JOURNAL OF E-LEARNING AND KNOWLEDGE SOCIETY
Vol. 17, No. 1 (2021), pp. 90-100

E-Learning & decision making system for automate students assessment using remote laboratory and machine learning

Fahd Ouatik[a,1], Farouk Ouatik[b], Hind Fadli[c], Abdelali Elgorari[a], Mohmmed El Mohadab[b], Mustapha Raoufi[a], Belaid Bouikhlene[b], Mohammed Skouri[a]

[a]*Laboratory of Physics, High Energy and Astrophysics Cadi Ayyad University, Marrackech Faculty Science Semlalia, Morocco*

[b]*Laboratory Mathematics and Informatics, Sultan Moulay Slimane University, Beni Mellal Morocco*

[c]*Laboratory Mathemat of Physics i, Sultan Moulay Slimane University, Beni Mellal Morocco*

(submitted: 15/6/2020; accepted: 8/7/2021; published: 27/7/2021)

Abstract

This paper describes an implementation of a remote laboratory system for the practical works (PW) of electronics, this system make available to target and analysis the gaps, weaknesses and lack of scientific knowledge of students in the context of electric engineering through data mining algorithms and students' study behavior. Experimental work has traditionally been developed in laboratories. However, the increase in the number of higher education students in the last decades has put pressure on the physical structures and resources of laboratories. To overcome this, computational simulations and remote laboratories have been developed enabling the expansion of educational boundaries. this paper provides new opportunities to enhance the student's learning process. The results are presented and discussed according to two levels. The first is development a complete system of remote laboratory E@Slab and compare it with the related work. second level, we present an algorithms of Intelligence Artificial that automate evaluation and classify students in different groups attending to an assessment rubric. After this classification we compare the obtained results from algorithms of Intelligence Artificial with the levels obtained from interviews with the students and from the practical work review for to be a validation of sorts. Finally we compare the two results and we remark that algorithm classifies correctly the students with an accuracy of more than 90%.

KEYWORDS: E-Learning, Intelligence Artificial, Remote Laboratories, Embedded System, Behavioral Study, Online Practical Works, Automatic Evaluation, Data Mining Algorithms, Node Js.

DOI
https://doi.org/10.20368/1971-8829/1135285

CITE AS
Ouatik, F., Ouatik, F., Fadli, H., Elgorari, A., El Mohadab, M., Raoufi, M., Bouikhlene, B., & Skouri, M. (2021). E-Learning & decision making system for automate students assessment using remote laboratory and machine learning. *Journalof e-Learning and Knowledge Society, 17*(1), 90-100. https://doi.org/10.20368/1971-8829/1135285

1. Introduction

Assessment and evaluation [1] have a vital role to measure degree of transmission knowledge to the students and how students learn, and teachers teach. Evaluation has various purposes:

- Assessment informs teachers what students understand and allows them to plan and directed teaching by providing meaningful feedback to students.
- Assessment allows students to become aware of their learning methods for to adjusted and improved and advance their learning by assuming greater responsibility.
- The information gathered from the assessment allows students, teachers and parents, as well as the broader educational community, to be informed and to have idea about learning outcomes for to highlight successes, plan interventions and continue to foster success.

Within this framework E@Slab (Ouatik, 2017) integrate in these functionality a procedure allows the follow-up

[1] corresponding author - email: fahd.ouatike@gmail.com

and the behavior study of each student during the online practical work in order to evaluate it, by a new approach using a feedback of an oral evaluation made to an sample students, the results of this evaluation we will be generalized for all students thanks to machine learning that use artificial intelligence by the exploitation of data mining that use a set of algorithms from various scientific disciplines such as statistics, probability and computing, for to build models from the data got from oral assessment, that is to say to find interesting structures or patterns according to criteria previously set, and to extract a maximum of knowledge for classified other structure. It helps to better understand the links between seemingly distinct phenomena and to anticipate trends that are not yet discernible.

In the following an overview of artificial intelligence methods used in adaptive education systems. AI approaches are considered valuable tools, as they have the capacity to develop and replicate the decision-making process adopted by the population (Barana, 2017; Cronin, 2018). Different artificial intelligence techniques have been used in adaptive education systems, such as fuzzy logic (FL), decision tree, Bayesian networks, neural networks, genetic algorithms and hidden Markov models.

Fuzzy logic was first introduced by Zadeh in (Ehlers, 2011) where it quickly became a popular and effective technique for user modeling, as it could mimic human reasoning (Hodgkinson-Williams, 2014). Fuzzy logic can be seen as an extension of traditional set theory, as statements can be partial truths, falling between absolute truth and absolute falsehood (Inamorato dos Santos, 2016).

The fuzzy logic system (FLS) consists of four stages:

fuzzifier, rule base, inference engine and defuzzifier (Knox, 2013). In addition, FL are commonly used to examine and assess learning and knowledge outcomes (Koseoglu, 2018).

Specifically, FL can be adopted to assess and review task objectives as well as multi-criteria assessments, as demonstrated in (Marchisio, 2019).

A decision tree is a tree in which each branch node represents a choice between several alternatives and each leaf node represents a decision (Marchisio, 2020). Decision trees are commonly used to obtain information in order to make the decision (Mayer, 2014).

Nascimbeni (2018) presented a system of personalized learning paths in which decision tree techniques inform the e-Learning system of the creativity of the learners. The author used the ID3 decision tree technique to explore the dataset containing learner data collected over a three-year period.

Neural networks are increasingly used to model human behavior and therefore to replicate human actions and responses (Marchisio, 2019) provide a good overview on neural networks and their functioning. Essentially, a neural network (NN) consists of a large number of neurons or intertwined components that work together to process information and solve problems. In reality, it is a system that collects and analyzes information very close to biological nervous systems, for example the brain. RNs do not require any information about a particular problem before solving it (Marchisio, 2019). They can process information and produce much more complex results than other information processing paradigms, making them a very influential way to model human behavior.

Bayesian networks are widely used methods for modeling learners in intelligent learning systems (Knox, 2013). A Bayesian network (BN) is a direct acyclic graph (DAG), that is, a graph that shows and explains the distribution of probability in such a way as to allow efficient diffusion of probability as well as accurate representation.

