Risk Evaluation Approach on Student Projects using Failure Mode and Effects Analysis based on Fuzzy Rule-based System and Intelligent Agents

Issarapong Khuankrue
Electronics, Information and Media Engineering Major, Graduate School of Engineering
Nippon Institute of Technology (NIT), Saitama, Japan
Email: issarapong.kh@outlook.com

Fumihiro Kumeno
Department of Computer and Information Engineering
Nippon Institute of Technology (NIT), Saitama, Japan
Email: kumeno@nit.ac.jp

Yutaro Ohashi
Department of Computer and Information Engineering
Nippon Institute of Technology (NIT), Saitama, Japan
Email: ohashi@leo.nit.ac.jp

Yasuhiro Tsujimura
Department of Computer and Information Engineering
Nippon Institute of Technology (NIT), Saitama, Japan
Email: tujimr@nit.ac.jp

Abstract. In professional projects, failure mode and effects analysis (FMEA) has been utilized for risk analysis and reliability assessment. FMEA results help team members manage risks under uncertainty. However, traditional FMEA has several problems, especially with regard to the risk priority number (RPN). RPN depends on three factors that are subjectively weighed by team members: severity, occurrence and detection. While student projects differ from professional projects, students lack experience and are not ready to impose risks on all aspects of their project. In this study, an approach is proposed by adopting the traditional FMEA method of risk evaluation on student projects. Two main processes are investigated: 1) a fuzzy rule-based system is developed as a fuzzy FMEA model, including fuzzy reasoning, linguistic criteria, a rule-based model, and fuzzy inference systems and 2) the process of intelligent agents is developed by teaching agents to simulate the membership function and rule-based model on fuzzy inference systems based on expert opinions. A student project is used as an example, to illustrate the use of the proposed methods for risk evaluation on project-based learning.

Keywords: Failure mode and effects analysis, Student project, Fuzzy rule-based system, Intelligent agents

1. INTRODUCTION

In general, engineering education is a rapidly developing field. It involves constructing educational plans for learning in real-world experiences. Students today should aim at advancing their understanding and practical skills on their field. In addition, the student project approach or project-based learning is a widespread approach. This form of situated learning in the real-world context allows students to gain a deeper understanding of the material (Sawyer, 2014). Therefore, the student project is a part of the educational plan, which focuses on individual learning. However, in practice, most assessors often evaluate only the project's results and typically focus only on successful learners instead of addressing the learners' lack of understanding and basic skills.

In this case, the risks are abnormal states for projects that probably failed in the overview. The outputs or products are directly related to the expected learning outcome. However, the real situation is complicated and requires a high-performance tool to assess the risks.

The selected risk analysis tool in this study is failure mode and effects analysis (FMEA), which is a systematic failure analysis technique used to identify resultant effects on system operations. FMEA is widely used for effective risk analysis in professional projects. However, student projects, which differ from professional projects, are not usually analyzed through this method; this is because students lack the experience and expertise to provide necessary opinions for such an analysis and cannot easily make decisions by assessing risks. Regarding risk assessment, FMEA has a limitation. This technique requires expert opinions in the form of scoring in each failure mode that may occur in the software development process.

In the present study, we examine the hypothesis that project-based learning greatly contributes to learning required skills and gaining knowledge. However, learners are unable to independently gain knowledge through project work and they lack the experience that would allow them to identify risks on their own. Thus, other risk assessment methods are used to assess the specific failure mode, analyse the risks, identify the relation of each factor on student projects, and encourage individual learners to gain specific skills and knowledge.

The above statement is investigated using two proposed interacting components. First, risk assessment is based on learning analytics under the fuzzy FMEA approach. In this approach, risks are identified in the interaction between the users, both team members and project advisors. Then, the fuzzy FMEA approach is used to assess the overall risks on student projects. A fuzzy rule-based system is developed, including fuzzy linguistic criteria, a belief structure and rule-based methods, which define the fuzzy inference systems. Moreover, an agents-based model is used to address problems on student's projects. Traditional FMEA cannot evaluate risk priority numbers (RPNs) with great accuracy. In several approaches, calculation is based on subjective weighting of RPNs by team members. However, students are not experts and cannot evaluate RPNs as professional projects do. Therefore, the agents-based model is used as an expert system to simulate the membership function and rule-based model on fuzzy inference systems.

