Optimization of engineering student learning and assessment by cognitive methods

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Abstract
This study addresses the learning objectives and the student outcomes of industrial engineering students by examining them at three different levels: course level, program level, and graduate level. Three learning domains are developed and analyzed for this purpose to assess the performance of students during and after graduation. These domains are labeled as the house of cognitive learning, which shows the level of learning, its outcome elements, and the depth of understanding.

In the higher education system, the correct assessment of student learning is always considered as a challenging task. The aim of this study was to develop an integrated integer-programming algorithm to accurately determine the learning level of students. The method incorporates quality control charts and statistical assessment tools to present the findings. In this study, level of learning is calculated as a learning index that presents the contribution of a course to the respective student outcomes. Moreover, it depicts the overall achievements of students during their learning. Therefore, another aim of this study was to explore how to better utilize the collected data for the assessment of learning level. The outcomes of algorithm and statistical approaches are quite encouraging for the evaluation of students’ learning, thus improving the quality of engineering program.

Keywords: Learning quality, Qualitative assessment, Student outcomes, Learning objectives

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Introduction

Student outcomes (SOs) are related to learning objectives and indicate what students have to learn and what they are able to do or perform at the end of a learning process. Reich et al. (2014) stated that transfer of knowledge from teachers to students is just one part of learning, while students’ experiences and interaction with society are the other components. Freeman and Dobbins (2013) showed that measuring and assessing students’ learning is one of the most challenging tasks in the whole education and teaching process. According to Accreditation Board for Engineering and Technology (ABET), students’ learning outcomes (Hargreaves, 2007) clearly reflect what is expected from an engineering program. Similarly, the course learning outcomes (CLOs) are designed by instructors in accordance with the objectives of the whole engineering program. Therefore, SOs and course learning objectives must be designed complimenting each other, as both are based on program objectives. Implementation of SOs at the course level also carries much importance despite their reflection at the institute or university level (European Commission, 2011). Student outcomes must be observable, achievable, and measurable. However, accurate measurement of SOs is a challenging task and requires continuous assessment and professional judgment from all program constituents. In this regard, different direct and indirect assessment tools are used to assess SOs for higher education practices. Rogers (2003), however, stated that besides other difficulties, which hinder the assessment of student learning process, inconsistent use of assessment tools often creates disparity among instructors engaged in the assessment process. Northwood (2013) and Tamburri (2013) discussed the trend in which SOs are regarded as one of the major quality assurance tools to measure the learning objectives. Polikoff and Porter (2014) claimed that quality of any education system can be gauged from the level of skills that students develop within the classroom and exhibit in their professional life. Although learning assessment (Brookhart, 2013) methods are widely available, Liu, Frankel, and Roohr (2014) identified various challenges affecting their usefulness. They emphasized on the development of effective qualitative methods, which not only assess the achievement of students but also realistically measure the usefulness of program. Grez and Valcke (2013) presented an innovative technique to assess the oral presentations of students during research projects that integrates their higher order cognitive skills with scientific communication. Dadach (2013) and Lopes, Lanzer and Barcia (1997) proposed qualitative and quantitative methods to assess active learning of students and found many fuzzy connotations in it; however, Ma and Zhou (2000) assessed student learning outcomes through well-defined integration of fuzzy logics. A similar study was conducted by Wang, Kang, Chang, and Chang (2007), in which the fuzzy set theory was used for the evaluation and grading of students. Results of the study indicated the effectiveness of fuzzy systems in resolving the complex and ambiguous human reasoning due to its simultaneous handling of qualitative and quantitative data. Meanwhile, Taylan & Karagozoglu (2009) developed a flexible neuro-fuzzy system to better predict the learning performance of students. Tian and Lowe (2013) revealed that cultural differences create several emotional and psychological challenges among students during the initial period of their courses. Spelt, Luning, Boekel, and Mulder (2014) developed, implemented, and evaluated a research method to improve learning in the interdisciplinary field of food industry, with an objective to determine the effectiveness of this method in developing multidimensional learning among students.