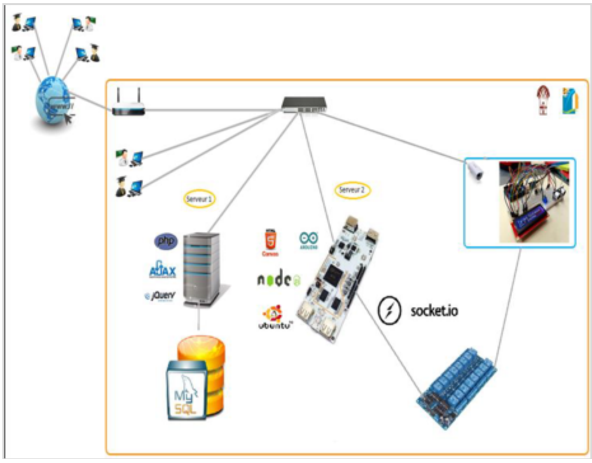


Figure 1 - Architecture and technology of E@Slab system.

1.1 Logical view

E@Slab is divided into 2 parts:
Admin Part is a web application where the administrator organizes the laboratory by the management of students, using a set of criteria (branch, group, module...), and creation appointments for practical work.

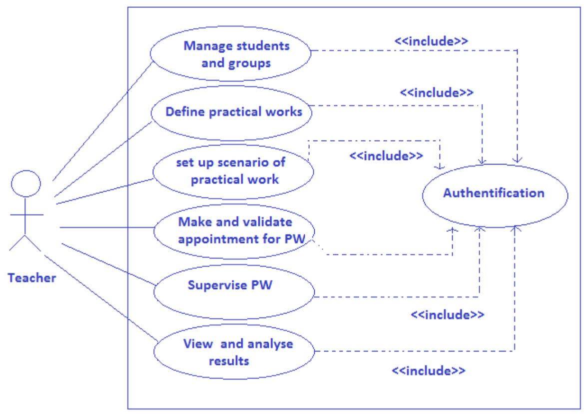


Figure 2 - Use case of Admin.

Actor: "Admin or Teacher":

- Authentication: for to validate the legitimacy of access.
- Manage classes: allow teachers to manage classes, specialty and students.
- Define PW: allows teachers to implement the PW and theoretical part.
- Define the scenario: allows the teacher to define a practice scenario and question to students
- Make reservation: allows teachers to create appointments for each students to a specific practical work.

The second part concerns the student, after authentication in management platform, will see if he has an appointment for a manipulation; he will even know the date and time with which to start the PW. If the time comes, the link of the manipulation will appear and who will send towards the 2nd application that are the our electronic interface controller.

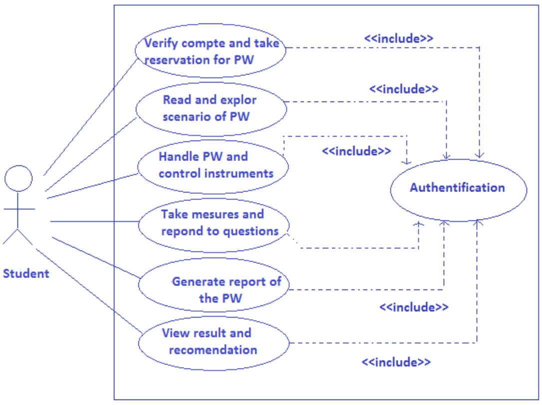


Figure 3 - Use case of student.

Actor: "Student"

- Authentication: for access authorization.
- Check there is a PW: allows students to check if they have an appointment to practical work.
- Gather information about the PW: allows the students to read a reminder about the theoretical notion.
- manipulate PW: Allows students to handle the practical work Using another application in server 2 (user interface for remote laboratory) but this will appear to students only when the reservation time is checked.

1.2 Physical view

Diagram of Figure 1 present two perimeters. The first is the web (Internet) and the second is the perimeter of the university (specifically the local school network LAN).

In the perimeter of LAN, we have two web servers, one containing the learning platform that represents the central university information system, where all information is found. The second server is a pcduino or raspebery that contains the application that will allow students to handle the practical work.

The process would work as follows.

Teacher connect either using the web or the local network; each teacher defines one or more PW, puts the theoretical part and the scenario after having made the PW reservation for all students.

On the other side, students connect using either the web. If student has an appointment for practical work, he consults and reads the scenario, then he checks the reservation. If the reservation time comme, he manipulates and remote the practical work; during this stage each reservation is destined and directed towards the server 2 (pcduino card). If the reservation time elapses, the PW ends and the material resources are released for a future reservation.

2. Evaluation And Make Decision About student gap

2.1 Logical vision: Why oral and interview assessment and difficulty

In this whole process our aims it's not just the system and the technology used but our goal is learning, student must be understand the principle and aims of the courses and do practical work correctly. The classical methods to see their level of understanding is to do an assessment by feedback, test, report or exam, these methods are not efficient and not reflect the true level of the student and do not allow to target the gaps and problems that the student faces during the exam or test. For to properly assess the level of the students it is necessary to make an oral and interview based on precise and meaningful criteria, but that becomes very difficult in front of the big number of the students so the solution is to define a pedagogical and precise evaluation grid and criteria for assessment, then computerize and automate the evaluation but always keeping the benefits and advantages of the oral assessment that target the student gaps correctly, this is why this computerization is done thanks to Machine learning which uses the artificial intelligence algorithm and data mining.

