A Neuro Control Teaching & Learning (T&L) Framework for Improving Learning and Retention in Higher Education[1]

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***Abstract*— This paper describes an Innovative Practice Work-In-Progress for improving student learning and retention in higher education. Student dropout (inverse of retention) causes loss of millions of dollars in revenue. Studies have shown that an increase in retention is related, among other things, to improvement in teaching and learning. In this paper we describe a Neuro Control T&L Framework to improve student learning and retention. The framework is based on control system structure and Neural Networks (NNs). It has a controller, a process, dual Neuro feedback modules, and knowledge base. The controller component is the teaching methodologies, based on established learning theories and best practice. The process consists of lecture design and delivery, real-time formative and summative assessments. The feedback modules are based on fuzzy ARTMAP NNs. Initial results, produced 85.6% satisfactory improvement of student learning, compared to traditional approach.**

***Keywords*— learning, retention, higher education, control system, neural networks, fuzzy ARTMAP, formative assessment.**

I. Introduction

Student learning and retention are two key indicators in Higher Education Institutions (HEIs) that reflect the success or failure of an institution commitment to students. As stated by Vincent Tinto [1]:

> *"It is a commitment that springs from the very character of an institution's educational mission" (p.146)*

Despite many studies, the relationship between the two indicators is rather complex to determine. However, as shall be shown in section *B*, there is a positive correlation between student learning and retention, and both can be improved by improving the teaching and learning, among other things.

Student dropout (invers of retention) in many HEIs is staggering. In a study published by the Hechinger Report [2], 3.9 million undergraduates with federal student loan dropped out of college in the US, of which 23% dropped out of for-profit universities. Another study published by Forbes in 2018 [3], showed that 48% of first-time, full-time students who enrolled in a four-year college in the US, six years earlier had not completed their study. In 19 OECD countries, 31% of students drop out of college [4]. The same rate ranges from more than 40% in Hungary and New Zealand to below 24% in Belgium, Denmark, France, Germany, and Japan. In the Middle East and Brazil, the dropout rates are around 40%.

A. The Cost of Dropout

The financial cost associated with dropout is a function of the total enrollment, the attrition rate, and the tuition fees. The annual projected attrition loss can be estimated by the following formula [5]:

$$Cost\ of\ Attrition = \frac{SL\ x\ T}{2} \qquad (1)$$

where, *SL* is the number of students lost and *T* is the tuition. In a 4-year program, the average graduation time is 6 years (1.5 times the normal study time), and the number of students lost is:

$$SL = FTE\ x\ A \qquad (2)$$

where, *FTE* is the Fall Full-Time Enrollment, and *A* is the six-year attrition rate.

For an FTE of 5000 students, an attrition rate of 30%, and an annual average tuition of $ 20,000.00, the cost of attrition is $15 million. Such an amount should not be ignored, and thus, it is of a paramount importance to identify the reasons of dropout, predict it, and reduce it to the minimum possible.

B. Reason of Student Dropout

Student retention (the inverse of attrition or dropout) has a life span of more than 50 years. At that time, student dropout was blamed on the student's lack of skill and motivation, and this vision has changed in 1970's through the seminal works of Spady [6] and Tinto [1]. Tinto developed the following model of student retention [1]:

> *"a longitudinal process of interactions between the individual and the academic and social systems of the college during which a person's experiences in those systems…continually modify his goals and institutional commitments in ways which lead to persistence and/or to varying forms of dropout."*

This model suggests that retention is a consequence of teaching, learning, advising, and supporting services of an institution. However, there are external factors affecting retention that are beyond the control of an institution. But, nevertheless, the institution through its Quality Assurance Process, must continuously monitor student retention rate, determine its causes, and formulate a strategy to increase it, which will consequently lower the dropout rate.

Aina *et al* [4] argue that students drop out of higher

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education, if their expectations of the academic programs are lower than expected, and the efforts required to maintain the study is greater than expected.

C. Research Goal

Based on the above, it is evident that there is a positive correlation between learning and retention. The more effective the learning, the higher the retention.

This paper presents a *work-in-progress* of a framework for improving student learning and retention, based on control system and NNs, termed as Neuro Control T&L (Teaching and Learning) Framework.

The goal is to develop a real-time and adaptive framework to continuously monitor the teaching and learning processes and provide feedback to enhance teaching and student achievement of learning outcomes at the lecture level and at the end of a course. The framework uses neural networks to provide intelligent feedback to instructor to adjust lecture delivery, based on learning theories, to improve student understanding.

