2020). Logic mining in league of legends. *Pertanika Journal of Science and Technology*, *28*(1), 211-225.

Kowalski, R. (1979). *Logic programming for problem solving*. New York, NY: Elsevier Science Publishing.

Kushairi, A., Ong-Abdullah, M., Nambiappan, B., Hishamuddin, E., Bidin, M. N. I. Z., Ghazali, R., ... & Parveez, G. K. A. (2019). Oil palm economic performance in Malaysia and R&D progress in 2018. *Journal of Oil Palm Research*, *31*(2), 165-194.

Li, X., Shang, W., & Wang, S. (2019). Text-based crude oil price forecasting: A deep learning approach. *International Journal of Forecasting*, *35*(4), 1548-1560.

Liu, Y., Wang, Z., & Liu, X. (2006). Global exponential stability of generalized recurrent neural networks with discrete and distributed delays. *Neural Networks*, *19*(5), 667-675.

Mainzer, K. (2020). Logical thinking becomes automatic. In K. Mainzer (Ed.), *Artificial intelligence-When do machines take over?* (pp. 15-45). Berlin, Heidelberg: Springer.

Malaysia Timber Industry Board. (2019). *Malaysia timber industry board*. Retrieved January 01, 2020, from http://www.mtib.gov.my/en/.

Malaysian Cocoa Board. (2019). *Ministry of plantation industries and commodities*. Retrieved January 01, 2020, from https://www.koko.gov.my/lkm/index.cfm.

Malaysian Palm Oil Board. (2019). *The official portal of Malaysian palm oil board*. Rerieved January 01, 2020, from http://www.mpob.gov.my/.

Malaysian Rubber Board. (2019). *Malaysian rubber board*. Retrieved January 01, 2020, from http://www.lgm.gov.my/.

Mansor, M. A., & Sathasivam, S. (2016, June). Performance analysis of activation function in higher order logic programming. In *AIP Conference Proceedings* (Vol. 1750, No. 1, p. 030007). Melville, NY: AIP Publishing LLC.

Mansor, M. A., Kasihmuddin, M. S. M., & Sathasivam, S. (2019). Modified artificial immune system algorithm with Elliot Hopfield neural network for 3-satisfiability programming. *Journal of Informatics and Mathematical Sciences, 11*(1), 81-98.

Mansor, M. A., Sathasivam, S., & Kasihmuddin, M. S. M. (2018, June). Artificial immune system algorithm with neural network approach for social media performance metrics. In *AIP Conference Proceedings* (Vol. 1974, No. 1, p. 020072). Melville, NY: AIP Publishing LLC.

Mekonnen, Y., Namuduri, S., Burton, L., Sarwat, A., & Bhansali, S. (2020). Machine learning techniques in wireless sensor network based precision agriculture. *Journal of the Electrochemical Society*, *167*(3), 1-11.

Nájera, M. A. C., Mechaca, J. L., Martínez, S. I., Villanueva, J. D. T., & Vega, D. A. M. (2020). Prevention of obesity using Hopfield networks in patients with obese ancestry. *International Journal of Combinatorial Optimization Problems and Informatics*, *11*(2), 61-66.

Nambiappan, B., Ismail, A., Hashim, N., Ismail, N., Nazrima, S., Idris, N. A. N., ... & Kushairi, A. (2018). Malaysia: 100 years of resilient palm oil economic performance. *Journal of Oil Palm Research, 30*(1), 13-25.

Rahman, A. K. A. (2012). *Impact of palm oil supply and demand on crude palm oil price behavior.* Kelana Jaya, Malaysia: Malaysian Palm Oil Board Press.

Ramakrishnan, S., Butt, S., Chohan, M. A., & Ahmad, H. (2017, July 16-17). Forecasting Malaysian exchange rate using machine learning techniques based on commodities prices. In *2017 International Conference on Research and Innovation in Information Systems (ICRIIS)* (pp. 1-5). Langkawi, Malaysia.

Sathasivam, S., & Abdullah, W. A. T. W. (2010). The satisfiabilty aspect of logic on little Hopfield network. *American Journal of Scientific Research, 2010*(7), 90-105.

Sathasivam, S., & Abdullah, W. A. T. W. (2011). Logic mining in neural network: Reverse analysis method. *Computing*, *91*(2), 119-133.

Sathasivam, S., Fen, N. P., & Velavan, M. (2014). Reverse analysis in higher order Hopfield network for higher order horn clauses. *Applied Mathematical Sciences, 8*(13), 601-612.

Sathasivam, S., Ng, P. F., & Hamadneh, N. (2013). Developing agent based modelling for reverse analysis method. *Journal of Applied Sciences, Engineering and Technology*, *6*(22), 4281-4288.

Shen, W., Zhang, X., & Wang, Y. (2020). Stability analysis of high order neural networks with proportional delays. *Neurocomputing*, *372*, 33-39.

Shevchuk, A. V. (2016). Artificial intelligence and intellectualization: New prospects for economic development. *Міжнародний науковий журнал" Науковий огляд"*, *4*, 1-9.

Songsiengchai, P., Sidique, S. F., Djama, M., & Azman-Saini, W. N. W. (2020). Asymmetric adjustments in the Thai palm oil market. *Kasetsart Journal of Social Sciences*, *41*(1), 220-225.

Swapna, M., Sharma, Y. K., & Prasad, B. M. G. (2020). A survey on face recognition using convolutional neural network. In *Data Engineering and Communication Technology* (pp. 649-661). Singapore: Springer.

Udomraksasakul, C., & Rungreunganun, V. (2018). Forecasting the price of field latex in the area of Southeast Coast of Thailand using the ARIMA Model. *International Journal of Applied Engineering Research*, *13*(1), 550-556.

Weijermars, R., & Sun, Z. (2018). Regression analysis of historic oil prices: A basis for future mean reversion price scenarios. *Global Finance Journal*, *35*, 177-201.