sciendo

PRODUCTION ENGINEERING ARCHIVES 2021, 27(1), 50-57

PRODUCTION ENGINEERING ARCHIVES

ISSN 2353-5156 (print)
ISSN 2353-7779 (online)

Exist since 4th quarter 2013
Available online at https://pea-journal.eu

A Gap Study between Employers' Expectations in Thailand and Current Competence of Master's Degree Students in Industrial Engineering under Industry 4.0

Sirorat Pattanapairoj[1], Krisanarach Nitisiri[1], Kanchana Sethanan[2]

[1] Department of Industrial Engineering, Faculty of Engineering, Khon Kaen University, Thailand,
[2] Research unit on System Modelling for Industry, Faculty of Engineering, Khon Kaen University, Thailand,
Corresponding author e-mail: krisni@kku.ac.th

Article history
Received 07.01.2021
Accepted 01.03.2021
Available online 31.03.2021

Keywords
Industry 4.0
Gap study
Engineering Education
MSIE curriculum

Abstract
Industry 4.0 is an era in which the manufacturing industry has adopted digital technologies and the Internet to enable smart manufacturing system, machines used in the production now can communicate with each other and exchange information between each other, and the machinery used in the manufacturing process is more modern and precise. Therefore, educational institutions should develop the curriculum to produce qualified graduates with the knowledge required for the Industry 4.0 era, especially Industrial Engineering graduates who are directly related to the industry sector. The purpose of this research is to collect the data for the Master of Industrial Engineering (MSIE) curriculum development. The Analytic Hierarchy Process (AHP) technique is used to rank the indicators of knowledge that is important to the employment of graduates with a master's degree in Industrial Engineering, and study the gap between the expectations of employers and the ability of the current MSIE students of Khon Kaen University. The results of the study reveal that the first indicators that are most important to the employment of MSIE graduates is the knowledge of Industry 4.0 strategy and the knowledge that the students should have developed are the collaboration of humans and robots, big data analytics, real time data usage and databased decision making.

DOI: 10.30657/pea.2021.27.7

JEL: L23, M11

1. Introduction

Nowadays, manufacturing companies around the world have entered the 4th industrial revolution, so called Industry 4.0 era, which is the digital transformation of the manufacturing and related industries primarily focuses on the use of large-scale machine to machine communication (M2M) and Internet of Things (IoT) deployments to increase automation, communication and self-monitoring, including intelligent machines that can provide big data for analyzing and diagnosing problems with little human intervention (Bonekamp and Sure, 2015).

In Thailand, the 12th National Economic and Social Development plan is being used for Thailand's 20 years industrial development, started from 2017 to 2036. The plan mainly focuses on becoming a stable and sustainable industry by transforming the machine dominant manufacturing to the digital manufacturing. However, this change needs cooperation from many related sectors, including the government, private sector, and educational institutions, especially in Industrial Engineering (IE) education, which is directly relevant to various industries in Thailand.

Industrial engineering is an engineering profession that is concerned with the optimization of complex processes and systems by developing, improving and implementing integrated systems of people, money, knowledge, information, equipment, energy, materials, as well as the mathematical, physical and social sciences together with the principles and methods of engineering design to specify, predict, and evaluate the results to be obtained from such systems or processes (Kádárová et al., 2014). Industrial engineers use mentioned integrated systems combined with modern technology to help the companies create products or services efficiently. Moreover, master's degree of industrial engineers (MSIE) will play a major role in solving complex problems with the perfect combination of using industrial engineering knowledge and advanced applied technology.

Since the Industry 4.0 has become a pioneer in Information Technology (IT) industry which is revolutionizing manufacturing engineering, many countries around the world have begun to adjust their industrial infrastructure to meet the requirements of the Industry 4.0 policy. An important part of preparation for Industry 4.0 is the adaptation of higher education to meet the needs of this policy, especially the higher education in industrial engineering (Coşkun et al., 2019). Our ultimate objective of this study is to develop the curriculum for the MSIE at Khon Kaen University (KKU) in Thailand to produce a qualified master's degree graduates and conform the needs of the industrial sector in the Industrial 4.0 era.

Having ability to create qualified graduates with the Industry 4.0 requirement skills, the gap between the expectation of Industry 4.0 and the ability of the current student must be discovered. This research applied the dimensions that have been used to assess the readiness of Industry 4.0 as a cognitive dimension that influences the employment of MSIE graduates in Industry 4.0 era. Since there are several indicators in each cognitive dimension, the thirteen experts from thirteen different industries will determine the indicators which affected to the consideration of MSIE job hiring by using a 5-level (1 to 5) measurement of the Likert Scale. The indicators with the highest score were used to prioritize by the Analytic Hierarchy Process (AHP) method and then continue to the gap analysis phase. The gap analysis between the expectation of Industry and the ability of the current MSIE KKU will be used to improve the master's degree of Industrial Engineering curriculum for KKU in 2022.