D. Research Objectives

This research focuses on the acquisition of feedback data in real time, building a knowledge base of teaching and learning styles, developing a mathematical model of the framework in terms of the system transfer function and a set of Key Performance Indicators (KPIs) to measure the effectiveness of teaching, learning, and achievement of learning outcomes. In this paper, we shall discuss the structure of the framework and the acquisition of feedback data, specifically the formative assessment feedback.

The paper is divided into 4 sections. Section 2 provides literature review on the common learning theories and methods of enhancing student learning. Section 3 describes the proposed framework, and section 4 presents discussions and future studies.

II. LITERATURE REVIEW

A. Learning Theories

Student learning is the process whereby a student acquires a body of knowledge and skills, during a lecture, a course, or a period of a program. Many theories have been proposed to understand the learning process. They are grouped under three main categories: Behaviorist Learning Theories, Cognitive Information Processing Learning (CIP) Theories, and Constructivist Learning Theories.

1) Behaviorist Learning Theories

Behaviorist learning theories are based on the work of Skinner [7]. Skinner believed that knowledge is acquired as a result of the association between stimuli and responses, without the need to understand how the cognitive brain constructs knowledge. This theory focuses on reinforcement, praise or sense of accomplishment, to produce the response.

An example, in the context of education, is that student performance is rewarded with grades, and reinforced (encouraging them to continue with their learning) through formative and summative assessments during the semester.

2) Cognitive Information Processing

Cognitive Information Processing (CIP) learning theories, founded on the work of Atkinson and Shiffrin [8], view human brain as "computer" that receives information from the environment, processes them, and generates an output in the form of knowledge or skills. There are 3 main processing stages: Selection Attention, Rehearsal and Chunking.

In the context of cognitive psychology, selection attention is the brain ability to focus on one or more types of sensory information and ignores other types for their contextual irrelevancy. An example in the context of learning is when a learner is attending a lecture, and mentally processes auditory and visual information to make sense of the lecture contents. Thus, lecture contents must be effectively designed to optimize selective attention to enhance student learning and achievement of course outcomes.

Rehearsal and Chunking are parts of Short-Term Memory (STM), where information is compared to previously stored information or concepts in long-term memory. STM has limited capacity and finite duration. It can store between 6 and 9 digits of information (average 7), and storage lasts for about 30 seconds. The capacity and duration of STM varies from one person to another [8].

How STM is related to teaching and learning? In a class of students of varying levels of cognitive skills (varying degrees of STM capabilities), instructors should explain in a slow, comprehensible way, and repeat when asked, or based on *formative feedback*, to enhance the learning of students who are slow in processing and recognizing sensory information.

To facilitate learning of sensory information, Rehearsal and Chunking are used to help encode information into the long-term memory. When a person is repeating a word or a number, he is encoding it into the LTM. Chunking is dividing a long string of information into smaller strings that can easily be recognized. For example, dividing a phone number into chunks of 2 or 3 digits, helps encoding and memorizing [8].

In the context of teaching and learning, chunking may be applied by breaking down a complex definition, or concept, into smaller parts that could easily be understood by students.

3) Cognitive-Constructivist Learning Theories

These theories are based on two fundamental theories: Developmental Constructivist, pioneered by Piaget [9], and Social Constructivist, developed by Vygotsky [10]. Both theories advocate a learner-centered approach, as opposed to teacher-centered approach, whereby knowledge is not merely received, but constructed by the learner.

As an example, consider the scenario of two instructors A and B giving a statistics lecture on Central Tendency Measures (the average). Instructor A is a type of a teacher who merely transmits knowledge (recites), by writing formulas and examples and students write everything that is on the board. Instructor B, on the other hand, explains the practical concept of the average in a way that involves students in the process of teaching, by drawing examples from real life situations and making students assimilate mentally the concept of the average. At the end of the lecture, students of instructor A, will have one or two pages of handwritten text that, undoubtedly, static and can only be used to apply the formula for calculating the average; and students of instructor B, on the other hand, will have lesser text, but a dynamic mental picture of the concept of the average.

B. Enhancing Student Learning

In the context of higher education, studies on enhancing student learning could be divided into three categories, in terms of the mode of delivery; those that focus on face-to-face learning and those based on partial or complete online learning. These studies suggest that student learning could be enhanced by using technology and/or engagement among learners themselves, and learners and teachers.

A framework has been proposed to enhance student learning in online environment [11]. The authors suggested that learning enhancement is dependent on student-related factors such as skill; organization and delivery; and student learning experience.

