Personalized Student Assessment based on Learning Analytics and Recommender Systems

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Abstract— **This paper presents a process based on learning analytics and recommender systems with the objective of analyzing student assessment in order to provide clues that can help teachers in scaffolding the students' performance. For this, a set of tests was used to evaluate students' competence in direct current circuits. The tests had multiple versions and to solve them each student had to use multiple approaches. The results indicate a better performance in calculus and simulations approaches when compared with hands-on and remote laboratories approaches. The analyses also provide support for the recommendation step allowing the configuration of a knowledge base. The process as a whole is consistent in what regards its ability to make suggestions to the students as they complete a given test and to provide teachers with information that can help them formulate strategies to positively impact students' learning.**

Keywords—personalized student assessment; learning analytics; recommender systems

I. Introduction

The current stage of development of science and technology demands the interconnection of different approaches in order to make students achieve their best level of performance. "*Engineering education has solid needs of experimental competence developments, regardless the area*" [1]. In this way, calculus classes, hands-on laboratories, simulations and remote laboratories are education resources with particularities and complementarities. Considering complex scenarios and problems, as stated by [2], students have to become *fluent in the language of nature and a successful designer, and for that (...) must perform numerous experiments practice laboratory work*. Thus, competencies developed along their education process will impact their professional carrier. Experimental work has been developed traditionally in laboratories. However, the increase in the number of higher education students in the last decades has pressed for physical structures and resources. Simultaneously, researchers started developing computer simulations and remote labs, enabling the expansion of learning frontiers. This increases the students' access time to these learning resources, respecting their preferences and needs.

This situation affords new opportunities to improve the students' learning process. With the advent of computation and mainly via online systems, the information generated by student interactions in online simulations and remote laboratories can be collected and analyzed. In this context, learning analytics (LA) plays an important role in providing tools that can leverage students' learning experiences in addition to insights for teachers to learn and improve their classes. Thus, LA as a knowledge discovery paradigm can provide valuable findings and help stakeholders to better understand the learning process and its interconnections [3].

From LA's perspective, analyzing the collected data allows creating opportunities to offer suggestions directed to the various stakeholders in educational contexts. In this sense, recommendation systems (RS) can provide suggestions aimed at increasing students' performance in learning activities. RS aim to recommend items that may be of interest for a particular user. Although it emerged in the 1990s focusing on e-commerce through the collaborative filtering approach [5] [6], other approaches have been developed as well. Among them is the knowledge-based approach, which uses structures capable of representing a particular domain knowledge. In this way, recommendations can be targeted to a specific end as they consider domain knowledge. Its evolution has provided solutions in many areas, among them e-learning. This kind of recommender system generally intends to assist students in choosing courses, subjects and learning materials or activities [4], but can also help them to achieve a better performance on tests, for instance.

This paper presents a process based on learning analytics and recommender systems toward personalized student assessment. It intends to offer recommendations to students during their tests involving multiple class resources such as calculus, hands-on laboratory, simulation and remote laboratory. Section II presents the background of the study. Section III introduces the experimental process. Section IV shows the scenario used in the experimental design. The results and the analysis of the scenario and a general discussion about the process are discussed in section V. Finally, section VI draws conclusions.

II. Background

A. Class Resources

1) Calculus Classes and Hands-on Laboratories: These kinds of resources provide a face-to-face interaction in a specific time and place. Despite the online education growth in the last decades, more traditional areas, such as engineering, still widely use those resources. Among such resources are calculus and laboratory classes. Calculus classes follow more abstract and methodic aspects involving mathematics and knowledge about the topics [7]. On the other hand, laboratory classes can address more complex competences, enabling, for instance, the connection between concepts when not provided like recipes [7][8]. They can, if well conducted, help students to achieve haptic skills and instrumentation awareness [9]. Furthermore, considering the fact that physical lab classes are usually offered for short periods and regarding the students' questions on technical and operational issues, there is little time left to reflect on and interact with experiments [9].

