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Automated Assessment and Monitoring Support for Competency-Based Courses

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ABSTRACT Competency-based education is becoming increasingly adopted by higher education institutions all over the world. This paper presents a framework that assists instructors in this pedagogical paradigm and its corresponding open-source implementation. The framework supports the formal definition of competency assessment models and the students' evaluation under these models. It also provides distinct learning analytics for identifying course shortcomings and validating corrective actions instructors have introduced in a course. Finally, this paper reports the benefits of applying our framework to an engineering course at the Pontifical Catholic University, Valparaíso, Chile for three years.

INDEX TERMS Competency-based education, course assessment, course monitoring, learning outcome.

I. INTRODUCTION

Competency-Based Education (CBE) can be broadly defined as a pedagogical approach focused on the students' mastery about a given subject [1]–[3]. In CBE, students have to demonstrate their progress by validating their *competency*, which means that they prove to master the knowledge and skills required to overcome a particular course [4]. Thus, the assessment strategies acquire a key role in the correct implementation of CBE programs, especially, in courses where teachers usually have different assessment strategies. Nevertheless, the current literature reveals that still there is no uniformity (or standards) regarding how CBE programs should be structured and assessed [5].

With the aim of supporting CBE, this paper presents a framework that helps to (i) formally define assessment models for academic courses, (ii) compute students' competency achievement from these models, and (iii) monitor the course evolution over time, facilitating this way the course continuous improvement. Let us discuss briefly the tremendous impact that the competency-based paradigm has in higher education nowadays, the motivations of our work and also its principal contributions.

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Higher education institutions regularly face processes of new degree accreditations and curricular updates to renovate their contents and educational models, and also to certify their educational quality [6]. At present, there is a clear tendency to that academic institutions redirect their teaching methodologies towards CBE; for instance, in Europe the Bologna Declaration [7] has promoted the CBE adoption in twenty-nine countries, in the USA several states recently introduced and enacted legislative actions related to CBE [8], [9], and in Chile most universities have started their conversion from a traditional teaching scheme towards CBE in the last decade [10].

Using *Quality Assurance Agencies for Higher Education*, academic institutions all over the world conduct external reviews to check the quality of its internal processes. In this context, the fulfillment of graduate profiles with quality standards [11] is strictly revised by agencies. As a response, universities must demonstrate clearly and with evidence that the curriculum offered for a career are met rigorously. This latter is particularly difficult for the case of the implementation of CBE models [5], [12], [13], since the number of new pedagogical concepts, definitions, and additional aspects to be handled by the teaching staff are not few and their correct application strongly depends on the level of knowledge that each teaching team member has on this educational model.

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This is especially true with regard to the redesign of the course programs and their assessment methodology where, at least, the following issues should be considered [4], [14], [15]: (i) how to define the competency model, (ii) how to generate the evidence of its development, (iii) how to collect this evidence, and (iv) how to evaluate it. The latter should provide objective information on the students' performance not only in terms of the contents studied but also concerning the achievement of competencies of the graduate profile reached by them.

To overcome the issues mentioned above, this paper proposes the *Competency Assessment and Monitoring* framework (C-A&M), which provides a formal language to define competency assessment models accurately, detailing all their elements and how those elements depend on each other. C-A&M also implements an automated procedure for processing these formal models efficiently, aggregating fine-grained students' grades to obtain more abstract information about their competency acquisition levels. Finally, C-A&M enables tracking how a competency-based course evolves by giving descriptive and inferential statistics. The paper reports the C-A&M application during five editions of an engineering course at the Pontifical Catholic University of Valparaíso in Chile, from 2016 to 2018, showing how C-A&M helped (i) to identify distinct shortcomings in the course, and (ii) to check if the corrective actions the instructors implemented for solving the problems were effective.

The remainder of this paper is structured as follows: Section II describes C-A&M. Section III reports the application referred above of C-A&M to a university course. Section IV discusses work related to ours. Finally, Section V summarizes the main conclusions of this paper.