2. Literature review

Since 2015, many researchers have studied about the dimensions which used to evaluate the Industry 4.0 readiness for the manufacturing companies such as Leyh et al., (2016) McKinsey (2016), Schumacher et al. (2016), Chouhan et al. (2017), Horvat et al. (2018), Machado et al. (2019), Nick et al. (2019) and Schumacher et al. (2019). The indicator of knowledge, which is the most important to considerate the MSIE employment will prioritize using Analytic Hierarchy Process (AHP) techniques. Thus, this section reviews several previous studies on AHP technique and gap analysis applications as follows:

2.1. Analytic Hierarchy Process (AHP) techniques

AHP techniques includes three key principles which are hierarchy framework, priority analysis and consistency verification. AHP were applied in Multi Criteria Decision Making (MCDM) problem and found effective in evaluation of the alternatives in order to select a suitable team reader based on four criteria which are personality type, academic achievement, team work experience, and previous programming grade (Muhsin et al., 2015). Including to the evaluation and selection of suppliers using the specific measures in the automotive industry, an integrated Balanced Scorecard-Fuzzy Analytic Hierarchy Process (BSC-FAHP) model was proposed to select the best suppliers (Galankashi et al., 2016). Also, in marketing, AHP was employed to identify the right strategy marketing plan for Ghavamin Bank. Determining the priority of various factors considered by managers which consists of: economic factors, competition with customers and prospects, and future plans. Thus, those finding factors should be prioritized in the strategy marketing plan (Sadeghpour et al., 2017). Abdel-Basset et al. (2018) studied an extension of AHP for strategic planning and decision-making under a neutrosophic environment, the AHP is able to estimate both qualitative and the qualitative elements by weighting and ranking. SWOT analysis and the AHP technique were integrated, called Neutrosophic AHP-SWOT Analysis presented to achieve the strategy planning and decision making in real case study of Starbucks Company.

Since Industry 4.0 initiatives influence whole business system including to Indian manufacturing industry. AHP technique was also employed to prioritize the recognized key challenges to Industry 4.0 initiatives and the identified key challenges for effective Industry 4.0 concepts for supply chain sustainability in emerging economies. Results of the study showed that the highest four importance are Organizational challenges, Technological challenges, Strategic challenges, and Legal and ethical issues, respectively (Luthra et al., 2018).

Not only industry and business, but AHP also applied to education sector. Creating engineering or professional students skilled and employable for industries is important mission for any education institute. Thus, a need of proper understanding between student, teacher and industry with respect to various skills and making them consider of various engineering, professional and management practices and methodologies must be discovered. That is why AHP has been used to identify common perspective on expectations of student, teacher and industry (Pawar et al., 2019). Putting right men on right job is one of the employee selections. It is a process of matching organizational requirements with the employee's skills and qualifications. Petruni et al., (2019) implemented AHP to support the evaluation and the choice of a suitable Human Reliability Analysis (HRA) technique selection by providing a way of assisting safety managers and risk assessors in selecting the right methodologies for their job and therefore improving the level of safety within their organization. AHP allows the selected HRA techniques to be evaluated based on relevant criteria for an automotive manufacturing environment application. These prove that AHP has been preferable tool for Multi Criteria Decision Making.

2.2. Gap Analysis

A gap analysis is comparison process of actual (current) performance with expected or desired (future) performance. Lee et al., (2016) proposed the service quality evaluation from the perspectives of customers, service providers, and managers by using gap analysis for Taiwanese hotel industry. The service quality could be clearly measured through gap analysis which is more effective for introducing direction in developing and improving service quality. Recently, Industry 4.0 is an issue of the current discussing among manufacturing leaders, industrial practitioners, policy makers and researchers. There are many successful studies applying gap analysis tool to find the gap skills amongst expectations of industry and higher education students' ability in the context of Industry 4.0. Therefore, investigating the gap between the expectation of Industry 4.0 employers and the ability of the current MSIE KKU student is the highly important to improve the curricula.

