Enhanced Community Detection Based on Cross Time for Higher Visibility In Supply Chain: A Six-Steps Model Framework

Zuraida Abal Abas, Nurul Hafizah Mohd Zaki, Siti Azirah Asmai, Ahmad Fadzli Nizam Abdul Rahman, Zaheera Zainal Abidin

Abstract: Increasing the visibility in supply chain network had decrease the risk in industries. However, the current Cross-Time approach for temporal community detection algorithm in the visibility has fix number of communities and lack of operation such as split or merge. Therefore, improving temporal community detection algorithm to represent the relationship in supply chain network for higher visibility is significant. This paper proposed six steps model framework that aim: (1) To construct the nodes and vertices for temporal graph representing the relationship in supply chain network; (2) To propose an enhanced temporal community detection algorithm in graph analytics based on Cross-time approach and (3) To evaluate the enhanced temporal community detection algorithm in graph analytics for representing relationship in supply chain network based on external and internal quality analysis. The proposed framework utilizes the Cross-Time approach for enhancing temporal community detection algorithm. The expected result shows that the Enhanced Temporal Community Detection Algorithm based on Cross Time approach for higher visibility in supply chain network is the major finding when implementing this proposed framework. The impact advances industrialization through efficient supply chain in industry leading to urbanization.

Keywords: Supply Chain Network, Temporal Community Detection, Graph Analytics, Internet of Things, Risk.

I. INTRODUCTION

According to the [1], the problem of many industries when it comes to supply chain is they are operating with little insight beyond the relation between suppliers and customers. This implies the risk of unpreparedness and without mitigation strategies in place whenever disruptions occur. Therefore, increasing the visibility in supply chain in order to lessen such risk is in the interest of the industries. With the emergence of Industrial Revolution 4.0, industries are now adopting Internet of Things (IoT). A real time visibility to material, suppliers, distributors and customer is one of the key stages when adopting IoT [2]. However, the connectivity between the raw supplier, distributors, and materials cannot be represented by linear model. Instead, graph analytics is becoming an essential technique to discover, capture and make sense of complex relationships and interdependencies. Yet, there are still open problem fundamentally for graph analytics that is required to be solved [3].

It should be noted that most of the underlying connection and relationship are now varying over time and display more dimensionality than static graph can capture at no time frame. On the other hand, temporal graphs represent nodes and relationship that is changing over time. However, according to [3], there are not so many works focus on temporal graph analytics due to its infancy stage. Currently, there are recent works done for new temporal graph analytics algorithm [4], [5] which focuses on shortest path earliest arrival time, shortest temporal fastest path, temporal closeness and temporal betweenness. Nevertheless, only few in the literature focus on the community detection for temporal graph analytics. In graph theory, community means a set of nodes that are heavily connected to each other but sparsely connected to the other parts of the graph.

There are three approaches for dynamic community detection in graph theory: (1) Instant optimal, (2) Temporal Trade-off and (3) Cross-Time. In fact, the Cross-time approach focusing on searching communities when considering the whole graph evolution. It directly searches one single partition for all time steps [6], [7]. Using this approach, the communities found at time t are depending on both past and future evolution, in which produce communities that are completely temporal smoothed. However, the current Cross-Time approach for temporal community detection has fix number of communities and lack of operation such as split or merge [6].

Therefore, there is a need to have an enhanced community detection algorithm in graph analytics that specifically cater on the unfix number of communities with complete appropriate operation for community detection. The enhanced community detection algorithm must be able to capture the dynamics relationship of the supply chain network in order to have valuable insight for better and efficient operations. This dynamics relationship need to be formulated and enhanced in terms of temporal community detection in the graph analytics (the body of knowledge) for representing the complexity of the supply

Revised Manuscript Received on November 05, 2019.

***** Correspondence Author

Zuraida Abal Abas, (OptiMAS), Faculty of Information Communication and Technology, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka Malaysia, Email: zuraidaa@utem.edu.my

Nurul Hafizah Mohd Zaki, Faculty of Information Communication and Technology, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka Malaysia, Email: fizahzaki@gmail.com

Siti Azirah Asmai, (OptiMAS), Faculty of Information Communication and Technology, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka Malaysia, Email: azirah@utem.edu.my

Ahmad Fadzli Nizam Abdul, (OptiMAS), Faculty of Information Communication and Technology, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka Malaysia, Email: fadzli@utem.edu.my

Zaheera Zainal Abidin, (INSFORNET), Faculty of Information Communication and Technology, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka Malaysia, Email: zaheera@utem.edu.my

chain network that has been upgraded when adopting IoT.

