Cognitive Load Dynamics: How to Increase Effectiveness of SD-based Learning Environments

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Abstract: A system dynamics (SD) model without an instructional overlay is not a sufficient learning tool (Spector and Davidsen 1997, Alessi 2000). We propose Cognitive Load Theory (CLT, Sweller 1988) as a theoretical framework for devising effective instructional context for SD models. Providing a systematic distinction between the several sources of cognitive load, CLT specifies what (and why) should be considered when the instructional overlay for a learning environment is designed. Having developed a simple SD model of the theory, we use it to explore how various instructional choices might impact effectiveness of the learning process. Finally, we consider the CLT recommendations in the context of SD-based learning environments and discuss how they may provide input to developing a set of guidelines for design of effective ways to communicate insights of SD models to a broader audience.

Introduction

Given the same content material, why some learning interventions are more effective than others? What aspects of the intervention – characteristics of learners, used instruments, or the structure of learning situation – determine its effectiveness?

These questions are among the central issues investigated by educational psychologists and instructional designers. They also have been raised within the system dynamics community with respect to effectiveness of the SD-based simulators. In the recent paper, Großler and Maier (2004) enlist issues related to each of the three aspects of the learning intervention and encourage the SD researchers to consider these issues carefully when developing SD-based simulators.

The Cognitive Load Theory (CLT, Sweller 1988) as a theory of the cognitive system suggests that effectiveness of any learning intervention depends not only on the particular characteristics of the learners, used instruments or the structure of the learning

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situation, but rather on their *interplay*. In this paper we present a system dynamics model of CLT (Cognitive Load Theory). Using the model we explore the dynamic interaction between the cognitive system and the instructional design of a learning intervention. The results are discussed in the context of the design of SD-based simulators for learning, providing some preliminary set of generic guidelines for developing more robust and effective SD-based learning environments.

The search for such guidelines seems especially timely in the light of the recent finding indicating that the use of SD-based simulators for learning is a controversial issue within the system dynamics community. We believe that the controversy is due to both the limited theoretical exploration of the issue and scares empirical data. Our discussions in this paper address the theoretical aspect of the use of SD-based simulators for learning.

The first section of the paper discusses briefly the controversy surrounding the use of SD-based simulators. In the second section, we present CLT as a theoretical perspective for understanding the interaction between knowledge development and instruction during the learning process. We develop a system dynamics model that captures the basic dynamics of the interaction as postulated by CLT. In the third section, we review some of the instructional design recommendations from the CLT research. Influence of the various instructional designs on the learning dynamics are illustrated using our system dynamics model. In the fourth section, we consider how the results of the CLT research could inform design of SD-based learning environments. In the final section we summarize our discussions, indicating directions for further research.

Are SD-based simulators effective learning tools?

In the 2001-2002 survey, Martinez-Moyano and Richardson (2001, 2002) elicited from system dynamics experts best practices with regard to each of the six basic stages of the model building process: (1) problem identification and definition, (2) system conceptualization, (3) model formulation, (4) model testing and evaluation, (5) model use, implementation and dissemination, (6) design of learning strategy / infrastructure. The collected data indicated that along the best practices shared by the SD-experts, there are a number of practices that the experts judge as indistinctive or controversial. One of the controversial practices was the use of *interactive gaming versions of the models* or *management flight simulators* for learning about the model. The survey data did not allow the investigators to provide any elaboration of the possible causes for this particular controversy. While the controversy may reflect the genuine disagreement with respect to the effectiveness of the SD-based simulators as learning tools, it is also possible that the controversy is an artifact of other factors. In this section we want to speculate over some of the possible sources of the controversy.

One of the reasons for the controversy may be the fact that various respondents could have interpreted the term '*management flight simulator*' or '*interactive gaming versions of the models*' in a different way. As indicated by Großler and Maier :

"[I]n the literature, as well as in discussions among scientists and practitioners, there exists some confusion. (…) [T]his confusion is often caused—or at least increased—by problems connected with terminology. Many different words symbolize the same object, or a single word is used for different objects. Microworld, management flight simulator, business simulator, business game, management simulator, learning environment all sometimes describe the same kind of simulation." (2004, p. 135)

Further Großler and Maier point out that "*sometimes two objects both called* management flight simulators *are quite distinct*" (2004, p. 135). And sometimes the same ‘*management flight simulator*’ may result in quite different learning outcomes, depending on the way in which it is used.

In general, we can distinguish between SD-based simulators used for *facilitated* learning and those that are supposed to support *individual learning*. The simulators for facilitated learning should be used in the workshop settings, where the learning process is overseen and modulated by a facilitator. These simulators – often referred to as ‘*management flight simulators*’ – typically do not reveal to the learners the causal structure of the underlying model. The students are supposed to ‘discover’ the structure while engaging in a double-loop learning process that involves active and reflective experimentation (Sterman 1994, Isaac and Senge 1994, Davidsen 1994, see also Argyris 1985). This type of learning puts the students in the center of the learning process. The students’ active engagement in explorations of the ‘virtual world’ is crucial to the overall success of the learning intervention. Still, left alone with a *management flight simulator*, the students are not likely to learn effectively. The learning process requires appropriate facilitation. Lane indicates:

*“It is important that participants are told enough in their briefings (…). Few things are worse than seeing a good set of game materials used unproductively because the participants do not know the rules and so become confused and frustrated and finally withdraw from the process. (…) The debrief can be very important in helping people to reflect on what they have experienced (…). A good debrief is vital if one seeks to avoid the so-called ‘video arcade syndrome.’ ” (*1995, p. 616*)*

In this context, it is may be not so surprising that some of the respondents in the best practice survey evaluated the use of ‘*management flights simulators*’ as having little potential for effective support of learning: For a *management flight simulator* to be effective, it must be embedded within an appropriately facilitated process.

However, it is also true that not all SD-based simulators for learning require such facilitation. Some effort has been underway to explore the feasibility of stand-alone SD-based simulators that would facilitate learning. SD-based simulators of this type are rarely referred to as *management flight simulators*; they are more commonly referred to as *Interactive Learning Environments* or *transparent box simulators*. A key feature of this type of simulators is that along with the outcome feedback, provided by the management flight simulators, the learners receive also cognitive feedback. In particular, they are provided with insight into the causal structure of the underlying model and how this structure relates to the model behavior.

One of the most comprehensive studies on effectiveness of such transparent SD-bases simulators for learning was conducted by Machuca and the GIDEAO research group (Machuca, Ruiz et al. 1998). Data collected over the period of 3 years suggested that the students learn best with the transparent simulators. A positive effect of providing the students with information about the causal structure of the underlying model was also observed in other studies on effectiveness of learning with SD-based simulators (Großler, Maier et al. 2000, Sengupta and Abdel-Hamid 1993 and Hillen 2004, p. 259). However, most researchers noted also that while the cognitive feedback seems to have a positive impact on the learners’ performance, its use is not a natural tendency. For example, Großler, Maier et al. (2000) could not evaluate the effect of the online help function detailing the casual structure of the environment on learning because the subjects did not use the function frequently enough. Also Machuca, Ruiz et al. (1998) reported that in their experiments the person supervising the experiments had to explicitly instruct the learners to utilize the online help materials. Similar comments were made by Sengupta and Abdel-Hamid (1993).

These results indicate that while the stand-alone SD-based simulators may support self-directed learning, there is a need not only for further experimental explorations, but also for some explicit guidance on how to design this type of simulators. Until now this type of guidelines has been discussed only occasionally in the system dynamics literature.

Among the first publications proposing some guidelines for an improved design of SD-based simulators for learning were those proposed by Vicente (1996). Presenting the Ecological Interface Design (EID) framework, Vicente encouraged the use of the EIDs design principles to develop interfaces of SD-based simulators that would allow for easier learning. The experimental results presented in Howie, Sy et al. (2000) showed that following the basic principles of EID one can indeed influence learning effectiveness of a SD-based simulator. While these interface principles guide the interface design process, they do not inform how to develop and structure the learner's exploration of the complex issue represented by the model.

A step towards developing such guidance has been made by Spector and Davidsen. In a series of papers (Spector and Davidsen 1997, 1998, 2000), they argued that a simulator alone is not sufficient for obtaining an effective learning environment and that it is essential that the SD-model is embedded in a well designed instructional environment. Drawing on a range of learning and instructional design theories, they proposed an instructional design approach called *model-facilitated learning* (MFL). This approach calls for an instruction closely supported by the model-based explorations, emphasizing the need for a careful design of the learner interaction with the model. In particular, it stresses the importance of gradual exposure to the dynamic complexity. The proposed MFL approach still awaits the empirical verification.

