Industry 4.0 Gap Analysis for Thai Industries with Association Rules mining

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Abstract

Industry 4.0 is an emerging term that has drawn great attention the past few years. It consists of variety of technologies including internet of things, cloud computing, sensor, mobile devices, big data. The goal of industry 4.0 is to incorporate these technologies to create the factories that are highly efficient and highly adaptive to meet organizational goals. The adoption of this concepts has been reported worldwide in various name such as "Industrial Internet of Things" in the US or "the Made in China 2025 initiative" in China. However, there is no publication of the current situation of the adoption in Thailand. This paper presents a survey of current adoption of the concept of industry 4.0 in Thai industries in the attempt to identify the gap between the current situation and the ideal situation that the industries want to position themselves. The survey was conducted using questionnaires with 50 factories located throughout Thailand and across many sectors. The results were analyzed using association rule mining techniques. It was founded that industry 4.0 technologies that has highest percentage of implementation at presents are mobile devices and sensor technologies but still there are gaps of need for both technologies. The technology that has not yet implemented but has highest need is big data technology. The overall results suggested that, at the moment, it was not found the evident that Thai industries have explicit plan to transform their organization with respect to industry 4.0 concept.

Keywords (12 font)
Industry 4.0, Association rules, Data mining, Thai industry survey

1. Introduction

Industry 4.0, a term develop in German, has been regarded as the next generation of industry (Lee, Bagheri, & Kao, 2015). It is also known in other synonyms such as Smart Manufacturing, Smart Production or Internet of Things (Kamble, Gunasekaran, & Gawankar, 2018). Industry 4.0 refers to the collection of current concepts for example smart factory, cyber-physical systems, self-organization, and corporate social responsibility (Heiner & Kemper, 2014). It focused on creating intelligent factory that increase manufacturing flexibility in the same time mass customized, improved quality and productivity. Factory should be able to monitor physical processes and make smart decision real-time (Zhong, Xu, Klotz, & Newman, 2017).

The adoption of this concept have been reported world-wide. In German, industry 4.0 plan was launched in 2013 in which factory occupied by intelligent machines and products are able to communicate with each other autonomously. In The United States, the Industrial Internet Consortium (IIC) was founded in 2014 with the support of GE, AT&T, Cisco, Intel and IBM to provide resources and ideas on the Industrial internet of Things (IIoT). In China, the Made in China 2025 initiatives was set up by the Ministry of Industry and Information Technology (Zhong et al., 2017). In Korea, the term the fourth industrial revolution is more widely accepted by Korean government and numbers of initiatives has been setup (Sung, 2018). However, there has been no report on the current adoption in Thailand.

This research is a part of MSIE-CBHE project or the Erasmus+ Curriculum Development of Master's Degree Program in Industrial Engineering for Thailand Sustainable Smart Industry -MSIE4.0 project funded by the European Commission (project number 586137-EPP-I-2017-I-TH-EPPKA2-CBHE-JP). The objective of the project is to design a master's degree program that prepare Thai student to have adequate skill in the context of industry 4.0. The project is the association of 6 universities in Thailand including Asian Institute of Tech ology, Chiang Mai University, Khon Kaen University, Princes of Songkla University, King Mongkut's University of Technology North, and Thammasat University and 3 EU university which consist of University of Minho from Portugal, Częstochowa University of Technology from Poland and University Politehnica of Bucharest from Romania.

The first phase of this research is to identify the current status and the ideal status of industry 4.0 adoption in Thailand through extensive survey with questionnaires. The questionnaire consisted of 3 parts. The first part is regarding company basic information such as company name, industry type, workforces, revenues. The second part is called the "strategy level" where strategy of companies regarding industry 4.0 is assessed. This includes the current technology adopted and long term plan in both 2 and 5 years. The third part is the "adoption level". In this part the concept of industry 4.0 in operation level is assessed in four main areas; smart product, smart factory, smart operation, and data driven services. 50 questionnaires were collected with the help of Thai university partners in the project and has been responded by manager level. Graphs and charts were used to summaries basic information, but there are needs for more advance analytic techniques in order to study relationship among variables in individual level.

