Using Simulations to Automatically Generate Authentic Constructivist Learning Environments

Dr. Imran A. Zualkernan
American University of Sharjah
izualkernan@ausharjah.edu
May 2004

Abstract

With increasingly short life-cycles, hand-crafting authentic constructivist environments for learning will become increasingly unfeasible. As the complexity of designed systems and devices increases, however, so does the role of simulations to support design. This paper presents an approach and an example of how naturally occurring simulations in design can be used to automatically generate authentic constructivist learning environments.

1. Introduction

A critical issue in the development of authentic constructivist learning environments (ALE) is the cost of development. As opposed to the page-turner e-learning modules, ALE's can be an order of magnitude more expensive.

The problem of elevated cost is exacerbated in situations where these environments are designed to apply to designed systems. Designed systems (as opposed to natural systems) can be as simple as a coffee maker to an ERP software to a semi-conductor manufacturing line that may consist of hundred of steps to produce an incredibly complex device. The one overwhelming problem is the shorter and shorter life cycles that necessitate "maintenance" or in the worst-case, a complete re-design of the ALE. For example, every time a new version of the software comes out, the authentic learning environment needs to be updated with the new features and menus.

As the complexity of the designed systems has increased, however, simulations play an increasingly important role and in fact have become necessary by-products of the design process itself.

This paper explores how an ALE can be automatically generated from simulations that occur naturally as a part of the design process. We assume that the task of constructing an authentic learning environment consists of creating a "learning curriculum" [1] which consists of "situated opportunities" [2] and that the learner learns though a centripetal participation with this learning curriculum.

2. Framework

We extend a framework presented in [3] to conceptualize the problem of generating authentic environments from simulations. The primary components of this framework are shown in Figure 1.

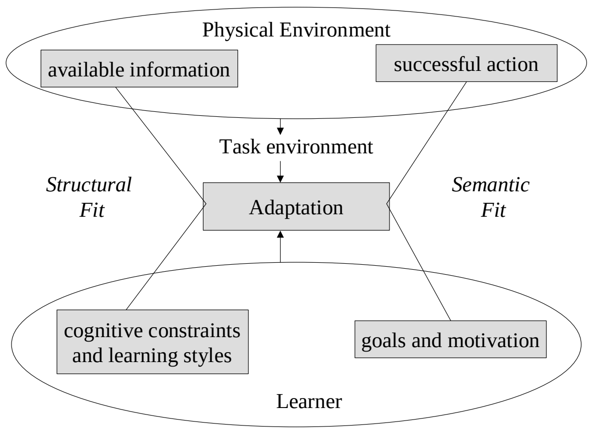

Figure 1. Framework for developing authentic learning environments

Briefly, the *Physical environment* is a description of the objectively observable characteristics. In our case, the physical environment, for example, may contain the device itself (e.g., the coffee maker) and its surroundings (e.g., the kitchen including the power outlets). The available information part of the physical environment may also consist of artifacts such as books, manuals, databases that exist as well as interaction with peers, experts and teachers. For example, the user's guide to the coffee maker including checklists on what to do if the coffee maker does not work.

Specific characteristics of the environment require specific actions by the learner. For example, the coffee maker not making the coffee may require an action of repair. The *Task Environment* is the subset of the physical environment that is relevant to a class of agents (e.g., people who fix coffee makers).

The *Adaptation* is a representation of what is "learnt" under the mutual constraints of the *Task Environment* and the constraints from the learner. The constraints on the learner will contain cognitive constraints and goals and motivation on the other.

Loosely, the "fit" describes how well a Learner is adapted to the *Task Environment* (e.g., how good is the coffee maker fixer?).

Fit can be classified into two dimensions; semantic and structural. The semantic dimension is a measure of how well the Learner's actions are acceptable in the particular environment (e.g., how well are coffee maker fixer's operations received in the physical world – how many coffee maker are actually fixed). The structural dimension of fit describes how closely do the cognitive constraints and learning styles of the learner "match" to the information present in the environment (e.g., does the coffee maker fixer accept a particular type of coffee maker as suited to her fixing skills).