Evaluation by oral and interview using data mining is usually done in 3 steps:

1. We take a sample of students who are going to do a practical work of analog electronics in front a teacher who will ask oral questions with each student for to analyze their behavior during practical work and to assess his level of understanding and mastered the theoretical and practical notions and noted all the problems that confront the student during this PW. For the results obtained for each student will be a class (trained data) that will used by data mining to evaluate the other student automatically.
2. Evaluated students automatically through the system E@slab which collects all reactions of the students from the user interface by JavaScript and their behavior during the PW online and it will evaluate them by datamining according to a set of

Criteria		Level unacceptable	Level insufficient	Level correct	Level excellent
A. KNOW-HOW: Relate to the involvement, the autonomy,	A-1 Anticipating the TP session	The student arrives without having done the preliminary work	The preliminary work is very incomplete	Preliminary work has been made seriously and drafted cleanly	The preliminary work is impeccable (complete, accurate and properly worded)
	A-2 Manage the TP session time	Some important parts of the TD were not addressed for lack of time	The pairs often wait to be relaunched by the teacher to move forward	The pair managed their time correctly (full work or appropriate reaction to a difficulty)	The binome benefits from its efficient management of time to deepen the subject
	A-3 Distributing work and helping each other within the binomial	The work is distributed unevenly among the students AND they do not cooperate	There is an imbalance in the distribution of work between the students OR they do not cooperate	The workload is fairly distributed AND the students cooperate so that everyone can master the overall work	Level and the student is able to help the other pairs at the time the teacher allows it .
	A-4 Working independently	The binomial does nothing without soliciting the teacher	Only the basic tasks are performed autonomously	The binomial answers the questions posed in the statement autonomously or asks the teacher wisely	Level and the pair poses pertinent questions for further discussion
B. EXPERIMENTAL KNOW-HOW: Relate to the ability to handle, compliance with a protocol, quality of measurements and recording of results	B-1 Using experimental equipment	The student uses the material in a hazardous or inappropriate manner (Possible damage)	The student uses the adapted material but he does not know how it works (unsuitable settings)	The student uses the material wisely and he knows how it works (settings Adapted)	Level and the student knows the limits of the equipment used
	B-2:Estimate measurement uncertainties	The binomial does not worry about the uncertainties	Uncertainty is poorly estimated or unjustified	Uncertainties are properly estimated and justified	Level and the binomial refines the experimental protocol to minimize them
	B-3:Record experimental results	Some important information is not readings	Results are uncoordinated (draft copy,...)	The student notes the results but he is the only one who can exploit his notes	The results can be easily a colleague
C. KNOW-HOW EDITORIALS: Are related to the exploitation and the analysis of the results, to the writing of a report including the capacity of synthesis, the taking of retreat	C-1 Write an introduction that specifies the context	No introduction	The introduction takes up exactly the text of the TP	The introduction is reworded, but it remains focused on the course of the session	The introduction is reworded with reference to the context and potential applications
	C-2 Establish a Scheme of the Experimental Device	No schematic	The schema is incompletely drafted, or remains inoperative for a reader not familiar with the system	The scheme is complete and exploitable but lacks care or rigor	The schematization is complete, exploitable, neat and rigorous
	C-3 Introduce the principle and the experimental protocol	The results are presented directly without the manipulation or associated principles being described	The principle and the protocol are copied without appropriation by the student	The experimental protocol is reformulated in a clear and justified way	Level and at least one proposed improvement of the protocol is formulated
	C 4. Draw a graph from measurements	The graph is very rough, the space is badly used (scale), it lacks the title, the label of the axes (magnitude represented • unit), graduations ...	The scale is adapted, the axes are graduated regularly, but badly denoted (absence of the magnitude represented unit), lack of title	The axes are labeled, the scale is adapted, the graph contains a title and a legend, the measurements are well reported with a trend curve	Level correct and error bars materialize uncertainties or annotations make it easier to interpret the results
	C-5 Establish a literal expression (including Uncertainties)	Literal expressions prior to numerical calculations are often Absent	The literal expressions are established, but often erroneous	The literal expressions are generally correct and the notations introduced by the student are explicit	The literal expressions are systematically correct and the notations explicit
	C-6 Present a finalized result	The results are presented in a Disordered	Units are missing or numeric values are false	The results are correct, with good results units, and with a number appropriate numbers significant	Level and an original presentation highlights important results
	C-7 Interpret the results, draw conclusions	No interpretation	The student discusses the results obtained in aVery superficial (repetitionof the speech of The teacher, ...)	Results are compared to expected values, and outliers are reported	Level and the conclusions put the results in a more general context in relation to the introduction

Table 1 - Criteria of evaluation.

parameters and according to the feedback from Trained Dataset.

3. Assessment criterion for practical work. We have defined 3 pedagogical criteria and each criterion contains a set of skills and competencies to be assessed it's well detailed in the grid it is a generic synthesis tool for the teacher and it offers 4 levels of evaluation and each level the condition that must fulfil.

2.2 Technical vision: Automatic and Computerize evaluation

Different steps are necessary to Computerize evaluation using datamining:

- Teacher prepares the practical work in the laboratory by realization the electrical circuit and related to the relay (Figure 7) which will be controlled by students.
- We choose a group of students to do the practical work really in laboratory ahead a teacher for to be a sample and datatest of datamining for prediction evaluation of all students.
- When student starts the practical work, teacher will record the note of their behavior, movements and answer and the way in which handled the practical work for to have additional information about their behavior.
- The same students who did the practical work, we will do them an interview depends on the practical work they did and we will try to find their level of understanding and target the gaps and problems that the student faces during the practical work.
- This sample group of students will become a exemplary and a model by which we will generalize the oral assessment for all students based on the principle of data mining, with this way we properly assess the level of the all students and target the gaps and problems that the student faces and met during the practical work automatically without doing the interview with all the students.
- For automated evaluation, we used the principle of data mining; that is to say evaluated the students by prediction of datamining algorithms by operating the interviews which made to the previous sample group based on a set of parameters.
- Our Organigramme system **S= {I, P, O}** can be modeled in the proposed system is represented in Figure 6 where:

  S = represent the proposed system

  P = {A, B, C} Where P=Processes: They Are the criteria that we have described in the table above figure and They are the criteria that our system must evaluate from the input parameter I.

  A = Know-how = $\{A_1, A_2, A_3, A_4\}$

  B = Experimental know-how = $\{B_1, B_2, B_3\}$

  C = Know-how editorials = $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7\}$

  O = $\{O_1, O_2, O_3, O_4\}$ where O = output of our system and is the result of decision evaluation:

  O_1= Level unacceptable.

  O_2= Level insufficient.