2) Simulations: As stated by [7], computer simulations have advantage over hands-on laboratories once learners can deal with them any time without being afraid of damaging or being monitored by someone. Learners can use simulations to evolve at their own pace. On the other hand, during simulations students have to understand that they deal with models and not with reality. According to some authors, simulations can lead to some problems once learners can face some kind of disconnection between real and virtual worlds [10]. Other researchers have tried to define the learning potential by means of computer simulations. The study carried out by Ghang et al. [11] identifies a relation between studends' higher abstract reasoning and computer simulations. In [12], evidences are presented supporting the notion that simulations can improve laboratory classes in traditional education.

3) Remote Laboratories: Remote labs can be a step forward in the learning process by enabling real experimental apparatus, once they require space and devices even without the students' presence. Thus, such conditions increase the frequency and places in which experiments can be carried out [9]. Authors also mention that experimental devices can be shared, hence extending the capability of conventional laboratories. Thus, remote laboratories can be seen as complementary tools in the students' learning process and may have some of the advantages of hands-on and computer simulations. In this scenario, students can access real hardware in order to have a learning experience outside the classroom [13]. Moreover, for some experiments, availability can be a problem, once remote labs must be connected to real equipments. On the other hand, simulations are quite common and can be easily found on the Internet by students. In this way, the educational goals of remote and simulation labs are more specific and commonly used to complement other teaching resources [9][14].

B. Learning Analytics

Learning is a theme with several implications and impact on students' lives. According to [15], learning is increasingly distributed across space, time, and media, producing substantial volume of data about students and learning. The interaction with online education environments leaves traces about the students' experiences, enabling more robust analyses. In this context, regarding students' behavior, learning analytics (LA) has become a valuable learning tool by attempting to positively impact their performance.

Learning analytics has many definitions, one of the most cited being "*the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs*" [16]. In [17], it is stated that LA has its basis from business intelligent concepts, which have been appropriated by education institutions. Additionally, [18] mentions other fields such as web analytics, educational data mining and recommender systems. Primarily focused on the capture and report of data by educational administrators and the performance enhancement of educational institutions, learning analytics evolved to a more operational perspective in order to provide tools targeted to students and teachers for the achievement of a better understanding of student experience.

C. Recommender Systems

Recommender Systems (RS) have become an important field of research since the mid-1990s [5][6][19]. Their main objective is to make suggestions mainly where there is a great volume of options, as in such situations the selection process can become difficult for the user [20]. RS starts with the proposition of the collaborative filtering approach, although currently giving support for a wide range of research areas and applications.

What makes this type of system useful for both the user and the service provider is its ability to assist in the selection of items, making the task more enjoyable and possibly delivering better results. Based on these arguments, [21] states that "*the purpose of RS is to generate valid recommendations for items that may be of interest to a set of users*". As stated by [22], an "item" is a piece of information that refers to a tangible or digital object, such as a product, a service or a process that an RS suggests to the user in an interaction through the web, email or text message. An item is understood as the content of the recommendation that will be offered to the user. According to [23], "item" is the general term used to designate what the system recommends to users.

Several RS approaches are described in the literature, among them, content-based filtering (CBF), collaborative filtering (CF) and hybrid filtering [24][25]. Currently, RS have taken advantage of semantic web technologies to effectively overcome the challenges associated with the incredible growth of the web, more precisely addressing the overload of information and heterogeneous data sources [26]. These systems are gaining maturity and have some different approaches. For instance, the approach that uses formal structures representing knowledge, such as ontologies, to make suggestions is called knowledge-based recommendation [27].

Many are the areas of applicability of RS. In the educational context, e-learning recommender systems have evolved since the 2000s based on the development of traditional e-learning systems [4]. These systems aim to help learners/students on what courses, subjects or learning activities to choose, and assist them in those activities thus helping them achieve a better performance.

