Can we (control) Engineer the degree learning process?

Can we (control) Engineer the degree learning process?

AS White[1], M Censlive[1], D. Neilsen[2]
[1]School of Science and Technology, Middlesex University, The Burroughs, Hendon NW44 BT
[2]Business Faculty, University of Greenwich, 30 Park Row, London SE10 9LS

E-mail: a.white@mdx.ac.uk, d.nielsen@gre.ac.uk

Abstract. This paper investigates how control theory could be applied to learning processes in engineering education. The initial point for the analysis is White's Double Loop learning model of human automation control modified for the education process where a set of governing principals is chosen, probably by the course designer. After initial training the student decides unknowingly on a mental map or model. After observing how the real world is behaving, a strategy to achieve the governing variables is chosen and a set of actions chosen. This may not be a conscious operation, it maybe completely instinctive. These actions will cause some consequences but not until a certain time delay. The current model is compared with the work of Hollenbeck on goal setting, Nelson's model of self-regulation and that of Abdulwahed, Nagy and Blanchard at Loughborough who investigated control methods applied to the learning process.

Keywords: Learning, control theoretic model, simulation, Kolb model

1. Introduction
The role of learning theory in Engineering Higher education in the UK has only been a topic of serious investigation since the 1970's following the expansion of higher education in the late 1960's, leading to the integrated use of the student centred project method of teaching. In the 1970's investment was put into the use of teaching machines (Skinner [1]) with few consistent results reported. This basic technology was replaced by the use of personal computers in the 1980's.

If we are expected to use the new online techniques embodied by "Massive Open Online Courses" (MOOC) then we need to have a much better understanding of the process of learning in engineering education. The accepted view in the UK is described in Houghton [2] which uses the Kolb [3] theory in terms of:
1. Concrete Experience
2. Observation and reflection
3. Abstract conceptualisation
4. Testing concepts in new situations

These learning concepts can be mapped to the SARTOR (Engineering Council [4]) three part scheme: Knowledge; Skills and Understanding

These components of learning are compatible with a control theoretic approach and the principle of feedback is a key component of all reflection activities. A Delay or knowledge "soak time" is acknowledged by most academics to be a normal component of the learning process.

2. Review

The idea that people rely on mental models of situations was first proposed by Kenneth Craik [5] and this process was used to construct small scale models of reality to underlie reason, to anticipate events and to help with explanation. Norman [6] describes Mental Models as follows; "In interacting with the environment, with others, and with the artefacts of technology, people form internal, mental models of themselves and other things with which they are interacting. These models provide predictive and explanatory power of understanding the interaction." This will mean that people will map the observations of the real world to the simplest model that fits the facts as observed or interpreted by that individual.

The uses of control theoretic models in psychology dates back to Erez's [7] work on feedback and goals. Campion and Lord [8] applied control theory in light to goal-setting. This work was developed by Klein [9] studying work motivation and Hollenbeck [10] looking at work environments. In engineering the model described by Kolb was adopted by a number of investigators because it seemed to fit the existing engineering pedagogy. Abdulwahed et.al. [11] Summarises the work undertaken at Loughborough to develop control models of learning using the Kolb theory of learning.

Seri [12] illustrates a model of learning (figure 1), showing the necessary feedback paths and recognition of difference and error which agrees with the models used by Abdulwahed et.al.

White [13] reviews the results of experiments of control and mental models combining all these observations together with existing double loop learning models to create an integrated model (figure 2). Here all the aspects of prior education, environment and poor judgement combine to make a given strategy and subsequent decisions.

This model shows how difficult it is to isolate the circumstances for a successful learning process. An et.al [14] created a System Dynamics/control theoretic model of service levels for IBM. One of the key aspects of System Dynamics models of project developments is the important contribution of time pressure operating within deadlines. This is included in the model shown in figure 3.

3. Control model of learning in higher education

In this section we propose a control model of a constrained learning process, the learning target for the model is gaining the knowledge and skill to manipulate a given computer package. The model shown in figure 3 represents the process of obtaining capability in using specialist software. It has been developed using the Kolb model of experiential learning and building on the control models of Abdulwahed et.al. This implementation incorporating a delay is supported by experimental data for the exponential model of delay to the learning process from the results of Towill [15].

The capability *Cap* has a desired value *Cdes* which is rated as 1 or 100%. The effort needed to reach this level of capability is *E* and the time delay between the effort being applied and the *Cap* value observed is represented by a time delay transfer function $\frac{KEC}{(T_L s+1)}$. The time constant T_L is the time to reach 66% of the final value.