  O_3= Level correct.

  O_4= Level excellent

  I = inputs data to our system {I1, I2, … , In}

  I_1: Last general note got by student.

  I_2 : The note of the theoretical part of the PW

  I_3: The note of the practical part of the PW

  I_4: Number of absences in module.

  I_5: Number of inscriptions in module.

  I_6: Genre. The statistics we did on students behavior we noticed that there is a difference between girls and boys at the level of number of absences (3% for girls are absent in module and 11% for boys) and preparing practical work at home (90% for girls are preparing practical work at home and 70% for boys), for that we must take sex of students in consideration. On the other hand, when there is a phenomenon that we can't be modeled mathematically, in this moment we use artificial intelligence and dataminig algorithm which takes in consideration a set of parameters. These parameter, we have does not know is it affected on the phenomenon or not that is to say it is necessary to use all the parameters that we doubt have impact on the phenomenon. Concerning the input parameters I1, I4, I5, I6 are extracted directly from information system of the university and I2, I3 Are the notes of each practical work. Then the system uses these parameters to calculate the probability for the 4 levels O1, O2, O3, O4 for each Criteria then takes the level that has the high probability. The system repeats this method for all the criteria and for all students.

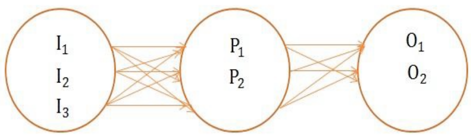


Figure 6 - Venn diagram of Proposed System.

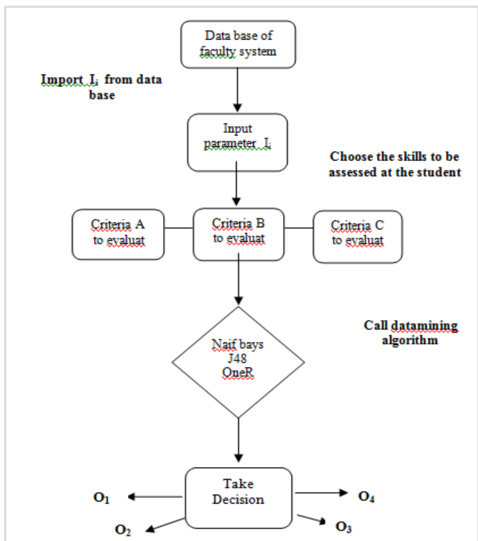


Figure 7 - Organizational chart of algorithms.

3. Application In Real Test And Results

3.1 Application

System test was done by 50 students of 2nd year university in physical science at the Semlalia science faculty of the cadi ayyad university and we followed the following steps:

- When we have completed the courses of the Analog Electronics module we have prepared a practical work of the operational amplifier in real laboratory for to be used by students from the web, Figure 7 describe instruments used.

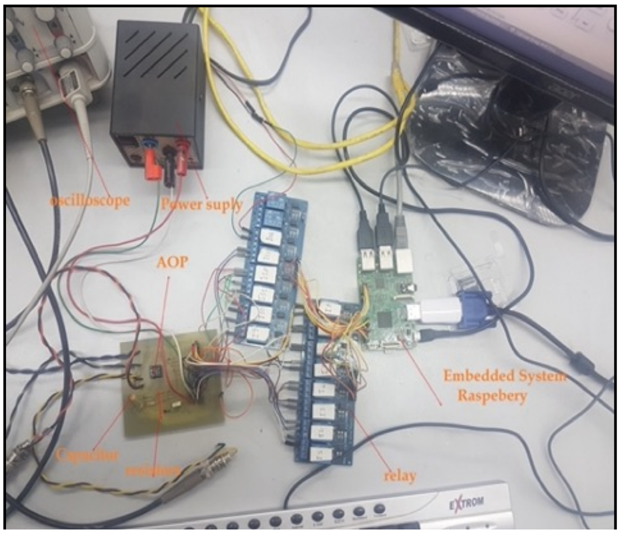


Figure 8 - Electronic Component in laboratory.

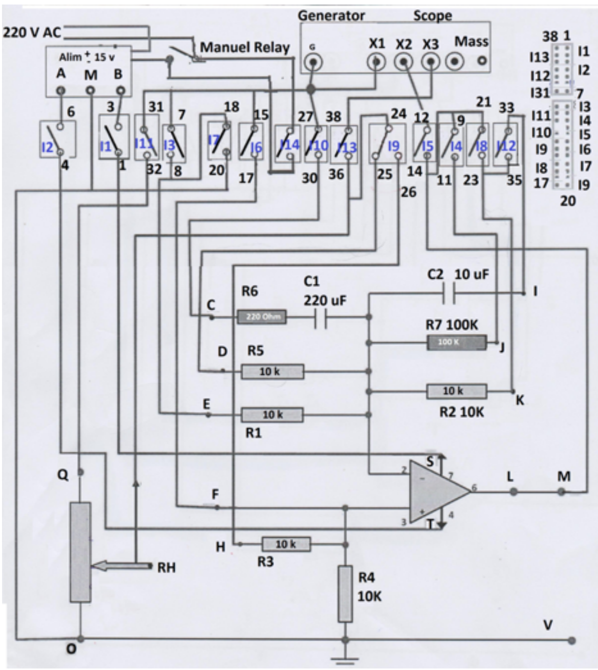


Figure 9 - Internal schema of practical work.

Practical work and Handling

Students see only the user interface displayed on the pc screen as it is indicated in figure 6 and from this interface they can control all instruments of laboratory.

Students are asked to do all the circuits of the operational amplifier with these flax diet and saturated according to the electronic component available on the screen of pc in Figure 10.a.