In conclusion, there are two main problems worth to be highlighted that drives this paper:

(1) In the view of application domain – most industries are operating with little insight beyond the relation between suppliers and customers in supply chain network. Therefore, there is an urgent need to increase visibility in terms of the relationship in supply chain network in order to lessen the risk of unpreparedness whenever disruptions occur.

(2) In the view of fundamental technique – the current Cross-Time approach for temporal community detection algorithm has fix number of communities and lack of operation such as split or merge. Therefore, there is a need to enhanced temporal community detection algorithm to represent the relationship in supply chain network for higher visibility.

II. RELATED WORKS

The industries as well as the industry processes are constantly evolving. According to [8] the first industrial revolution was in the middle on 18th century and was driven by the steam engine. It then followed by the second industrial revolution in second half of 19th century, which centered at the introduction to mass production as well as the replacement of previous steam engine with the chemical and electrical energy. The third industrial revolution was in the second half of 20th century and it drove the application of electronics and IT to assist the production and automation. Currently, the fourth industrial revolution that the world is facing focus on the use of digital technology to make the industries becoming more agile, flexible as well as responsive to the customers. Internet of things (IoT), 3D printing, augmented reality and cloud technologies are among the digital technologies being emphasized in industry 4.0 [9]. The definition of IoT based on the common idea from various group of people such as researchers, academicians, innovators, practitioners, developers and corporate people are as follows [10]:

“An open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data and resources, reacting and acting in face of situations and changes in the environment”

In other words, RFID tags, sensors/actuators and communication technologies that are integrated serves as the foundation of IoT [11]. This explain how a variety of devices and physical objects around us is associated to the internet and thus allows these devices and objects to communicate and cooperate with each other in order to reach common goal. In industry, the adoption of IoT leads to the term Industrial Internet of Things (IIoT). It refers to the utilization of IoT in industry and implies the usage of actuators and sensors, machine-to-machine, control systems, data analytics and security mechanism. It must be noted that numerous significant applications of IIoT are emerging. According to [12], the IIoT is able to strengthen modern industries through three pillars: (1) the process optimization, (2) the optimized resource consumption and (3) the creation of complex autonomous systems.

With regards to the IIoT, data generated from the utilization of the sensors embedded in various machine tools, cloud-based solutions and business management are endlessly increasing exponentially. As a result, huge amount of data will be collected and analyzed. Based on the report produced by Accenture [2], The IIoT will change the way the industries think about production process, resource allocation material handling as well as the workforce. Hence, the IIoT adoption require changes in almost every aspect of the business such as customer relationship, supply chain, product design, service model, profit & loss and many more [2], [13].

According to the survey made to the industry player [14], one finding that worth to be highlighted is that through the IIoT adoption, the industry players are looking forward to have novel methods to optimize the supply chain processes, especially through real time data collection, reasoning as well as monitoring. With IIoT, the traditional supply chain is now moving forward to transform into digital supply chain with its ultimate goal is to fully integrate and make it visible every aspect of the raw material and good or product movement [15]. Moreover, according to [15], the new digital supply chain depend on a number of key technologies: (1) integrated planning and execution systems, (2) logistics visibility, (3) autonomous logistics (4) smart procurement and warehousing, (5) spare parts management and finally (5) advanced analytics.

Advanced analytics is one of the strategies to achieve the ultimate goal of full integration and visibility in the era of digital supply chain when leveraging IIoT. The connectivity between the raw supplier, distributors, materials and processes cannot be represented by linear model. Instead, graph analytics as one of the advanced analytics is becoming an essential technique to discover, capture and make sense of complex relationships and interdependencies. A graph is consists of a set of nodes and a set of edges to represent the relationship that connects the nodes [16]. For example, it can be used to represent paths in a city, a circuit networks such as telephone and computer ones or even represent social networks in which each node contains various information like id, name, gender, location and etc. It is apparent that the data used in wide range of application can be formulated into graph structure thus providing holistic view of the underlying correlation and can be extended to both visualization and analytics field [17]. With respect to this, the term Graph Analytics emerged and it refers to the study and analysis of the data that can be transformed into the representation of graph. Graph analytics is exploited at various multi-disciplinary and high-impact application for obtaining various pattern in a given real world system [3], [16]. Graph analytics is very suitable with IoT because its capability to deal with unstructured data, integrate different data sources, able to express complicated patterns in intuitive ways as well as it enables advanced topological analytics [18].