III. Process Proposition

This section presents the process used in the analysis and recommendation of possible suggestions during the assessment of tests performed by the students. It intends to provide ways to scaffold students' performance on tests. Fig. 1 demonstrates the process in which the student takes a test composed of different practices. A particular test consists of Calculus, Hands-on Laboratories, Simulations and Remote Laboratories practices. Each test performed by the students is stored in a database, allowing a set of analyses trying to support students' learning and teachers' understanding.

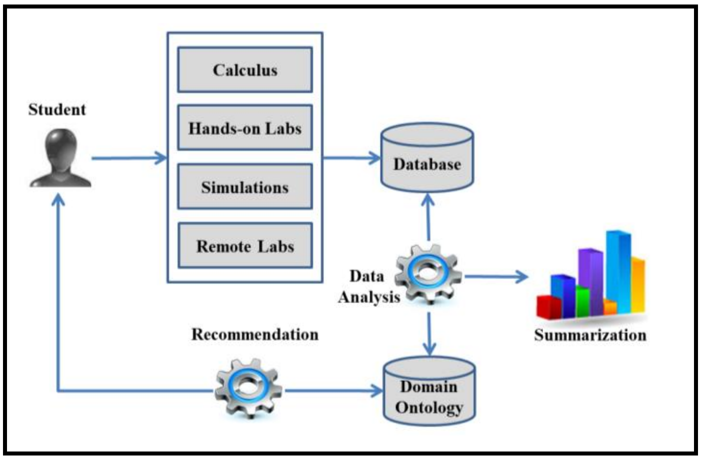

Fig. 1. Process towards personalized student assessment

During the process, there are two main phases, consisting of data analysis and recommendations. Data analysis has two essential functions. The first one focuses on online monitoring of student test answers. Each answer provided to a given question in a particular test is retrieved from the database and stored in a domain ontology, forming a knowledge base. In that ontology, there are also the rules that allow inferences in order to support the recommendations. The second function is to summarize the data in order to provide information that may help teachers to better understand the students' performance.

In the recommendation phase, the answers are monitored and stored into the knowledge base supported by a domain ontology. With this, each answer is analyzed through inferences in the knowledge base taking into account some criteria, and if the criteria do not satisfy some values, the student is advised to better re-evaluate the solution provided. For example, if the answer is outside a certain acceptable range for a particular question, a check of the unit of measure used is recommended. By this means, the student has a new attempt before definitively confirming the answer to a specific question.

The original answers of each question and the possible answer obtained after a given recommendation can provide interesting inputs for teachers in order to have information about the difficulties faced by the students. It allows an analysis of the causes of deficiency in specific questions and can therefore guide the teacher in actions of revision or improvements in the theoretical and hands-on classes.

IV. Curricular Design

The proposal was implemented within a course entitled "Electricity" (2013/14), which is part of the 1st year, 2nd semester of a 3-year degree on Automotive Engineering, following the Bologna model (180 ECTS). The course has 5 ECTS and comprises 1 hr of recitation classes (lectures, hereafter referred to as T classes), and 1 hr of calculus practice classes immediately followed by 1 hr of lab classes (hereafter referred to as PL classes) per week, during 15 weeks. The course had 79 enrolled students, distributed by 3 PL classes with 25-26 students. Finally, in the PL classes the students were divided into 5 groups of 5 students each, usually during hands-on exercises, as the lab is equipped with 5 demo boards. During the calculus, simulation, and remote lab exercises, students work in pairs (two students per PC, max.) or as they wish to (individually or larger groups), as they can use their own laptops or tablets.

A. *Methods used in Lectures and Practice Classes - Calculus*

In lectures, the teacher used presentations to explain theoretical subjects and the whiteboard to solve theoretical problems. Also, students showed the teacher their results from some of the simulations. Usually, there were discussions among students and with the teacher. During practice classes dedicated to calculus, students had to solve a number of written exercises, based on a script provided on day 1 through the course page on the Moodle learning platform. Students were also encouraged to post their results on Moodle so as to provide evidence of having completed the homework assignment, even though it did not count for the summative assessment.