Both direct and indirect methods, other than qualitative and quantitative techniques, are commonly used for evaluation purposes. However, the data used for this purpose are mostly...
collected using diversified assessment methods. Thus, in the absence of any unified assessment technique, these varied data inputs further emphasize the need for flexible and integrated methods of data evaluation. Terminologies such as outcome, goal, objective, student performance criteria (Baird, 2013), and standards can be understood in either similar or different ways. As a result, faculty members have to spend much time in understanding and comprehending the use of these terminologies, which not only create demotivation among them but also contribute toward incorrect assessments (Rogers, 2003). The aim of this study was to standardize the learning quality of students by bringing improvement in the evaluation method of SOs. An integrated integer-programming approach is developed to assess the learning level of students and their understanding to apply that knowledge, because it is evident that students’ real-life behavior directly reflects the quality of program from which they are graduated. However, accurate assessment of the engineering program is one of the difficult tasks in the whole process of learning and teaching, as evidence-based approach is required to assess students’ level of learning through specific SOs. Similarly, grades cannot be taken as the only basis for student assessment because faculty members for the same course vary in their teaching quality, content selection, and delivery methods (Polikoff & Porter, 2014). Another reason of the reduced dependency on grades is disparity within faculty members toward grading policy and assessment criterion. Numerical scores and letter grades mostly show the relative position of students among their class mates but unable to show the results of authentic assessment about the clarity of concepts, understanding of topics, and their ability to apply knowledge in real life (Liu et al., 2014).

The scope of this study includes the assessment of student learning and their levels for which the numerical scores are directly related to students’ learning objective. Therefore, the collected data would subsequently be utilized to improve the program. In this study, the program outcomes are considered to be SOs, which have already been identified by ABET with letters aligned from “a” to “k.” Initially described methodology is followed up by a discussion related to the assessment of learning quality, and finally, a quantitative approach called mixed integer-programming algorithm is employed for the assessment of engineering program. The calculations and results are then presented and discussed. The paper culminates with the main conclusions drawn.

Learning quality assessment of engineering students

Learning in a structured educational system (Hayward, 2015) is usually considered as a two-step process, involving the reception and processing of information. Extensive use of Bloom’s Taxonomy of educational objectives proved to be very effective in the development of students’ learning outcomes. Three main domains of Bloom’s Taxonomy – cognitive, affective, and psychomotor – are generally described as content, values, and skills, respectively.

The first one, the “cognitive domain” is related to creative thinking and intellectual capabilities (Bloom, 1956). Linguistic tools for measurement, such as “knowledge, comprehension, application, analysis, synthesis, and evaluation” can be used to describe this domain. The second one, the “affective domain,” is related to attitudes and feelings. The attitudes of students before, during, and after the learning process in which “they receive knowledge, respond, and value it” are the subjects of the “affective domain” (Krathwohl, 2002). Similarly, Dominguez et al. (2014) described how instructors of engineering students use online peer-review methods to endorse
their critical thinking and communication skills. Meyer, Knight, Callaghan, and Baldock (2014) developed a methodology for students to identify salient issues of any problem and then apply their knowledge for its analysis and immediate solution. Therefore, Figure 1 shows the three learning domains that students should attain during and after graduation.

![Figure 1: Relationship between student learning outcomes and program outcomes.](image)

Similarly, Figure 2 shows the level of learning, its outcome elements, and the depth of understanding. For instance, knowledge and comprehension indicate that students are novice and still at the introduction level of learning. This is called skill level 1 in Bloom’s Taxonomy.

![Figure 2: The house of cognitive learning.](image)

Skill level 2 in Bloom’s Taxonomy stands for application and analysis. This intermediate level focuses on the application of knowledge and analysis of findings. A student at this level of learning can identify new applications, recognize different patterns of real-life problems, and analyze their relationship with each other. However, intermediate level demands better understanding of both structure and content. In Skill level 3 of Bloom’s Taxonomy, synthesis and evaluation is performed by students. They learn to develop a complete picture by integrating different components of any problem. Assessing engineering program SOs is different from assessing SOs at the class level (Palermo, 2011); thus, faculty members should carefully determine the course objectives of students. The “knowledge” level that comes under the domain of cognitive skills alerts students about different dimensions of a problem. In the comprehension
level of learning, students try to summarize scattered pieces of information and find the
emerging trends (Anderson & Krathwohl, 2001). The next level of application equips students with
necessary skills to learn how to apply what they have learnt (Black, 2015). Similarly, they learn
about different components of a problem in the analysis phase, while the synthesis phase guides
them to integrate different components. In the evaluation phase, students develop their critical
thinking skills to see the outcome of their planning. Correct and comprehensive assessment of
SOs during all these phases has always been a challenging task for the faculty members, as
every student outcome should be related to certain skills. Table 1, therefore, shows rubrics for
each of the SOs and its associated skills.