Each learner has a measure of the value of the capability achieved *Cap*. This measured value is FE*Cap and is different for each actor. The student recognises an error between the measured capability and the desired performance. He/she will then adjust the effort by a gain value *Keff*. This gain is in two parts, one fixed rate and an element caused by the pressure due to time remaining. These are indicated in figure 4. The effective gain increases as time progresses. This model uses a linear increase in gain but would probably be a greater rate e.g. parabolic. The model is described in equations 1 to 5

$$Cap = Cap_p + Cap_s + \frac{E\,KEC}{T_L s+1} \tag{1}$$

$$E = Keff(Cdes - FE\,Cap) \tag{2}$$

$$Cap_p = \frac{Kip}{T_p s+1}\big(Cdes - FE_p Cap\big) \tag{3}$$

$$Cap_s = \frac{Kis}{T_p s + 1}(Cdes - FE_s Cap) \tag{4}$$

$$Keff = K_0 + K_t \left(\frac{1 - e^{-Tms}}{s^2}\right) \tag{5}$$
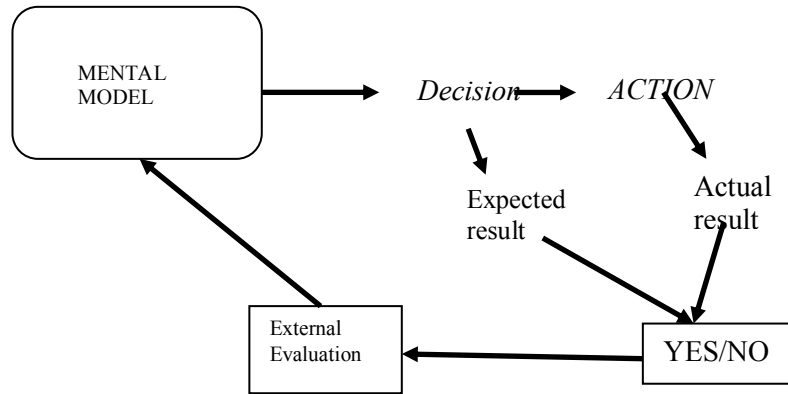

Figure 1. Individual loop of Learning adapted from Seri [13]
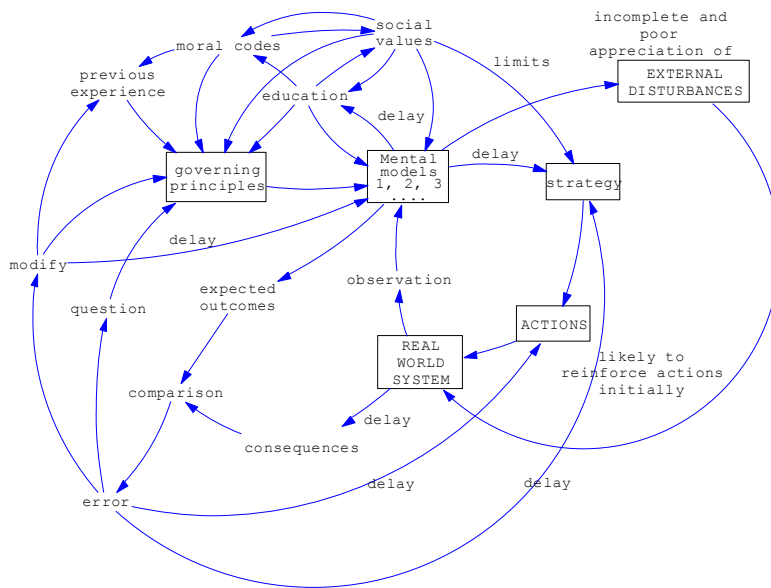

Figure 2. Model of Human control Learning Process from White [14]