B. *Method used in Lab*

Typically, students are first introduced to the lab where they will have the hands-on activities. They are divided into working groups (typically of 5 students) and introduced to the equipment, devices and demo boards that will be used along the 1st part of the semester (DC circuits). This initial class was purely illustrative, i.e. students did not mount any circuit or make any measurements. In the two following classes, students practiced with the simulator and the remote lab to practice where to insert the multimeter for doing basic measurements (resistance, voltage, and current). During the subsequent 3 PL classes, students completed a series of 20 experiments, described in a manual that encompasses the demo boards and the components donated by Toyota® (Fig. 2) to the Automotive Engineering undergraduate course. Finally, students were assessed for this initial part through an individual lab assignment targeting all competences (calculus, simulation, remote lab, and hands-on).

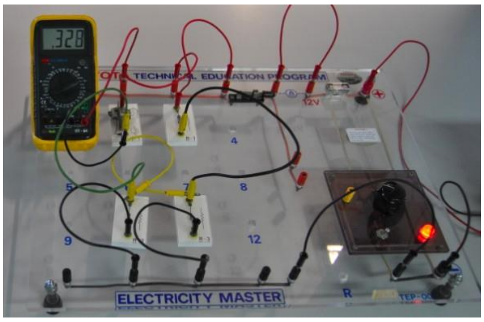

Fig. 2. Example of a circuit that students had to assemble in the Toyota demo board

Falstad's Circuit Simulator Applet [28] was used in both T and PL classes for simulating the circuit behavior and extracting the voltage drops and current flows in any circuit component. Also, Virtual Instrumentation Systems in Reality (VISIR) [29] was used in both T and PL classes. During one theoretical class, the teacher used VISIR and the simulator to ascertain a number of calculations made in the circuit that was used in the individual lab assessment. This particular circuit was an enhancement (i.e. it included one additional resistor) of the circuit used for the homework assignment, where students had to obtain and compare results from calculus, simulations and remote lab.

C. Assessment Test Design

The assessment was designed taking into account the need to address all basic concepts and competences developed along the classes, namely: to know the Ohm's law and to know how to apply it to calculate voltage/current in any circuit component; to distinguish series and parallel connections; to know how to calculate an equivalent resistor; to know the Joule's law; to be able to measure voltages and currents in a circuit; and to understand resistance variation with heat. The assessment test consisted of the analysis of two circuits (Fig. 3 shows an example of a circuit 1 (C1) - left, and circuit 2 (C2) - right).

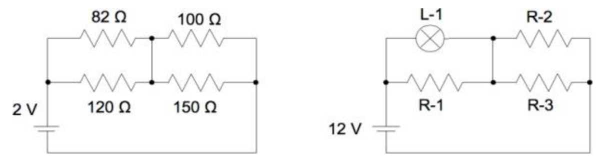

Fig. 3. Examples of the two types of circuit used in the assessment test

In C1, it was necessary to develop calculus work, simulation and remote lab. In C2, it was required to perform hands-on lab and simulation. This test design aimed to verify if: (1) students gained the required skills to make simple calculations involving simple circuits; (2) students were able to simulate the circuit behavior and extract circuit variables such as voltages and currents (Fig. 4); (3) students could measure voltages and currents in a real circuit, using a multimeter; (4) students could quickly mount the circuit in a remote lab and measure voltages and currents (Fig. 5); and (5), students could understand the benefits and pitfalls of each method.