Given the relatively limited theoretical discussion of the ways in which effective SD-based simulators for learning can be developed and the rather scarce empirical evidence, it is again may be not so surprising that a controversy of the effectiveness of '*management flight simulator*' or '*interactive gaming versions of the models*' arose among respondents to the survey conducted by Martinez-Moyano and Richardson (2002). As indicated at the beginning of this section, while the controversy reflects a disagreement among the experts, we believe (and hope) that the controversy reflects skepticism on the part of some respondents rather than their rejection of SD-based simulators as potentially effective tools to propagate learning with SD models. We also believe that such skepticism is warranted in the light of the rather limited theoretical exploration of the issue and the scarce empirical evidence. Both theoretical and empirical work is needed to asses the potential contribution of SD-based simulators.

This paper contributes directly to the theoretical explorations by presenting an instructional framework based on Cognitive Load Theory (CLT) that explains the dynamic interaction between the instructional process and the learners' cognitive processes. In the following sections we present the theory and demonstrate how the CLT-based framework may inform the design of SD-based simulators.

Cognitive Load Theory

Description of the theory

Cognitive Load Theory (CLT), proposed by Sweller 1988 at the end of 1980s (Sweller 1988, Sweller 1989), has been since developed rapidly providing now an elaborated and established theory guiding instructional design (see e.g., introductory articles to special issues on CLT of *Learning and Instruction*, Kirschner 2002, and *Educational Psychologist*, Paas, Renkl et al. 2003). As indicated by Chandler and Sweller , CLT is concerned with *"the manner in which cognitive resources are focused and used during learning and problem solving"* (1991, p. 294). Based on the insight into the way the cognitive processes facilitate learning we should be able to arrive at instructional designs that facilitate learning effectively. CLT is based on the assumption that human mind consists of a potentially unlimited long-term memory and a working memory with a strictly limited and small capacity (Miller 1956, Baddeley 1992, Pollock, Chandler et al. 2002).

The working memory facilitates the ongoing information processing. Given its limited capacity it could seem that only the most basic information could be processed; still, human mind appears to be able to handle surprisingly well even quite complex information. This more complex processing is attributed to schemas stored in the long-term memory. Schemas constitute cognitive constructs that consist of information elements and production rules for combining the information. If a schema is brought from the long-term to working memory it only represents one entity and hence reduces working memory load (Kirschner 2002). This principle is captured schematically in Figure 1 where the same information is processed by two different persons. Person A is more knowledgeable in the particular domain (holds more elaborated schemata) and therefore is able to process the presented material at once. Person B on the other hand would need several steps in order to comprehend the information, due to the lack of relevant schema.

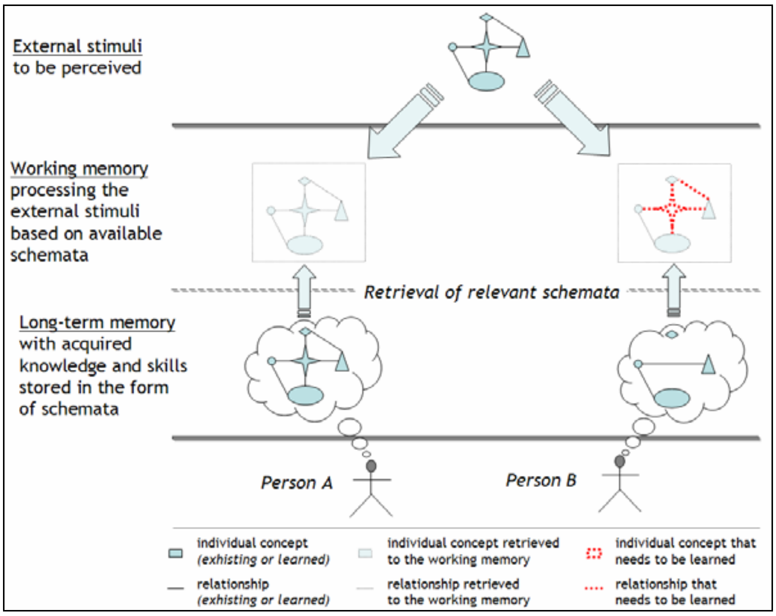

Figure 1 Schematic illustration of the role of working and long-term memory: The more advanced the schemata stored in the long-term memory, the more complexity may be perceived at once. Given less developed schema (see *Person B*), there is a need to gradually examine the information.

CLT focuses on *"the ease with which information may be processed in working memory"* and sees *"the construction and the automation of schemas that are useful for solving the problem of interest"* as the primary goals of instruction (Sweller, van Merrienboer et al. 1998, pp. 258-9). Under CLT, the working memory load may be affected both by the intrinsic nature of the material and the learning activities. The first type of cognitive load is referred to as <u>intrinsic cognitive load</u> (ICL): *"intrinsic cognitive load cannot be altered by instructional interventions because it is intrinsic to the material being dealt with"* (Ibid., p. 259). The cognitive load that results from the learning activities is inflicted exclusively by the instructional design and is referred to as extraneous cognitive load (ECL). The instructional design induces also the so-called germane cognitive load (GCL). Like ECL (extraneous cognitive load), GCL (germane cognitive load) is due exclusively to instructional intervention. Unlike ECL, GCL *"reflects the effort that contributes to the construction of schemas"* (Ibid.). Cognitive load theory emphasizes the role of the working memory limitations and advocates a reduction in extraneous cognitive load and an increase in germane cognitive load of an instructional material; it is this type of material that is likely to facilitate most efficiently the learning process. To elucidate further these principles, in the next section we use a system dynamics model that simulates a learning process according to CLT.

A system dynamics model of a learning process according to CLT

Learning occurs if some new knowledge or skills are acquired and stored into long-term memory (see e.g., Kosslyn and Rosenberg 2001, Medin, Ross et al. 2005). CLT indicates that acquisition of the new knowledge is feasible only if the sum of ICL and ECL is below the working memory capacity. Only then the unused capacity may be utilized to facilitate development of schemata. Schemata acquisition is rarely automatic. Rather it requires the instructional intervention to induce the GCL to redirect the working memory 'surplus' toward development of new or more elaborated schemas (van Merrienboer 1997).

Before we present the system dynamics model that captures the dynamics of learning postulated by CLT, we need to comment on the concept of schemata. This concept is similar to the concept of *mental models* commonly used in the system dynamics literature (Doyle and Ford 1998): both schemata and mental models refer to some knowledge representation (Winn 2004), involving declarative (information elements) as well as procedural (production rules) knowledge (Steiner 2001). Since our current discussion is addressed primarily toward the system dynamics community, in the reminder of our discussion we will use the term *mental model* to refer to the cognitive constructs that represent knowledge stored in long-term memory.

In Figure 2 we present the system dynamics model that captures the main tenets of CLT. Starting at the right-hand side of the diagram we have a stock-and-flow structure that captures the process of instructional material presentation. The process is modelled as a simple, first-order linear negative feedback: The rate at which the complexity of the learning material is revealed (*Revealing_material_complexity*) depends both on how much complexity remains to be revealed (*Unrevealed_material_complexity*) as well as the assumed sequencing speed (*Avg_time_to_present_an_instructional_unit*). Complexity of the material presented at the moment is captured by the *Revealed_material_complexity* stock.

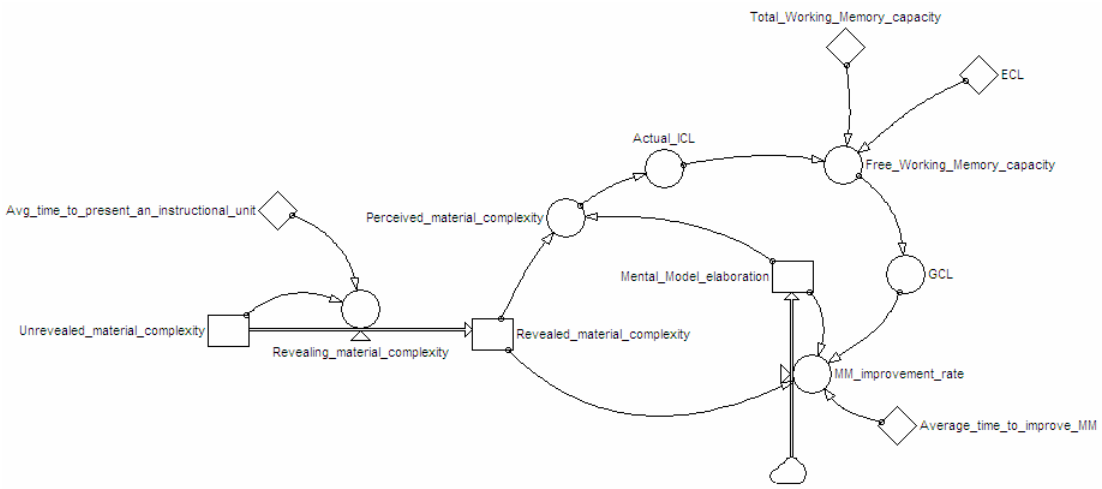

Figure 2 A system dynamics model of a learning process according to CLT.[1]

Both *Unrevealed_material_complexity* and *Revealed_material_complexity* are expressed using a qualitative scale ranging from 0 to 1, where 1 indicates the total complexity of the material foreseen for particular instructional intervention. A similar qualitative scale is applied to variables that describe the current knowledge of the learner with respect to the relevant domain (captured by the *Mental_Model_elaboration* stock) and the relative complexity of the currently presented material as perceived by the learner (captured by the *Perceived_material_complexity* variable). The perceived complexity of the presented material is estimated by comparing the currently presented material with the elaboration of available mental models:

Perceived_material_complexity = MAX(Presented_material_complexity-Mental_Model_elaboration,0)

The greater the difference between the complexity of the presented material and the elaboration of the held mental models, the greater is the perceived complexity of the presented material. In cases when the elaboration of available mental models equals or exceeds complexity of the presented material, the perceived material complexity equals 0.