<table>
<thead>
<tr>
<th>Learning outcomes</th>
<th>Associated skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical and creative thinking</td>
<td>Inquiring and analyzing knowledge, solve problems, creativity, depth and breadth of understanding.</td>
</tr>
<tr>
<td>Literacy</td>
<td>Information, quantitative, technological, and visual literacy.</td>
</tr>
<tr>
<td>Global understanding</td>
<td>Global understanding, sense of historical development, intercultural competence.</td>
</tr>
<tr>
<td>Communication skills</td>
<td>Oral, written and integrative communication, reading comprehension.</td>
</tr>
<tr>
<td>Professional and ethical behavior</td>
<td>Ethical reasoning, professional leadership, teamwork, personal organization, time management.</td>
</tr>
</tbody>
</table>

**Quantitative approach for engineering program assessment**

In the higher education system, student grades are important, but when assessment is carried
out at the program level, weightage of individual course grades become less. However, this
cannot undermine the importance of classroom assessments, as the SOs are eventually reflected
and aligned in program outcomes. Thus, different direct or indirect assessment methods are used
to measure students' knowledge and skill level in their classroom activities. Although direct
assessment is considered an easy way in which students are directly examined for the required
skill, yet, many activities are difficult to measure directly, so we employ indirect assessment
methods. However, both these methods have their own limitations that led to the use multiple
methods with multiple inputs (Klenowski et al., 2006).

Direct assessment tools consist of simulations, behavioral observations, performance
appraisals (Grisom and Loeb, 2015), and oral and written exams. Examples of indirect exams are
exit and entry surveys, interviews, archival data, focus groups, and written surveys. In this study,
a mixed integer-programming model is developed to assess the student learning level of the
course “Industrial Quality Control,” at Industrial Engineering Department, King Abdul-Aziz
University. According to ABET, the ability of students to apply knowledge of math, sciences, and
engineering is defined as “a” and the ability to plan and perform experiments together with the
analysis and interpretation of data is defined as “b.” Similarly, “e” represents the ability of
students to categorize, articulate, and resolve engineering problems, and “k” represents their
ability to apply methods and ways in solving engineering problems. Therefore, the algorithm for
quantitative assessment of student learning level is as follows:
Let $F$ be the set of students undergoing a course and $f_i$ be the frequency of students acquiring same marks. Therefore, the total marks obtained can be presented as follows:

$$F = \{f_1, f_2, \ldots, f_n\} = \sum_{i=1}^{n} f_i$$

Similarly, let $A$ be the set of assessment tools, such as exams, homework, and in-class studies:

$$A = \{a_1, a_2, \ldots, a_k\}.$$

$G$ be the mark a student acquired in a course at the end of the semester:

$$G = \{g_1, g_2, \ldots, g_m\}.$$

$CLO_i$ be the course learning outcomes:

$$CLO_i = \{CLO_1, CLO_2, \ldots, CLO_n\}, \text{ and }$$

$SO_j$ be the student outcomes, from “$a$ to $k$”:

$$SO_j = \{a, b, c, d, \ldots, k\}.$$

On the contrary, let $R$ be the rate of the relation between $CLO$s and $SO$s, depicting the maximum level of relation.

$$R = \text{Max} \ (r_{ij})$$

where $r_{ij} = 1, 2, \text{ or } 3$; therefore, it is an integer and shows the level and the relevance of course learning outcomes $i$ with program educational objectives $j$ (SOs). The relevance of addressed program educational objectives is estimated in percentage by the instructor or a course design team. In this study, a senior-level course “Industrial quality control” and additional five courses were considered, which address the SOs “$a$, $b$, $e$, and $k$.” Therefore, they can be presented as follows:

The relevance of $CLO_i(s)$ (course learning outcomes) and program outcomes ($PO_i; SO_j(s) = \{a, b, e, k\}$) is given in percentages ($\rho_i$). The design team determined the weight of relevance in percentage sequentially as follows. $PO_i$ for $\rho_i = \{0.2, 0.3, 0.3, 0.2\}$ is:

$$PO_{ij} = \sum_{i=1}^{k} \rho_i = 1$$

The contribution of CLOs to the program outcomes is obtained by multiplying maximum level learning for each outcome with relevant addressed program outcome:

$$CLO_{ij} = \sum_{i=1}^{k} f_{ij} \rho_i, \quad k = 1 \ldots n, \quad \text{Where } n \text{ is the number of course learning outcomes.}$$