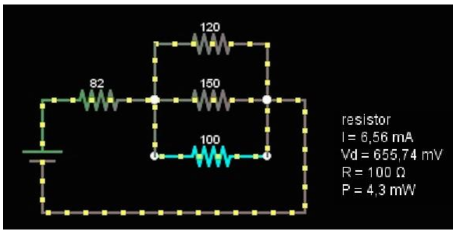

Fig. 4. Using the Circuit Simulator [28] to read the voltage/current in the 100Ω resistor, in one of the circuits used in the individual lab assessment (in one of the test versions)

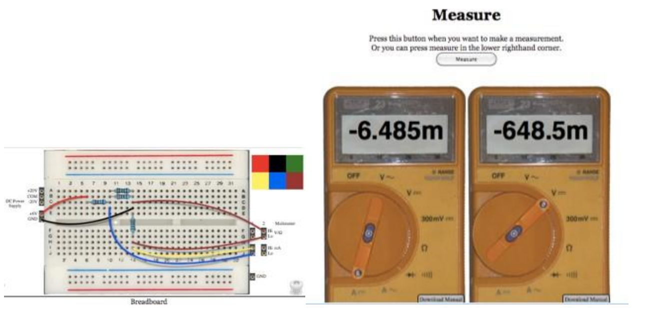

Fig. 5. Using VISIR to measure the voltage/current in the 100Ω resistor, in one of the circuits used in the individual lab assessment (in one of the test versions)

Since there were 3 classes distributed along several days of the week and students were on-line during the assignment, it was necessary for the teacher to undertake replication of similar tests (with the same difficulty level), but different enough to avoid copying. Twenty-four different test versions were produced (changing the components' placement, and/or slightly changing the circuits, or changing the component under inspection, i.e. asking for the voltage/current of a different circuit component – see an example in Table I. This fact was communicated to students.

TABLE I. EXAMPLE OF A TEST VERSION SOLUTION

<table>
<tr><th colspan="9">Circuit 1</th></tr>
<tr><th colspan="3">Calculus</th><th colspan="3">Simulation</th><th colspan="3">Remote laboratory</th></tr>
<tr><th>R_{eqv} (Ω)</th><th>I_{total} (mA)</th><th>P_{total} (mW)</th><th>Read voltage (mV)</th><th>Read current (mA)</th><th>P_{total} (mW)</th><th>Measure voltage (mV)</th><th colspan="2">Measure current (mA)</th></tr>
<tr><td>108.7</td><td>18.4</td><td>36.8</td><td>U_{R82} 896.2</td><td>I_{R82} 10.93</td><td>36.8</td><td>U_{R82} 895.0</td><td>I_{R82} 10.70</td><td>I_{total} 18.21</td></tr>
<tr><th colspan="9">Circuit 2</th></tr>
<tr><th colspan="5">Simulation</th><th colspan="4">Hands-on laboratory</th></tr>
<tr><th colspan="3">Read voltage (mV)</th><th colspan="2">Read current (mA)</th><th colspan="2">Measure voltage (V)</th><th colspan="2">Measure current (mA)</th></tr>
<tr><td colspan="3">U_{L1} 78.42</td><td colspan="2">I_{L1} 98.56</td><td colspan="2">U_{L1} 1.049</td><td colspan="2">I_{L1} 80.1</td></tr>
</table>

V. RESULTS AND ANALYSIS

In this section, the main results are summarized after the analysis of the data. Additionally, a discussion about the recommendation phase is presented, as shown in the process described in Section III.

A. Data Analysis

A total of 63 students (80%) participated in the (compulsory) assessment test. As the test maps different competencies, since different resources are used, the results were obtained by item and by each student. The test itself consists of the analysis of two circuits (Fig. 3) in which each circuit has a set of questions, according to Table I. The results obtained by the students in each part can be seen in Fig. 6.