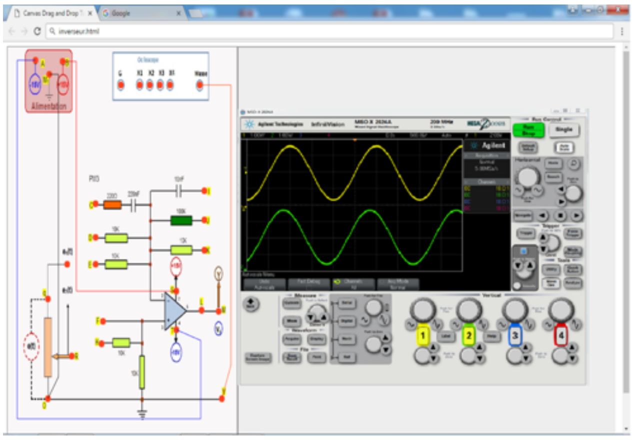


Figure 10.a - User interface student.

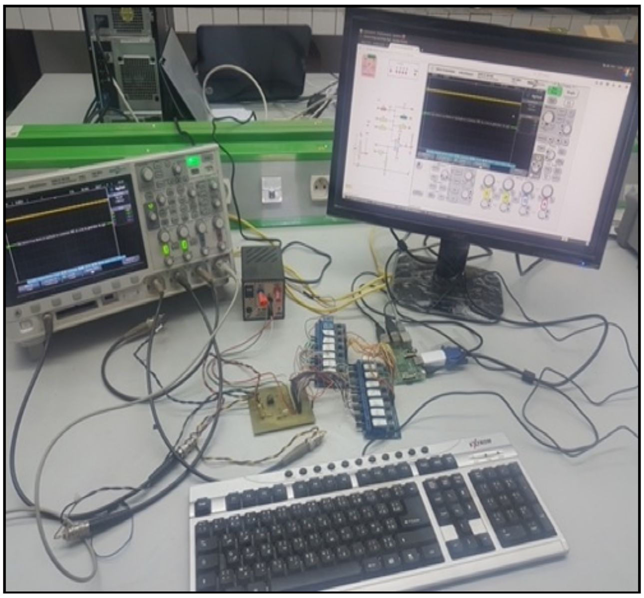
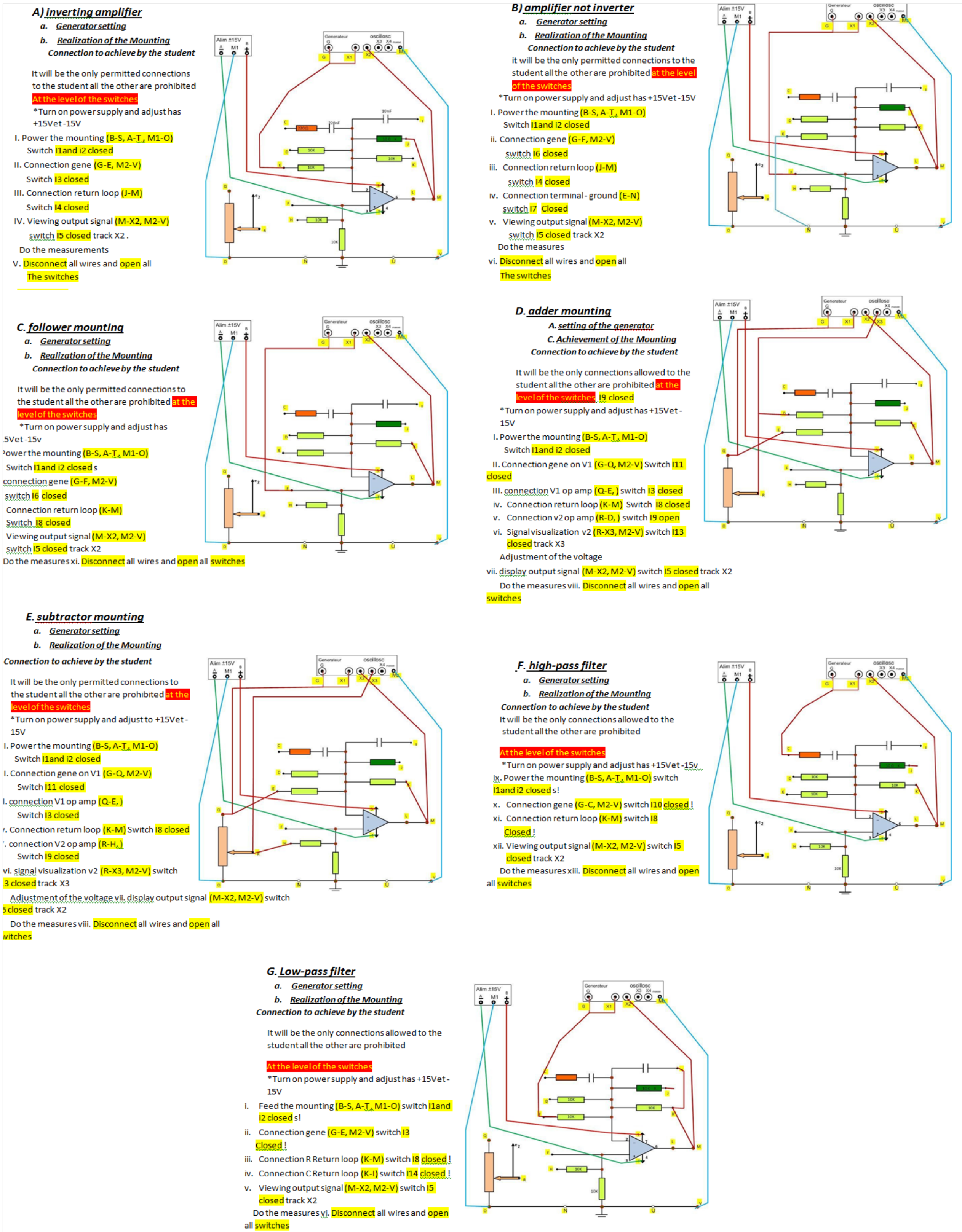


Figure 10.b - Real assembly in laboratory.

- Students have a week to read their homework and prepare the theoretical notion.
- At the day of the practical work. The students have subbed individual interviews front a professor in our physic lab before doing the practical work in front of their machine. in this interview the professors will evaluate in the student all the criteria described in the table above without given any sign or indication about response because we want to compare the results of the evaluation from an interview with the evaluation from algorithm of datamining.