Association rule mining is a data mining technique that uncovers relationships among variables. A common use of association rules is market basket analysis, in which items that customers buy are analyzed for their associations with or likelihood of buying other products. There are several publications of the application of this technique to questionnaire data (Chalaris, Chalaris, Skourlas, & Tsolakidis, 2013; Chen & Weng, 2009; Yamananishi & Li, 2002) which confirms the applicability of the method.

This paper therefore aims of applying association rule mining technique to analyze industry questionnaire regarding industry 4.0 adoption in the 4 domains of smart product, smart factory, smart operations and data driven service in order to study relationships between actual status and ideal station of Thai industries. The rest of the paper is organized as follows, the next section is the findings of questionnaire using basic descriptive statistics. Section 3 describes how to set up each of the 4 association rules mining models. Section 4 provides results and discussion of the rules obtained and the final part is the conclusion.

2. Literature review

Several recent literatures report the survey based on literature regarding industry 4.0. Lu (2017) conducted a survey in 2017 on 88 papers. It was founded that Industry 4.0 have been defined from scholars in diverse perspective. It is expected that cyber-physical systems (CPS) offer promising solutions to transform industrial operational system. key industry 4.0 technologies include mobile computing, could computing, big data, and the IoT. Other than these technologies, industrial techniques used are business process management (BPM), workflow management (WM), enterprise application integration (EAI), service-oriented architecture (SOA), grid computing, enterprise resource planning (ERP), and supply chain management (SCM). Applications of industry 4.0 reported in literature are smart factory and manufacturing, smart product, and smart city.

In the same year, Liao, Deschamps, Loures, and Ramos (2017) conducted a literature survey to summarize the current research activities and indicate existing deficiencies and potential research directions. 224 papers were included in this survey. It was founded that paper regarding industry 4.0 have been reported the most in Europe and there have been dramatic increase in number of publications in 2015. Technology often referring to are for example Ethernet, internet protocol (IP), radio frequency identification (RFID), machine-to-machine (M2M).

While most of the survey on industry 4.0 were conducted purely by literature review, Mittal, Khan, Romero, and Wuest (2018) combine both literature result with some SME manufacturing cases from different countries. Nine dimensions including strategy, leadership, customers, products, operations, cultures, people, government and technology were used to compute industry 4.0 maturity index.

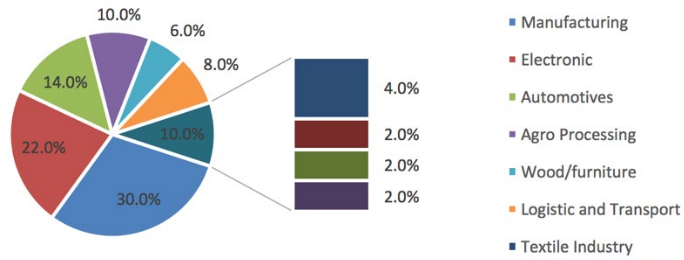
Even though some surveys are available, most of them are literature based. There have been no reports on extensive survey that collect actual status of industry adoption. This paper attempts to fill this gap by conducting questionnaire survey from 50 companies in Thailand. The results and key findings can be found in the next section.

3. Results from industry 4.0 assessment questionnaire

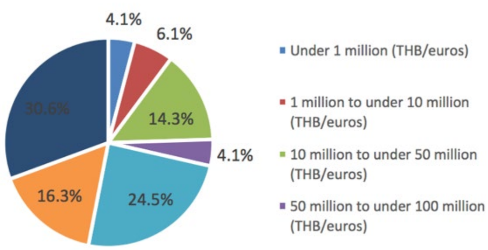
Industry 4.0 questionnaire consists of 3 parts which are basic information, strategy level and adoption level. Some interesting findings for each parts are as follows;

3.1 Basic information

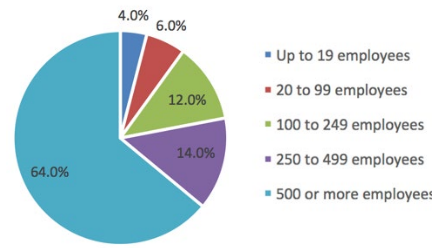
50 questionnaires were collected from Thai companies. Figure 1 shows the sample distribution of the 50 Thai companies across different sectors.