The average class performance ($\bar{X}_i$) was calculated by the total final grade obtained, where $f_i$ is the frequency of students who obtained grade and $g_i$ is the mark obtained by a student:

$$\bar{X}_i = \frac{\sum_{i=1}^{n} f_i g_i}{\sum_{i=1}^{n} f_i}$$
The level of learning achievement (LOL) is calculated in percentage by multiplying course learning outcome and average class performance:

$$LOL_i = \overline{x}(CLO_i)/100$$

Therefore, the level of learning was calculated as a learning index. The learning index presents the contribution of a course to the SOs. Moreover, it depicts the overall learning level achievement of students. The program-targeted level of learning is [60,100].

**Results of quantification of learning level and its assessment**

Evaluation of student learning starts with the development of well-defined course and program learning objectives. Weightage of learning objectives can be modified according to the overall performance of students; therefore, questions in the exams carry much importance. Table 2 shows the articulation matrices that present the distribution of CLOs into corresponding SOs. However, these distributions are subject to change, if the designer decides for a different level of contribution. These levels are denoted by 1, 2 or 3. For instance, CLO5 stands for the application of subject called “variable control charts.” The contribution of this CLO toward “a; ability to apply math, science and engineering” is high (3), which means that a student who learned how to apply the control charts must show his/her ability to apply the knowledge of math and engineering at high level. The relationships and contributions of all CLOs with other SOs can be explained in a similar way.

**Table 2**: Contribution of course learning outcomes to program outcomes.

<table>
<thead>
<tr>
<th>Course learning outcomes</th>
<th>a</th>
<th>b</th>
<th>e</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLO1: Define quality, quality control, SQC and TQM</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>CLO2: Define TQM tools &amp; techniques</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>CLO3: Discuss the fundamentals of statistics &amp; probability</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>CLO4: Apply and analyze the variable control charts</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>CLO5: Apply and analyze the control charts for attributes</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>CLO6: Develop and design the acceptance sampling by attributes</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>CLO7: Determine the sampling plan by different methods</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

According to Table 2, the contributions of CLOs to the student outcome “a” occur at different levels. The contributions of all CLOs for learning and applying knowledge of mathematics, science and engineering seemed high for students who have enrolled in industrial quality control. Table 3 shows the weightage of addressed program educational objectives estimated by an instructor or a design team in percentage.

**Table 3**: Weightage of addressed program outcome in percentage.

<table>
<thead>
<tr>
<th>Relevance of addressed POs for the course percentage</th>
<th>a</th>
<th>b</th>
<th>e</th>
<th>k</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20</td>
<td>30</td>
<td>30</td>
<td>20</td>
<td>100</td>
</tr>
</tbody>
</table>
As the maximum level of learning for each program outcome is 3, the contribution of course learning outcome is obtained by multiplying the maximum level of learning for each program outcome with the relevance of addressed SOs. Table 4 presents the total contribution of CLOs to each program educational objective.

Table 4: Total contribution of CLOs to each program outcome.

<table>
<thead>
<tr>
<th>Contribution of CLOs to each program outcome</th>
<th>a</th>
<th>b</th>
<th>e</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>60</td>
<td>90</td>
<td>90</td>
<td>60</td>
</tr>
</tbody>
</table>

On the contrary, the average class performance ($\bar{X}$) is calculated on the basis of the total final grade (achievement). As it was stated, $f_i$ is the number of students obtaining grades and $(g_i)$ is the numerical value of grades. Therefore, Table 5 presents the course final grades and the achievements of students in “Industrial Quality Control.”

Table 5: Course final grades and frequency distribution.

<table>
<thead>
<tr>
<th>Grades</th>
<th>Numerical values ($g_i$)</th>
<th>Number of students obtaining grades ($f_i$)</th>
<th>Achievement</th>
</tr>
</thead>
<tbody>
<tr>
<td>A+</td>
<td>95</td>
<td>4</td>
<td>380</td>
</tr>
<tr>
<td>A</td>
<td>90</td>
<td>4</td>
<td>360</td>
</tr>
<tr>
<td>B+</td>
<td>85</td>
<td>2</td>
<td>170</td>
</tr>
<tr>
<td>B</td>
<td>80</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C+</td>
<td>75</td>
<td>7</td>
<td>525</td>
</tr>
<tr>
<td>C</td>
<td>70</td>
<td>1</td>
<td>70</td>
</tr>
<tr>
<td>D+</td>
<td>65</td>
<td>5</td>
<td>325</td>
</tr>
<tr>
<td>D</td>
<td>60</td>
<td>7</td>
<td>420</td>
</tr>
<tr>
<td>F</td>
<td>37</td>
<td>6</td>
<td>222</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>36</td>
<td>2472</td>
</tr>
</tbody>
</table>

If $X_i$ is the grade obtained by a student, it can be calculated as follows:

$$\bar{X} = \frac{2472}{36} = 68.67$$

Table 6 presents the achievement of students calculated by multiplying the contribution of CLOs to POs and average class performance.