- The teachers take their time to properly evaluate the students in the practical work proposed and have met the criteria explained in Table 1 and we found the results presented in Table 2: in this table we have given for each creature the percentage of each level among the 50 students.

Note: The role of this interview is to obtain the true level of the students of each criteria for to have a reference by which we will compare the performance of the 3 algorithms of datamining which will replace the interview for automate the assessment.

Criteria		Oral Interview Result
A	A-1	Level unacceptable 0% Level insufficient 25.47% Level correct 56.16% Level excellent 18.37%
	A-2	Level unacceptable 6.85% Level insufficient 30.27% Level correct 50.02% Level excellent 12.86%
	A-3	-- Individual interview with students
	A-4	Level unacceptable 0% Level insufficient 27.3% Level correct 67.2% Level excellent 5.5%
B	B-1	Level unacceptable 25.7% Level insufficient 34.8% Level correct 36% Level excellent 3.5%
	B-2	Level unacceptable 10.25% Level insufficient 33.45% Level correct 52.3% Level excellent 4%
	B-3	Level unacceptable 0% Level insufficient 25.5% Level correct 65.3% Level excellent 9.2%
C	C-1	Level unacceptable 0% Level insufficient 65.5% Level correct 27.3% Level excellent 7.2%
	C-2	Level unacceptable 25.32% Level insufficient 30.2% Level correct 40.58% Level excellent 3.90%
	C-3	Level unacceptable 10.25% Level insufficient 33.45% Level correct 54.3% Level excellent 2.00%
	C 4	Level unacceptable 23.54% Level insufficient 33.56% Level correct 41.70% Level excellent 1.20%
	C-5	Level unacceptable 0% Level insufficient 17.50% Level correct 77.50% Level excellent 5.00%
	C-6	Level unacceptable 0% Level insufficient 27.60% Level correct 56.47% Level excellent 15.93%
	C-7	Level unacceptable 24.64% Level insufficient 30.56 % Level correct 40.25% Level excellent 4.55%

Table 2 – Oral interview Results.

4.2 Result analyze and description

In our work, we choose to work with free software Weka for compare the performance of datamining algorithms for evaluate students, because it contains different classifiers in order to make decision for grants and funding. Firstly, we choose to work with Naïve Bayes classifier, decision trees classifier and OneR classifier. The three classifiers are highly efficient in evaluating a series of parameters to predict the forecast of an overall annual grant that the institution manages according to its needs.

Decision Tree classifier

The reasons for this choice are:

1. Classify correctly as much of the training sample as possible.
2. Generalize beyond the training sample so that unseen samples could be classified with as high accuracy as possible.
3. Be easy to update as more training samples become available.
4. Have as simple a structure as possible.

Naive Bayes classifier

The reasons for this choice are [11] :

1. For each hypothesis: we associate a probability observation of one or several instances may change this probability.
2. We can talk about the most hypothesis likely, based on the conditional probabilities and Bayes rule.
3. Forecasting the future from the past, while assume independence attributes.
4. Bayesian probability is the estimation of an event knowing a preliminary hypothesis is verified (knowledge).
5. The probabilistic model for a classifier is the conditional model: P (Oi | I1, I2, …. In) Where Oi is a dependent class variable whose instances or classes are few in number, conditioned by several variables I1, I2, ... In characteristics. Using the Bayes theorem, we write

$$P(Oi \mid I1, I2, \ldots In) = \frac{P(Oi)P(I1,I2,\ldots In \mid Oi)}{P(I1,I2,\ldots In)} \quad \textbf{(1)}$$

In practice, only the numerator interests us, since the denominator does not depend on Oi and the values of the characteristics Ii are given. The denominator is therefore constant. The numerator is subject to the probability law with several variables and can be factorized in the following way, using several times the definition of the conditional probability:

$P (O_i)* P (I_1 , I_2, I_n \mid O_i)$
$= P (O_i)P (I_1 \mid O_i) P (I_2,\ldots ,I_n \mid O_i ,I_1)$
$= P (O_i)P (I_1 \mid O_i) P (I_2 \mid O_i ,I_1) P (I_3,.. ,I_n \mid O_i ,I_1,I_2)$
$= P(O_i)P (I_1|O_i)P(I_2|O_i,I_1)P(I_3|O_i ,I_1, I_2)P(I_4, ,I_n|O_i ,I_1,I_2, I_3)$

:

$= P (O_i)P (I_1/O_i) \ldots\ldots\ldots P (I_n/ O_i ,I_1,I_2, I_3 \ldots\ldots I_{n-1})$

(2)

This is where we apply the naive hypothesis: if each Ii is independent of the other characteristics Ij ≠ i, conditionally to Oi So $P (I_i / O_i , I_j) = P (I_i / O_i)$ **(3)**

For all j ≠ i, therefore the conditional probability can be written, hence the conditional probability can be written $P (I1 , I2, In/ Oi) = \prod_{i=1}^{n} P (Ii / O)$ **(4)**

$P(Oi / I1 , I2, \ldots In) = \frac{1}{Z} P(Oi) \prod_{i=1}^{n} P (Ii / O)$ **(5)**

The OneR Classifier

The reasons for this choice are:

1. For each attribute and each value of this attribute, create a rule**.**
2. Counts how many times each class appears, and finds the most frequent class.
3. Creates a rule: attribute-value-> class.
4. Calculates the error rate of the rule.
5. Chooses the rules with the lowest error rate.

Intelligence artificial tools are a type of application software designed to retrieve, analyze, transform and report data for business intelligence. The tools generally read data that have been previously stored, often, though not necessarily, in a data warehouse or data mart.
To analyze and measure the performance of scientific learning at the university, managers or policy makers need synthetic indicators that are cleverly grouped one indicator that can offer for the leaders necessary tools to improve scientific research in UCA University.

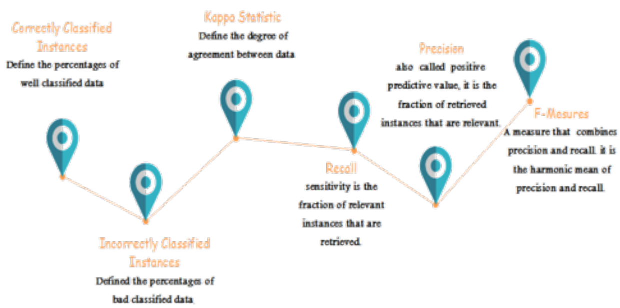


Figure 11 - The keys parameters.