Given the particular complexity of the presented material, we may estimate its ICL. As indicated above, ICL depends exclusively on the content and complexity of the presented material; it is independent from the way in which the material is presented. In our model we assume that ICL equals the perceived complexity of the presented material:

Actual_ICL= Perceived_material_complexity

As indicated in the previous section, ICL is only one of the components of the total cognitive load associated with any instructional intervention. Another inherent component of any instruction is ECL – the cognitive load inflicted as a result of the instructional design. In our model, we assume ECL constant and equal to 0.2.

Note that we use the same qualitative 0…1 scale to estimate the various types of cognitive load. We use also the same scale to express the working memory capacity. The overall working memory capacity is constant and equal to 1:

Total_Working_Memory_capacity = 1

Given current level of ICL and ECL we may estimate how much working memory capacity is unused at any point during the instruction:

Free_Working_Memory_capacity = MAX (Total_Working_Memory_capacity-(Actual_ICL+ECL), 0)

[1] Fully documented Powersim Constructor model is enclosed in the supplementary materials.

The free capacity is estimated as a difference between the total working memory capacity and the sum of ICL and ECL. The free capacity is estimated in order to know what resources are available for construction/elaboration of the learner's mental models. For now, we assume that all unused working memory capacity will always (and entirely) be redirected to facilitate mental model development. Accordingly:

GCL = Free_Working_Memory_capacity

Development of new mental model structures is modelled as a simple goal-seeking process. The ultimate desirable result of the instructional intervention is that the learner acquires mental models that allow for comprehension of the presented material. Hence, the desired elaboration of the mental model should equal the complexity of the presented material. Accordingly, *Presented_material_complexity* is a goal in our goal-seeking structure that captures mental model development:

MM_improvement_rate = GCL(Presented_material_complexity-Mental_Model_elaboration) / Average_time_to_improve_MM*

As we can see the improvement rate is conditioned upon the currently available resources, represented by GCL: the greater GCL, the faster the improvement of the mental models will be. In the following section we present the basic behaviour patterns generated by our model.

Dynamics of the learning process according to CLT

Figure 3 presents the basic simulation run for an instruction where the learner has no prior knowledge of the learning material, i.e. at time t_0 *Mental_Model_elaboration=0*[2] and *Unrevealed_material_complexity=1*.

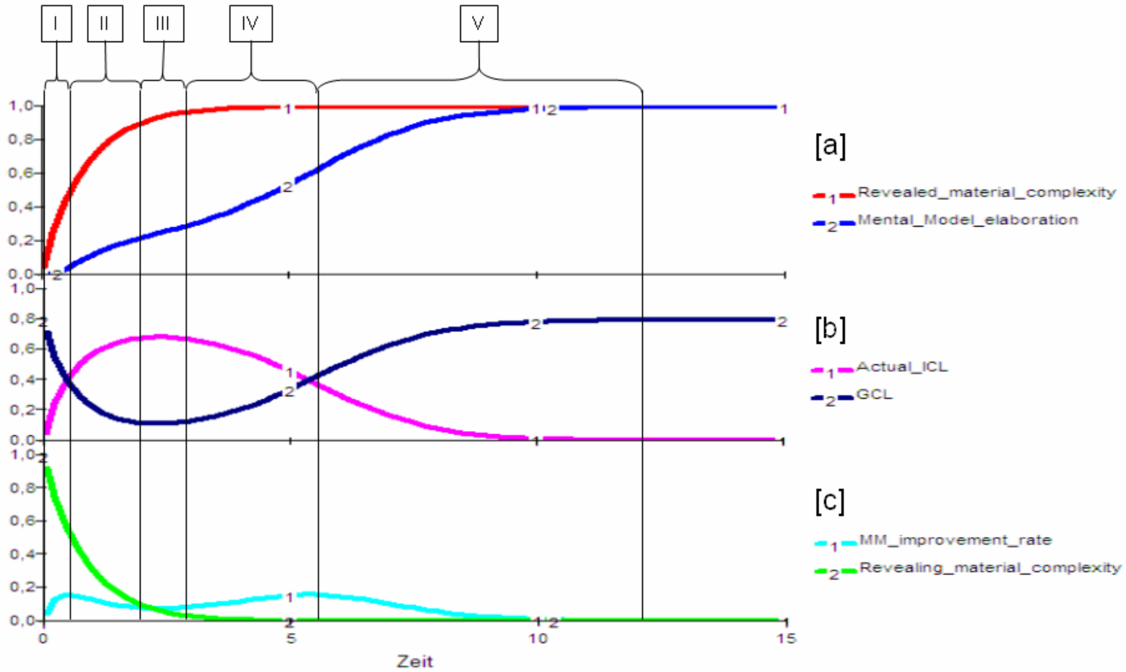

Figure 3 Dynamics of the learning process according to CLT: basic run. (The five stages are described in the text.)

[2] The initial state zero of the *Mental_Model_elaboration* means that the learner has no elaborated mental model only everyday life knowledge of the material to be learned. The SD-model is calibrated to this state and initializes therefore at zero.

In Figure 3 we distinguished five stages of the learning process:

I. The initial stage reflects the first, introductory presentation of the learning material. In this stage, the mental model improvement rate increases rapidly (graph [c]). This is due to the fact that the presented material complexity is not too overwhelming (*Actual_ICL* is rather low), allowing for devoting the unused resources towards mental model improvement (high *GCL*) – see graph [b]. Note that at any point in time the sum of ICL and GCL does not exceed 0.8; this is due to the fact that 20% of the capacity is constantly devoted to deal with the extraneous cognitive load imposed by the instructional material (ECL=0.2), not shown in the behavior graphs.

II. While the mental models are constantly improved, their improvement rate is much lower at first than the increase in complexity of the presented material (see graph [c]). Thus, in the second stage in graph [b] we see that the experienced ICL (*Actual_ICL*) increases constantly, surpassing GCL. Due to the reduced GCL, the mental model improvement rate decreases (graph [c]).

III. In the third stage the learner eventually does not experience any more increase in the intrinsic complexity of the presented material; the *Actual_ICL* levels off (graph [b]). This is due to the fact that the learner managed to develop sufficiently elaborated mental models – see *Perceived_material_complexity* in graph [a]. Simultaneously, the resources that may be devoted to further development of mental models are no longer reduced (*GCL* levels off, graph [b]), and the decline in mental model improvement rate is inhibited and bounces back to increase slowly again (graph [c]).

IV. In the fourth stage the learner is able to deal with the presented material more and more effectively. This is seen in graph [b]: the decrease in the experienced complexity of the presented material (*Actual_ICL*) allows for more capacity to be directed towards GCL. An increase in *GCL* leads to faster improvement of mental models (see graphs [a] and [c]).

V. The fifth stage begins when the mental model improvement rate reaches again its maximum (graph [c]). At this point, also the working memory capacity devoted to mental model improvement equals the capacity necessary to deal with the intrinsic complexity of the presented material (*Actual_ICL* = *GCL*, see graph [b]). As the mental models are improved, the material is easier and easier to understand (graph [a]), less capacity is necessary to deal with the intrinsic complexity of the presented material and more resources are devoted to mental model improvement (graph [b]). However, the mental model improvement rate gradually decreases (graph [c]). This is due to the fact that at this point the learner's mental model matches quite closely the complexity of the presented material. The complete match is achieved at the end of this stage when the learner's knowledge is sufficient to deal with the entire instructional material.[3]

Having outlined the basic principles of CLT, we are now ready to consider what specific implications the theory has for the design of instructional intervention.

[3] Note that the final state of the mental model elaboration represents only the state one could reach within a specific learning environment.

Managing cognitive load

Reducing ECL: Creating low cognitive load instructions

ECL – the cognitive load required to process learning instructions – is sometimes referred to as *'ineffective'* cognitive load (Gerjets and Scheiter 2003). This is because ECL not contributing in a direct manner to learning, i.e. acquisition of improved mental models, consumes the limited capacity of working memory. There has been much empirical work conducted to identify how ECL affects the learning process and how its reduction may improve learning. Given the limited scope of the paper, we discuss only three ways in which ECL-related instructional design decisions might influence the learning efficiency: (1) the split-attention effect, (2) the redundancy effect, and (3) the modality effect.