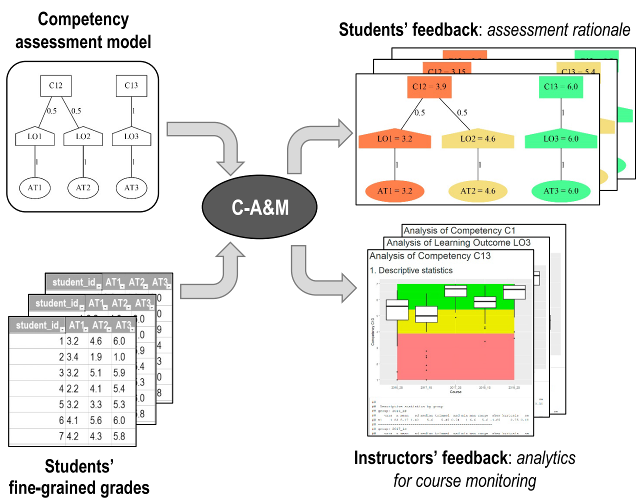

FIGURE 1. Inputs and outputs of the C-A&M framework.

II. C-A&M: A FRAMEWORK TO ASSESS AND MONITOR COMPETENCY-BASED COURSES

Figure 1 provides a general overview of C-A&M, depicting it as a "black-box" that:

1) Receives a *competency assessment model* specifically designed for a course, and the fine-grained grades obtained by the students in one or more course editions. Section II-A describes this input.
2) Generates:
   a) A report, personalized for each student, about the competency level she has achieved. This feature is explained in Section II-B.
   b) A report, for every element of the competency model, that analyzes students' competency acquisition evolution along several course editions. This analysis is summarized in Section II-C

An open-source prototype implementation of C-A&M is freely available at: https://github.com/rheradio/C-AM/.

A. COMPETENCY ASSESSMENT MODEL

C-A&M is founded on the underlying concepts of CBE. An academic degree promotes a set of *competencies*, and it is composed of different courses that focus on subsets of these competencies. Each competency is developed by a set of *learning outcomes* that students should evidence by means of the different *assessment tools* applied in the course. Educators use different types of assessment tools (diagnostic, formative, summative, norm-referenced, criterion-referenced, among others) to collect feedback on all aspects of the student learning experience along the course. In this sense, a set of concrete and evaluable behaviors that allow verifying the achievement of a learning outcome must be defined. Such behaviors are named *indicators* and these can address content, skills, and long-term attitudes or values [16]. Once the indicators are defined, the selection and creation of the assessment tools are done based on them. These are designed to measure a subset of indicators, preferably using evaluation rubrics so that objectivity of the assessment process is guaranteed.

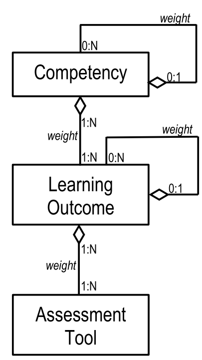

FIGURE 2. Competency assessment metamodel.

In C-A&M, the assessment model of a course is defined as a particular instance of the *metamodel* in Figure 2. For instance, Figure 3 represents a course that promotes seven Competencies $C_1, C_2, \ldots, C_7$, with seven Learning Outcomes $LO_1, LO_2, \ldots, LO_7$, an ten Assessment Tools $AT_1, AT_2, \ldots, AT_{10}$. In this example, students will be evaluated with a numerical scale from 0 to 10.

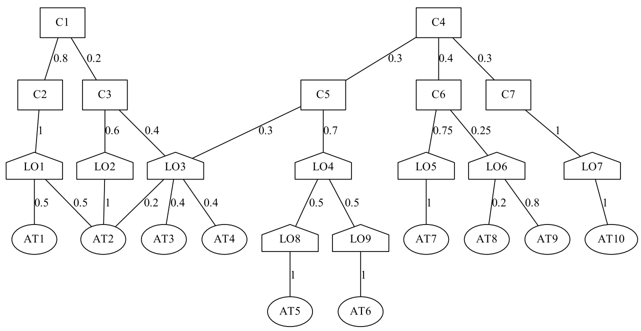

FIGURE 3. Graphical representation of a competency assessment model.