Table 6: Achievement of students addressed by the contribution of CLOs to POs.

<table>
<thead>
<tr>
<th>Achievement of students in percentage</th>
<th>41.17%</th>
<th>61.75%</th>
<th>61.75%</th>
<th>41.17%</th>
</tr>
</thead>
</table>

As it was stated, the “Industrial Quality Control” course was considered for the assessment of learning level. The number of students enrolled in this course was 36 for spring 2012 semester. The number of students obtaining grades A+ to D was 30. Therefore, the first row in Table 7 shows the program achievement level of this course. The course supports four POs and there are
five more courses supporting the same program educational objectives, whose achievements are presented in Table 7.

Learning and its level is a quality characteristic that normally cannot be represented numerically. However, due to the current applications, it has to be presented numerically for people to understand its assessment. In this study, we have defined specification limits for learning quality and developed control charts to present the contribution of courses to the program educational objectives. Different assessment tools are used to evaluate the learning level of students. These evaluations are then presented as percentage, grades (e.g. A, B, C, D or F) or linguistically (Law, 1995), such as “Fail”, “Pass”, “Excellent” and “Outstanding”. Figure 3(a)–(d) shows the control charts depicting the contribution of courses to the SOs.

![Figure 3](image-url)

**Figure 3**: Control charts for the contribution of courses to POs.

*Figure 3(a)* shows that course #1 addressing the learning objective “a,” which is the ability of students to apply knowledge of math, science and engineering, does not meet the required performance of learning level. The learning level of students is 43.4, which is below the lower

<table>
<thead>
<tr>
<th>Courses</th>
<th>a</th>
<th>b</th>
<th>e</th>
<th>k</th>
<th>Program-targeted max. learning level</th>
<th>Program-targeted min. learning level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>43.4</td>
<td>65</td>
<td>65</td>
<td>43.4</td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>2</td>
<td>78.6</td>
<td>83.2</td>
<td>67.5</td>
<td>75.3</td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>3</td>
<td>82.1</td>
<td>74.3</td>
<td>75.4</td>
<td>81.2</td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>4</td>
<td>76.5</td>
<td>70.6</td>
<td>58.5</td>
<td>86.3</td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>5</td>
<td>70.3</td>
<td>68.6</td>
<td>67.4</td>
<td>55.4</td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>6</td>
<td>68.9</td>
<td>72.2</td>
<td>70.6</td>
<td>56.3</td>
<td>100</td>
<td>60</td>
</tr>
</tbody>
</table>

Table 7: Program achievement level for six courses addressing the program outcome.
specification limits. The instructor needs to take immediate and sustainable measures to address the problems. Similarly, Figure 3(d) shows that courses #1, 5 and 6 have problems supporting the student outcome “k,” which is the ability to apply methods and techniques for solving engineering problems. Also in this case, the instructor should take remedial actions to resolve these issues.

Figure 3(b) and (c) depicts that the CLOs of six courses addressing SOs “b” and “e” have achieved the desired goals. Students not only can plan and perform tasks well but also can analyze and interpret the data. One of the basic objectives of these assessments methods is to ensure effective and efficient learning. As evident in a simple curving system, the instructor determines beforehand that very few students will do either very well to get As or very poor to get Fs, whereas the majority will cluster in the middle to get Bs, Cs and Ds (Svinicki, 2005).

A normal probability plot and grade distribution of learning performance is shown in Figure 4 for a real data set obtained from the outcomes of students who have taken industrial quality control, where some reliability error occurred due to the lack of sufficient information about student performance.