Dumitrescu et al. (2019) presented a gap analysis for determining the gap between the required and the actual competences of students from two universities in Romania. The analysis results showed various areas of Master programmes' curricula in industrial engineering that need to be revisied. Pinzone et al., (2017) studied in the technical skills evolution under Industry 4.0 era. This provided qualitative insights gained from an on-going collaborative research project involving a various manufacturing stakeholders in Northern Italy (e.g., manufacturing companies, industrial associations, academic and education experts, recruiting companies, IT providers, consultants, etc.) with first indications to discover skill gaps and initiate capability development. Furthermore, there were several previous applications on gap analysis in academic field. Since higher education institutions are more attentive in improving decision-making tools. Those allow them to estimate the industry expectations and perceptions of engineering graduates' skill with the aim of attracting and keeping them satisfied. Ramadi et al. (2016) found the skills that graduates needed most four improvements include communication, time management, and continuous learning. By applying gap analysis to discover the gaps between industry expectations and perceptions of engineering graduates' skill sets in the Middle East and North Africa (MENA) region. Those skill gaps calculated from importance and satisfaction levels for each skill. In the same period, Pimentel et al. (2016) studied a gap analysis among employers and engineering versus non-engineering students. This aims to identify the main gaps between competencies provided by the traditional education system and the missing competencies provided by the employers. Results of the study found that the employers expect higher level of personal competencies than the students thought they have.

Skills gap is defined as the difference between the demand and the current supplies. In this context, students should be aware of the needs and relate their abilities to be able them to meet their future employers' requirements. Patacsil and Tablatin (2017) demonstrated the skills gap methodology, which was applied the respondent experiences in the internship program to measure the importance of the IT skills gap as perceived by IT students and the industry. The questionnaires were formulated, modified, validated, and tested. The IT students enrolled in internship were respondents of the study while industry partner respondents were the internship supervisors of the IT students. In this case, the internship IT students were selected because of they have a strong record on the company requirements based on their experience. Then, affirm that teamwork and communication skills are extremely important soft skills. However, there was a big range of conflict on the hard skills since IT students understood that hard skills were essential while industry understood that hard skills were somehow important. Thus, education institute should promote the soft skills and hard skills component into the curriculum.

3. Methodology

3.1. Selection of Indicators

This study selected the cognitive indicators that affected the consideration of MSIE's employment using a mixed qualitative and quantitative research method. For the qualitative research, all dimensions and indicators were analysed from the literature review using content analysis and inductive analysis. For the quantitative research, the questionnaire was used as a tool to weight the significance of the metrics affecting the consideration of MSIE's employment by 1-5 rating scale, where:

1. refers to indicators that do not affect the employment considerations,
2. refers to indicators that have little effect on the consideration of employment,
3. refers to indicators that have moderate effect on the consideration of employment,
4. refers to indicators that have a large effect on the consideration of employment,
5. refers to indicators that have most effect on the consideration of employment.

The data were collected from 13 experts of from difference industries in Thailand: 1) sugar industry 2) logistics industry 3) plastics industry 4) electronic industry 5) apparel industry 6) automotive industry 7) beverage industry 8) hard disk drive industry 9) furniture industry 10) consumer electronics industry 11) textile industry 12) packaging industry and 13) food industry.

3.2. Indicator Priority Analysis by AHP

The indicators obtained from Section 3.1, which ranked in the first quartile and had average score is between 4.21 to 5.00 points, were prioritized by the AHP method before entering the gap analysis phase. AHP was invented in the late 1970s by Professor Thomas Saaty of the University of Pennsylvania. It is the method to that convert abstract thoughts and feelings into concrete measurement scale by using the weight values in the form of numbers. AHP is a widely popular method for solving MCDM problem decisions and providing accurate decision-making results to match the goal of the decision. The highlights of AHP are as follows: 1) the decision factor comparison performs a pair of comparisons to reduce the confusion of respondents and the consistency of the data throughout the error prevention analysis 2) AHP can measure the attributes and decision results in the priority diagram 3) AHP has a hierarchical structure diagram, which imitate the human thinking process, making it easier to use and understand 4) The result is a number volume, making it easy to rank the importance and can also compare the results (benchmarking) with other agencies.

Table 1. An exsample of pair-wise comparison matrix of 5 indicators

Criterias		Indicators				
		A_1	A_2	A_3	A_4	A_5
Indicators	A_1	1	a_{12}	a_{13}	a_{14}	a_{15}
	A_2	$1/a_{12}$	1	a_{23}	a_{24}	a_{25}
	A_3	$1/a_{13}$	$1/a_{23}$	1	a_{34}	a_{35}
	A_4	$1/a_{14}$	$1/a_{24}$	$1/a_{34}$	1	a_{45}
	A_5	$1/a_{15}$	$1/a_{25}$	$1/a_{35}$	$1/a_{45}$	1

Where a_{ji} is member of row i and column j in the matrix and refers to the importance comparison between the A_i and A_j indicator. In this study, there are 10 indicators. The value of A_{ji} is equal $1/a_{ij}$ while a_{ij} is not equal 0. The points of pairwise comparison are provided in Table 2.