a) Industry type



b) 2017 revenue



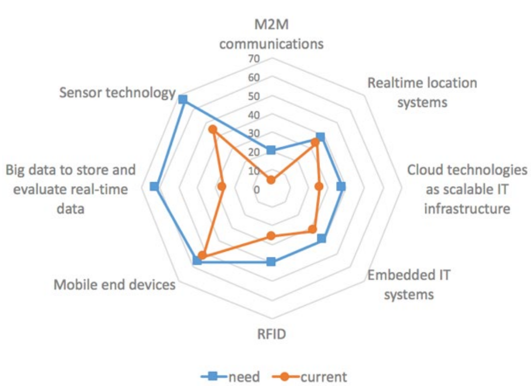
c) Domestic workforce

Figure 1: Basic information of respondent companies

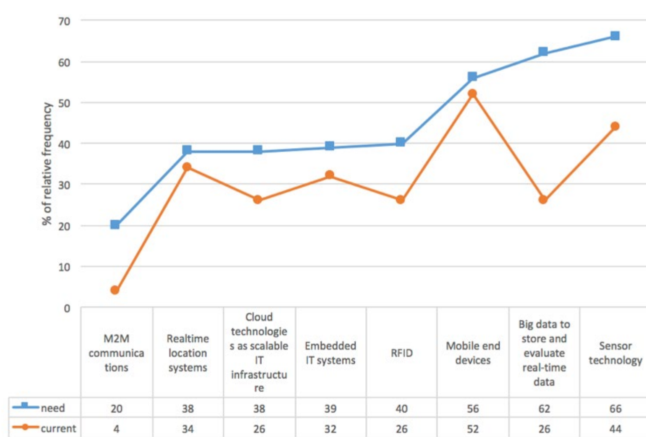
Figure 1a) shows industry type. The top 3 industry type are Manufacturing, Electronic and automotive with 31.9%, 18.8% and 15.9% respectively. Figure 1 b) and c) shows companies' revenue and domestic workforce which suggested that most of the companies are classified in to 'large' scale.

3.2 Strategy level

At strategy level, which are sensor technology, mobile and devices, embedded IT systems, realtime location systems, RFID, Big data, cloud technology and M2M communications were studied in order to compare the gap of these technologies between actual status and ideal (need) status. Strategic gap regarding technologies in industry 4.0 is shown in Figure 2. Top 3 Industry 4.0 technologies that are currently implemented are mobile devices, sensor technology, and realtime location systems, while top 3 technologies need are sensor technology, big data and mobile devices.



b) Radar chart



a) Line chart

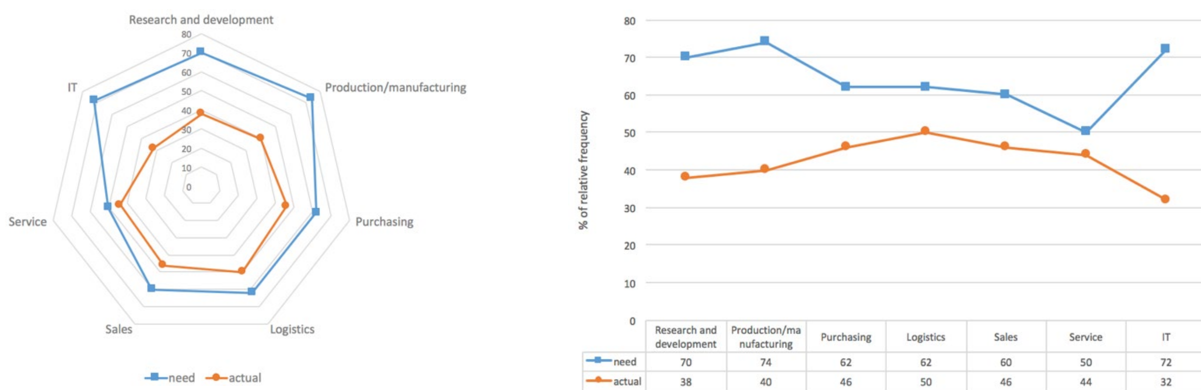
Figure 2: Industry 4.0 strategic gap regarding technologies