Abstract competencies can be decomposed into more concrete ones. For example, C_1 is decomposed into C_2 and C_3. A *weight* between 0 and 1 specifies the contribution of each concrete competency to the abstract one. The sum of all the descendant weights of any competency is 1 (indeed, this holds for any kind of element, including learning outcomes and assessment tools). For instance, C_2 and C_3 contribute 80% and 20% to C_1, respectively. Likewise, concrete competencies are developed by learning outcomes (e.g., C_3 is developed by LO_2 and LO_3), and abstract learning outcomes can be decomposed into more concrete ones, which are finally measured with assessment tools (e.g., LO_1 is measured with AT_1 and AT_2). The cardinalities in Figure 2 accurately set the inter-element relationship constraints that every model must satisfy: elements of the same type are decomposed as *Trees*, and elements of different kind are organized as *Directed Acyclic Graphs* (DAGs). For instance, C_3, C_5 and LO_3 follow a DAG structure since LO_3 has the two parents C_3 and C_5: LO_3 develops 40% of C_3, and 30% of C_5.

C-A&M provides a language to formally define assessment models. For example, the following code fragment specifies the decomposition of C_3 into LO_2 and LO_3; Lines 1-2 declare the *types* of C_3, LO_2 and LO_3 (i.e., `competency` and `learning_outcome`); and Lines 4-7 express the decomposition:

```
1 competency "C3"
2 learning_outcome "LO2", "LO3"
3
4 decompose "C3" into
5     "LO2" weights 0.6
6     "LO3" weights 0.4
7 end
```

B. STUDENTS' FEEDBACK

Once the students' fine-grained grades have been measured with the assessment tools, C-A&M computes the achievement levels of the competencies and learning outcomes, providing students with a graphical report of their results.

For example, Table 1 summarizes the grades of a student measured with the tools $AT_1, AT_2, \ldots, AT_{10}$; and Figure 4 depicts the derived achievement levels, which are calculated as weighted averages as follows: if an element e is decomposed into n elements with weights $w_1, w_2, \ldots, w_n$, and whose achievement levels $a_1, a_2, \ldots, a_n$ are known, then e achievement is $a = \sum_{i=1}^{n} w_i \cdot a_i$. In Figure 4, LO_3 is decomposed into AT_2, AT_3 and AT_4 and thus LO_3 achievement is $0.2 \cdot 3 + 0.4 \cdot 6 + 0.4 \cdot 7.5 = 6$.

TABLE 1. Fine grained grades of a student measured with the assessment tools $AT_1, AT_2, \ldots, AT_{10}$.

AT1	AT2	AT3	AT4	AT5	AT6	AT7	AT8	AT9	AT10
4	3	6	7.5	8	2.5	6	7	5	6.5

To obtain a more immediate and abstract understanding of students' competency achievement, instructors can transform numerical assessment values into linguistic ones. To do so, a *conversion range* needs to be specified. For instance, the following conversion range transforms numerical assessments a into the linguistic labels *not achieved*, *moderately achieved* and *achieved*:

$$\text{linguistic label} = \begin{cases} \text{not achieved} & \text{when } a < 5 \\ \text{moderately achieved} & \text{when } 5 \le a \le 7 \\ \text{achieved} & \text{when } a > 7 \end{cases} \tag{1}$$

As a result, the students' and course analysis graphical reports that C-A&M generates are enhanced with colors that account for the linguistic labels specified by the instructor. For example, in Figure 4 colors red, yellow and green represent the linguistic values *not achieved*, *moderately achieved* and *achieved*, respectively. The achievement levels of a student are computed with Algorithm 1, which traverses the assessment model in a depth-first fashion; `getAchLevels` is called as many times as top-abstract competencies the model has, receiving the model roots as argument.

Algorithm 1. Computing Student Achievement Levels

```
Function getAchLevels(e)
    mark(e) ← not mark(e)
    if e is not an assessment tool then
        ach[e] ← 0
        foreach descendant d of e do
            if mark(e) ≠ mark(d) then getAchLevels(d)
            ach[e] ← ach[e] + ach[d] · weight_{e,d}

foreach root competency e do
    getAchLevels(e)
```

There is a Boolean `mark` for every node e in the model, being either all true or all false when the algorithm execution starts; `getAchLevels` visits all nodes by recursively visiting the sub-models rooted by e. Whenever a node is visited, its `mark` value is complemented. Comparing the marks of e and its children, it is determined if they have already been visited. The method ensures that each node is visited exactly once and that, when `getAchLevels` finishes, all node marks have the same value. The computed achievement levels are stored in the global variable `ach` of type array.