We will start by defining some parameters for our analysis:

$$\text{Root Mean Squad Error} = \sqrt{\frac{(p1-a1)^2+\cdots\ldots+(pn-an)^2}{n}}$$

$$\text{Mean Absolute Error} = \frac{|p1-a1|+\cdots+|pn-an|}{n}$$

$$\text{Relative Absolute Error} = \frac{|p1-a1|+\cdots+|pn-an|}{|a1-\overline{a1}|+\cdots+|an-\overline{an}|}$$

$$\text{Root Relative squad Error} = \sqrt{\frac{(p1-a1)^2+\cdots\ldots+(pn-an)^2}{(a1-\overline{a1})^2+\cdots+(an-\overline{an})^2}}$$

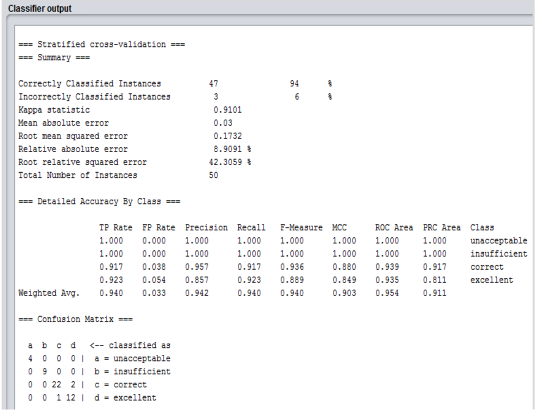
Precision: also called positive predictive value, it is the fraction of retrieved instances that are relevant.

Recall: sensitivity is the fraction of relevant instances that are retrieved.

F-Measures: A measure that combines precision and recall; it is the harmonic mean of precision and recall.

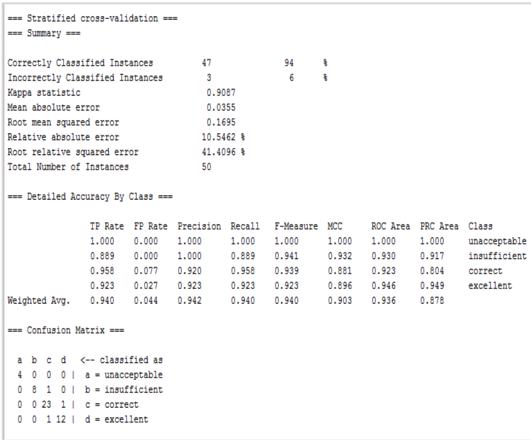
After the application of the tree classifiers we got the following results:

- Application of J48 Algorithm



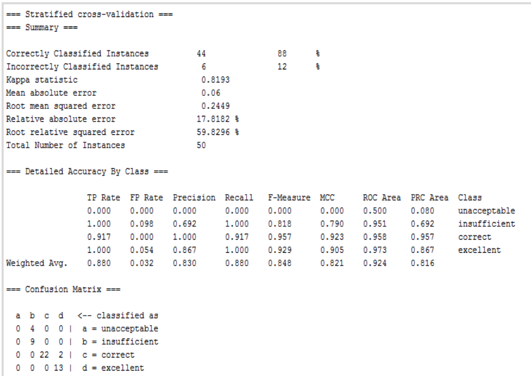
```
Classifier output

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          47               94      %
Incorrectly Classified Instances         3                6      %
Kappa statistic                          0.9101
Mean absolute error                      0.03
Root mean squared error                  0.1732
Relative absolute error                  8.9091 %
Root relative squared error             42.3059 %
Total Number of Instances               50

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000     unacceptable
                 1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000     insufficient
                 0.917    0.038    0.957      0.917    0.936      0.880    0.939     0.917     correct
                 0.923    0.054    0.857      0.923    0.889      0.849    0.935     0.811     excellent
Weighted Avg.    0.940    0.033    0.942      0.940    0.940      0.903    0.954     0.911

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  4  0  0  0 |  a = unacceptable
  0  9  0  0 |  b = insufficient
  0  0 22  2 |  c = correct
  0  0  1 12 |  d = excellent
```

- Application of Naïve Bayes Algorithm



```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          47               94      %
Incorrectly Classified Instances         3                6      %
Kappa statistic                          0.9087
Mean absolute error                      0.0355
Root mean squared error                  0.1695
Relative absolute error                 10.5462 %
Root relative squared error             41.4096 %
Total Number of Instances               50

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000     unacceptable
                 0.889    0.000    1.000      0.889    0.941      0.932    0.930     0.917     insufficient
                 0.958    0.077    0.920      0.958    0.939      0.881    0.923     0.804     correct
                 0.923    0.027    0.923      0.923    0.923      0.896    0.946     0.949     excellent
Weighted Avg.    0.940    0.044    0.942      0.940    0.940      0.903    0.936     0.878

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  4  0  0  0 |  a = unacceptable
  0  8  1  0 |  b = insufficient
  0  0 23  1 |  c = correct
  0  0  1 12 |  d = excellent
```

- Application of OneR Algorithm



```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          44               88      %
Incorrectly Classified Instances         6               12      %
Kappa statistic                          0.8193
Mean absolute error                      0.06
Root mean squared error                  0.2449
Relative absolute error                 17.8182 %
Root relative squared error             59.8296 %
Total Number of Instances               50

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.000    0.000    0.000      0.000    0.000      0.000    0.500     0.080     unacceptable
                 1.000    0.098    0.692      1.000    0.818      0.790    0.951     0.692     insufficient
                 0.917    0.000    1.000      0.917    0.957      0.923    0.958     0.957     correct
                 1.000    0.054    0.867      1.000    0.929      0.905    0.973     0.867     excellent
Weighted Avg.    0.880    0.032    0.830      0.880    0.848      0.821    0.924     0.816

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  0  4  0  0 |  a = unacceptable
  0  9  0  0 |  b = insufficient
  0  0 22  2 |  c = correct
  0  0  0 13 |  d = excellent
```

	J48	**Naïve bayese**	**oneR**
Correctly Classified Instances	94%	94%	88
Incorrectly Classified Instances	6	6	12
Kapp static	0.9101	0.9087	0.8193
Mean absolute error	0.03	0.0355	0.06
Root Mean Squad Error	0.1732	0.1695	0.2449
Relative Absolute Error	8.9091	10.5462	17.8182
Root Relative squad Error	42.3059	41.4096	59.8296

Table 3 - Comparison performance of algorithms.