Figure 2a) shows the technologies gap in the form of radar chart. The orange line with circle marker indicates current status of industry while the blue line with square marker indicates the ideal status. As can be seen, the area of current status is much smaller and completely inside the area of ideal status which indicates that right now all companies are operate at less than ideal situation in all technologies. Figure 2b) is a plot between the average value of “Actual need of industry” and “ideal of industry 4.0” where the orange circle marker represents current status and the blue square marker represents ideal status. Gap of each technology can be seen from the vertical distance between the square marker and the circle marker. Biggest gap of technology is in big data (36%), sensor technology (22%) and then M2M communication (16%). Not only does big data technology has the biggest gap, but it also has the second highest need comparing to other technologies. Sensor technology although has highest need, but the gap is much smaller as the current status of sensor technology is more advance than big data. M2M is another technology worth mentioning. Although the need for M2M is not very high but the current status is relatively low, which results in large technology gap.

3.3 Adoption level

The gap in adoption level is analyzed in order to answer which department among these 7 functions; research and development, production/manufacturing, purchasing, logistics, sales, service and IT; has highest gap in industry 4.0 adoption. Answer to question “In which part of your company have you invested in the implementation of industry 4.0 in the past 5 year?” in strategy level was used to represent the ideal status The answer to this question can be large, medium, small or none. The percentage of companies that answer large and medium were sum together and used to represent the ideal status. For example, in overall, for research and development in the next 5 years, 27.8% of companies answer large and 36.1% of companies answer medium, therefore, the ideal status of research and development is 63.9%.

the answer to question “have you integrated cross-departmental information sharing into your system externally with customers and/or suppliers?” in adoption was used to represent current status. The answer to this question can be either yes or no. The percentage of companies that answer yes to sharing data externally with customers and/or suppliers was used to represent the current status. Figure 3 show adoption gap in industry 4.0 regarding organizational function.



a) Radar chart

b) Line chart

Figure 3: Industry 4.0 adoption gap regarding organizational function

Similar to the technological results present in figure 2, departmental adoption in figure 3a) shows smaller area of actual status which is completely inside the area of ideal status which suggests the existing of gap between the two and also suggests that all departments are operate at less than ideal situation that they need to be. Figure 3b) shows that there is high need for industry 4.0 in most of the departments. The only department that has relatively low need comparing to other department is service which account for 50%. Large gap occurred in IT, production and manufacturing, and research and development at 40%, 34% and 32% respectively.

4. Association rule mining models

In this research, association rule mining is used to analyze industrial questionnaire answers in order to identify the relationship between the “actual need of industry” or the current status of industry and “Ideal of industry 4.0” or where the company wants to be regarding the concept of industry 4.0. 4 models were construed as shown in Table 1. This table provide details of each model setting including its description, the country of data used for model construction, list of questions used to represent both actual status and ideal need.

Table 1: Details of model developed to assess the gap between actual need and ideal of industry 4.0

model	description	Questions used to represent actual status	Questions used to represent ideal need
1	Model of relationship between current technology and ideal need of technology	Which technologies do you currently using in your company?	Which technologies do you need in your company to enhance business competitiveness?
2	Model of current smart factory and technology need	• How would you evaluate our equipment infrastructure when it comes to the following functionalities? • Are you ready collecting machine and process data during production? • Which data about your machinery, processes, and products is collected during production? • Which of the following systems do you use? (answers such as MES, ERP, PDM etc.)	Which technologies do you need in your company to enhance business competitiveness?
3	Model of current smart operation and technology need	• Where have you integrated cross-departmental information sharing into your system? (answers such as R&D, production, purchasing etc.) • Dose your company uses self-guided workpiece in production? • Does your production process response realtime? • How far along are you with your IT security solutions?	Which technologies do you need in your company to enhance business competitiveness?

The methodology of association rule mining used in this research is as follows

4.1 Relevance questions regarding to actual status and ideal need of industry were identified as shown in Table1.

4.2 Answers to the question selected in step 4.1 were converted into "true" and "false" since association rule only takes bi-nominal inputs. For example, the answer to question "Which technologies do you need in your company to enhance business competitiveness?" can be the selection of one or more of these technologies; sensor, mobile devices, RFID, realtime location systems, big data, cloud, embedded IT and M2M communications. These technologies were transformed into column headers and if the company select that technology the value in that column would be "true" otherwise the value becomes "false". Example of data set is shown in Table 2.