The split-attention effect occurs in situations when the learner must consult more than one source of information during the learning process to understand a particular instructional unit. The split-attention effect may occur for example when the learning material needs to be presented both in the textual and pictorial form (e.g., geometrical problem,[4] or a system dynamic model). If these presentations are not integrated well enough, learners will have to analyze them separately and perform the integration afterwards. The two-step process is likely to require more cognitive load than this necessary for analyzing the material presented in a well-integrated format.

While the split-attention effect would suggest that is beneficial to integrate textual and pictorial information, such integration should be carried out with care. This is because it may lead to the so-called redundancy effect. The redundancy effect occurs when the instructional material contains redundant presentations of the same information. This happens, for example, when self-explanatory schematic representations are cluttered with redundant textual information.[5] Still, the text-picture information redundancy is not always detrimental to the learning process. While it may hinder learning process of students who are more knowledgeable in a particular domain, it is likely to facilitate the learning of low-knowledge students (Kalyuga, Chandler et al. 1998, Kalyuga, Ayres et al. 2003).

While the redundancy effect indicates that providing the same information in both pictorial and textual form may impede the learning process, many experiments have shown that providing the same information simultaneously in a visual and auditory form is likely to facilitate learning. This effect is referred to as *modality effect* and builds upon Pavio's dual-coding theory and Baddeley's theory of working memory. These theories postulate that the working memory operates using two independent channels: auditory and visual (Pavio 1986). The information received through each of these channels is processed independently in the working memory: information received via the auditory channel is processed within the so-called "phonological loop"; diagrammatic/pictorial

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[4] For a good illustration of the split-attention effect see the example of a geometrical problem given in Sweller, van Merrienboer et al. (1998, Figures 2 and 3, pp. 278-9). The superiority of the integrated format was observed in a number of experimental studies, see e.g. Tarmizi and Sweller 1988, Chandler and Sweller 1992, Bobis, Sweller et al. 1993.

[5] Experimental results reported in Chandler and Sweller (1991) provide an excellent illustration of the redundancy effect. As a case for their studies, Chandler and Sweller used instruction regarding the blood flow in human body. They found that textual statements added to the self-explanatory schematic representation of the flow inferred with the learning process. Similar results were obtained also by Bobis, Sweller et al. (1993).

information perceived through the visual channel is processed via "a visual-spatial scratch pad" (Baddeley 1998). In accordance with the Baddeley's working memory theory, CLT assumes that both channels have limited capacity (Chandler and Sweller 1991, Mayer and Moreno 2003). Furthermore, although capacity of the two channels is not strictly additive, the available working memory capacity may be maximized only when both channels are used during the instruction (Brunken, Plass et al. 2003).

The significance of dual-channel instruction is especially important in the context of new multimedia enhanced instructional techniques. In a recent paper, Mayer and Moreno (2003) present an elaborated CLT model that explicitly incorporates the auditory and visual channels along with the description of experimental studies that illustrate the enhanced effectiveness of the dual-channel instruction.

We now return to the system dynamics model developed in the previous section and examine how the various ways of reducing ECL will affect the learning process. Explicit modelling of the changes to the instructional material is rather difficult. Thus, we decide to capture such changes by assuming some arbitrary reduction in ECL. In Figure 4 we present a simulation run where ECL from its original level of 20% was reduced to 10%. This 10% reduction is assumed to be achieved by a fundamental redesign of the instructional material through elimination of the features that may cause effects such as the split-attention or the redundancy effect, or through introduction of a dual-channel instruction.

When we compare the simulation outcomes presented in Figure 4 with our original simulation results (see Figure 3), we can see that the decrease in ECL has benefited improvement of mental models. A better designed instruction allows more working memory capacity to be devoted towards development of mental models.

ECL reduction has been among the first issues investigated in the context of CLT. While minimizing ECL increases efficiency of the learning process, it is also important to optimize the load imposed by the learning material itself (ICL) and devote as much of the working memory capacity as possible towards development of improved mental models. These issues are discussed in the following two sections.

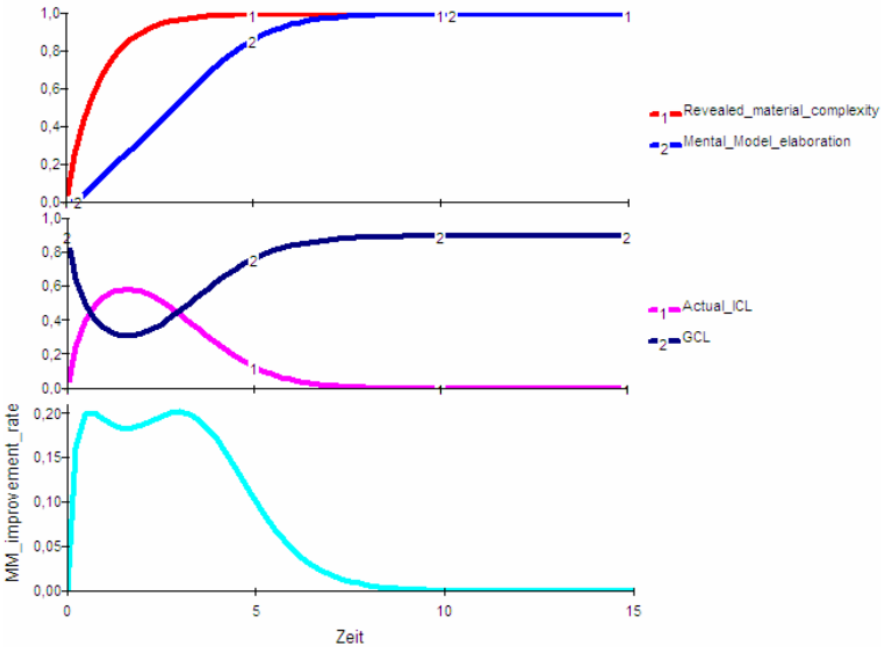

Figure 4 Exploring a decrease in ECL: ECL accounts only for 10% of the total cognitive load.

Decreasing ICL: Managing the intrinsic complexity of the learning material

Previously, we pointed out that ICL imposed by a particular learning material is independent of the instructional design (see p. 7). Although this is in principle true, in search for more effective facilitation of learning, the instructional design researchers began to explore how ICL could be reduced (see e.g. Pollock, Chandler et al. 2002). First, it is important to notice that the same learning task may pose different ICL on different learners. The experienced ICL caused by the task complexity depends on the elaboration of available mental models (see e.g. Sweller, van Merrienboer et al. 1998). On the other, the same learning material may be presented to the learner in its entirety at once, imposing the maximum ICL, or may be sequenced (see e.g. van Merrienboer, Kirschner et al. 2003), reducing the experienced ICL at any point of instruction. It is such sequencing strategy that has been advocated for more effective management of ICL imposed on the learners.

Appropriate sequencing of learning material is complex. There are several techniques to deal with the problem (see e.g., Bannert 2002,andPollock, Chandler et al. 2002). The point of departure is not only a careful assessment of the learning material complexity, but also the assessment of the learner's prior knowledge. Only given these two information, the learning material may be sequenced to achieve the optimal levels of ICL.

The issue may be well illustrated using our SD-model of the learning process. Indeed, the basic model developed in the previous section (see Figure 2 and the associated discussion) already captures the concept of sequencing. Note that the learning material is not presented at once, but rather it is gradually revealed to the learner. The speed with which the material is presented depends on the time used on average to present one instructional unit: The greater the time, the slower the presentation; the smaller the time, the faster the presentation. In our model, the average unit presentation time is captured by a time constant, *Avg_time_to present_an_instructional_unit* (see Figure 2 with SD-diagram). In our basic simulation run (see Figure 3), *Avg_time_to present_an_instructional_unit* was set to 1. To explore the impact of presentation pace – or sequencing pace –we increase and decrease the time. Simulation results are presented in Figure 5,

Looking at the simulation results presented in Figure 5(*a*), we see that in contrast to our basic run (see Figure 3), almost all the time there is the working memory capacity available for mental model improvement. The mental model improvement rate does not oscillate, but reaches one maximum. Also, over the whole period of instruction the difference between the learner's knowledge and the presented material is reduced. Thus, one could argue that decrease in the material presentation rate led to a more levelled learning process.

An increase in the presentation time did not led to significant changes in the final result – the learner acquired the knowledge of all the material in about the same time as in our basic run. This result is in a sharp contrast to the result obtained when the presentation time was reduced (see Figure 5(*b*)). In this case, the learner never masters the presented material. Only at the initial models some knowledge is acquired and the learner's mental models are developed. However, shortly after the start of instruction, all work memory capacity is used to deal with ICL and ECL. Having no spare resources, the learner is unable to continue to improve the relevant mental models and consequently, masters only about 5% of the presented material.