This paper is organized as follows. The fuzzy FMEA model, the traditional FMEA and the fuzzy rule-based system are described in Section 2. Section 3 presents intelligent agents within the framework of the agent-based model. Section 4 presents the proposed method and illustrates step-by-step an example on a model of project-based learning. Finally, Section 5 discusses the conclusion and contributions.

2. FUZZY FMEA MODEL

2.1 Traditional Failure Mode and Effects Analysis

In risk management, risk is defined as the possibility of loss or injury, which is unavoidable but manageable and intelligible. Risk exposure (RE), also called risk impact, refers to the relation between the probability of an unsatisfactory outcome and the loss to the parties affected if the outcome is unsatisfactory (Boehm, 1991). In the student project, assessing risks should be a simple process.

Failure mode and effects analysis (FMEA) is a systematic failure analysis technique used to identify resultant effects on system operations (Reifer, 1979). It is sometimes referred to as failure mode, effects and criticality analysis (FMECA) and is often the first step of a system reliability study. It involves reviewing as many components, assemblies, and subsystems as possible to identify failure modes, their causes and effects.

The 12 steps of FMECA typical flow are (Borgovini et al., 1993):

Step 1: Define the analysed system and the item indenture levels.

Step 2: Define ground rules/assumptions: *The analyst must repeat this step at each part of the analysis. Ground rules and assumptions involve the mission, operating time, severity categories, and so on.*

Step 3: Construct block diagrams: *Block diagrams illustrate the functional flow sequence or parallel dependence or interdependence of functions and operations. It provides the ability to trace the failure mode effects through each level of indenture.*

Step 4: Identify failure modes: *This step must be repeated for all items, interface failure modes, and their effect upon the immediate items, the system, and the mission.*

Step 5: Perform failure effects/causes analysis: *The failure effects or causes are analysed for each item of the block diagrams. Each failure under consideration may affect several indenture levels.*

Step 6: Classify failure effects: *It is important to define the worst potential consequence upon system level, which may result from item failure. A* *classification of severity must be implemented, and each effect level of the system must be classified accordingly, based on the failure mode evaluation.*

Step 7: Perform critical calculations for items/modes: *Failure detection methods are detected by the*

Table 1: Format of failure mode and effects analysis processes

Name / Function Requirements	Exiting Conditions									Action Results				
	Potential Failure Mode	Potential Effects of Failure	Severity (S)	Potential Causes of Failure	Occurrence (O)	Current Process Control	Detection (D)	Risk Priority Number (RPN)	Recommended Action	Action taken	S_r	O_r	D_r	RRN_r

system operation. The risk priory number (RPN) is calculated for each potential failure mode.

Step 8: Rank all items according to criticality: *After critical calculations in the previous step, the failure mode criticality is derived based on methodologies described above. A ranking can be developed to help determine item failures critical to the expected mission.*

Step 9: Determine critical items: *These are determined based on the ranking of the previous step with a focus on the failure mode with high criticality and severity of the end effect.*

Step 10: Perform maintainability information analysis: *The maintainability analysis is used to determine the test case and fault detection. Early criteria for system maintenance are provided.*

Step 11: Document analysis: *The report documents explaining all FMECA steps are created.*

Step 12: Develop recommendations to improve reliability and identify design changes*: The typical recommendations and design changes are developed for reliability improvement.*

For each component, the failure modes and their resulting effects on the rest of the system are recorded in a specific FMEA format (Table 1). As mention above, the risk priory number (RPN) is calculated by multiplying the three input factors, severity, occurrence and detection, as follows:

$$RPN = Serverity \times Occurrence \times Detection \quad (1)$$

where severity represents the seriousness of failure after it has occurred. Occurrence represents the probability of occurrence. Detection represents the probability of detecting a defect on system. All three factors are usually estimates by subjective numerical weighting, on a scale from 1 to 10. Moreover, FMEA offers a risk analysis for every project's time series and can deal with risks in a timely manner during project execution.