To date, the graph analytics technique dealing with static graph is very stable. However, according to [3], there are not so many works focus on temporal graph analytics because it is still infancy. Temporal graph is an extended structure of graph in which time label is associated to the edges. Based on [4], one obvious fundamental difference between a static graph and a temporal graph is that the latter is not transitive. Currently, there are recent works done for new temporal graph analytics algorithm [4], [5]. The work only focuses on shortest path earliest arrival time, shortest temporal fastest path, temporal closeness and temporal betweenness (centrality measure). Nevertheless, only few in the literature focus on the community detection for temporal graph analytics.

In graph theory, community means a set of nodes that are heavily connected to each other but they are sparsely connected to the other parts of the graph. There are three categories of the community discovery or detection method for temporal graph [6]: (1) Instant optimal (2) temporal trade-off and finally (3) cross-time community discovery. With regards to cross-time community discoveries, the different steps of evolution in the network is considered dependently [6].

There are four sub-categories for cross-time corresponding to the distinctive manners to solve problem as follows [6]: (1) Fixed Membership, fixed properties, (2) Fixed Membership, evolving properties, (3) Evolving membership, fixed properties and finally (4) Evolving membership, evolving properties. In the case of the fourth sub-categories (evolving membership, evolving properties), the methods that fall into this category do not have constraint on temporal communities: nodes are allowed to change among them as well as communities are allowed to emerge or vanish and the density may be different. To date, there are three methods for evolving membership, evolving properties reported in [7], [19], [20].

However, these methods have its drawbacks, which further explanation shows the gap of this study. Cross-Time approach is not based on usual principle of unique partition being associated with each step of graph evolution process. It requires to develop novel techniques and to make new assumptions on the nature of dynamic or temporal communities. As a result, the current Cross-Time approach for temporal community detection suffers from having fix number of communities and lack of operation such as split or merge [6].

Hence there is a need to have enhanced temporal community detection based on Cross-Time approach to overcome the current drawback. This paper will focus on fourth sub-categories in Cross-Time approach, which is evolving membership, evolving properties because it is most suited to the IIoT application in supply chain network. With these advance analytics in digital supply chain, supply chain network visibility will be increased, performance bottlenecks can be predicted, factory operation can be improved, workforce and supply chain risk can be better managed as well as product design process can be enhanced [2].

III. RESULTS AND DISCUSSION

The resulted proposed framework to conduct the research for enhanced community detection based on cross time for higher supply chain visibility is illustrated as in Figure 1. In general, this proposed framework is aimed to achieve the following three objectives in the research: (1) To construct the nodes and vertices for temporal graph representing the relationship in supply chain network; (2) To propose an enhanced temporal community detection algorithm in graph analytics body of knowledge based on Cross-time approach and (3) To evaluate the enhanced temporal community detection algorithm in graph analytics for representing relationship in supply chain network based on external and internal quality analysis.

The data collection will be from the supply chain network data obtain from the adoption of IIoT. It is expected that the data come from a variety of sources such as sensors/actuators, machines, raw materials, production processes, distributor, suppliers and many more. The connectivity between all of this data in supply chain network will be analyzed so that the whole system can be represented in graph structure. It must be noted that this data need to have temporal or timing properties since the proposed methods will enhanced the temporal community detection.

According to the proposed framework, once the data has been collected and analyzed, then the research will be followed by designing and developing the enhanced temporal community detection algorithm in graph analytics. In order to enhance the algorithm, all six steps as shown in Figure 1 will be done as follows:

Step 1 – Construct the nodes/vertices and edges for temporal graph representing the supply chain network using Neo4j software.