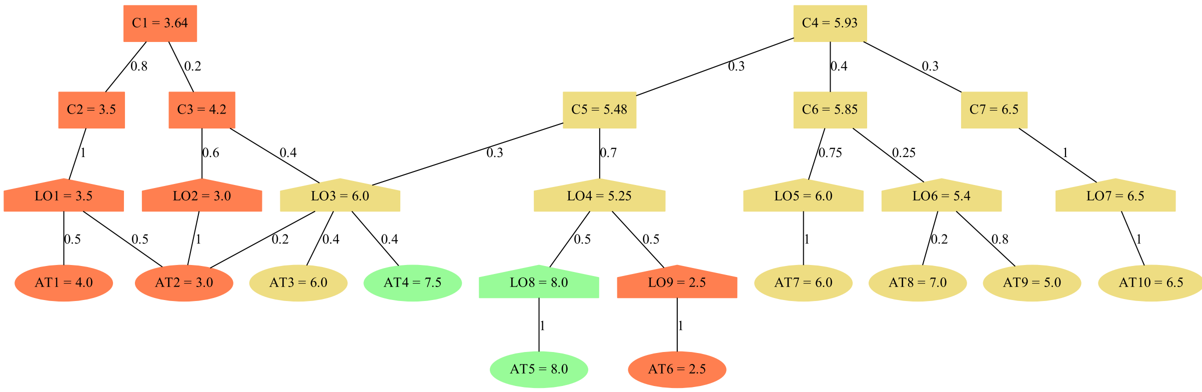

FIGURE 4. Achievement levels for the student in Table 1.

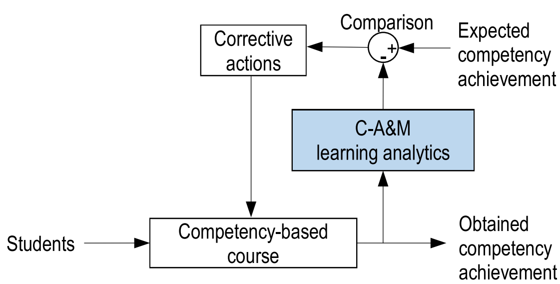

FIGURE 5. Instructors' decision making support to improve the competencies achievement in a course.

C. INSTRUCTORS' FEEDBACK

A C-A&M essential feature is rendering learning analytics for monitoring the students' competency achievement along different course editions and thus supporting the course continuous improvement. Figure 5 sketches this iterative improvement process: students obtain a given competency achievement, which is compared to the results instructors expect. Depending on the analysis, instructors may decide corrective actions to improve students' performance in the following course edition, which is later analyzed in a subsequent process iteration.

The following points summarize the analytics C-A&M currently supports; nevertheless, its architecture has been specifically designed so that it can be easily extended to incorporate new statistical analyses:

1) *Descriptive statistics*:
   a) For each model element, a summary is produced, showing students' mean, trimmed mean, standard deviation, minimum and maximum values, value range, median, median absolute deviation, skew and kurtosis.
   b) A box-plot is also generated for each model element (some examples will be presented in Section III-C).
2) *Inferential statistics*: to test if the students' competency achievement changes significatively along the successive course editions, C-A&M undertakes an ANalysis Of VAriance (ANOVA) that includes:
   a) Testing if the ANOVA requirements are satisfied:
      i) A Shapiro-Wilk normality test verifies if the residuals follow a normal distribution.
      ii) A Levene's test verifies the variance homogeneity.

      It is worth noting that the group independence requirement does not need to be tested since the competency level that students achieved in one semester/year does not affect the competency level that other students achieved in a different semester/year.
   b) ANOVA results (p-value, F-value, sum of squares, mean squares, and degrees of freedom.
   c) η^2 [17] to account for the effect size.
   d) Tukey's method for multiple comparisons of means to identify when instructors' corrective actions pay-off with statistical significance.