3. The Problem

As Figure 2 shows, this paper looks at the problem of generating an authentic learning environment (ALE) from a simulation of a designed system such as a coffee maker. The learner will develop an *Adaptation* in interacting with the ALE. In doing so, she will develop a "fit" with the ALE. How good the ALE is in part determined by the ability of this *Adaptation* to also show a high degree of "fit" with the actual designed system and its environment.

For example, coffee makers break in the physical world. A simulation of the electrical mechanisms within the coffee maker can be used to generate an ALE. Once the coffee maker fixer has become quite competent at interacting with the ALE, she can now go out in the real world of coffee makers and try to fix them. The degree to which she is able to perform in the real world will determine the effectiveness of the ALE.

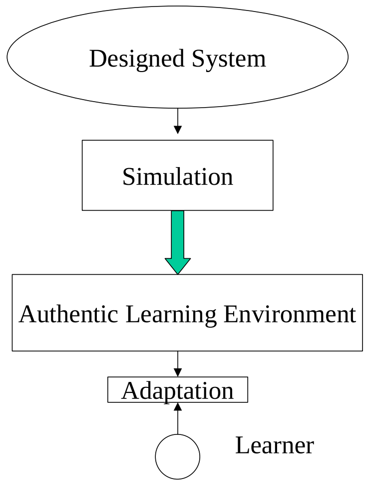

Figure 2. Problem Formulation

4. Methodology

The design of a good authentic learning environment, consists of creation of an appropriate set of situated opportunities. In our framework, each situated opportunity is described by 4-tuple <I, A, C, G> where

I: Information in the environment
A: Successful actions in the environment
C: Cognitive constraints and learning styles of the learner
G: Goals and motivations of the learner

A successful authentic environment has to create enough (and the right) situated opportunities to ensure that the *Adaptation* that arises for a specific learner has both a high structural as well as a semantic fit.

A methodology to create such an environment from naturally occurring simulations is presented below.

1. Determine the goals and motivations of the learner.
2. Determine what constitutes successful action in the task environment.
3. Determine the constraints of the semantic fit.
4. Determine the available information.
5. Determine how the cognitive constraints and learning style may filter this information.
6. Determine the constraints of the structural fit.
7. Use naturally occurring simulation(s) with the constraints derived in 1-6 to generate the situated opportunities for the ALE.

We use the process of VLSI fabrication as an example to demonstrate how the methodology works in a fairly complex and semantically rich environment.

5. Case Study VLSI Fabrication

Typical VLSI processes may contain hundred of steps and multiple manufacturing processes including epitaxial growth, ion implantation etc. where the various layers are grown and etched away in sequence to achieve a particular device topology [4].

Simulations are widely used in the design of these processes [5]. For example, a simulation programs such as SUPREM-IV is used to simulate the fabrication process. Other simulations tools such as PISCES are used to simulate the electrical characteristics of actual device thus produced.

Despite extensive controls, VLSI fabrication processes can go wrong and hence result in lower yields. When this happens, there is a need to look at the electrical characteristics of devices being manufactured and trace them back to the deviation in processes that may be responsible. This defines the *Task Environment* for this case study.

The development of *Adaptation* in this specific context by human experts has been previously studied and reported in [3] and will be used to illustrate the process of automatically generating ALEs.

5.1 Determine the Goals

When a device breaks, certain parameters such as the Sheet Resistance (SRB), for example, are no longer in their normal range. The goal of the learner is to map changes in these observable to changes in the physical characteristics of the device that can eventually pinpoint the process responsible for the deviation.

5.2 Determine Successful Action

A successful action in this environment is simply pointing out that particular parameters such as the concentration of Boron (NB) in a layer has gone up or down from its expected value. This level of action is sufficient to satisfy the goal of the learner in pointing out the steps in the process that may be causing the anomaly. Note that this does not have to be the case as a naïve learner may try to predict the exact values that are required to determine what has happened.

5.3 Constraints of Semantic Fit

A study of the individual *Adaptations* constructed by individuals in this environment [3] reveals that semantic fit favors *Adaptations* that have the following characteristics.

a. The *Adaptation* does not try to predict the exact values of what has gone wrong but simply the directions of change.
b. The *Adaptation* tries to make sure that all the changes are consistent. In other words, no values are getting changed in contradictory fashion.

5.4 Determine available Information

Not every thing in a complex environment is measurable. In this context, out of the numerous parameters available, only a few such as Sheet Resistance (SRB, for example), Inter-Layer Capacitance (CEB, for example) and Punch-through voltage (VPT) are measurable and hence observable.