However, AHP can lead to the inconsistency of comparison, importance, and pairwise comparison. So, it is important to check the consistency of the rating scoring between factors throughout the process. Therefore, using AHP with many alternative decisions may make it difficult to determine the consistency of the decision results. In this study, the analysis hierarchy process consists of the following steps:

1. Set the goals and the criteria for making decisions.
2. Structuring the hierarchy of decisions.
3. Consider comparing the priority of the criteria by pairwise comparison. This step is to compare the indicators affecting decision factors by expressing in the form of a scale of satisfaction level. The numbers of 1-9 were used as the quantify preference scale while performing pairwise comparison as shown in Table 1.
4. Normalized score values in each column of matrix.
5. Compute the eigenvector of each row.
6. Compute the consistency index (*C.I.*) using

$$C.I. = \frac{\text{Maximum Eigenvalue} - n}{n-1} \quad (1)$$

Compute the Consistency Ratio (*C.R.*) using

$$C.R. = \frac{C.I}{R.I.} \quad (2)$$

where $R.I.$ is the random consistency index.

The calculated $C.R.$ must be less than 0.10 to be considered acceptable. If the $C.I.$ value is less than 0.10, the rating scoring on each indicator is consistent. Eigenvector can be used as a weight of the importance of indicators. If the calculated $C.R.$ is greater than 0.10, the comparative weighting must be reviewed until an acceptable $C.R.$ is obtained.

1. Prioritize indicators by sorting an eigenvector.

Table 2. Scale of relative importance used in pairwise comparisons for AHP

Point	Description	Imply
1	Equally important	Both factors are equally important
3	Weakly important	The considered factor is slightly more important than the other
5	Essentially important	The considered factor is more important than another at a moderate level
7	Very strongly important	The considered factor is significantly more important than the other
9	Absolutely important	The considered factor is more important than the other at the most

Note: 2, 4, 6, and 8 are intermediate.

3.3. Gap analysis

The indicators from Section 3.2 were used for creating a questionnaire to collect the results from the MSIE KKU students and the respondents who work in industries. The questionnaire details for the industries were about the expectation skills of the MSIE graduates under Thailand Industry 4.0 policy. The questionnaire details for the MSIE KKU students were about their current ability in each skill. The respondents from both groups could answer the question by rating a score of 1-5 for each question, where 1 is the lowest level and 5 is the highest level. The range of the answers is equal to 5 - 1 or equal 4, and the distance of the criteria used to define the perceived level score range at each level is 4/5 or 0.80. Therefore, the average score range for data level interpretation can be specified as follows:

The lowest level has average score collected from the questionnaire between 1.00-1.80. Between 1.81-2.60 for low level, between 2.61-3.40 for middle level, between 3.41-4.20, for a high level, and between 4.21-5.00 for the highest level. Then, the gap analysis can be done by considering the difference between the average scores from the first sample group and the second sample group.

4. Results and discussion

4.1. The compilation of indicators from the literature review

Since 2015, there are several researchers have that studied about the dimensions which used to evaluate the Industry 4.0 readiness for the manufacturing companies. The synthesis of the dimension components obtained in literature review are shown in Table 3.

Table 3. The dimensions used to assess the readiness to be Industry 4.0 from literature reviews

	Authors	1) VDEM's Implus-Stiftung (2015)	2) Leyh et al. (2016)	3) McKinsey (2016)	4) Schumacher et al. (2016)	5) Confederation of Indian Industry (CII) (2017)	6) Horvat et al. (2018)	7) Machado et al. (2019)	8) Nick et al. (2019)	9) Schumacher et al. (2019)	**Frequency**
Dimensions	Strategy and Organization	•			•	•	•	•	•	•	7
	Smart Factory	•				•		•	•		4
	Smart Operations	•		•	•	•		•	•		6
	Smart Products and Se-rvice	•	•	•	•	•		•	•	•	8
	Employees	•		•	•	•	•	•	•	•	8
	Data Driven Services	•				•		•	•	•	5
	Technology		•	•	•		•			•	5
	Inventory			•							1
	Quality			•							1
	Supply-Demand Match			•							1
	Time to Market			•							1
	Interfirm Cooperation						•				1
	Production and Logistics						•				1
	Leadership				•						1
	Customers				•					•	2
	Culture				•						1
	Governance				•						1
	Value Creation Processes									•	1
	Corporate Standards									•	1

There are 19 dimensions used to determine the components of the performance indicators to assess the Industry 4.0 readiness. The dimensions that are widely and often used consists of: strategy and organization, smart factory, smart operations, smart products and service, employees, data driven services and technology. The results from many research indicate that these dimensions are very important to drive the Industry 4.0. Therefore, developing MSIE student to have the knowledge to meet the needs of the industry is also important. In this study, we interpret the indicators in each dimension, except for employee dimensions, as the cognitive indicator that MSIE student should have in Industry 4.0 era.