2.2 Fuzzy Rule-based System

The basic flowchart of the fuzzy rule-based system (Pedrycz and Gomide, 2007) is shown in Figure 1. Input X variable is a fuzzy set. The input interface is defined to receive the input fuzzy set. The rule-based system is composed of a set of fuzzy if-then rules, which relate input to output variables. The data-based system includes the parameter values of the rule-based model's scaling factor, including the details in the criteria, membership functions, and others.

Fuzzy inference is a process, which uses the rule-based and data-based systems to explore the mechanism of fuzzy inference and approximate reasoning. The output interface is defined to contain the results of fuzzy inference into output Y.

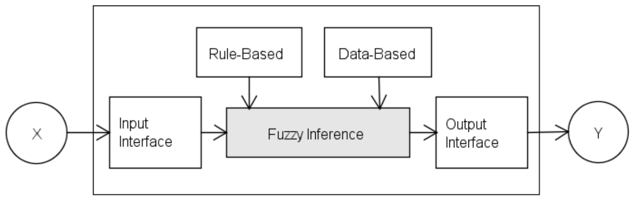

Figure 1: Flowchart of the fuzzy rule-based system

2.3 Basic Fuzzy If-then Rules and Membership Function

An if-then rule expresses a certain relation between a fuzzy variable, an input X and an output Y. The basic rule-based format is

$$\boldsymbol{IF} \quad X \text{ is } A \qquad \boldsymbol{THEN} \quad Y \text{ is } B \quad (2)$$

where A and B describe the some pieces of the domain knowledge of the problems. In case of fuzzy if-then rules, A and B represent the degrees of fuzzy values. For example, the rule is "IF the probability of system fails is high THEN the cost of maintainability is high."

Zadeh (1992) proposed the following process for calculating fuzzy if-then rules. 1) Explain a fuzzy if-then rule. 2) Explain a collection of fuzzy if-then rules. 3) Represent the proposition in a natural language as a collection of fuzzy if-then rules 4) Infer from the collection of fuzzy if-then rules. 5) Manipulate the blocks of fuzzy if-then rules. 6) Perform an algebraic operation. 7) Process fuzzy if-then rules as the induction based on observation. If-then rules are designed in different formats depending on the problems and characteristics of the domain knowledge.

Membership function refers to a classical subset A of X. It forms part of a data-based in a fuzzy rule-based system and depends on the combination of fuzzy sets. The notation $\mu_A(X)$ is a grade of membership of X in A. The rules and membership functions are defined relative to the situation of problems.

However, RPN in FMEA is a shortcoming. It is easy enough to design a process that work well, when everything is going well on professional project. However, student projects differ from professional projects. Students are not ready to impose risks in all aspects of their project, because they lack experience. At the same time, risks identification using the fuzzy FMEA model also has problems related to the fuzzy rule-based and membership functions. Advisors or assessors cannot define the rules and membership functions as well as in professional projects. Consequently, this paper proposes a method to improve the traditional fuzzy FMEA approach for risk evaluation on student projects by applying intelligent agents.

3. AGENTS-BASED MODEL

In general, intelligent agents are autonomous agents, who perceive the data through sensors and acts upon the environments. (Russell and Norvig, 1995) Intelligent agents may learn or use historical knowledge to achieve the expected goals (Figure 2). The basic structure of agents includes three main components: a monitor for perceiving the environments, a set of goals leading to the desired results, and an actuator for responding to the results.