Faour, Hamoudah, and Al-Ghamdi [12] proposed a virtual learning environment to enhance student learning, based on social constructivist methods [10] and providing constructive feedback to students. Their approach is based on the established concept that learning should be student-centered.

Several other studies have been proposed based on the concept of Adaptive e-Learning Systems [13] [14] [15] [16] [17]. These approaches are based on presenting the course contents and sequence according to student learning styles.

III. Neuro controller T&L Framework

The studies summarized above focused on enhancing student learning in online adaptive lecture delivery, without emphasis on formative assessments and types of feedback mechanism. The absence of these two elements renders learning, in face-to-face or online delivery, ineffective and impacts student retention and satisfaction [18].

Formative assessment, a method of enhancing student learning, is first coined by Michel Scriven in 1967 [19] and used by Benjamin Bloom in 1968 to illustrate its use to enhance teaching and learning [20]. A comprehensive review of formative assessment in online learning is provided in [21].

In this paper we propose a framework based on closed-loop control system, neural networks, and real-time and interactive formative assessment mechanism.

The processes of Teaching and Learning (T&L) is complex, non-linear, and involve many parameters. We argue that T&L processes in an outcome-based education, can be modeled by a control system with an input, controller, process, output, feedback, and a knowledge base.

Control systems are used in diverse areas [22] such as industry, car manufacturing, autonomous flights, space technology, healthcare, etc. Rossiter [23] applied the concept of control system with feedback loop and demonstrated, mathematically, that students should receive feedback on their assignments and assessments in a timely fashion to allow them to reflect on their work and improve their learning [23].

Christopher Benjamin discussed the types of control systems, namely open-loop and closed-loop, and their parallelism to academic feedback [24]. He demonstrated that feedback must relate to the input of the process, as well as accurately reflecting the output, and should be considered when designing assessment schemes within units of study and producing individual assignment tasks.

A. *Overview of Closed-Loop Control System*

A general diagram of a control system with a feedback loop is shown is Fig. 1. The input *u(t)* represents the reference point (the desired output), and *y(t)* is the system output. The feedback is a component that measures the output and converts it to a proper signal compared to the input at the Comparator, and error signal *e(t)* is generated. This signal is used by the Controller to adjust the Controlled Input, *r(t)*, to process and keep track of the input. The objective is

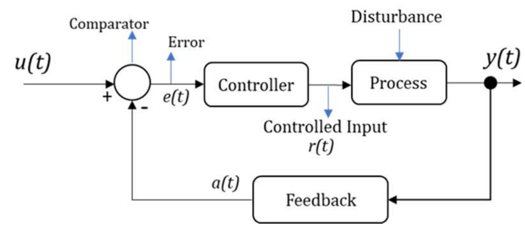

Fig. 1 - General diagram of a control system.

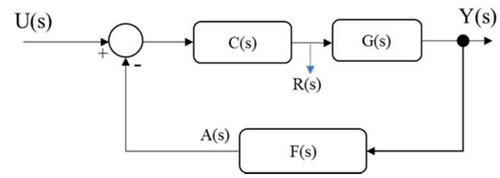

Fig. 2 - Laplace Transform.

continuous improvement of the system performance so that the output approaches the desired reference point *u(t)*.

In terms of Laplace Transform, the feedback control system is shown in Fig. 2 and its mathematical model is described by equation 3:

$$H(s) = \frac{Y(s)}{U(s)} = \frac{C(s)G(s)}{1+C(s)G(s)F(s)} \tag{3}$$

If the absolute value of the numerator is much larger than 1, and the feedback value is close to 1, the processed output is expected to approach the reference point (the desired output). In mathematical form, this is expressed as follows:

$$if\ |C(s)G(s)| \gg 1, and\ F(s) \approx 1 \tag{4}$$

then:

$$\lim \frac{Y(s)}{U(s)} \approx 1; and \quad Y(s) \approx U(s) \tag{5}$$

Ideally, the system output approaches the desired value.

B. *Architecture of the Neuro Controller T&L Framework*

A block diagram of the proposed Neuro Controller T&L framework is illustrated in Fig. 3 in the following page. It consists of an input, Controller, Process, desired output, Knowledge Base (KB) and two NNs feedback modules.

The input *u(t)* is the target value of course learning outcome, to be achieved either after a set of lectures, or at the end of a course, and the output *y(t)* is the achievement of learning outcomes at the end of the course. The *Controller* is the teaching methodologies based on learning theories, and best practice. The *Knowledge Base* (KB) is a set of QA Code of Practice (QPC) and Teaching and Learning Methodologies (TLMs), some of which are based on learning theories, both contain sets of rules and procedures updated and extracted based on the feedback signals $a_1(t)$ and $a_2(t)$. The error signal *e(t)* is an indication of the achievement of learning outcomes.