4.3 FP-growth algorithm was applied to identify "frequent itemset". Frequent item set is the item that occurred in that databased at the frequency more than a threshold value called "minimum support". For example, if minimum support was set at 0.5, in order for RFID to be in frequent set at least 50% of the company must have selected RFID technology.

4.4 Frequent itemset identified in step 3.3 was used to create association rule. "Strong rule" will be select for interpretation and in order for the rule to be selected as strong it has to pass minimum confidence threshold.

4.5 Graph for strong rules were created to help for visualization and interpretation of the result.

Table 2: Example of data prepared in the format for association rule mining

Row No.	THAI	Need_RFID	Need_M2M	Need_Sensor	Need_BigData	Need_mobile
1	1	true	false	false	false	false
2	69	false	false	true	true	true
3	4	false	false	false	true	false
4	5	false	false	true	false	false
5	6	false	false	true	false	false
6	7	false	false	true	false	false
7	8	false	false	false	true	false
8	9	false	false	false	false	true
9	10	true	false	true	true	true
10	11	false	false	true	false	false
11	12	true	false	true	false	true
12	13	true	false	true	false	false

5. Association rule mining results and discussion

5.1 Model 1: relationship between current technology and ideal need of technology

This model results in 10 strong rules with the setting of minimum support = 0.4 and minimum confidence = 0.6. There rules can be represented as graph as shown in Figure 4.

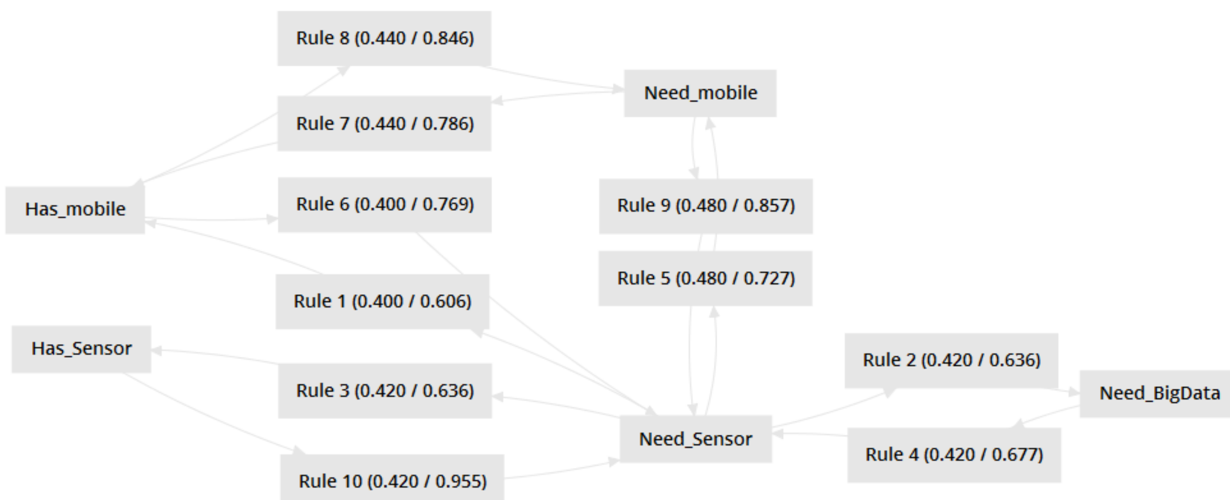


Figure 4: Graph of association rules obtained from model 1

As can be seen from Figure 4, the technology that Thai industry already have is the mobile devices and sensor technology. Among several domains of technologies that are adopted by Thai industries, we also found that mobile and sensor has been used concurrently together most often. There are strong links between the companies who already obtained those technologies with the need of both technologies. There also a strong link between the company who need sensor with the need of Big data technology. This relationship is essentially true as sensor helps in gathering lots of data and Big data is a technology to analyze them.