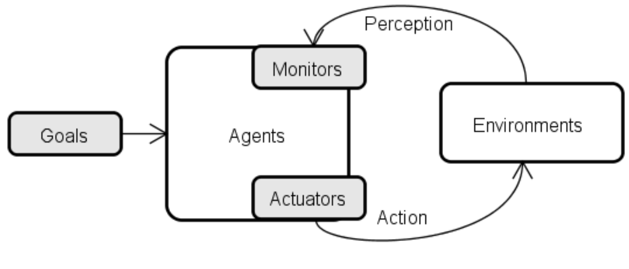

Figure 2: Basic concepts of intelligent agents

Intelligent agents function as learning agents in an expert knowledge system for membership functions construction and fuzzy rule-based classification that allows them to propose solutions to the problems of the fuzzy FMEA approach.

3.1 Learning Agents as an Expert Knowledge System for Membership Functions Construction and Fuzzy Rule-based Classification

Hong and Lee (1996) proposed learning methods for automatically deriving fuzzy rules and membership function from a given set of training instances as the knowledge acquisition facility. Based on this method, here we propose the use of learning agents as an expert knowledge system to construct the membership function and to forward it into the fuzzy rules-based classification in the fuzzy FMEA model. The steps are briefly description below

Step 1: Define the input space

$$V_{S,O,D} = \{v_1, v_2, \dots, v_n\} \quad (3)$$

V is the input space of the historical membership data of each risk factor in FMEA, S is severity, O is occurrence and D is detection. The variable v refers to the values of the risk factors and n is the total amount of v in the historical input space V.

Step 2: Sort the value before learning: Sorting the input values is performed in order to find the relation between each value. The result of this step is:

$$v'_1, v'_2, \dots, v'_n$$
$$where \quad v'_i \le v'_{i+1} \; (for \;\; i = 1, \dots, n-1) \quad (4)$$

Step 3: Perceive the input value: The input values are perfected by monitors of agents.

Step 4: Find the difference and similarity: The difference (d) between the values in step 2 provide the data about similarity (s) between them. For each pair values v'_i and $v'_{i+1} (i = 1, \dots, n-1)$. The difference is calculated, as $d_i = v'_{i+1} - v'_i$, and we convert each d_i to a real number of s_i as follows

$$s_i = 1 - (d_i \; / CP \;\; \times sd \;) \;|\;\; d_i \;\le CP \;\; \times sd \quad (5)$$

where s_i is the similarity between each pair of values v'_i and v'_{i+1}, CP is the control parameter to shape the membership functions, and sd is the standard deviation of each values. Note that, a greater similarity is obtained for a larger CP.

Step 5: Cluster values into a group: determine the number of groups as goals. This step is adopted from the □-cut of similarity. The variable *alpha* is the threshold for a pair value to be included in a group, and use *p* and *q* as iteration variable. The approach followed in this step is shown as a pseudocode as follows

```
FOR p=1 to list size
    FOR q=1 to list size
#Cluster group
    IF (s_i < alpha) THEN
        Divide a pair value into the difference group
        Next q, Next p
    ELSE
        Divide a pair value into the same group, Next p
    ENDIF
#Learning to a goal
    IF (length(q) == 5) THEN
        RETURN 0
        ELSE IF (length(q) < 5) THEN
                alpha = alpha + 0.2
            ELSE
                alpha = alpha - 0.2
        ENDIF
    ENDIF
#Check amount in each groups
    IF(amount in each groups < 3) THEN
        Send to the near group above
        Do LOOP again
    ENDIF
END LOOP
```

Step 6: Determine the central value b_j and calculate the results for the similar value: The value is the peak value for each group. Next step is dividing a pair value into a group.

Step 7: Find a minimum value and a maximum value in each group as follows.