The *Process* consists of lecture design and delivery, *Formative*, and *Summative* assessments. The output *signal* $y_1(t)$ is a measure of student understanding of a given lecture topics or Course Learning Outcome (CLO). The controlled input *r(t)* is a qualitative signal generated by KB to guide the processes of lecture design and delivery, formative, and summative assessments.

Formative assessment is conducted in real time, before, during, or after a lecture, using an interactive cloud-based application (*Bluepulse*[3]) currently in pilot phase. It allows

[3] https://explorance.com/solutions/social-feedback/

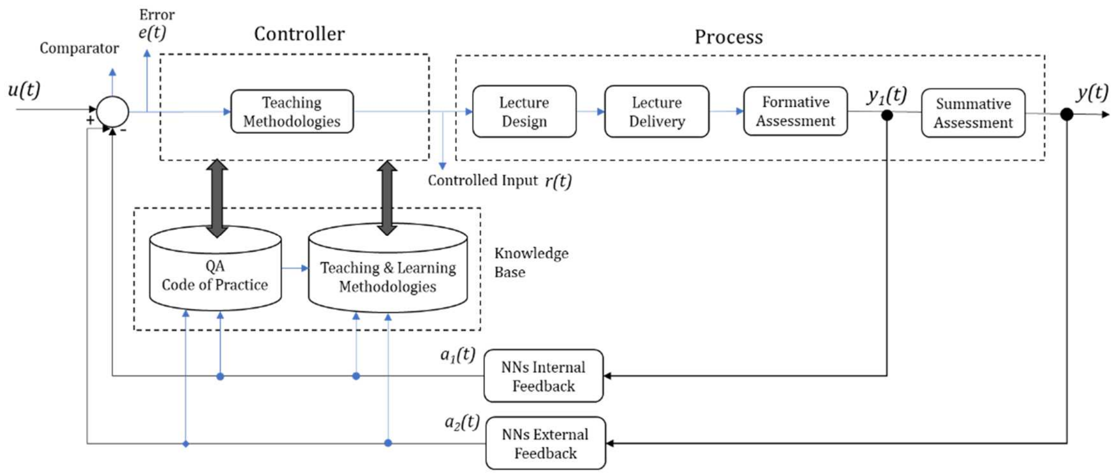

Fig. 3 Block diagram of the Neuro Control T&L Framework.

instructor to post question(s) to students and receive feedback in real time. Summative assessments include course works, tests, and exams.

There are two Neural Networks (NNs) feedback modules. The Internal NNs Feedback (INNF) analyzes $y_1(t)$ and triggers the appropriate KB components, to be followed by the instructor to adjust teaching methodologies necessary to modify the *Process* to enhance learning. The External NNs Feedback (ENNF), activated at the end of the semester, analyzes $y(t)$ and provides the instructor with quantitative and qualitative assessments to be adopted to improve student learning when the course is offered in the subsequent semester.

Neural Networks have been used in control to develop a model of the system and to either design or train the controller. In the proposed framework, each INNF/ENNF module employs fuzzy ARTMAP NN to learn in real time and suggest the appropriate sets of teaching methodologies to improve student understanding and achievement of learning outcomes. The fuzzy ARTMAP was selected because of its ability to learn new patterns without forgetting previously learned ones, which makes it plausible for real-time applications; and it has few parameters to adjust during learning compared to other feedforward/probabilistic networks.

C. *Neuro Control T&L Theoretical Operation*

The Neuro Control T&L provides instructors and academic department with continuous enhancement processes of teaching and learning, at the lecture and course levels, through the stages of Design, Deliver, Assess, Measure, Analyze and Improve, similar to the PDCA methodology developed by Walter A. Shewhart and renamed in 1950 by the Japanese as Deming Cycle.

At the lecture level, the instructor designs and delivers the lecture according to guidelines from the knowledge base, to achieve the CLO associated with the lecture. Formative assessment is conducted in real time, before, during, or after the lecture and consists of question(s) to measure student understanding of a specific lecture topic. Student answers are mapped to a 5-degree Likert scale and analyzed at the INNF module. The instructor receives the responses from the INNF module, with suggestions to improve lecture delivery, if a percentage of students' responses is below an established threshold, for example 75%. Alternatively, the instructor may introduce new teaching methods to suit the student cognitive level. In either case, all methods used by an instructor are stored at the KB module with their associated feedback results. This association is learned by the INNF module.