The individual effort, whether by using electronic sources or by critical thought, is modified by two factors; one is the action of the supervisor or tutor who then intervenes when the student is struggling and the other due to the student gaining peer group help, which may be substantial. Both of these add to the final capability without learning (usually). Both of these are represented in the same way but with different feedback errors; gains and time delays. The capability acquisition through the module is shown in figure 3.
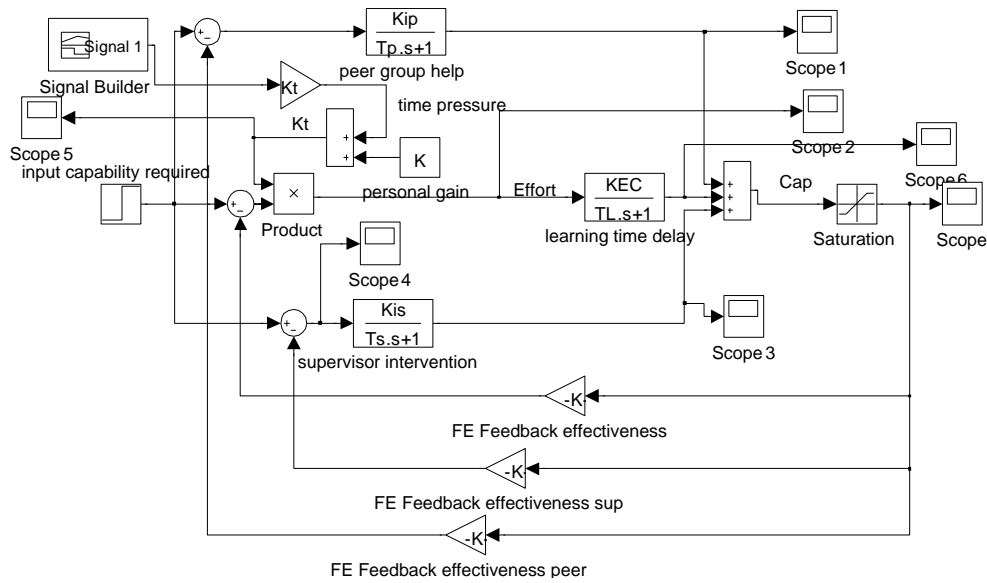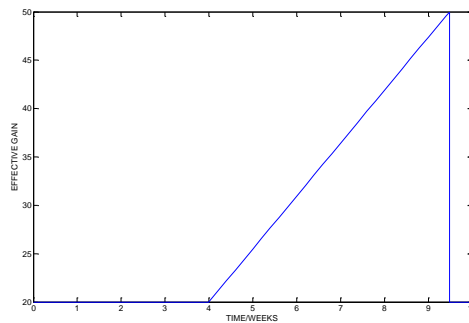
Figure 3. Control model of Learning

Figure 4. Effective gain

With the constants used in this first example half the final capability is due to the action of the peer group support and help from the tutor. Note that even then in this case the student does not achieve 100% capability. Figure 6 shows the sensitivity of the capability to reduced student performance or reduced peer group contribution. The data used is based on observations of teaching MATALB to two sets of students in 1999 and 2010. In the two cases the contributions of peer effects were greater in 2010 than in 1999.

4. MOOCs for Learning

The early stage assessments of MOOCs, based on the uptake by the number of students registered, indicated a very promising trend towards a new way of learning. Various studies have now raised questions about the success rates and effectiveness of MOOCs for student learning (Santos et al, [17]). Ramesh et al, [18] found a small clustering of student behaviour demonstrating engagement using these learning resources. Chen [19] argued that formal inclusion of regular feedback and interactions between the teacher and learner throughout the duration of the course is necessary for a successful and increased percentage of learning completion. In view of this and the applicable concept of value added feedback from supervisor intervention in the Control Model of Learning (figure 3) the design for

MOOCs courses must be reassessed to ensure the incorporation of these elements. Specific and clear pedagogical designs must be embedded to facilitate and encourage this model of learning.
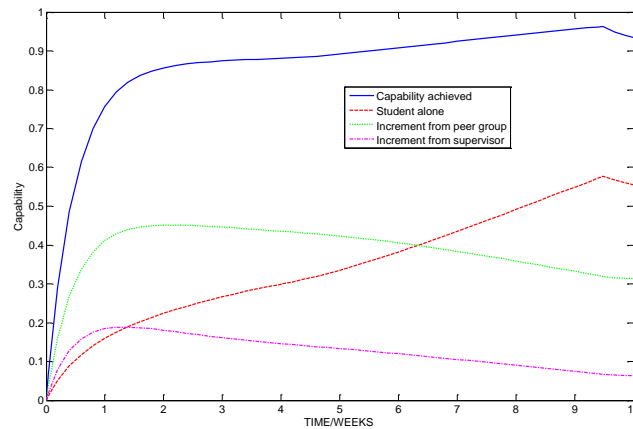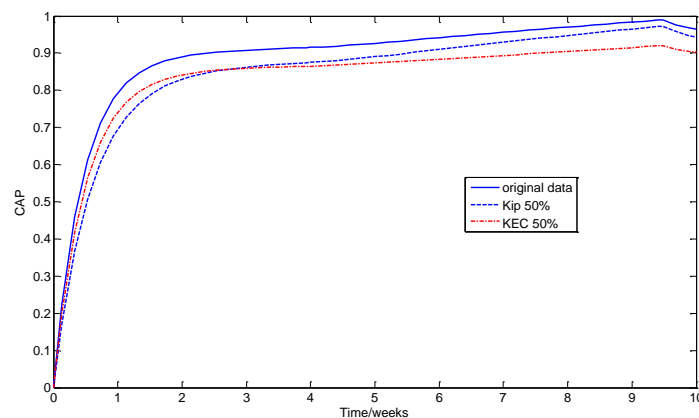

Figure 5 Capability performance

Figure 6 Overall performance sensitivity

5. Conclusions

A new control model has been devised building on the work of Abdulwahed et al. and White using the experiential model of Kolb

This model enables the effect of supervision and peer group interaction to be incorporated as well varying the effectiveness of the students own contribution.