5.2 Model 2: current smart factory and technology need

Model 2 is used to study the current status regarding the implementation of smart factory concept in Thai industry with respect to the need of industry 4.0 technology in the future. 23 factors were identified from those 4 questions for example is M2M technology is currently in use, is inventory data collected manually or automatically, is MES (manufacturing execution system) currently in used. Similar to other model, answers from each questions were mapped into "true" and "false". For example, if MES is in use that would be code to "true" otherwise would be "false".

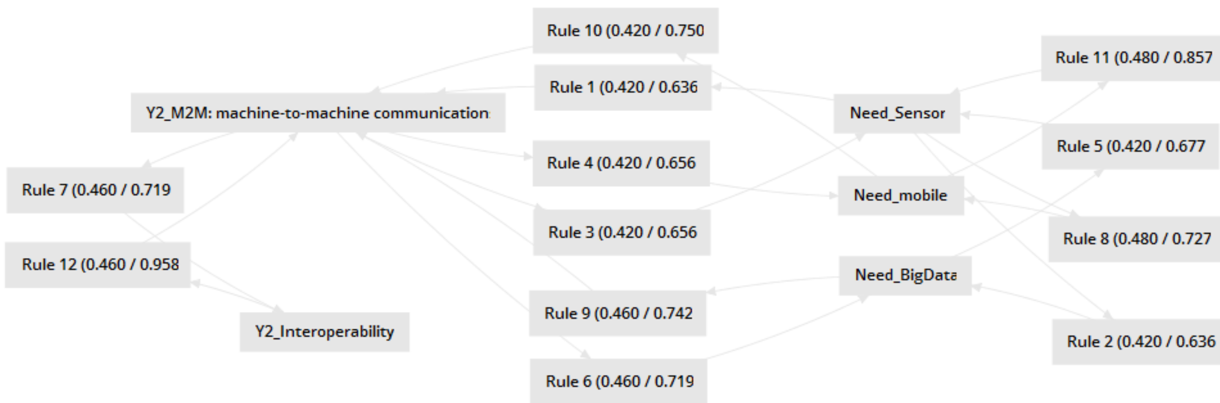


Figure 5: Graph of association rules obtained from model 2

Association rules graph in Figure 5 shows that smart factory features adopted in most Thai factory is M2M and Interoperability. M2M has links to the need of sensor, mobile device and big data. Mobile device technology could be used to report M2M status while big data could be used to analyze machine data for realtime solving machine problems.

5.3 Model 3: current smart operation and technology need

This model is used to study the relationship between status of smart operation in Thailand and technology needed to execute them. Frequent itemset shows that the factors that pass minimum support of 0.5 for the current status of smart operation are the sharing externally of finance data, research and development data, production data, service data, sales and purchasing data and also workpiece guides system. Factor representing technology need that are significant are the need of sensor, mobile devices, and big data technology. However, as shown in Figure 6, it does not seem to have any link between current smart operation status to the need of industry 4.0 Technology.