III. CASE STUDY

This section reports the C-A&M application to an Automatic Control course of a competency-based study program of the master degree on Electrical Engineering at Pontifical Catholic University of Valparaíso (PUCV), in Chile.

A. COMPETENCY ASSESSMENT MODEL

The graduate profile of the study program promotes a total of twenty competencies. In particular, the Automatic Control course contributes to developing two of them: C_{12} and C_{13}, which are supported by three learning outcomes: LO_{12_1}, LO_{12_2} and LO_{13_1}. Table 2 describes each competency and its associated learning outcomes. Figure 6 depicts the relationship between competencies and learning outcomes. C_{12} is developed with LO_{12_1}, related with control systems analysis, and LO_{12_2}, related with control systems design, both contributing with the same weight (50%) to the competency. In addition, C_{13} is developed with LO_{13_1}, related to control systems simulation, therefore contributing with a 100% to the competency.

The learning outcomes are evaluated with three assessment tools: two exam-like partial tests AT_1 and AT_2; and one

TABLE 2. Competencies and learning outcomes for the automatic control course at PUCV.

Competency C_{12}	Solving open and complex problems of Electrical Engineering and/or that require disciplinary approaches
Learning outcomes	**Indicators** (content, skills, and long-term attitudes or values)
LO_{12_1}: students will be able to apply methodologies of control system analysis to solve electrical engineering problems	The student identifies processes and their variables and it models their behavior
	The student analyses the transient and steady state response of a control system
	The student analyses the stability of a control system using the typical analysis tools known as LGR, BODE and/or NYQUIST, as appropriate
	The student interprets and validates results obtained from the control system analysis
LO_{12_2}: Students will be able to apply methodologies of control system design to solve electrical engineering problems	The student selects an appropriate controller design strategy and justifies its choice through analysis
	The student designs conventional compensators, PID controllers and / or controllers by state feedback, applying the classic controller tuning procedures
	The student interprets and validates the performance of a controller by analysing the resultant closed-loop system
Competency C_{13}	Simulating electrical systems to represent its behaviour optimize its parameters and improve its operating conditions
Learning outcomes	**Indicators** (content, skills, and long-term attitudes or values)
LO_{13_1}: Students will be able to use computational tools to simulate and analyse control systems	The student models and simulates control systems using simulation software
	The student defines experiments to analyse the performance of a control system using simulation software
	The student interprets and validates results of control systems by analysing response graphs obtained by means of simulation

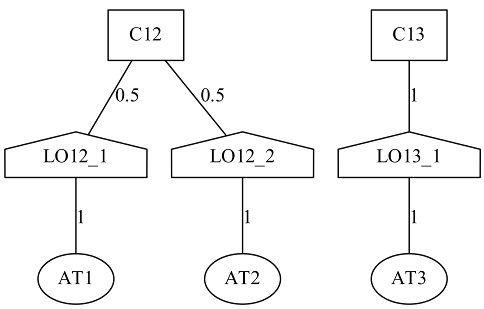

FIGURE 6. Competency model for the automatic control course at PUCV.

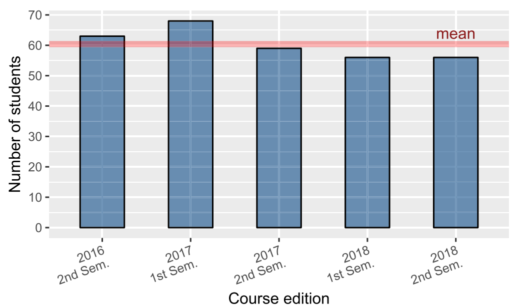

FIGURE 7. Number of enrolled students per course edition.

knowledge integration activity AT_3. AT_1 and AT_2 are intended to measure specifically the theoretical knowledge acquired by the students about the analysis and design of control systems (*content indicators*). AT_3 relies on virtual laboratories for conducting online experiments [18]–[21]; these labs enable students to apply their control designs on real processes by conducting practical experiences to train fine control skills and checking the validity of a control strategy with simulation techniques (*skill indicators*).