The minimum point *(a, 0)* in each group is defined as

$$a = b_j - (b_j - v_i/1 - \mu_j(v_i) \tag{6}$$

The maximum point *(0, c)* is defined as

$$c = b_j + (v_k - b_i/1 - \mu_j(v_k) \tag{7}$$

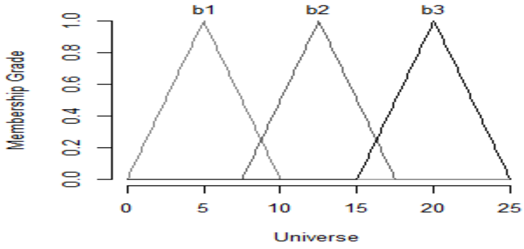

Figure 3: Example of the triangle membership function

Step 8: Actions by constructing the membership function: In the previous step, the membership function was constructed using the three variables to form a triangle for each group, which gives the minimum variable a, the central value b and the maximum variable c, as shown in Figure 3.

After constructing all membership functions for each risk factor, the if-then rules classification can be obtained. Ishibuchi et al. (1999) proposed a way to classify these rules by fuzzy reasoning based on voting both a single winner rules and multiple rules. Later on, Liu, et al. (2013) presented fuzzy evidential reasoning and a belief rule-based method. Focused on rule-based belief and voting by multiple fuzzy if-then rules, as mention above, here we propose the fuzzy if-then rule classification system in the last step;

Step 9: Classification of fuzzy if-then rules: Generally, the numbers of rules (*R*) are generated and equal to the number of possible combinations of different grades of assessments of risk factors, in this case three risk factors: severity (*S*), occurrence (*O*) and detection (*D*). The grade of assessment is calculated and the fuzzy if-then rules are classified using the average value voting by multiple rules as below;

$$\gamma_{class\ T} = \sum_R \mu_T(\bar{x}_i) \times CF_T \quad , T = 1,2, \ldots . m \tag{8}$$

where γ is the voting result of compatibility grade of each input value. Variable $\bar{x}_i$ is the average value of each membership function, and T is a number of classes with amount *m*. Variable *CF* is the grad of certainty, which can be adjusted by the learning processes (Ishibuchi et al., 1995). Then, the calculation results from the above equation can be plotted to the belief rule table (Table 2).

Table 2: Rule table

Rule no.	**Risk factors (weight)**			**Class no.**
	$S(\bar{v}_i)$	$O(\bar{v}_i)$	$D(\bar{v}_i)$	$\gamma_{class\ T}$
1	A_S^i	A_O^j	A_D^k	$\gamma_{class\ 1}$
2	A_S^i	A_O^j	A_D^{k+1}	$\gamma_{class\ 1}$
…	…	…	…	…
n	A_S^n	A_O^n	A_D^n	$\gamma_{class\ m}$

The fuzzy FMEA model and the agent-based model are combined in order to evaluate the risk on the student The proposed method of risk evaluation for student processes followed by the thesis statements.

4. RISK EVALUATION APPROACHS AND ILLUSTRATIVE EXAMPLE

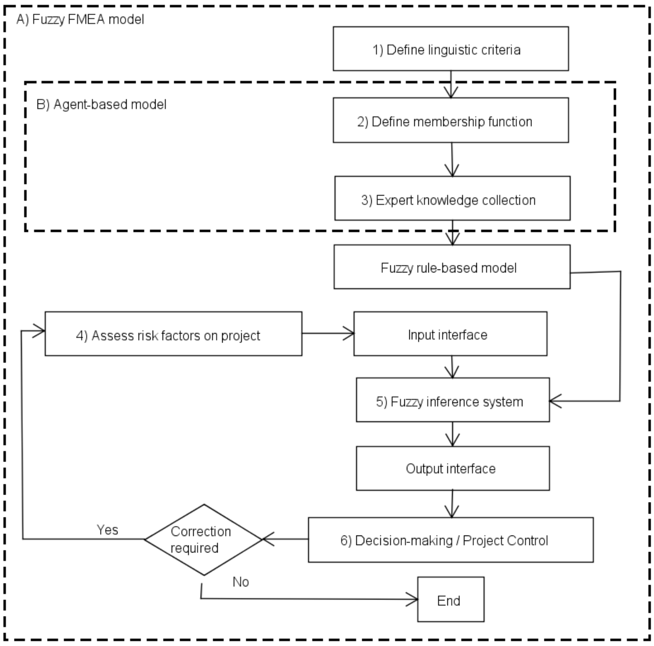

Figure 4: Flowchart of the proposed risk evaluation approach

projects derives from the combination of: A) a fuzzy FMEA model and B) an agent-based model (Figure 4). The illustrative example is a student project of undergraduate level in a software development course. The project aim is to develop an e-learning software for language studies.