(*a*) (*b*)

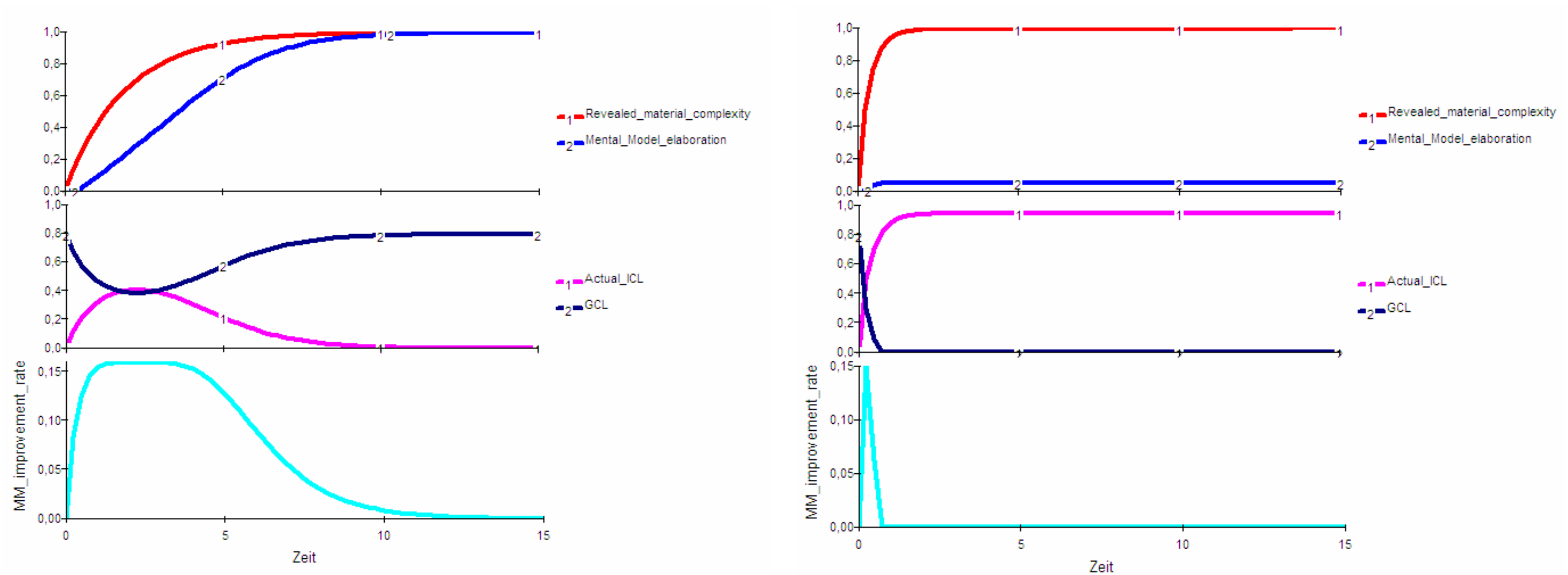

Figure 5 Impact of the instructional material sequencing: Exhibit (*a*) presents learning dynamics for a slower sequencing (*Avg_time_to_present_an_instructional_unit=2*), exhibit (*b*) presents learning dynamics for a faster sequencing (*Avg_time_to_present_an_instructional_unit=0.5*)

Our simulation results are consistent with empirical findings that show that appropriate sequencing of the learning material may facilitate the learning process (see e.g. Sweller, van Merrienboer et al. 1998, van Merrienboer, Kirschner et al. 2003).[6] In the next section we explore how instructional design may help to increase GCL that is so fundamental for the actual learning, i.e., development of new, improved mental models.

Increasing GCL: Enhancing improvement of mental models

As indicated previously, learning processes can only take place, if ECL and ICL do not occupy the entire capacity of working memory. Only in such situations the unused capacity may be devoted towards improvement of mental models. The latest research focuses, however, not only on how to minimize ECL and ICL, but also on how to manage GCL so most effective learning is achieved.

In our basic SD-model we assumed all working memory capacity that remains free after dealing with ECL and ICL will be devoted to improvement of mental models. This of course would be ideal. However, in reality the degree to which the unused work memory capacity is engaged in the mental model improvement is likely to vary. To engage in mental model development and improvement, learners typically need some external stimulation (Bannert 2002). Instructional measures such as worked-examples, tasks involving comparison of various cases, different types of elaborations are all likely to stimulate the learners to engage in cognitive processing that leads to construction of mental models. They also increase GCL and thereby facilitate improvement of mental models.

Another, relatively recent development within the CLT research indicates that GCL may be increased yet otherwise. The new strategy involves simultaneous management of ECL and GCL, and places the responsibility for appropriate 'customization' of the learning environment on learners rather than instructional designers. Learners manage themselves their cognitive load by choosing their preferred training formats. In that way they are able to influence both the experienced ECL and GCL. As indicated by Gerjets and Scheiter :

"Learners provided with a superior instructional environment (e.g., with multiple worked-out examples) may perform better (by increasing germane cognitive load) or even worse (by suffering from extraneous cognitive load) compared with learners provided with a more inferior instructional environment (e.g., without worked-out examples). Which outcome can be expected depends on whether learners make use of the opportunities to engage in germane processing provided by the instructional design (e.g., by comparing examples within and between problem categories) or not. In case they do not take a chance on these hypertext capabilities, the disadvantages of additional control demands for handling the enriched instructional environment may outweigh the benefits (e.g., decisions related to the selection and sequencing of information pages). These additional demands mainly increase extraneous cognitive load and, therefore, impair schema acquisition." (2003, pp. 39-40)

In the context of this most recent research Valcke (2002) has proposed that *"within* germane *cognitive load, we can distinguish between cognitive load related to the processing and storage of the schemas [referred to as 'mental models' in our paper], next to cognitive load related to metacognitive monitoring of the latter activities"* (Ibid., p. 151). Thus, not only processing directly aimed at improvement of mental models is

[6] It is important to note that sequencing through simple fragmentation of the learning material is not likely to be successful in the context of more complex tasks (van Merrienboer 1997). In such cases, 'sequencing' is not obtained through paced presentation of parts of the learning material but rather through a gradual increase in complexity of the presented task (see e.g., Scandura 1983, White and Frederiksen 1990). This is consistent with the elaboration theory by Reigeluth (1999) obtained through a gradual increase in the complexity of the material.

important, but also meta-cognitive activities that monitor and coordinate such processing. There is some experimental evidence indicating that learners engaging in meta-cognitive activities indeed ‘manage’ their learning process in a more effective manner. For example, it has been observed that learners who are able to choose themselves training measures achieve better results. Also, learners who may manage material sequencing on their own are likely to outperform learners who must follow a predefined sequencing.

We first extend our model to account for the fact that not all working memory capacity that is available after dealing with ICL and ECL might be involved in mental model improvement. The extended model is presented in Figure 6.

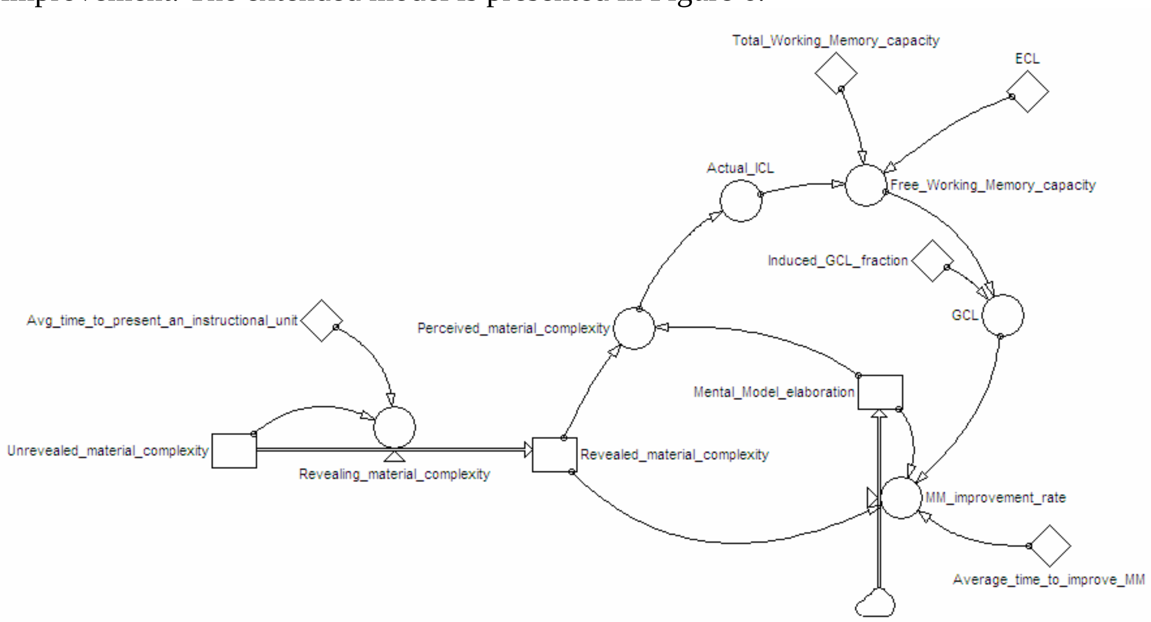

Figure 6 An extended system dynamics model of the learning process according to CLT: The model accounts for the fact that not all available working memory capacity may be directed towards germane processing.[7]

We introduce *Induced_GCL_fraction* to capture the extent to which the available working memory is engaged in mental model development. The more the instruction stimulates cognitive processing related to the mental model improvement, the more of the available resources will be devoted to mental model construction, i.e., the higher the *Induced_GCL_fraction*. The impact of reduced utilization of the available working memory capacity is illustrated in Figure 7.