All the elements of the assessment model (competencies, learning outcomes and assessment tools) are measured with a numeric scale that goes from 1 for the lowest qualification up to 7 for the highest qualification. An element is approved when its grade is greater than or equal to 4 (exigency factor of 50%). The numeric scale is translated to a linguistic achievement scale as follows: *Not achieved* (grade $<$ 4), *Moderately achieved* (4 $\leq$ grade $<$ 5.5), and *Achieved* (grade $\geq$ 5.5).

B. METHOD

C-A&M was applied in the last five editions of the Automatic Control course previously described. Figure 7 shows the number of students enrolled in each course edition. There were 60.4 students per course on average. The maximum and minimum number of students were 68 and 56, in the 1st semester of 2017 and both the 1st and 2nd semesters of 2018, respectively.

C-A&M was used to inform students about their grades, justifying their results at all abstraction levels: competencies, learning outcomes, and assessment tools (see Section II-B). Moreover, C-A&M was applied to monitor the course evolution over time. Instructors were responsible for measuring, registering and tracking the academic performance of the students. Subsequently, based on the periodical analysis of the obtained competency achievement in comparison with the expected performance, they implemented corrective actions to improve the next course edition competency attainment.

C. RESULTS AND DISCUSSION

The data presented in this section (students' grades obtained with the assessment tools AT_1 AT_2 and AT_3, their derived competency achievement levels, and the competency longitudinal analysis) are available at: https://github.com/rheradio/C-AM/tree/master/examples/PUCV

FIGURE 8. Students' results for C_{12}.

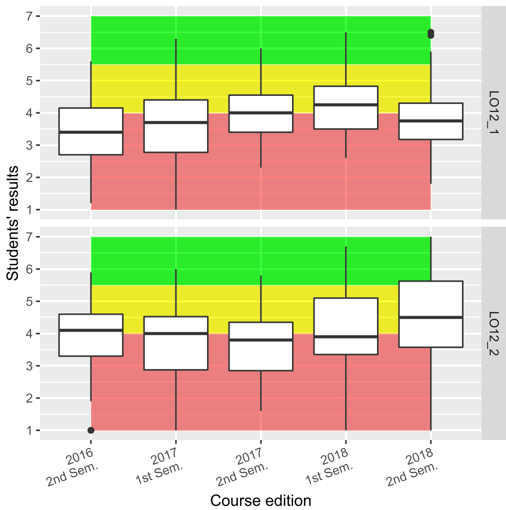

FIGURE 9. Students' results for LO_{12_1} and LO_{12_2}.

1) MONITORING C_{12}

The boxplot in Figure 8 represents students' C_{12} fulfillment over time. Colors red, yellow and green represent the linguistic grade values *Not achieved*, *Moderately achieved* and *Achieved*, respectively.

Instructors were extremely concerned about the low competency achievement in the first course editions. For instance, in the 2nd semester of 2016 most students failed to achieve C_{12}: students' mean and median were 3.64 and 3.75, respectively; and the standard deviation was just 0.93.

One of the advantages of C-A&M is that it supports moving between distinct assessment abstraction levels to understand better the causes of an educational problem. Figure 9 descents one abstraction level to depict students' evolution for LO_{12_1} and LO_{12_2}. At this level, LO_{12_1} seems to be the main responsible for the low C_{12} achievement in the 2nd semester of 2016: whereas LO_{12_1} median is 3.4, LO_{12_2} median is 4.1. Hence, instructors focused their efforts on improving LO_{12_1}. As a result, they modified the control system analysis teaching material and redistribute the course schedule to dedicate more hours to LO_{12_2}. As a result, in the 1st semester of 2017, LO_{12_1} students' grades slightly increased but at the cost of reducing students' performance for LO_{12_2} (having less time for LO_{12_2} had a negative impact). So, next time instructors' efforts shifted towards improving LO_{12_2}.

TABLE 3. ANOVA for C_{12}, LO_{12_1} and LO_{12_2}.