For define the algorithm which allows a good prediction, in this case the superior CCI (Correctly Classified Instances) is the CCI (J48 and Naïve Bayes)=94%. Furthermore, to have good results the error must be minimal; in this case Naïve Bayes is the only algorithm which satisfies this condition.

The algorithms by which we worked is naif bays, oner, j48. We don't used SVM because is need a big nember of trainedatest and in our lab we only trainedatatest just for one year university and the algorithms used mostly naif bayes give good result in the clasifcation even if datatest is not big.

E@Slab are not only to give students grades, but also to implement remote labs that can guide and lead students during the learning process and during the PW by predicting their behavior before their reaction as a recommended system. Even This system could guide students to different practical work to improve their knowledge in engineering electrical. Thanks to these algorithms, this recommendation will be individual, personalized. it gives the teachers statistics and information about the behavior of students and their reaction with the theoretical and practical courses, thanks to these recommendation statistics can be concluded by the teacher to know the effectiveness and the level of success of this course and their teaching method in order to adapt the aims of the course to the students' skills, And it's a novelty to define the Learning Circle.

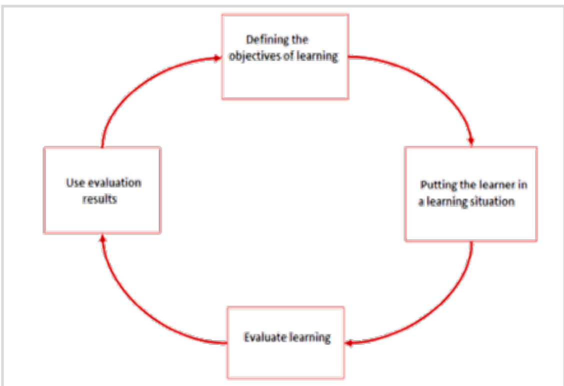


Figure 12 - Learning circle.

Conclusion

Thanks to this system, teacher will have statistics and a global vision of their working methodology for develop a syntactic strategy begins by defining the learning objectives, then put the learner in a learning situation then evaluate learning and use the results for defining new learning objectives, using the tools of artificial intelligence integrated in management education system of remote Laboratory and also the data of scientific research imported from the Presidency of the university.

We conclude that our new approach in the system evaluated student correctly, with any classification algorithm uses supervised learning.

References

Barana, A., Bogino, A., Fioravera, M., Marchisio, M., Rabellino, S. (2017). Open Platform of self-paced MOOCs for the continual improvement of Academic Guidance and Knowledge Strengtheningin Tertiary Education. Journal of E-Learning and Knowledge Society, 13(3). https://doi.org/10.20368/1971-8829/1383

Baumgartner, P., Payr S. (1997). Erfinden lernen. In: Müller, K.H und Stadler F. (Hg.): Konstruktivismusund Kognitionswissenschaft. Kulturelle Wurzeln und Ergebnisse. In honour of Heinz von Foersters. Wien-New York: Springer, 89–106.

Beetham, H., Falconer, I., McGill, L., Littlejohn, A. (2012). Open practices: Briefing paper. JISC. Retrieved from https://oersynth.pbworks.com/w/file/fetch/58444186/Open%20Practices%20briefing%20paper.pdf, last accessed August 23rd, 2020.

Cronin, C., MacLaren, I. (2018). Conceptualising OEP: A review of theoretical and empirical literature in Open Educational Practices. OpenPraxis, 10 (2), 127-143.

Ehlers, U.-D. (2011). Extending the territory: From open educational resources to open educational practices. Journal of Open, Flexible and DistanceLearning, 15 (2), 1-10.

Hodgkinson-Williams, C. (2014). Degrees of ease: adoption of OER, open textbooks and MOOCs in the Global South. Cape Town, University of CapeTown. http://hdl.handle.net/11427/1188

Inamorato dos Santos, A., Punie, Y., Castaño-Muñoz, J. (2016) Opening up Education: A Support Framework for Higher Education Institutions. JRCScience for Policy Report, EUR 27938 EN; https://doi.org/10.2791/293408

Knox, J. (2013). The limitations of access alone:Moving towards open processes in educationtechnology. Open Praxis, 5(1), 21-29. https://doi.org/10.5944/openpraxis.5.1.36

Koseoglu, S., Bozkurt, A. (2018). An exploratory literature review on open educational practices, Distance Education, 39 (4), 441-461.

Marchisio, M., Operti, L., Rabellino, S., Sacchet, M. (2019). Start@unito: Open Online Courses for Improving Access and for Enhancing Success in Higher Education. In: Proceedings of the 11th International Conference on Computer Supported Education (CSEDU), Volume 1, 639-646, Heraklion, Crete, Greece.

Marchisio, M., Sacchet, M. (2020). Analysis Items to Assess the Quality of Open Online Courses for Higher Education. In: proceedings of the 14th International Conference on e-Learning 2020 (EL2020), to appear.

Mayer, R. (Ed.). (2014). The Cambridge Handbook of Multimedia Learning (2nd ed., Cambridge Handbooks in Psychology). Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781139547369

Nascimbeni, F., Burgos, D., Campbell, L., Tabacco, A. (2018). Mapping Open Educational Practiceswithin universities: a case study. Distance Education, 39 (4).

Ouatik. F., Raoufi.M, Bouikhalen.B, Skouri. M, (2017). The EOLES project remote labs across the Mediterranean: an example of a successful experience. Proceedings of the 2017 International Conference on Smart Digital Environment doi>10.1145/3128128.3128152