In this step, Temporal graph G=(V, E, T) in which V denotes a set of triplets of the form (v, t_s, t_e) with v is a node of the graph and t_s, t_e is entity in set T are respectively the starting and ending timestamp of the corresponding nodes;

E denotes a set of quadruplet (u, v, t_s, t_e) in which it is an edge that connect vertex/node u and v with associated t_s and t_e.

Step 2 - A series of graph snapshot need to be created and defined as follows:

A snapshot Graph, G_t is defined by an ordered set $(G_1, G_2, G_3 \ldots, G_t)$ where each snapshot $G_i=(V_i,E_i)$ is univocally identified by the sets of nodes Vi and edges E_i.

Step 3 – Create a single graph in which meta-node corresponding to the existence of a node at a specified snapshot G. Two kind of edge will be described as follows:

i. The usual connectivity between nodes at the same time-step

ii. Supplementary edges which connect nodes that belong to different and adjacent time-steps.

Step 4 – Formulate the community detection procedure for temporal graph by having the unfix community number and complete operations based on Greedy algorithm on the transformed graph.

Step 5 - Enhanced the community detection algorithm for temporal graph based on Cross Time approach. Communities that have nodes which belong to different time steps, interpretable as dynamic communities will be identified. In this step, unfix number of communities as well as complete appropriate operation will be the major focus to be enhanced for temporal community detection algorithm. Moreover, this framework focus on the fourth categories of cross-time approach: Evolving membership and also evolving properties since the data will likely comes from IIoT application.

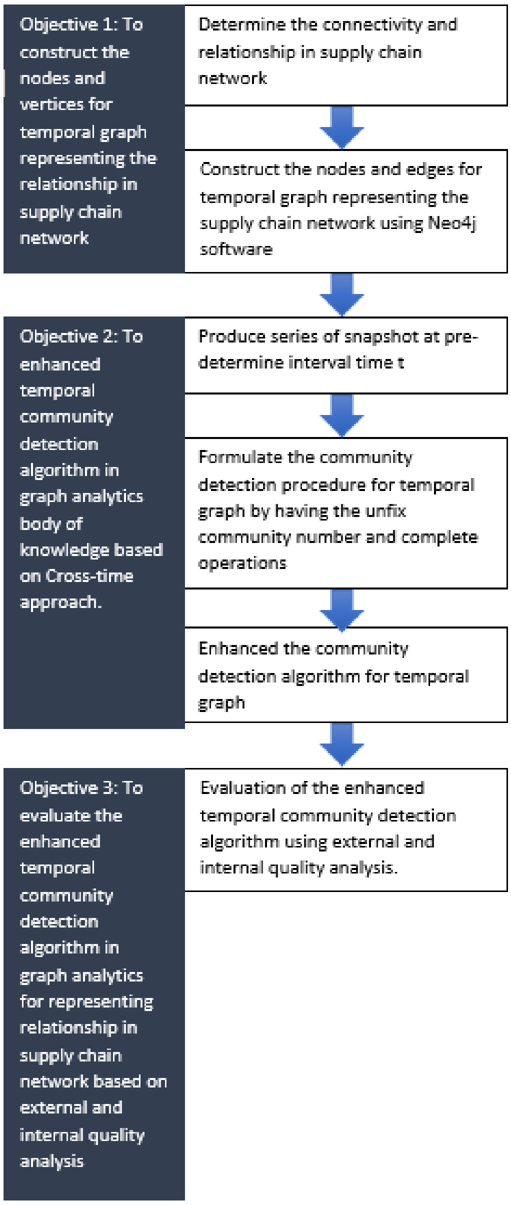

Fig. 1.The Proposed Six-Step Framework Model for Enhanced Community Detection based on Cross-Time Approach for Higher Visibility in Supply Chain.

Step 6 - As for testing and evaluation, temporal community detection will be evaluated using external and internal quality analysis as proposed by [6]. The external quality assumes the existence of an external ground truth that need to be retrieved or a specific community score. In this analysis, the following formula of Normalized Mutual Information (NMI) score is computed [6]:

$$NMI\ (X,Y) = [H(X) + H(Y) - H\ (X,Y)]/[(H(X)+H(Y))/2]$$

Where H(X) is the entropy of the random variable X associated to an identified community, H(Y) is the entropy of the random variable Y associated to a ground truth and H(X,Y) is the joint entropy.