Element	ANOVA		Effect Size
	F value	p value	η^2
C_{12}	4.171	0.002	0.053
LO_{12_1}	6.268	7.45e-05	0.077
LO_{12_2}	4.301	0.002	0.054

TABLE 4. Tukey multiple comparisons of means for C_{12}, LO_{12_1} and LO_{12_2}.

Element	Pair	Mean difference	Adjusted p-value
C_{12}	2016 2S *vs* 2018 1S	0.525	0.030
	2016 2S *vs* 2018 2S	0.502	0.043
	2017 1S *vs* 2018 1S	0.524	0.026
	2017 1S *vs* 2018 2S	0.500	0.038
LO_{12_1}	2016 2S *vs* 2017 2S	0.592	0.016
	2016 2S *vs* 2018 1S	0.835	0.000
	2017 1S *vs* 2018 1S	0.696	0.002
LO_{12_2}	2016 2S *vs* 2018 2S	0.649	0.040
	2017 1S *vs* 2018 2S	0.785	0.005
	2017 2S *vs* 2018 2S	0.839	0.003

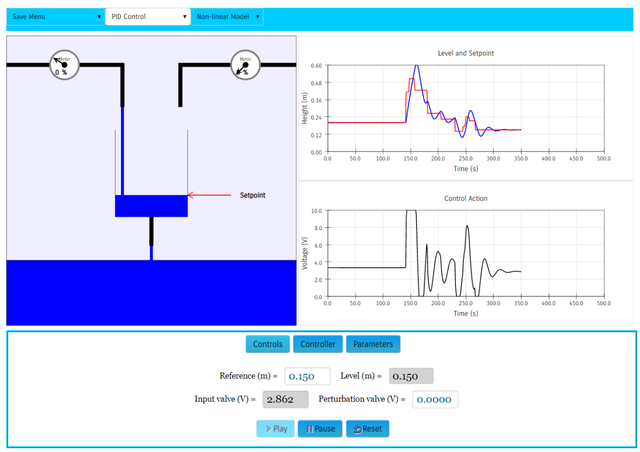

FIGURE 10. One of the virtual labs used to support C_{13}: controlling a single tank system.

As Figure 9 shows, instructors have struggled to find a balance between LO_{12_1} and LO_{12_2} over the successive course editions. Table 3 shows the ANOVA analysis of C_{12}, LO_{12_1} and LO_{12_2} evolution. Instructors' corrections produced a moderate and statistically significant change (η^2 values around 0.06 [22], and p values < 0.05). Table 4 helps to identify in which precise moment those corrections paid-off thanks to the Tukey multiple comparisons procedure (only the statistically significant pairs are included).

Accordingly, instructors' actions were producing an accumulative effect in C_{12} that finally became significant in the 1st semester of 2018.

2) MONITORING C_{13}

C_{13} refers to the students' capacity of using computational tools to simulate and analyze control systems. In particular, students undertook practical experiences on virtual labs, like the one in Figure 10.

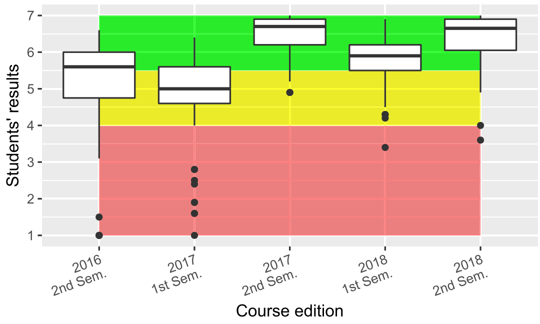

FIGURE 11. Students' results for C_{13}.

TABLE 5. ANOVA for C_{13}.

ANOVA		Effect Size
F value	p value	η^2
33.53	<2e-16	0.311

TABLE 6. Tukey multiple comparisons of means for C_{13}.