5.5 Determine cognitive constraints

The important thing about determining cognitive constraints is that only a fairly high level of detail is required. It is not necessary to postulate elaborate memory structures or cognitive architecture [6], for example. Based on existing *Adaptations*, it is sufficient to assume that it is not possible to generate precise point predictions based on complex equations, but that qualitative reasoning about changes in quantities as they change or remain the same are plausible.

5.6 Constraints of Structural Fit

The structural fit of the observed *Adaptations* [3] favors those that have the following characteristics:

a. *Adaptation* only pays attention to changes in direction of a few measurable parameters.
b. *Adaptation* seems to prefer information that includes changes in single parameters as opposed to two at a time.

5.7 The Generation Process

Both SUPREM-IV and PISCES simulations are functional blocks that take a large number of parameter to generate precise electrical characteristics of devices [5]. However, in the context of this task environment, once we impose the constraints derived earlier, these simulations simply become a single black box with a few inputs and outputs.

We illustrate the generation process using one set of parameters that can go wrong in a VLSI fabrication process. These are the two parameters of width (WB) and concentration (NB) of one layer in the device.

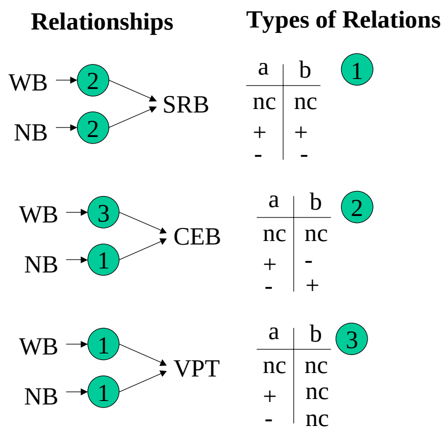

Figure 3. Simulation after applying the constraints

After applying the constraints derived earlier, the complex simulations are reduced to the relationships shown in Figure 3. Figure 3 shows that three types of relationships (1, 2 and 3) can exist between variables. For example, in the first relationship (1), if one variable (say, a) is not changed (nc), the other (say, b) does not changed as well. If one variable goes up (+), the other goes up as well.

Hence, as Figure 3 shows, the two parameters of the layer (WB and NB) are related to the three observable (SRB, CEB and VPT) through different combination of the three types of relations. For example, if WB goes up, using (3), we see that there is no change on CEB. However, if NB goes up, using (1), we see that CEB goes up as well.

Once the simulation has been reduced according to the constraints, we can now articulate the situated opportunities to be generated as follows.

I: <**SRB**(+, -, nc), **CEB** (+, -, nc), **VPT** (+,-,nc)>
A: <**WB**(+, -), **NB**(+,-)>

This shows that the information available (I) is simply whether the three observable (SRB, CEB, VPT) are the same or have increased or decreased. Successful action is simply determining whether the WB or NB have increased or decreased (Note that we do not specify the goals or the cognitive constraints as they have already been used to arrive at I and A).

The reduced simulation in Figure 3 can now be used to derive the learning curriculum that consists of a set of situated opportunities as shown in Figure 4.

	Actions		Information			
	NB	**WB**	**SRB**	**CEB**	**VPT**	
1	nc	+	-	nc	+	commonly occurring
2	nc	-	+	nc	-	
3	+	nc	-	+	(+)	
4	-	nc	+	-	(-)	
5	+	+	-	+	+	unusual but possible
6	-	-	+	-	-	
7	-	+	nc	-	(+)	
8	+	-	nc	+	(-)	

Figure 4. The Learning Curriculum

As Figure 4 shows, the learning curriculum consists of eight classes of situated opportunities depending on the information available in the environment. So for example, if SRB goes down (-), CEB is not changed (nc) and VPT goes up (+), then an appropriate action is simply that WB has gone up (+). Varying the WB in the simulation while keeping NB fixed can generate many instances of this particular class of situated opportunities. The first four classes are commonly occurring, as they are consistent with the single parameter change constraint of the structural fit; the others are possible but less likely.

How good is this learning curriculum? One way to determine this is to see how well this curriculum explains the existing *Adaptation* of individuals who have adapted naturally to the environment.