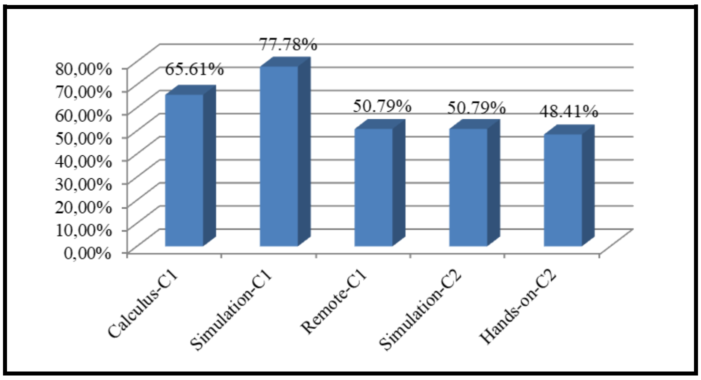

Fig. 6. Tests results aggregated by resources

In general, the students performed well considering C1 and C2. As can be noticed, the best results were achieved in the simulations and calculus in C1 with 77.78% and 65.61% of correct answers, respectively. For C1, the worst performance was achieved in the questions referring to the remote experimentation, with 50.79%. This indicates a certain difficulty that can be explained by the lack of understanding of certain concepts and the verification that students who attended fewer classes performed worse, which suggests a positive correlation between grades and students' attendance. In C2, the worst results obtained were for simulation and hands-on laboratory, achieving 50.79% and 48.41% of correct answers, respectively. Likewise, in hands-on laboratory a correlation between class attendance and the obtained results is noticed.

As already mentioned, 24 different versions of the test were prepared, each one distributed to 2 or 3 students randomly. In order to have a clearer understanding of the students' aggregate performance, an analysis of each one of the questions was produced verifying the correctness of the answers. An answer to be considered correct to a particular question and a test version should not surpass the standard deviation of 5%. Above this value, the answer was considered wrong. Fig. 7 presents the data of each question considering the different test versions.

The analysis was performed individually considering all 13 questions (see Table I) for C1 and C2. Taking into account the answers provided by the students in each of the 24 versions, the standard deviation for each question was determined. Questions with up to 5% of standard deviation were considered correct. In other words, if the standard deviation of the students' answers in a given test model showed a variation of up to 5% in relation to the correct answer, the question in that particular model was considered to have been answered successfully. Questions of a particular test model with a standard deviation greater than 5% were considered incorrect. The best results were obtained in C1 (Questions 1 to 9 - See Table I), with emphasis on the calculus and simulation approaches. The question with the best performance was the number 5 with correct answers in 20 (83.33%) of the test models. The worst performances were obtained in the questions in C2. Question 13 stands out with only 1 (4.17%) model in which the students provided answers respecting the limit of 5%. It is possible to observe that in general the errors occurred due to the use of measure units different from those requested in each question in a particular test version. For example, when a question whose result should be given in milliampere (mA) was instead answered in microampere (μA) or ampere (A), or even in volt (V).

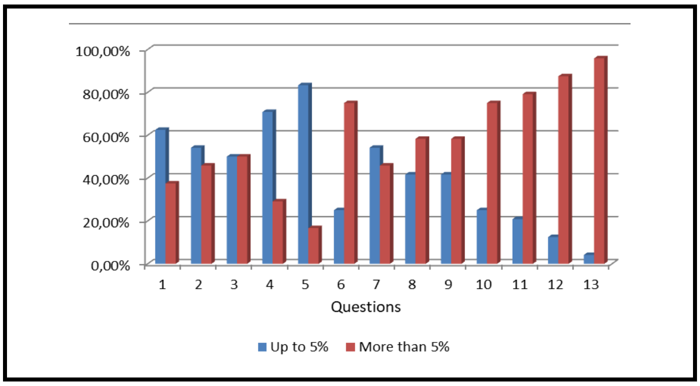

Fig. 7. Tests results aggregated by questions taken into account the 24 versions

B. Recommendation Approach

In the second phase of the process, possible recommendations occur as the student answers the questions. For this purpose, there is an ontology populated with information coming from the database (previous phase) to create a knowledge base. The knowledge base enables inferences in order to make possible that recommendations be offered to students. Fig. 8 presents a fragment of the proposed ontology that supports this work. The ontology is composed of a set of classes representing the student, the test and the relationship between student and test.