In Figure 7a we present the simulation runs for the case when only 90% of the available capacity is engage in germane processing. As we can see, the learner needs more time than in the original case when all the unused capacity was devoted to germane processing to master the material. In Figure 7b we see that further reduction in the degree to which the available working memory capacity is engage in germane processing severely impedes the learning process: the learner masters only about 18% of the learning material.

[7] Fully documented Powersim Constructor model is enclosed in the supplementary materials.

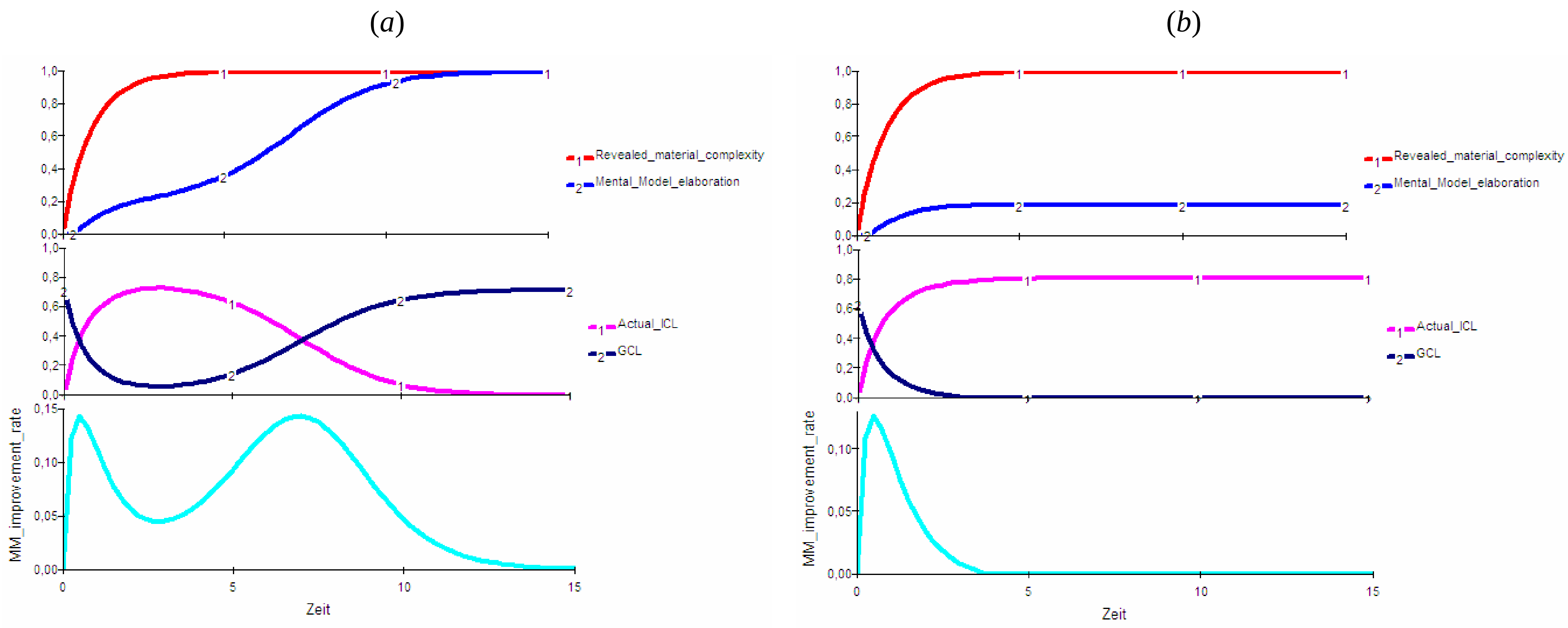

Figure 7 Effectiveness of the learning process and degree to which available working memory capacity is engaged in germane processing: (*a*) 90% of available working memory capacity is directed towards mental model improvement, (*b*) 80% of available working memory capacity is directed towards mental model improvement.

In Figure 8 we extend our model further to capture the fact that GCL may be used not only to improve mental models, but also to provide the ‘metacognitive monitoring’ of the learning process.[8] Degree to which GCL is involved in metacogntive activities is capture by *Fraction_of_metacognitive_GCL*. We assume that anywhere from 0 to 25% of GCL may be involved in the metacognitive processing. This assumption is of course arbitrary – as of now there is no empirical indication on how the GCL is actually utilized to support both mental model processing and metacognitive activities. Current research allows only for concluding that given appropriate instructional design (e.g., giving the learner control over type of training, see e.g. van Merrienboer, Schuurman et al. 2002) some part of GCL is likely to be devoted to metacognitive activities.

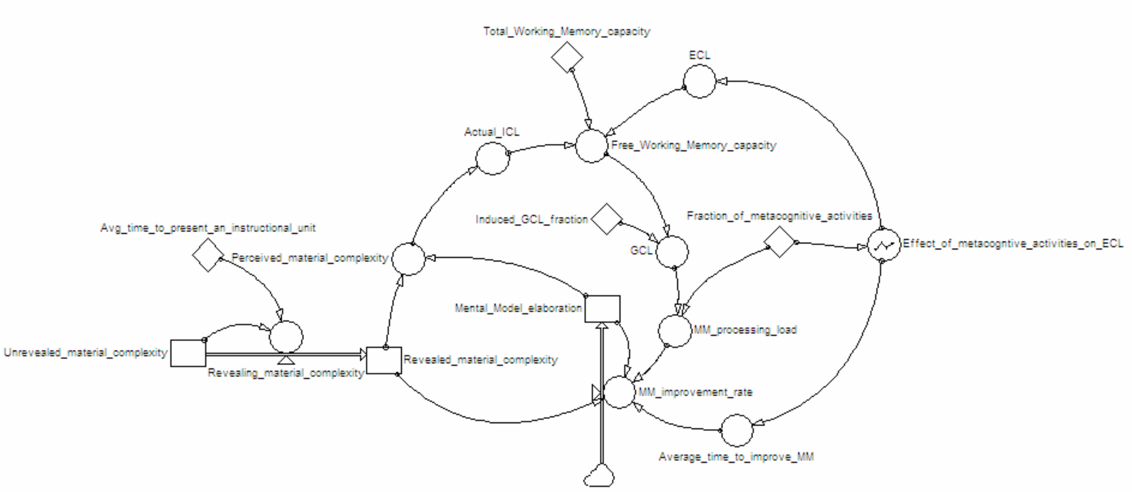

Figure 8 An extended system dynamics model of the learning process according to CLT: The model accounts for the fact that not all available working memory capacity may be directed towards germane processing, and that germane processing involves processing directly related to mental model improvement as well as metacognitive activities that may reduce ECL or increase efficiency of mental model development.[9]

The higher the *Fraction_of_metacognitive_GCL*, the less GCL will be involved in mental model improvement. Accordingly:
*MM_processing_load = GCL * (1-Fraction_of_metacognitive_GCL)*

The higher the *Fraction_of_metacognitive_GCL*, the greater the involvement in metacognitive activities. These metacognitive activities allow the learner to interact with the instructional material more effectively as well as to increase efficiency of the learning process. The positive impact of the metacognitive load on experienced ECL and the efficiency of the mental model development are mediated through *Effect_of_metacognitive_activities.* In our current model, we assume the impact to be linear: When maximum fraction of GCL is devoted to metacognitive activities (*Fraction_of_metacognitive_activities=0.25*), the learner is able to reduce both ECL and the average time necessary to improve mental models by 50%. Given no fraction of GCL devoted to metacognitive activities, efficiency of the learning process is not impacted.

In Figure 9 we present the simulation results for the case when the maximum 25% of GCL is devoted to metacognitive activities. Comparing the results with this obtained by

[8] See our earlier discussion on p. 14.
[9] Fully documented Powersim Constructor model is enclosed in the supplementary materials.

our basic model (see Figure 3), we see that the current learning process is much more effective. The elaboration of the learner's mental model also matches quite closely the presented material. The learner masters the entire material in just over 5 time units.