![Figure 4: Desirability and acceptability of learning level.](image)

The desirability of students’ learning level is illustrated in Figure 4(a) and (b), which illustrate the performance of two groups of students. The mean of each group is the same; however, the standard deviations are different. It is clear that when the standard deviation is large, the shape of the curve is platykurtic and when the standard deviation of the learning level is small, the curve is leptokurtic. Some people may not consider the distinction between the two cases in terms of students’ learning quality; that is, in both cases, virtually all students are in the passing limits. However, the students represent two different learning levels, a clear distinction exists between the students in Figure 4(a) and those in Figure 4(b) with regard to quality of learning. For instance, an instructor analyzing the exam performance of students would categorize students with scores of 58 and 62 as the same, but much poorer from those who got 85 or 95. Even though 60 is the lower limit for passing grade, no one would view two students with grades of 62 and 95 as the same from a quality standpoint. This low-level learning might not only have harmful effects in the future work life of students’ but also bring higher cost to the society in terms of poor work quality and low productivity. Figure 5 shows the normal distribution of students’ learning level for industrial quality control, which is a senior-level
course. It shows that 2.3% of students achieved highest scores (86.04–96.99): (μ + 3σ) with their learning level considered as an advance level. These students can easily evaluate and synthesize the data to see the emerging trends. A proportion of 13.6% of them scored within (75.09–86.04): (μ + 2σ), and this learning level is considered as an intermediate level and students are supposed to apply what they have learnt. Similarly, 68.2% of students fall between the learning limits of (64.14–75.09): (μ + 1σ) and (53.19–64.14): (μ − 1σ). This is a novice-level learning, and these students can only apply what they have learned. However, the remaining 15.9% of students are very poor. They need to repeat the course to improve the level of learning. It is evident that few students have succeeded to achieve the highest learning level. On the contrary, the majority of students are in the average group.

Table 8 presents the courses addressing SOs on the basis of average course contribution. These averages show the learning level for each of the POs. Therefore, in Table 8, the average contribution of 28 courses to program outcome is presented. It is realized that average contributions provide useful information about course level learning, which is low in some cases.

![Distribution Plot](Normal, Mean=64.14, SD=10.95)

**Figure 5:** Quality distribution of student outcome.

<table>
<thead>
<tr>
<th>Courses</th>
<th>Course contributions to program outcomes (“a” to “k”); (Achievement level)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a</td>
</tr>
<tr>
<td>1</td>
<td>43.4</td>
</tr>
<tr>
<td>2</td>
<td>78.6</td>
</tr>
<tr>
<td>3</td>
<td>82.1</td>
</tr>
<tr>
<td>4</td>
<td>76.5</td>
</tr>
<tr>
<td>5</td>
<td>70.3</td>
</tr>
<tr>
<td>6</td>
<td>68.9</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>28</td>
<td>58.3</td>
</tr>
<tr>
<td>Average</td>
<td>70</td>
</tr>
</tbody>
</table>
but can be improved by well-designed courses, and with regard to program assessment, senior-level courses provide better understanding of subjects with better overall learning performance. Figure 6 shows the overall learning assessment for each of the student outcome indicating that students have grasped some additional information and improved their learning levels, which were initially poor. However, graduated students have shown certain problems and missed some criteria for program educational outcomes “c, f and h.” Similarly, the level of learning can be stated as follows: 60–70 is novice-level learning; 70–85 is intermediate-level learning and 85–100 is advanced-level learning.

**Conclusion**

Student learning levels are strongly dependent on course designs and assessment tools. Therefore, courses and other programs should not be changed on the basis of intuition alone, rather real and relevant data must also be considered. Learning objectives together with course contents should be clearly explained to students, and reciprocally, students’ expectation from teachers also need to be properly addressed.

In this study, three learning domains have been investigated systematically. These domains are designed as the house of cognitive learning to explore different learning levels of students, which they are supposed to attain in their engineering course. In higher education system, the assessment of right learning level is an important phenomenon. Therefore, an integrated integer programming approach was developed to assess the correct learning level of students. The proposed algorithm assesses the learning quality of students and presents the outcomes as a learning index. The outcome is further evaluated using quality control charts and statistical tools to enrich the findings. The level of learning is graphed by quality control charts from novice-level learning to advanced-level learning.

As a conclusion, these assessment tools will help students in taking more responsibility toward their studies. They are expected to do frequent self-evaluations and feel more confident in developing their own plans for a better learning. Continuous learning and improvement tools
can be adopted in curriculum design to achieve the planned goals. On the contrary, educational IT infrastructure can be developed to encourage students for submitting their scholarly works on- or off-campus and prepare them for interactive discussions during classes. The major limitation of this study is the natural learning fluctuation among students, which can create difficulties for researchers to achieve consistency in SOs.

References


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