The team includes three team members; everyone in the team acts as a risk evaluator on their projects. An advisor is the main risk evaluator. This project was implemented in the previous year, and historical risk assessment data exist from the last project. The results are computed by R, including data on the structure and basic operations of the software package (Meyer and Hornik, 2009). The six steps of the proposed method and the illustrative example are explained below.

Step 1: Define linguistic criteria

The linguistic terms and the fuzzy number are set up. A set of linguistic criteria is

$$L = \{VeryLow, Low, Moderate, High, Veryhigh\}$$

Step 2: Define membership function

The membership functions are constructed as an expert knowledge system. For example, the membership functions of severity, occurrence and detection are defined by four sup-steps as follows

Sup-step 2.1: Define the input space from the historical data (3), including;

$$V_S = \{9.36, 7.59, 3.19, 0.22, 6.96, 1.97, 2.24, 0.81, 5.36, 7.49, 5.97, 6.51, 9.96, 7.99, 0.40, 6.02, 0.39, 4.91, 9.95, 7.44, 9.68, 6.44, 8.67, 8.74, 3.54\}$$

$$V_O = \{5.16, 5.05, 9.37, 0.44, 1.18, 7.71, 5.69, 4.41, 7.68, 7.81, 0.51, 2.32, 2.37, 7.82, 4.25, 6.63, 2.75, 1.90, 6.28, 5.25, 5.42, 7.56, 1.37, 7.94, 8.61\}$$

$$V_D = \{4.05, 6.66, 2.38, 2.16, 4.80, 1.84, 6.33, 8.58, 6.28, 0.44, 7.44, 8.87, 1.89, 4.99, 1.45, 3.04, 2.29, 3.71, 2.41, 1.37, 1.40, 2.15, 9.71, 2.674, 0.39\}$$

Sup-step 2.2: Sort the values before learning using (4)

$$V'_S = \{0.22, 0.39, 0.40, 0.81, 1.97, 2.24, 3.19, 3.54, 4.91\ 5.36, 5.97, 6.02, 6.44, 6.51, 6.96, 7.44, 7.49, 7.59, 7.99, 8.67, 8.74, 9.36, 9.68, 9.95, 9.96\}$$

$$V'_O = \{0.44, 0.51, 1.18, 1.37, 1.90, 2.32, 2.37, 2.75, 4.25\ 4.41, 5.05, 5.16, 5.25, 5.42, 5.69, 6.28, 6.63, 7.56, 7.68, 7.71, 7.81, 7.82, 7.94, 8.61, 9.37\}$$

$$V'_D = \{0.39, 0.44, 1.37, 1.40, 1.45, 1.84, 1.89, 2.15, 2.16\ 2.29, 2.38, 2.41, 2.67, 3.04, 3.71, 4.05, 4.80, 4.99, 6.28, 6.38, 6.66, 7.44, 8.58, 8.87, 9.71\}$$

Sup-step 2.3: Perceive the input value and find the difference *(d)* and similarity *(s_i)* using (5) and the pseudocode in step 5 of chapter 3, assuming *CP* = 0.5 and *sd* = 4. The results of this sub-step are shown in Table 3.