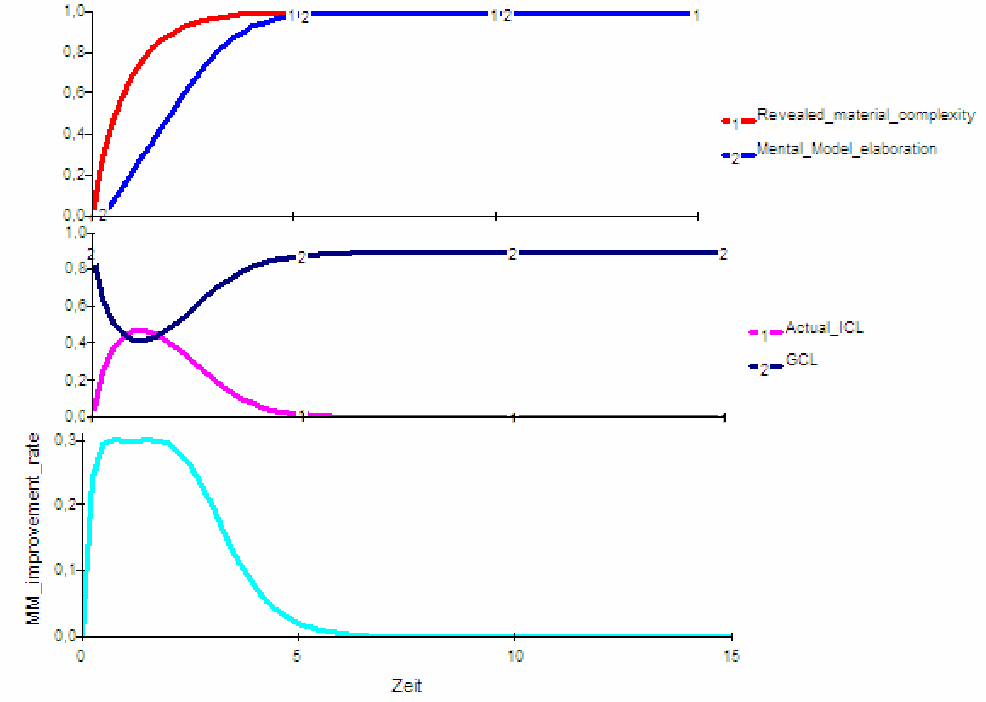

Figure 9 Impact of metacognitive activities on the learning process: In the presented simulation run 25% of the GCL is engaged in the metacognitive activities.

As indicated at the beginning of this section, the research concerning management of GCL is still in its initial phase. However, the first empirical results indicate that germane processing is of a vital importance to the learning process. In particular, an increasing number of researchers advocate that a successful instructional environment should delegate a substantial control over the final shape of instruction to the learners who are most capable of effective management of their own cognitive load (van Merrienboer, Schuurman et al. 2002, Valcke 2002).

Managing cognitive load of SD-based learning environments

Several authors within the system dynamics community called for an improved instructional support within SD-based learning environments (Spector and Davidsen 1997; 2000, Alessi 2000, see also Sawicka and Campbell 2001). By elucidating the relationship between the structure of instruction and the process of learning, CLT seems to be a convenient framework to guide this effort. Drawing on our earlier discussions,[10] in this section we consider how CLT recommendations might be implemented in the context of SD-based learning environments.

To illustrate the points made, we will refer to existing SD-based learning environments. Our primary example will be a business simulator developed at the University of Mainz (Berendes 2002, Hillen, Paul et al. 2002, Breuer and Molkenthin 2004). The simulator features *solarSYDUS* – an enterprise producing solar cells. *solarSYDUS* competes in a

[10] See discussions in the previous section, pp. 10-18

simulated market with two other enterprises. Each enterprise consists of a number of interrelated activities, corresponding to elements of the Porter's value chain (Porter 1985). Learners control only *solarSYDUS*, making decisions regarding raw material ordering, production planning, marketing expenditure, etc. The simulator has been developed as a web-based application, with the underlying system dynamics model developed in Powersim Studio 2001. The *solarSYDUS* simulator is used to teach business dynamics in the vocational education; it also supports the on-going research on how to improve people's learning in complex and dynamic environments.

The structure of this section is analogous to the structure of the previous section: We first discuss how one could deal with ECL in the context of SD-based learning environments. Next, we consider ICL and GCL in turn.

ECL in SD-based learning environments

From the point of view of learning, ECL is the least desired cognitive load. It does not contribute directly to mental model improvement, but reflects an effort the learners need to invest to deal with instructions. To increase efficiency of the learning process, it is essential that ECL is minimized (see Figure 4, p. 11). One way of doing it is to utilize fully the available working memory capacity and to design the instruction so that both processing channels, i.e. the auditory and the visual channel, are engaged. Facilitated interaction with SD-based learning environments may be seen as an example of implementation of such dual-channel instructional design.

During the facilitated learning sessions the learners not only interact with the simulator, but also receive coaching from a SD instructor. Such coaching may be seen as a source of the auditory input to the learning process. There is some research indicating that facilitated-instruction indeed improves performance in the context of SD-based learning environments. Shields (2001), for example, found that, when interacting with a business simulator, groups that were facilitated outperformed the non-facilitated groups. Also the results obtained by Großler, Maier et al. (2000) seem to suggest that facilitation matters: subjects, who were given a traditional lecture[11] during which the SD model underling the used simulator was presented, outperformed those who were not lectured.

These results suggest that interaction with SD-based learning environments should be facilitated. However, relying only on facilitated interaction would limit reachable audience. Therefore, it seems warranted to consider how the benefits of facilitation could be provided in the context of stand-alone applications. One way of doing it would be to enhance the applications by a set of auditory components. In such case the learner could use not only the visual but also the auditory channel to deal with the instructions. Consequently, the original ECL would be reduced and more cognitive capacity would become available to deal with processes directly related to learning. To the best of our knowledge, such multimedia solutions remain relatively unexplored within the context of SD-based learning environments.

While including the dual-channel instruction in a stand-alone SD-based learning environment requires employment of more advanced software development techniques, the CLT-research reviewed in this paper suggests that excessive ECL may be induced

[11] A traditional lecture involves an instructor presenting the learning material orally with support of various visual aids (i.e., slides, comments and explications made on a white board, etc.).

even in the context of the least advanced presentations of SD models. This is likely to occur if the presentations induce split-attention or redundancy effects.

In the context of computer-based training, one frequent source of the split-attention effect is the way in which the learner receives instructions. It was found that providing the instructions in a format that involves simultaneous interaction with printed materials and the application causes excessive ECL. The excessive ECL is reduced when the learners are provided with the self-contained printed instructions that do not require interaction with the computer application (Sweller and Chandler 1994, Chandler and Sweller 1996). Integration of the instructions into the computer learning environment seems just as effective (Cerpa, Chandler et al. 1996). Some of the SD-based learning environments seem to provide either self-contained instructions (see e.g., former versions of *solarSYDUS* presented in Hillen, Paul et al. 2002) or instructions embedded in the learning environment itself (see e.g., Bois 2002 or the current version of *solarSYDUS*, see also Alessi 2000). Still, in many cases the instructions only describe the type of system to be controlled or the decisions to be made, without a clear reference to the actual decision-making interface (see e.g, Diehl 1992, Moxnes 2004). Integration between the learning environment and the printed instructions could be improved by either incorporating the instructions into the learning environment or enhancing the printed materials with screenshots of the relevant decision-making interfaces.

While dealing with the excessive ECL caused by the inefficient presentation of the task instructions seems to be not very complicated, dealing with the split-attention and redundancy effects in the context of other aspects of instruction about SD models may be trickier.

Consider *solarSYDUS*. The underlying model involves more than 100 variables embedded in a complex causal net with a number of delays and feedback loops. The learning environment is developed as a transparent-box simulator (Machuca 1992, 2000), i.e. the learners have access to the causal structure of the underlying SD model. Still, due to its inherent complexity, presenting this structure in case of *solarSYDUS* in an effective way has been a challenging task. First, textual descriptions of each activity within the *solarSYDUS* enterprise are provided in the respective sections of the learning environment (see Figure 10, p. 21). Second, there is a section featuring the stock-and-flow model with the various activity-sectors delineated (see Figure 11, p. 21).

Combining the two sources of information would lead to an extremely cluttered presentation, likely to induce redundancy effect. On the other hand, keeping the two types of information completely separate is likely to cause split-attention effect, especially for learners less familiar with the concepts within the Porter’s value chain theory and the corresponding enterprise structure. For them the stock-and-flow representation might be too complex and the fact that the relevant textual descriptions are available only in a separate part of the learning environment could cause an increase in ECL. To address this, the stock-and-flow map implemented in the *solarSYDUS* simulator has a tool-tip function that allows the learner to evoke temporarily textual description associated with a particular variable or a model sector (see Figure 12, p. 22). In that way, the split-attention effect – likely in case of less knowledgeable learners – might be avoided through provision of more detailed information in the context of a more abstract representation. The redundancy effect, on the other hand, is avoided by making the detailed explications conditional on user interaction.