On the other hand, the internal quality focuses on the inspection and description of topologies identified as well as on the evaluation of the proposed enhancement's complexity and scalability [6]. In this step, the research will focus on the algorithmic complexity.

IV. CONCLUSION

The risk of unpreparedness whenever disruption occur can be lessen if the visibility in supply chain is increased. As a matter of facts, increasing the visibility in supply chain has been one of the interests of the industries. Graph analytics has the ability to discover, capture and make sense of the complex relationships and interdependencies in increasing the visibility in supply chain. One of the promising techniques in graph analytics for this purpose is community detection. However, there is a need to enhance community detection algorithm in order to meet the requirement of Industrial Revolution 4.0. This paper proposed a six-step framework model to enhance community detection based on cross time approach for higher visibility in supply chain. It is expected that the Enhanced Temporal Community Detection Algorithm based on Cross Time approach for higher supply chain network visibility will be the major finding when implementing this proposed framework. It should be noted that this proposed framework will be one of the driving factor for advancing industrialization through efficient supply chain in industry as well as leading to urbanization.

ACKNOWLEDGMENT

Appreciation to Ministry of Education Malaysia for research grant FRGS/2018/FTMK-CACT/F00394, Malaysia Research Assessment (MyRA), Universiti Teknikal Malaysia Melaka (UTeM), Fakulti Teknologi Maklumat dan Komunikasi (FTMK) and research group of Centre for Advanced Computing Technology (C-ACT) – Optimisation, Modeling, Analytics and Simulation (OptiMAS) research group.

REFERENCES

1. L. Carstens, J. L. Leidner, K. Szymanski, and B. Howald, "Modeling Company Risk and Importance in Supply Graphs," in ESWC 2017, 2017, vol. 1, pp. 18–32.
2. E. Liongosari, P. Mullan, M. Muller, and P. Guittat, "Smart Production Finding a way Forward: How Manufacturers can make the most of the Industrial Internet of Things," 2016.
3. D. Yan, Y. Bu, Y. Tian, A. Deshpande, and J. Cheng, "Big Graph Analytics Systems," in SIGMOD'16, 2016, pp. 2241–2243.
4. W. Ligtenberg, "Tink , a temporal graph analytics library for Apache Flink," Department of Mathematics and Computer Science, University of Technology, 2017.
5. F. S. F. Pereira, S. d. Amo, and J. Gama, "Evolving Centralities in Temporal Graphs: A Twitter Network Analysis," in 2016 17th IEEE International Conference on Mobile Data Management (MDM), 2016, vol. 2, pp. 43–48.
6. G. Rossetti and R. Cazabet, "Community Discovery in Dynamic Networks : a Survey Community Discovery in Dynamic Networks : a Survey," Cornell Univ. Libr., no. July, 2017.

7. P. J. Mucha, T. Richardson, K. Macon, M. A. Porter, and J.-P. Onnela, "Community Structure in Time-Dependent, Multiscale, and Multiplex Networks," Science, no. July, May-2010.
8. A. C. Pereira and F. Romero, "A review of the meanings and the implications of the Industry 4.0 concept," in Manufacturing Engineering Society International Conference 2017, 2017.
9. Pierre-Olivier Bédard-Maltais, "Industry 4.0: The New Industrial Revolution Are Canadian manufacturers ready?," 2017.
10. S. Madakam, R. Ramaswamy, and S. Tripathi, "Internet of Things (IoT): A Literature Review," J. Comput. Commun., vol. 3, no. May, pp. 164–173, 2015.
11. L. Da Xu, W. He, and S. Li, "Internet of Things in Industries : A Survey," IEEE Trans. Ind. INFORMATICS, vol. 10, no. 4, pp. 2233–2243, 2014.
12. D. Mourtzis, E. Vlachou, and N. Milas, "Industrial Big Data as a result of IoT adoption in Manufacturing," Procedia CIRP, vol. 55, pp. 290–295, 2016.
13. R. Chitkara and R. Mesirow, "The Industrial Internet of Things," 2016.
14. C. Perera, C. H. Liu, and S. Jayawardena, "The Emerging Internet of Things Marketplace From an Industrial Perspective: A Survey," IEEE Trans. Emerg. Top. Comput., no. 61272509, 2015.
15. S. Schrauf and P. Berttram, "Industry 4.0: How digitization makes the supply chain more efficient , agile , and customer-focussed," 2016.
16. I. Robinson, J. Webber, and E. Eifrem, Graph Databases: New Opportunities for Connected Data, 2nd ed. United: O'Reilly Media, 2015.
17. A. Drosou, I. Kalamaras, S. Papadopoulos, and D. Tzovaras, "An enhanced Graph Analytics Platform (GAP) providing insight in Big Network Data," J. Innov. Digit. Ecosyst., vol. 3, no. 2, pp. 83–97, 2016.
18. Emil Eifrem, "Why graph databases are perfect for the Internet of Things," SIlicon Angle, 2015.
19. M. Ben Jdidia, C. Robardet, and E. Fleury, "Communities detection and analysis of their dynamics in collaborative networks," in 2nd International Conference on Digital Information Management (ICDIM), 2007.
20. T. Viard, M. Latapy, and C. Magnien, "Computing maximal cliques in link streams," Theor. Comput. Sci., vol. 609, no. Part 1, pp. 245–252, 2016.