Table 3: Occurrence level definition

	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
S	0.91	0.99	0.79	0.42	0.87	0.53	0.82	0.31
O	0.96	0.66	0.90	0.73	0.79	0.97	0.81	0.24
D	0.97	0.53	0.98	0.97	0.81	0.97	0.86	0.99
	s_9	s_{10}	s_{11}	s_{12}	s_{13}	s_{14}	s_{15}	s_{16}
S	0.78	0.69	0.97	0.78	0.96	0.77	0.76	0.97
O	0.92	0.67	0.94	0.95	0.91	0.86	0.71	0.82
D	0.93	0.95	0.98	0.86	0.81	0.66	0.83	0.62
	s_{17}	s_{18}	s_{19}	s_{20}	s_{21}	s_{22}	s_{23}	s_{24}

S	0.94	0.80	0.66	0.96	0.69	0.83	0.86	0.99
O	0.53	0.94	0.98	0.95	0.99	0.94	0.66	0.62
D	0.91	0.35	0.97	0.83	0.61	0.43	0.85	0.57

Sup-step 2.4: Construct the membership function: Determine the central value as the goal and the results using the nearest value. Find a minimum point and a maximum point in each group from (6) and (7), respectively. Variable a is the minimum point and c is the maximum point in each group of membership functions, and define the risk factors as shown in Tables 4, 5 and 6

Table 4: Severity level definition

Linguistic terms	**Definition**	**Fuzzy Number (a, b, c)**
Very Low (VL)	Very minor effect.	(0.22, 1.00, 2.24)
Low (L)	Small effect. - Product does not require repair.	(0.81, 3.14 ,5.36)
Moderate (M)	Moderate effect. - Product requires repair.	(2.24, 5.83 ,7.99)
High (H)	Product performance is severely affected.	(5.36, 7.09, 8.74)
Very High (VH)	System is inoperable. System operation is suspended.	(7.99, 9.11 ,9.96)

Table 5: Occurrence level definition

Linguistic terms	**Definition**	**Fuzzy Number (a, b, c)**
Very Low (VL)	Failure does not seem reasonable.	(0.44, 1.08, 1.90)
Low (L)	Fairly few failures.	(1.37, 3.40, 5.16)
Moderate (M)	Infrequent failures.	(4.25, 5.18, 6.28)
High (H)	Frequent failures.	(5.05, 6.08, 7.68)
Very High (VH)	Failure is almost unavoidable.	(7.56, 8.06, 9.37)

Table 6: Detection level definition (Tay and Lim, 2006)

Linguistic terms	**Definition**	**Fuzzy Number (a, b, c)**
Very Low (VL)	Controls probably will not detect.	(0.39, 1.15,1.84)
Low (L)	Controls may not detect.	(1.37, 2.09 ,3.04)
Moderate (M)	Controls are able to detect.	(1.84, 2.78,4.80)
High (H)	Controls are able to detect and have high impact.	(3.04, 5.26,7.44)
Very High (VH)	Controls will detect and have very high impact.	(4.80, 7.09,9.71)

Step 3: Collect the expert knowledge by classify the fuzzy if-then rules

In the student project, only the maximum risk on the projects needs to be considered. Thus, the fuzzy if-then rules are placed into a rule table based on (8), and assuming $CF_T = 1.0$. The numbers of rules are generated equal to the number of possible combinations of different grades of assessments that is 125 rules. The risks are classified into five levels: Very low, Low, Medium, High and Very high (Table 7). The voting result of compatibility grade varies from 0 to 10, depending on each input value.

Table 7: Example of rule table and results

Rule no.	**Risk factors (weight)**			**Class**
	Severity	**Occurrence**	**Detection**	γ_{classT}
1	VL	VL	VL	$\gamma_{classVL} = 0.01$
2	VL	VL	L	
…	…	…	…	
63	M	M	M	$\gamma_{classM} = 0.22$
64	M	M	H	
…	…	…	…	$\gamma_{classH} = 0.30$
95	H	H	H	
96	H	H	VH	
…	…	…	…	$\gamma_{classVH} = 0.52$
125	VH	VH	VH	

Step 4: Assess risk factors while project running

The team members and advisors assess the risk based on the FMEA worksheet, following Table 1.

Step 5: Process the fuzzy inference system

After the risk assessment process, the assessment input is sent to the fuzzy inference system. The input data is fuzzy rule-based, whereas the linguistic terms and the membership function are data-based. The results of this step are summarized on the decision table.