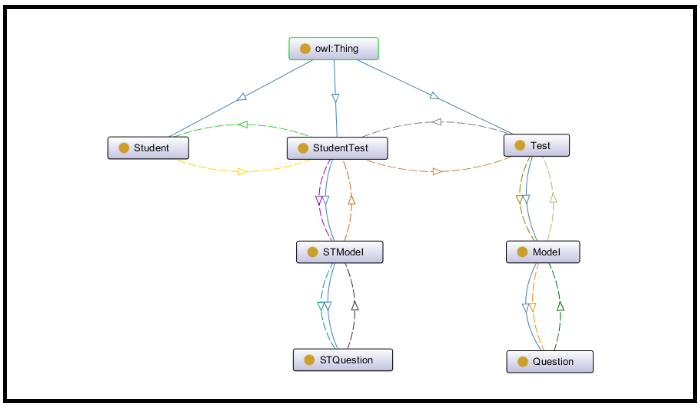

Fig. 8. Ontology proposed to support the recommendation phase.

The **Test** class has a subclass that represents a model (**Model** class) since one test in particular can have several models. From the **Model** class, there is a hierarchical relationship with the **Question** class. The **Question** class allows composing the various instances of questions linked to a specific test model. The same hierarchy exists in the **StudentTest** class, which is related with the **Student** and the **Test** classes through object properties. From this class (**StudentTest**), it is possible to link each test model with a specific student thus maintaining students' answers individualized. Considering the answers provided for each question, it is possible to analyze the expected results of a particular question by inference. Therefore, if the answer is outside some predefined boundaries in the ontology, recommendations can be provided trying to lead students to the correct answer. One of the possible recommendations would be to check the expected measure unit of a question when the value provided by the student is outside the boundary.

At the end of the inference, if the answer for a particular question is wrong, the property that describes the measure unit can be used to provide a recommendation. Therefore, the student can accomplish a new attempt to answer that question. However, a retry can only be performed once. The new attempt is stored in the database to support further analysis of students' performance in the process. This provides teachers with a better understanding of the difficulties identified in each test model with possible impacts on the classes and on the students' learning process.

VI. CONCLUSION

The current scenario in engineering education demands approaches that combine new proposals of teaching with sustainability. Better understanding of students' performance on tests can positively impact the learning process. In this regard, a process supported by the concepts of Learning Analytics and Recommender Systems is presented in this paper. The results of a set of tests carried out by undergraduates of Automotive Engineering, following the Bologna model, were used as a case study. Each test aimed to evaluate the student in more than one approach, including calculus, simulation, hands-on and remote laboratories.

The analysis of the tests aimed to obtain an overview of the performance on the various test models considering the various approaches used. A better performance was verified for circuit C1 in the calculus and simulations approaches. However, in the remote laboratory approach for C1, a performance inferior to that of the other resources was observed. This can be explained in part because the resource requires a higher level of training, having a greater learning curve. An individual analysis of the questions was also carried out. Again, considering the correct answers in each test model and with standard deviation of 5%, questions regarding circuit C1 for the calculus and simulation approaches showed better performance. The negative behavior in the questions referring to circuit C2, in which the percentage of questions with a standard deviation up to 5% was low, is highlighted. A predominance of questions with a standard deviation greater than 30% can be observed, as well as the use of unit measures incompatible with the expected answer.

Individually, the analysis of each question also aimed to create evidence to establish a knowledge base that could support the recommendation phase. To exemplify that, a rule that aims to analyze the answer provided by the students to a particular question and test is discussed. If the answer remains outside of established boundaries, the student receives a suggestion to review the measure unit. The suggestion is made only once so that the student can make one more attempt to improve the final answer. The recording of the original answer and the new attempt can generate important inputs to provide teachers with information that can improve the classes and contribute to the students' learning process.

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