An example of formative assessment is given here. In a pilot experiment of a class of statistics the instructor asks the question: How confident are you in calculating the standards deviation? Students receive the question in their mobiles, through *Bluepulse*, and respond by selecting one of 5 possible answers, based on their understanding, as follows: Very Confident (5), Confident (4), Somewhat Confident (3), Unsure (2), Very Unsure (1). The instructor receives the responses in a visual form (Fig. 4), and takes action, based on the established success threshold and information received from the INNF module.

At the end of the semester, the ENNF module compares the achievement of learning outcomes, denoted by $y(t)$ in Fig. 3, to the desired target value, denoted by $u(t)$, and suggests changes to be followed to the course delivery when it is given in a subsequent semester.

IV. DISCUSSION AND FUTURE STUDIES

In this paper we have presented an *Innovative Practice work-in-progress* of a Neuro Control T&L Framework based on control system, real-time formative assessment, and NNs. The goal is to develop a framework that operates in real time and allows instructor to improve lecture design and delivery, enhance learning and achievement of CLOs, through real-time formative assessment and intelligent feedback loops, and eventually, increase retention. The framework can be used in face-to-face and online learning.

The framework is being developed in two stages. Stage one focused on formulation of the framework architecture and the application of a real-time formative assessment. At this

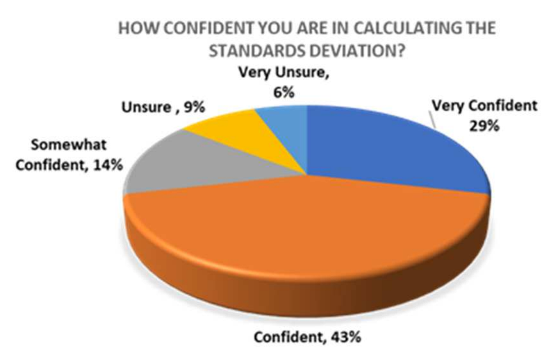

Fig. 4. Student Formative Assessment Responses.

stage, two instructors each gave a course on statistics, and one instructor gave a course on computer programing,

The three instructors were trained to design and deliver lectures according to the learning theories described above, and apply formative assessment using Bluepulse to post questions before, during, or after the lecture. The questions measured student understanding of a lecture topic, as illustrated in the example shown above. A success threshold of 75% was established for formative assessment, and 70% for CLO achievement. If the threshold is reached, the instructor will move to the next topic and enhance learning of those who were below the threshold, by giving them extra homework. On the other hand, if the threshold is not achieved, the instructor adjusts the lecture design and delivery, to reach the target values. All information is entered manually in the KB module by the instructors. The three classes had a total of 45 students who were also enrolled in other classes that did not follow the Neuro Control T&L framework.

At the end of the semester, a survey was conducted to measure student satisfaction (45 students) with the course delivery in the three courses mentioned above, and in the other courses that did not follow the framework. The overall results showed 85.6% satisfaction and overall CLO achievement of 88.3% in the courses that followed the Neuro Control T&L framework, compared to 78.2% and 79.1% in the courses that did not follow the framework. Furthermore, qualitative feedback from the students revealed that the interactive and real-time formative assessment and the consequent immediate improvement of lecture deliver by instructors, enhanced their learning considerably.

Stage two will focus on completing building the Knowledge Base, training the NNs feedback modules, defining a set of KPIs to assess the effectiveness of the framework, developing the transfer function, and representing student knowledge by applying the concept of *State* in control theory.

Based on the concept of *State*, we define student knowledge and skills by a time-variant knowledge state, *k(t)*. At the beginning of a course, this knowledge state could be assumed to be "0", and it increases over time, during the period of the course, and it is expected to reach the success threshold target of CLO achievement, at the end of the course. The student knowledge state **K** is represented by the following matrix:

$$\mathbf{K} = \begin{bmatrix} k_{1,1} & k_{1,2} & \dots & k_{1,j} \\ k_{2,1} & k_{2,2} & \dots & k_{2,j} \\ \dots & \dots & \dots & \dots \\ k_{i,1} & k_{i,2} & \dots & k_{i,j} \end{bmatrix} \tag{6}$$

where *i=1 to n* denotes the number of CLOs, *j=1 to m* denotes the number of periods during which the CLOs are covered, $k_{i,j}$ denotes the knowledge state related to the *ith* CLO after the *jth* period. The knowledge state **K** is independent of the system transfer function and will allow us to model learning at different times of the process.

In addition to the above, we are investigating modeling the framework with neural networks.

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