Step 6: Project control

The results are provided to the advisors, who evaluate the project risks. If the project is still ongoing, this step is an iteration to step 4. The expected results are the risk levels for each failure mode each week during the semester, as shown in Table 9. The time series of the results reveals the evolution of the project and the most important problems.

Table 9: Example of expected results

Failure mode	Risk level / weeks				
	Week1	Week2	Week3	…	Week15
1	VH	VH	H	…	L
2	H	H	M	…	M
3	VH	H	M	…	L
4	M	M	M	…	VL

5. CONCLUSION

In this study, we developed a method for risk evaluation using FMEA, fuzzy rule-based system and learning agents as the expert systems in fuzzy FMEA for student project. The difference between student projects and professional projects is significant. Most people in engineering education have been using project-based learning as a tool for teaching knowledge and practical skills but are not aware of the students' lack of experience and treat them as professional staff.

The present study had two limitations: the lack of real historical assessments, and the insufficient classification techniques available. As shown from the example, the input space may be defined from a random function based on the historical data. In a future work, we are going to address this function in detail. Moreover, the proposed classification techniques still require improvements for fuzzy rule-based agent system.

Therefore, the results of this study may contribute in the following three areas: 1) developing risk management approaches as learning analytics that can track and improve project direction throughout the teaching process, 2) developing intelligent agents that can support the risk analysis on student projects, functioning as an expert system and 3) providing feedback on the individual risks during project implementation that can be used to gain individual software engineering knowledge and skills.

REFERENCES

Boehm, B.W. (1991) Software Risk Management: Principles and Practices. *IEEE Software*. 8, 1, 32–41.

Borgovini, R., Pemberton, S., and Rossi, M. (1993). *Failure modes, effects and criticality analysis (FMECA)*. Reliability Analysis Center. Rome, NY.

Hong, T.P. and Lee, C.Y. (1996) Induction of fuzzy rules and membership functions from training examples. *Fuzzy Sets System*. 84, 1, 33–47.

Ishibuchi, H., Nakashima,T, and Mosirawa, T. (1999) Voting in fuzzy rule-based systems for pattern classification problems. *Fuzzy Sets System*. 103, 2, 223–238.

Ishibuchi, H., Nakashima, T. and Murata, T. (1995) A fuzzy classifier system that generates fuzzy if-then rules for pattern classification problems. *Proceedings of 1995 IEEE International Conference on Evolutionary Computation, Perth, WA*, 759–764.

Liu, H.-C., Lui, L, and Lin, Q. L. (2013) Fuzzy Failure Mode and Effects Analysis Using Fuzzy Evidential Reasoning and Belief Rule-Based Methodology. *IEEE Transections on Reliability*. 62, 1, 23–36.

Meyer, D. and Hornik, K. (2009). Generalized and Customizable Sets in R. *Journal of Statistical Software*, 31(2), 1-27. *http://www.jstatsoft.org/v31/i02/*.

Pedrycz, W. and Gomide, F. (2007) *Fuzzy Systems Engineering: Toward Human-Centric Computing*. John Wiley & Sons, Inc., Hoboken, NJ.

Reifer, D.J. (1979) Software Failure Modes and Effects Analysis. *IEEE Transections on Reliability*. 28, 3, 247–249.

Russell, S.J., Norvig, P. (1995) *Artificial Intelligence: A Modern Approach*. Prentice-Hall, NJ.

Sawyer, R.K. (2014) *The Cambridge Handbook of The Learning Sciences – Second edition*. Cambridge University Press, NY.

Tay, K.M., Lim, C.P. (2006) Fuzzy FMEA with Guided Rules Reduction System for Prioritization of Failures. *International Journal of Quality & Reliability Management*. 36, 301–310.

Zadeh, L.A. (1992) Fuzzy logic and the calculus of fuzzy if-then rules. *Proceedings of the Twenty-Second International Symposium on Multiple-Valued Logic, Sendai*, 480.