We compare the learning curriculum to the performance of *Adaptations* of two experts (E1 and E2) as reported in [3]. We do this by simply applying the methods that represent these expert's *Adaptations* on situated opportunities generated using the learning curriculum and the simulation as shown in Figure 4.

	E1	E2
1	C	CON
2	C	CON
3	C	C
4	C	C
5	P	P
6	P	P
7	N	P
8	N	P

C: Correct
CON: Contradiction
P: Partially Correct
N: No Answer

Figure 5. Performance of Experts on Problems generated from the Learning Curriculum

Figure 5 shows that as one would expect, expert E1, who has the most experience, tends to perform well on the commonly occurring situated opportunities (the first four classes). However, his *Adaptation* seems to completely breakdown on the last two classes of situated opportunities where he cannot come up with any answer (no action can be taken).

Expert E2, who had less experience, however seems to at least find partially correct answers to these classes. However, his *Adaptation* fails on the first two classes of situated opportunities by indicating a failure of structural fit; these combinations are simply not possible as "valid" in his *Adaptation*.

What we have shown is that this specific learning curriculum that was automatically generated using a simulation is sufficient to grow at least the *Adaptations* that are as robust as experts with many years of experience.

Obviously, once the learning curriculum is established it can form the basis of a learning environment that can take any of the commonly used pedagogical designs for constructivist learning such as Problem Based, Inquiry-Based, Role-Play Simulation and Game-Based and to a lesser extent Critical-incidence Based or Project-Based Learning ([7] and [8]).

For example, a Problem-Based pedagogical design based on this learning curriculum would generate scenarios from each of the classes of situated opportunities and allow the learner to solve these problems. They would, for example, be presented only with one parameter (say, SRB) and given options of what to do next; whether to collect more information or to try out an experiment on what can generate such a deviation.

Conclusion

In this paper we have presented a methodology for analysis and automatic generation of authentic constructivist learning environments. We have demonstrated how the methodology can be applied to the complex domain of VLSI fabrication to automatically generate a learning curriculum that can be the basis of an authentic constructivist-learning environment. A key component of the application of the methodology is the existence and availability of descriptions of existing successful Adaptations. This while useful, however, is not necessary. The methodology needs to be applied to various different environments to be refined, but the framework seems to hold well in guiding he development of a constructivist environment.

Knowledge Platform is a leading provider of innovative knowledge solutions to help companies succeed in the knowledge economy. By providing services such as E-Learning content, instructional design, training solutions, and E-Learning technology consulting, Knowledge Platform helps its clients to increase their learning efficiency. To learn more about Knowledge Platform please visit www.knowledgeplatform.com

How do I make it happen?

To get started, contact Knowledge Platform at info@knowledgeplatform.com

Knowledge Platform
19 China Street
03-02 Far East Square
Singapore 049561
Tel : 65-6236 7681
Fax: 65-6220 7031

Imran A. Zualkernan
May 2004

7. References

[1] J. Lave, E. Wenger, Situated Learning: Legitimate Peripheral Participation, Cambridge University Press, Cambridge, 1991, pp. 100.
[2] Ibid. pp 97.
[3] P.E. Johnson, L. K. Kochevar and I. A. Zualkernan, "Expertise and Fit: Aspects of Cognition", in Cognition: Conceptual and Methodological Issues, H.L. Pick, Jr., P. V. Broek, D. C. Knill (eds), American Psychological Association, Washington, D.C., 1992, pp. 305-331.
[4] S. Wolf, Silicon Processing for the VLSI Era – Vol. 2: Process Integration, Lattice Press, 1990.
[5] R. W. Dutton and Z. Yu, Technology CAD: Computer Simulations of IC Processes and Devices, Kluwer: Boston, MA., 1993.
[6] J. Anderson, The Adaptive Structure of Thought, Hillsdale, NJ: Erlbaum, 1990.
[7] A. IP and S. Naidu, "Experience-based Pedagogical Designs for eLearning", Education Technology vol XLI No.5, September-October 2002, pp.53-58.
[8] R. Oliver, "Developing E-learning environments that support knowledge construction in higher education" in Working for Excellence in the e-economy, S. Stoney and J. Burns (eds), We-B Center, Churchlands: Australia, pp. 407-416.

Imran A. Zualkernan
May 2004