The sub-indicators can be grouped in each dimension as shown in Table 4. The article that studied the sub-indicators were numbered in the parentheses, where:

1. VDEM's Implus-Stiftung (2015)
2. Leyh et al. (2016)
3. McKinsey (2016)
4. Schumacher et al. (2016)
5. Confederation of Indian Industry (CII) (2017)
6. Horvat et al. (2018)
7. Machado et al. (2019)
8. Nick et al. (2019)
9. Schumacher et al. (2019)

4.2. The cognitive indicators selection

The cognitive indicators were selected from the indicators have been obtained from 13 experts and have the average of rating score between 4.21 to 5.00 points. There are 10 indicators that will be used to assess the industry's expectations for MSIE students and the current potential of MSIE students as shown in Table 5.

4.3. The prioritizing and analysing the weight of indicators results using AHP

The cognitive indicators, that affect MSIE student employment considerations, were ranked by 13 experts using AHP method (section 3.2). These experts were chosen from person who have worked closely with industrial engineer for more than 10 years. This ensure that the ranked indicators are the most relevant to the needs of the industries under Industry 4.0 era. The ranking results is shown in Table 6.

Table 4. The dimensions detail and sub-indicators

Dimensions	Sub-indicators
Strategy and organization	- Industry 4.0 strategy (1,5,7,8) - Investment (1,5,7,8) - Innovation management (1,5,7,8) - Roadmap for Industry 4.0 (4,9) - Adaption of business models (4) - Available resources for realization (4) - Implementation of IT in companies (6) - Product lifecycle management (6) - Communication of Industry 4.0 activities (9) - Financial resources to realize Industry 4.0 (9) - Risk assessment for Industry 4.0 (9)
Smart factory	- Real time data usage (1,5,7,8) - Digital modelling (1,5,7,8) - Equipment infrastructure (1,5,7,8) - IT systems (1,5,7,8)
Smart operations	- Cloud usage (1,5,7,8) - Autonomous process (1,4,5,7,8,9) - Information sharing (1,5,7,8) - Flexibility of processes (4) - Decentralization of processes (4) - Digital modelling and simulation (4) - Smart energy consumption (3) - Intelligent lots (3) - Realtime yield optimization (3) - Remote monitoring and control (3) - Rapid experimentation and simulation (3) - Collaboration of humans and robots (9)
Smart products and service	- ICT add-on functionalities (1,5,7,8) - Data analytics in usage phase (1,5,7,8) - Digitalization of product (2,4,) - Remote maintenance (3) - Individualization of products (4) - Product integration into other systems (4) - Data processing components in products (9) - Internet connection of products (9) - Digital compatibility and interoperability of products (9)
Data driven services	- Data driven services (1,5,7,8) - Share of revenues (1,5,7,8) - Share of data used (1,5,7,8) - Automated data collection (9) - Analysis of collected data (9) - Databased decision making (9) - Automated information provision (9) - Digital process visualization (9)
Technology	- Cloud computing (2,3,4,9) - 3D-printing (3,4) - Big data analytics (3) - Advanced robotics (3) - Utilization of sensor (4) - Utilization of mobile devices (4) - Utilization of M2M communication (3,4,9) - Technology in R&D and design (6) - Technology in production (6) - Technology in purchasing (6) - Technology in inbound and outbound logistics (6) - Mobile devices on shop floor (9) - Sensors for data collection (9) - Integrated computer in machines (9) - Integrated computer in tools (9)

Table 5. The cognitive indicators that will be used to assess the industry's expectations for MSIE students and the current potential of MSIE students

Indicators	Average	S.D.
Industry 4.0 strategy	4.38	0.65
Communication of Industry 4.0 activities	4.31	0.48
Real time data usage	4.31	0.85
Information sharing	4.23	0.60
Digital modelling and simulation	4.38	0.65
Collaboration of humans and robots	4.46	0.52
Analysis of collected data	4.62	0.51
Databased decision making	4.54	0.66
Big data analytics	4.46	0.66
Technology in inbound and outbound logistics	4.38	0.96

Table 6. The ranking of cognitive indicators

Indicators	The avg. weight of each indicator	Rank
Industry 4.0 strategy	0.1579	1
Communication of Industry 4.0 activities	0.0559	9
Real time data usage	0.0857	7
Information sharing	0.0520	10
Digital modelling and simulation	0.0818	8
Collaboration of humans and robots	0.0985	6
Analysis of collected data	0.1196	2
Databased decision making	0.1148	4
Big data analytics	0.1144	5
Technology in inbound and outbound logistics	0.1194	3
Sum	1.0000	

The results show that the knowledge of Industry 4.0 strategy is the most important issue for the establishment to consider MSIE employment, follow by: the analysis of collected data, technology in inbound and outbound logistics, databased decision making, big data analytics, collaboration of humans and robots, real time data usage, digital modelling and simulation, communication of Industry 4.0 activities and information sharing, respectively.