Pair	Mean difference	Adjusted p-value
2016 2S *vs* 2017 2S	1.348	0.000
2016 2S *vs* 2018 1S	0.622	0.007
2016 2S *vs* 2018 2S	1.181	0.000
2017 1S *vs* 2017 2S	1.713	0.000
2017 1S *vs* 2018 1S	0.987	0.000
2017 1S *vs* 2018 2S	1.546	0.000
2017 2S *vs* 2018 1S	-0.725	0.001
2018 1S *vs* 2018 2S	0.558	0.029

The boxplot in Figure 11 shows students' C_{13} achievement evolution. After the 2nd semester of 2016, instructors decided to introduce a course improvement: students had not only to use the labs to conduct experiments but also save the gathered data and use them later in a specialized software tool for control analysis and design purposes.

According to the ANOVA analysis in Table 5, the course modification was both statistically significant and with large effect size (η^2 for C_{13} is almost six times greater than η^2 for C_{12}). In particular, the Tukey's post hoc tests in Table 6 show that the improvement became statistically significant from the 2nd semester of 2017.

Looking at the two first boxes in Figure 11, it seems that the "improvement" failed initially since it had a negative effect. Although the effect was statistically non-significant (Table 6 does not include the pair "2016 2S *vs* 2017 1S" because the correspondent p-value is 0.233; i.e., considerably greater than 0.05), instructors decided to give students in the 2nd semester of 2017 an introduction about the use of the software tool required to analyzed the gathered data, with a special focus on (i) the control toolbox that should be used, (ii) the interpretation of results, and (iii) some issues about the conversion of measurement units in the control loop. Once applied this action, C_{13} academic performance increased drastically (see "2016 2S *vs* 2017 2S" in Table 6).

Finally, as C_{13} performance was much higher than C_{12}, instructors decided to transfer some hours from C_{13} to C_{12} in the 1st semester of 2018. As a result, C_{12} improved but C_{13} got worse. In the next course edition, this latter modification was adjusted to balance better the results of both competencies.

IV. RELATED WORK

Competency assessment models are commonly defined as hierarchies of three types of interdependent elements: competencies, learning outcomes, and assessment tools [23]. Our work contributes to this mainstream by providing a general framework that processes these hierarchies for both assessing students and monitoring courses.

There are typically two approaches to derive students' competency achievement levels from assessment tool measurements: numerically and linguistically. The numerical approach assumes that both students' grades and relationship importance between each pair of elements (e.g. competencies and learning outcomes) can be accurately defined. Thus, competency levels are obtained by traversing the hierarchy in a bottom-up fashion, computing each element's grade as the weighted average of its descendants' grades [24]. In contrast, the linguistic approach premise is that neither the students' grades nor the relationship importance can be precisely expressed with numbers. For instance, [25]–[28] propose assessment procedures based on fuzzy linguistic logic to aggregate students' grades and relationship importance expressed in natural language (e.g., "learning outcome *LO* is *poorly* achieved" and "*LO* is *essential* for competency *C*", respectively).

C-A&M enriches current students' assessment proposals with a language to formally define competency models, and by providing Algorithm 1 to efficiently processing these models. It is worth noting that, although our approach is currently numerical, it can be easily extended to integrate linguistic information substituting Line 7 in Algorithm 1 by the corresponding fuzzy linguistic aggregation procedure. This would open new blended assessment possibilities unexplored to date; for example, supporting the combination of numerical students' grades with linguistic relationship importance.

Finally and to the extent of our knowledge, this paper presents the first automated approach for competency-based course monitoring, whose utility has been illustrated on the continuous improvement of a university course over three years.

V. CONCLUSIONS

C-A&M supports competency-based education in many fundamental aspects. It facilitates instructors the design of competency assessment models thanks to a formal language for specifying competencies, learning outcomes, assessment tools, and the inter-dependencies among all these elements. It provides an automated procedure for processing these models to calculate students' competency achievement. The method is efficient (its time-complexity is $O(N)$, being N the number of elements in the model) and easily extensible to incorporate new ways for aggregating achievement information (both numerical and linguistic). Finally, C-A&M

provides learning analytics to supervise competency-based courses. In particular, it has shown to be remarkably helpful to reform a university engineering course at the Pontifical Catholic University of Valparaíso in Chile. Along five course editions, C-A&M assisted instructors to (i) reason about students' competency achievement, (ii) identify shortcomings in the course, (iii) implement corrective actions, and (iv) subsequently check the validity of the actions.

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