Sample results show that the times of contribution and the amount of peer group contribution to be critical to reducing the time to learn a given set of operational skills for example the use of a given set of software applications.

References
[1]   Skinner, B.F. (1958) Teaching Machines, *Science,* Vol 128, No3330, 969-977.
[2]   Houghton, W, (2004) Learning and Teaching Theory for Engineering Academics, *Higher Education Academy*, Engineering subject centre.
[3]   Kolb, D (1984) *Experiential Learning: experience as source of learning and development*, Prentice-Hall.
[4]   Engineering Council (1985) Standards and Routes to Registration (SARTOR). EC 10 Maltravers Street, London WC2R 3ER, England.

[5]   Craik, K, (1943) *Nature of Explanation*, CUP

[6]   Norman, D. A. (1983). Some observations on mental models. In D. Gentner and A. L. Stevens (Eds.), *Mental models* (p. 7-14). Hillsdale, NJ: Lawrence Erlbaum.

[7]   Erez, M. (1977). Feedback: A Necessary Condition for the Goal Setting Performance Relationship. *Journal of Applied Psychology,* Vol.62, pp.624-627.

[8]   Campion, M. A., & Lord, R. G. (1982). A control systems conceptualization of the goal-setting and changing process. *Organizational Behavior and Human Performance*, Vol.30, pp.265-287.

[9]   Klein, H. J. (1989). An integrated control theory model of work motivation. *Academy of Management*, Vol.14, pp.150-172.

[10] Hollenbeck, J. (1989). Control Theory and the Perception of Work Environments: The Effects of Focus and Attention on Affective and Behavioral Reactions at Work. *Organizational Behavior and Human Decision Processes,* Vol.43, pp.406-430

[11] Abdulwahed, M., Nagy, Z.K. and Blanchard, R.E., (2008). Constructivist project based learning design, a cybernetics approach. IN: Malpica, F. et al. (Eds). Proceedings of the 2nd International Multi-Conference on Society, Cybernetics and Informatics, (IMSCI 2008), June 29th - July 2nd, 2008

[12] Seri, P (2001) Losing areas and shared mental models: towards a definition of the cognitive obstacles to local development, *DRUID Winter Conf.* Copenhagen, 18-20 Jan.

[13] White, A. S. (2013) Human Supervision of Automated Systems and the Implications of Double Loop Learning, *International Journal of Information Technologies and Systems Approach*, Vol.6, No.2, pp.13-21, July-December

[14] An, L, Jeng, J and Lee Y. M, (2007). "Effective Workforce Lifecycle management via System Dynamics Modeling and Simulation", Proc. *2007 Winter Simulation Conf.,* IEEE, pp.2187-2195

[15] Towill, D (1977) Exponential smoothing of learning curve data, *Int.J.Prod. Res.*, Vol.15, No.1, pp.1-15.

[16] Santos, J.L., Klerkx, J., Duaval, E., Gago, D. and Rodriguez, L., (2014). Success, activity and drop-outs in MOOCs an exploratory study on the UNED COMA courses, Proc. 4th Int. Conf. on Learning Analytics And Knowledge, *ACM, NY,* ISBN: 978-1-4503-2664-3 doi>10.1145/2567574.2567627 pp. 98-102

[17] Ramesh, A., Goldwasser, D., Huang, B., Daume, H., III and Getoor, L. (2014) Uncovering hidden engagement patterns for predicting learner performance in MOOCs, *L@S '14: Proc.1st ACM conference on Learning @ scale conference,* pp. 157-158, ACM NY, ISBN: 978-1-4503-2669-8 doi>10.1145/2556325.2567857

[18] Chen, P. and Chen Y. (2014) Facilitating MOOCs learning through weekly meet-up: a case study in Taiwan, L@S '14 *Proc. 1st ACM conference on Learning @ scale conference*, pp. 183-184, NY, ISBN: 978-1-4503-2669-8 doi>10.1145/2556325.2567872

Symbols

Cap   *Capability to perform computing task(0-100%)*

Cdes *Capability Desired*

E   *Effort expended in person hours*

FE   *Feedback effectiveness*

K   *Personal gain, increment of effort per difference of perceived gap between own performance and desired value*

K_0 *Initial value of personal gain*

K_t *effect of time pressure on personal gain*

KEC   *Personal capability increment per unit effort*

Keff *Effective personal gain allowing for time pressure*

Kip   *Peer group gain increment per unit time*

Kis   *Supervisor gain increment per unit time*

Kt   *Part of personal gain due to time pressure*

T_L *Learning time delay for the individual*

Tm   *Time to realise time pressure*

T_P *Time delay for effective peer group help*

T_S *Time delay for effective supervision.*