4.4. The gap analysis results

The 89 industries or employers were asked to rate the expectation knowledge of MSIE graduates under Thailand Industry 4.0 policy according to each knowledge aspect via 10 questions. The 53 currently MSIE KKU students were asked to rate their ability using the same 10 questions. The average scores of each skill from both sample groups were shown in Table 7.

The results show that the industries or employers expect graduates to have all knowledges almost in the highest level. There are only two fields of knowledges that are rated as high level which are communication of Industry 4.0 activities and information sharing

For the current ability of MSIE students, there are only four fields of knowledge that MSIE students have in the highest level. We can see that the most different in average scores are the knowledge of collaboration of humans and robots followed by big data analytics. The moderate difference average scores are the real time data usage and databased decision making. The difference in the average scores from industries expectation and students' current abilities are shown in Fig. 1

From Fig. 1, it can imply that the MSIE KKU students still need to improve the skills in term of the knowledge of collaboration of humans and robots, big data analytics, real time data usage and databased decision making

Table 7. The average scores from the factories and current MSIE students of Khon Kaen University

No.	Knowledges	Factories		Students		Diff. of Avg. Score
		Avg. Score	Level	Avg. Score	Level	
1	Industry 4.0 Strategy	4.42	highest	4.26	highest	0.15
2	Analysis of collected data	4.34	highest	4.21	highest	0.13
3	Technology in inbound and outbound logistics	4.30	highest	4.36	highest	- 0.06
4	Databased decision making	4.27	highest	4.00	high	0.27
5	Big data analytics	4.36	highest	3.89	high	0.47
6	Collaboration of humans and robots	4.31	highest	3.81	high	0.50
7	Real time data usage	4.35	highest	4.06	high	0.29
8	Digital modelling and simulation	4.33	highest	4.43	highest	- 0.11
9	Communication of Industry 4.0 activities	4.10	high	4.15	high	- 0.05
10	Information sharing	3.93	high	3.87	high	0.06

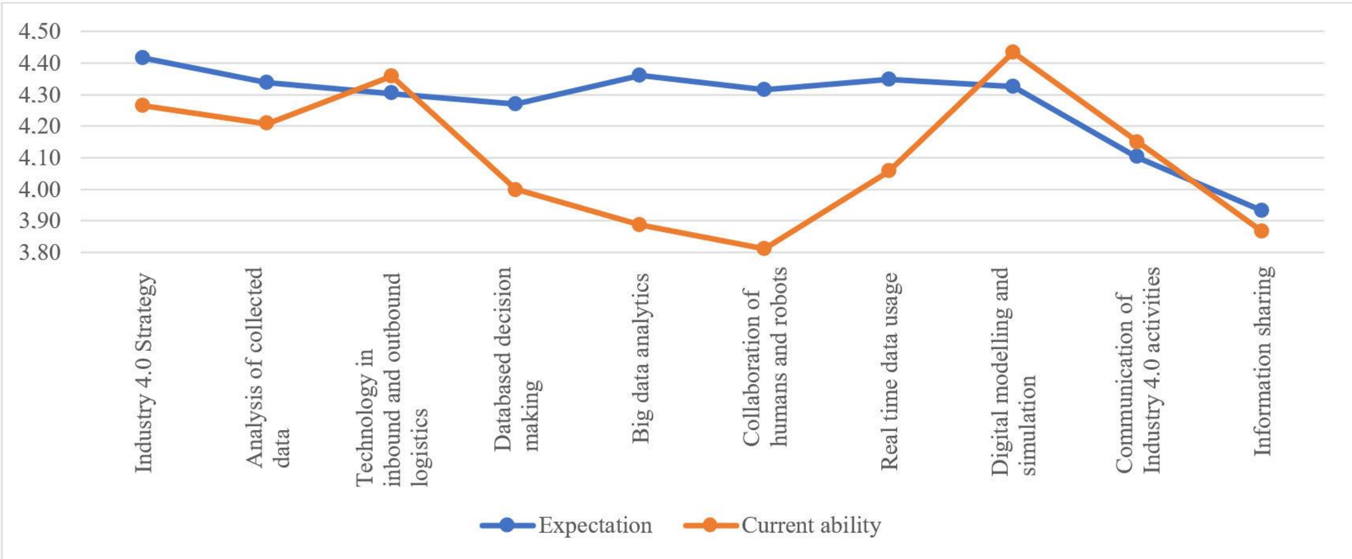

Fig. 1. Image of a gap between expectation of Industry 4.0 and the abilities of the current MSIE in Khon Kaen University.