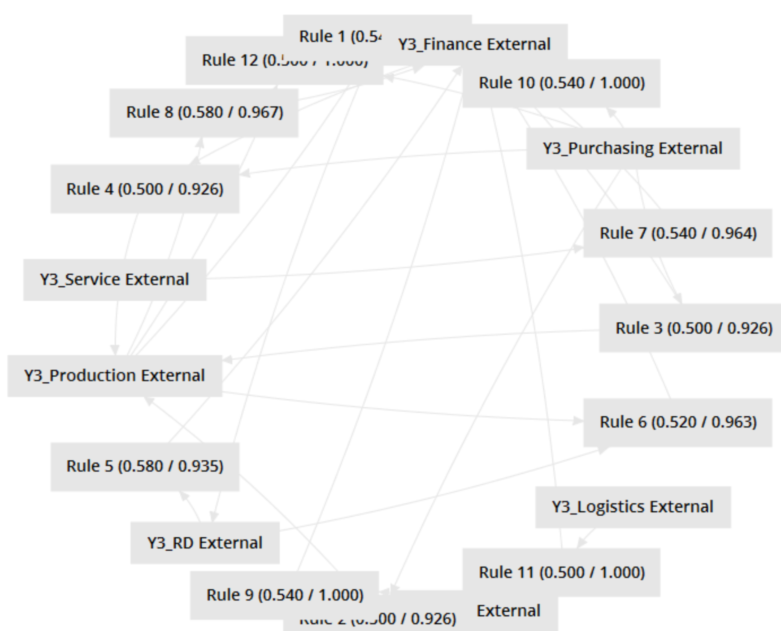


Figure 6: Graph of association rules obtained from model 3

Figure 6 shows links between features of smart operations concepts. Most of the links are highly correlated between data collected and shared cross-enterprise (externally). For example, there are connections between production and research and development data, purchasing and production data, sales and finance data, purchasing and finance data.

Table 3 lists 10 rules extracted from the total of 18 rules extracted from model 3. Association rules use "if/then" statements to uncover relationships in data. The premises column in Table 3 is the "if" part, while the conclusion column is the "then" part. Support is the probability that both premises and conclusion are found together in the database. Confidence measures how often the rule has been found to be true. For example, rule number 3 (RD external ⇒ Production external) showed support of 0.54 and confidence of 0.871; this means that in 54% of company who select both sharing R&D data externally and sharing production data externally, and 87.1% of companies that select sharing R&D data externally also select sharing production data externally.

Table 3: Association rules from model 3.

No.	Premises	Conclusion	Support	Confidence
1	Y3_Finance External, Y3_Production External	Y3_Purchasing External	0.500	0.862
2	Y3_Production External	Y3_Finance External, Y3_RD External	0.520	0.867
3	Y3_RD External	Y3_Production External	0.540	0.871
4	Y3_Service External	Y3_RD External	0.500	0.893
5	Y3_Finance External, Y3_RD External	Y3_Production External	0.520	0.897
6	Y3_Finance External, Y3_Production External	Y3_RD External	0.520	0.897
7	Y3_Production External	Y3_RD External	0.540	0.900
8	Y3_Purchasing External	Y3_Production External	0.500	0.926
9	Y3_Purchasing External	Y3_Finance External, Y3_Production External	0.500	0.926
10	Y3_Finance External, Y3_Purchasing External	Y3_Production External	0.500	0.926

Table 3 shows highly correlation among data sharing externally. For example, R&D and production data are related together (rule 3, and rule 7), purchasing data are correlated with production data (rule 8) and service data are correlated with R&D data (rule 3).

6. Conclusion

This paper presents the analysis of survey result from the questionnaire of 50 Thai large scale companies regarding to the adoption of industry 4.0 concept. The results suggested that most Thai companies are operating at less than ideal status. Biggest gaps in terms of technologies are founded to be Big data, M2M and sensor technology. Currently, less than half of the companies surveyed applied some of the industry 4.0 concept in their operational function especially sales, logistics and purchasing. However, ideally they would like to increase their adoption in all the fuctions. The functions that shows the biggest gap are IT, production, and R&D.

The results from association rules mining reveal that for Thai industry, in strategy level, technologies that Thai companies already have are mobile devices and sensor. These technologies have direct links to their need, for example. the company who has mobile device technology also express need for that technology. Most Thai industry does not have big data technology yet but there is a strong link of those who already need and have sensor technology to the need of big data in the future. Big data can be identified as a gap for Thai Industry that need to be fulfilled.

For the adoption level, For Thai companies regarding the concept of smart factory, the technologies already implemented are M2M and interoperability. M2M communication has link to sensor, mobile device and big data. The link between M2M and sensor is obvious since sensor is one of the most important parts in order for M2M to work. Mobile device helps to access M2M data anywhere and big data helps to analyze M2M data.

For the concept of smart operation, the results suggested that for Thai and EU data are stored and used externally and they are highly co-related. There is no link to technology need on the Thai side but there are link from current smart operation data to the big data technology. For data driven service aspects, only frequent itemset can but found but no rules between them.

To sum up there are certain gaps between current status of companies to the concept of industry 4.0, both in strategy level and adoption level. Once the gaps have been identified, there is immediate need for the design of new industrial engineering curriculum that incorporate those need in to the design in order to prepare workforce with the right skill that are able to work efficiently regarding to industry 40 concept.

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Biographies

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