AUTHORS PROFILE

Zuraida Abal Abas PhD is an associate professor Universiti Teknikal Malaysia Melaka (UTeM). Graduated with first class degree in BSc in Industrial Mathematics from Universiti Teknologi Malaysia (UTM), obtained MSc in Operational Research from London School of Economics (LSE) and received PhD in Mathematics from Universiti Teknologi Malaysia (UTM). Very passionate in research in which obtained more than 15 grants from the university and several government agencies. Has authored and co-authored more than 100 academic papers and presented in local and international conferences. Has been invited as keynote speaker in some of the international conferences.

Nurul Hafizah Mohd Zaki received her Bachelor of Science Computer (Software Engineering) from University Teknikal Malaysia Melaka (2017). She was joined Malayan Banking Berhad (Maybank) as part of project technical team for Global Banking and Delivery Operation on 2017-2019. She is currently a Graduate Research Assistant and postgraduate student (MSc in Science Computer) at UTeM in collaboration with Ministry of Education Malaysia under FRGS grant with the aims to enhanced temporal community detection algorithm based on cross time approach for higher supply chain visibility. Her research interest includes computer system and graph analytics**.**

Siti Azirah Asmai received Bachelor of Computer Science from Universiti Teknologi Malaysia (2000) and she completed her MSc. in Information and Communication Technology for Engineers (2004) from Coventry University, United Kingdom and PhD in ICT (2014) from Universiti Teknikal Malaysia Melaka (UTeM). She is currently a senior lecturer at Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM) and also a member of Optimization Modelling Analytic and Simulation (OPTIMAS) research group. Her area of research interests includes Predictive Analytics, Data Analytics and Visualization, Time Series Forecasting and Applied Statistics.

Ahmad Fadzli Nizam Abdul Rahman is currently a Senior Lecturer in Department of Intelligent Computing & Analytics (ICA), Fakulti Teknologi Maklumat dan Komunikasi (FTMK). He received his MSc in Information Technology from Universiti Teknologi MARA (UiTM), Shah Alam, Selangor and his degree is in Bachelor of Applied Science (Computer Modeling) from Universiti Sains Malaysia (USM), Pulau Pinang. He has joined OptiMAS research lab since 2013 and his research interests, including Modeling and Simulation, Analytics, AI and Image Processing.

Zaheera Zainal Abidin received Bachelor of Information Technology from University of Canberra, Australia in 2002. She joined ExxonMobil Kuala Lumpur Regional Center as a Project Analyst in 2000-2001. She completed her MSc. In Quantitative Sciences (2004), MSc. in Computer Networking (2008) and PhD in I.T. and Quantitative Sciences (2016) from Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Selangor. She served as a lecturer at Universiti Kuala Lumpur (2005-2009) and senior lecturer & researcher in Universiti Teknikal Malaysia Melaka (2009 – present). She is a member of Information Security, Forensics and Networking (INSFORNET) research group. She is one of the certified CISCO Academy (CCNA) in computer networking field and certified Internet-of-Things specialists. Research interest in Internet-of-Things, biometrics, network security and image processing.