5. Conclusion and discussion

Many industrialized countries already started to adapt their industrial infrastructure to meet the requirements of the Industry 4.0 vision. It is an important task for the higher education sector to adapt and fulfil the requirements of the Industry 4.0 concepts. The gap between the qualifications of current graduate students and the industry needs is highly important issue for industrial engineering program. Therefore, the aim of this study is to find a gap between the qualifications of graduate students that the industry needs and the ability of the current MSIE KKU students. By using the same set of question, industries and graduate students were asked to rate the expectation and current skills. The Gap analysis results show that there are four fields of knowledge that the IE department of KKU should accelerate the development of the curriculum to produce master's degrees that meet the industry expectations.

To reduce a gap that was identified, more flexible MSIE curriculum is needed for developing different areas of knowledge, especially in big data and robotics knowledge. The curriculum needs to be reviewed and revised. According to a study on fourteen Industrial Engineering programs (Lima et al., 2019), the courses are encouraged to implement more problem and project-based learning (PBL) to allows different learning paths for the MSIE students. The development of both technical competences and transversal competences are needed to be considered. Additionally, the cooperation between industry section and education section in developing the student competences is highly recommended.

Acknowledgements

The research was financial supported by the Young Research Development Project of Khon Kaen University.

Reference

Abdel-Basset, M., Mohamed, M., Smarandache, F., 2018. An Extension of Neutrosophic AHP–SWOT Analysis for Strategic Planning and Decision-Making, Symmetry, 10(4), 116.

Bonekamp, L., Sure, M., 2015. Consequences of Industry 4.0 on Human Labour and Work Organisation, Journal of Business and Media Psychology, 6(1), 33-40.

Chouhan, S., Mehra, P., Dasot, A., 2017. India's Readiness for Industry 4.0 – A Focus on Automotive Sector, Confederation of Indian Industry (CII), Grant Thornton-An instinct for growth.

Coskun, S., Gençay, E., Kayikci, Y., 2019. Adapting Engineering Education to Industry 4.0 Vision, Technologies, 7(10), 1-13, DOI: 10.3390/technologies7010010

Dumitrescu, A., Lima, R., Chattinnawat, W., Savu, T., 2019. Industry 4.0 competencies' gap analysis. Industry 4.0, 4(3), 138-141.

Galankashi, M. R., Helmi, S. A., Hashemzahi, P., 2016. Supplier Selection in Automobile Industry: A Mixed Balanced Scorecard–fuzzy AHP Approach. Alexandria Engineering Journal, 55(1), 93-100.

Horvat, D., Stahlecker, T., Zenker, A., Lerch, C., Mladineo, M., 2018. A Conceptual Approach to Analysing Manufacturing Companies' profiles Concerning Industry 4.0 in Emerging Economies, Procedia Manufacturing, 17, 419-426.

Kádárová, J., Kováč, J., Durkáčová, M., Kádárb., G, 2014. Education in Industrial Engineering in Slovakia, Procedia - Social and Behavioral Sciences, 143, 156-162.

Lee, Y.C., Wang, Y.C., Chien, C.H., Wu, C.H., Lu, S.C., Tsai, S.B., Dong, W., 2016. Applying Revised Gap Analysis Model in Measuring Hotel Service Quality, SpringerPlus, 5(1), 1191.

Leyh, C., Schäffer, T., Bley, K., Forstenhäusler, S., 2016. SIMMI 4.0 – A Maturity Model for Classifying the Enterprise-wide IT and Software Landscape Focusing on Industry 4.0, Proceedings Of The 2016 Federated Conference on Computer Science and Information Systems, 8, 1297–1302, DOI: 10.15439/2016f478

Lima, R.M., Mesquita, D., Sousa, R.M., Monteiro, M.T.T., Cunha, J., 2019. Curriculum analysis process: Analysing fourteen industrial engineering programs.

Luthra, S., Mangla, S.K., 2018. Evaluating Challenges to Industry 4.0 Initiatives for Supply Chain Sustainability in Emerging Economies, Process Safety and Environmental Protection, 117, 168-179.

Machado, C.G., Winroth, M., Carlsson, D., Almström, P., Centerholt, V., Hallin, M., 2019. Industry 4.0 Readiness in Manufacturing Companies: Challenges and Enablers Towards Increased Digitalization, Procedia CIRP, 81, 1113-1118, DOI: 10.1016/j.procir.2019.03.262

McKinsey & Company, 2016. Industry 4.0 at McKinsey's model factories, Retrieved from https://capability-center.mckinsey.com/files/mccn/2017-03/digital_4.0 model_factories_brochure_2.pdf

Muhisn, Z.A.A., Omar, M., Ahmad, M., Muhisn, S.A., 2015. Team Leader Selection by Using an Analytic Hierarchy Process (AHP) Technique, JSW, 10(10), 1216-1227.

Nick, G., Szaller, Á., Bergmann, J., Várgedő, T., 2019. Industry 4.0 Readiness in Hungary: Model, and the First Results in Connection to Data Application, IFAC PaperOnLine, 52(13), 289-294.

Patacsil, F.F., Tablatin, C.L.S., 2017. Exploring the Importance of Soft and Hard Skills as Perceived by IT Internship Students and Industry: A gap Analysis. Journal of Technology and Science Education, 7(3), 347-368.

Pawar, S.S., Rathod, R.R., 2019. A Decision Support System Using Analytical Hierarchy Process for Student-Teacher-Industry Expectation Perspective: In Computing, Communication and Signal Processing, Springer, Singapore, 523-534.

Petruni, A., Giagloglou, E., Douglas, E., Geng, J., Leva, M.C., Demichela, M., 2019. Applying Analytic Hierarchy Process (AHP) to Choose a Human Factors Technique: Choosing the Suitable Human Reliability Analysis Technique for the Automotive Industry, Safety Science, 119, 229-239.

Pimentel, C., Silva, H., Dias, M.F., Amorim, M., 2016. Transversal entrepreneurial competencies for youth employability –a GAP analysis. Proceedings of 2100 Projects Association Join Conferences 5.

Pinzone, M., Fantini, P., Perini, S., Garavaglia, S., Taisch, M, Miragliotta, G., 2017. Jobs and skills in Industry 4.0: An exploratory research. In IFIP International Conference on Advances in Production Management System, Springer, Cham, 282-288.

Ramadi, E., Ramadi, S., Nasr, K., 2016. Engineering Graduates' skill Sets in the MENA Region: a Gap Analysis of Industry Expectations and Satisfaction, European Journal of Engineering Education, 41(1), 34-52.

Sadeghpour, F., Far, M.G., Khah, A.R., Amiri, M.A.A., 2017. Marketing Strategic Planning and Choosing the Right Strategy using AHP Technique (Case Study: Ghavamin Bank Mazandaran), Dutch Journal of Finance and Management, 1(2), 45.

Schumacher, A., Erol, S. & Sihn, W., 2016. A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises, procedia CIRP 52, 161-166, DOI: 10.1016/j.procir.2016.07.040

Schumacher, A., Nemeth, T., Sihn, W., 2019. Roadmapping Towards Industrial Digitalization based on an Industry 4.0 Maturity Model for Manufacturing Enterprises, Procedia CIRP, 79, 409-414.

VDMA's IMPULS-Stiftung, 2015. Industrie 4.0-readiness, Retrieved from https://industrie40.vdma.org/documents/4214230/5356229/Industrie%204.0%20Readiness%20Study%20English.pdf/f6de92c1-74ed-4790-b6a4-74b30b1e83f0

雇主对泰国的期望与工业4.0下工业工程硕士学位的当前能力之间的差距研究

關鍵詞
工业4.0 差距研究 工程教育 MSIE课程

摘要
工业4.0是一个时代，在这个时代，制造业已经采用数字技术和Internet来实现智能制造系统，生产中使用的机器现在可以彼此通信并彼此交换信息，而制造中使用的机器也可以相互交流。过程更加现代和精确。因此，教育机构应开发课程，以培养具备工业4.0时代所需知识的合格毕业生，尤其是与工业部门直接相关的工业工程毕业生。这项研究的目的是为工业工程硕士（MSIE）课程开发收集数据。层次分析法（AHP）技术用于对知识指标进行排序，这些知识指标对拥有工业工程硕士学位的毕业生的就业很重要，并研究雇主的期望与当前MSIE学生能力之间的差距。孔敬大学。研究结果表明，对于MSIE毕业生的就业而言，最重要的首要指标是工业4.0策略的知识，而学生应该发展的知识是人与机器人的协作，大数据分析，实时数据使用情况和数据库决策。。