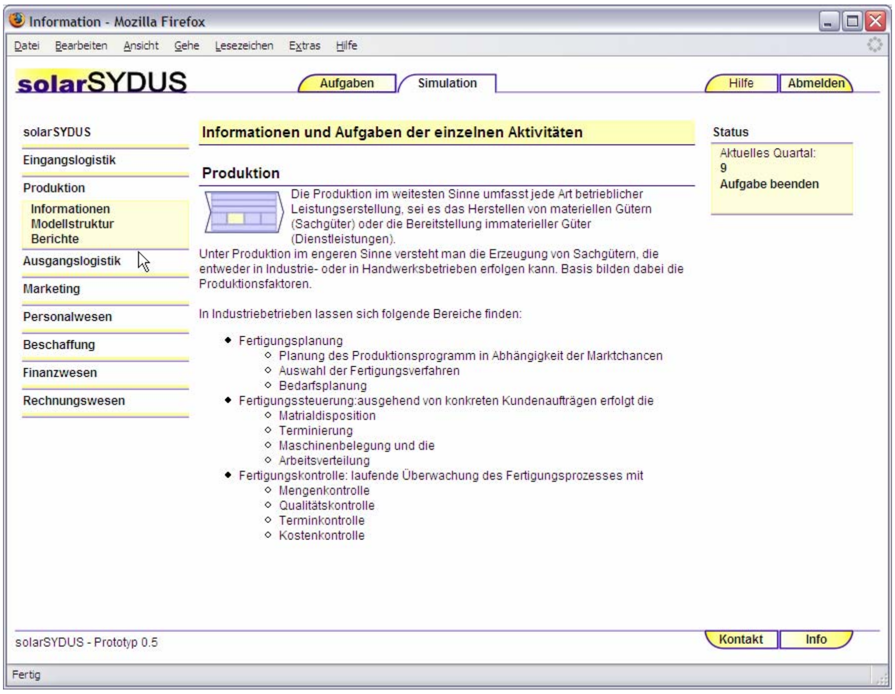

Figure 10 Screenshot of *solarSYDUS* with the various sections indicated and one of the sections containing an activity description opened. This example shows the information of the activity production.

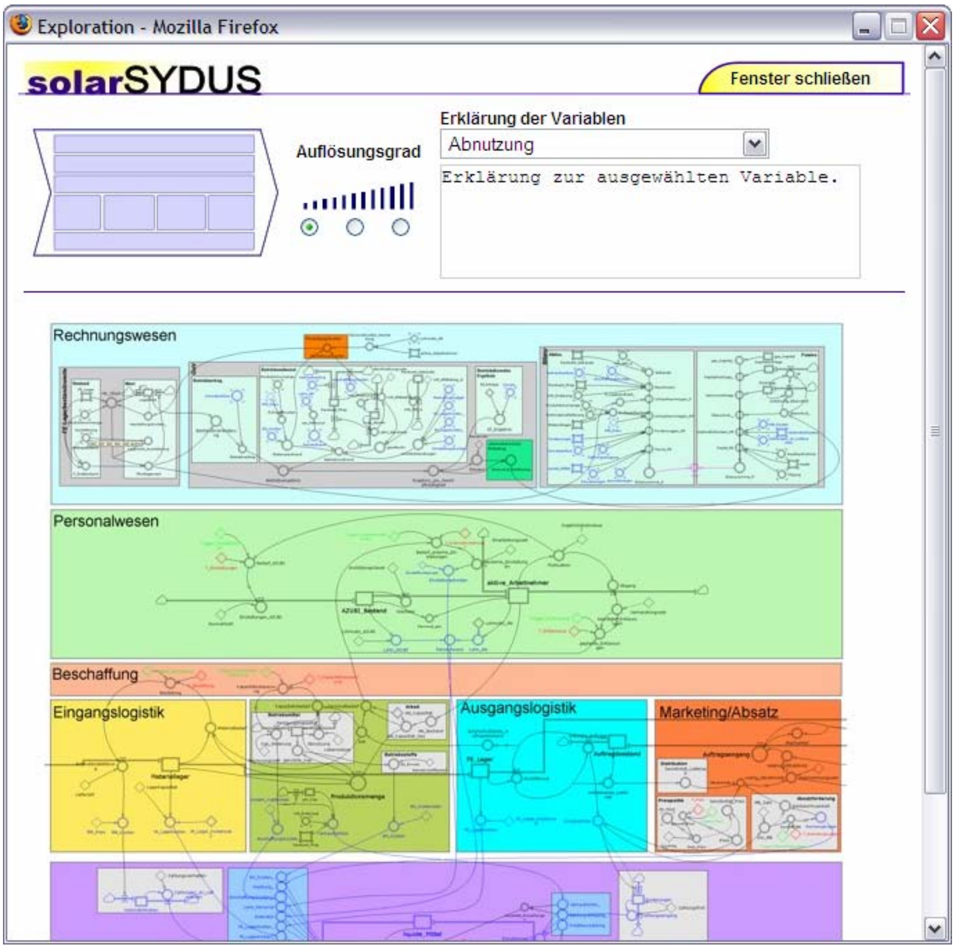

Figure 11 Screenshot of the stock-and-flow view of the *solarSYDUS*

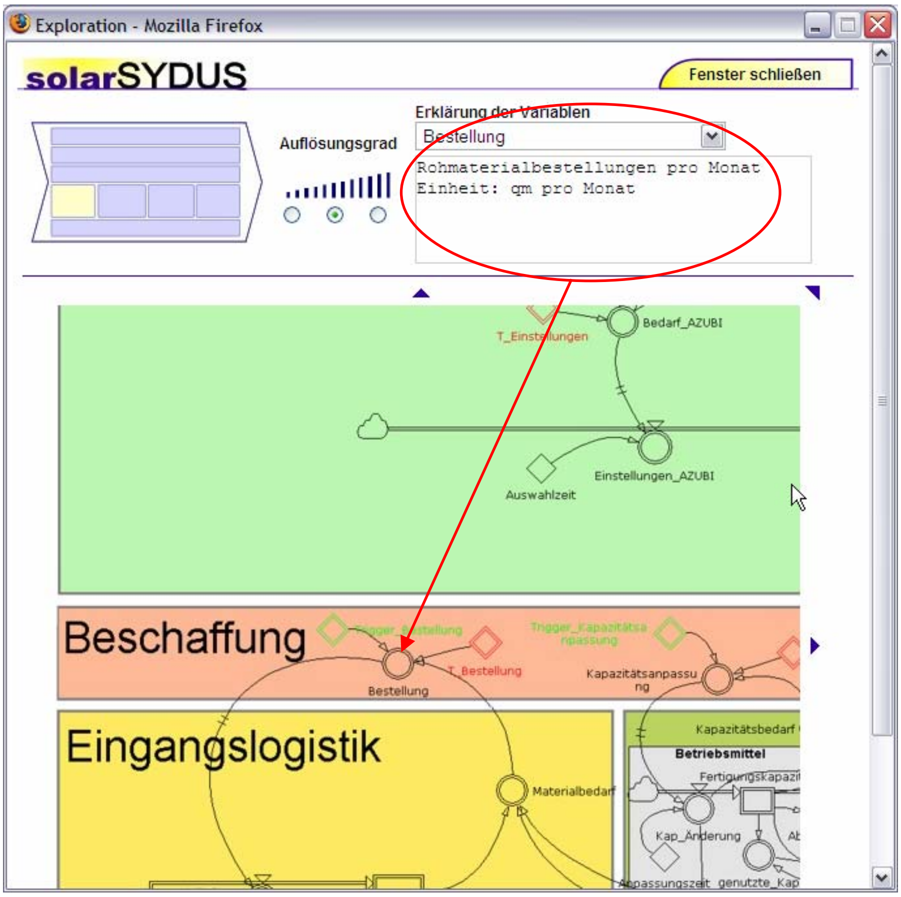

Figure 12 Screenshot of the stock-and-flow view of the *solarSYDUS* with a tool-tip information invoked (red ellipse and arrow). Blue ellipse marks the control of the stock-and-flow model resolution (compare the setting with Figure 11, p. 21)

The above discussion suggests that a well-designed presentation of the model structure is likely to ease cognitive load imposed by the SD-based learning environment on the learner. Still, understanding the structure is not equivalent to understanding the relationship between the model's structure and behaviour – one of the key aspects that need to be understood for the learner to perform effectively in the dynamic setting (Forrester 1961, Sterman 2000). Most of the SD-based environments provide the learner with graphs illustrating an overtime development of key model variables. This information is typically provided not in the context of the model structure (see e.g., Sterman 1987, Sengupta and Abdel-Hamid 1993, Großler, Maier et al. 2000). This is also the way the system's behaviour is reported in the *solarSYDUS* simulator (see Figure 13). Given that the learner should understand how the behaviour arises from the structure, it could be argued that such independent presentation of behavioural and structural information may induce the split-attention effect, impeding the learning process. Existing SD research is not sufficient to provide a clear insight into whether the behavioural and structural information should be closely integrated: From the study by Sengupta and Abdel-Hamid (1993), we know that provision of over-time behavioural graphs is likely to have a positive effect on performance; the graphs, however, were not embedded in the context of the model structure. Other learning environments provided various degrees of integration between the model structure and behaviour (see e.g., Warren and Langley 1999, Howie, Sy et al. 2000). Further research is needed to determine to what degree structure and behaviour should be integrated in the learning environments that feature SD models.

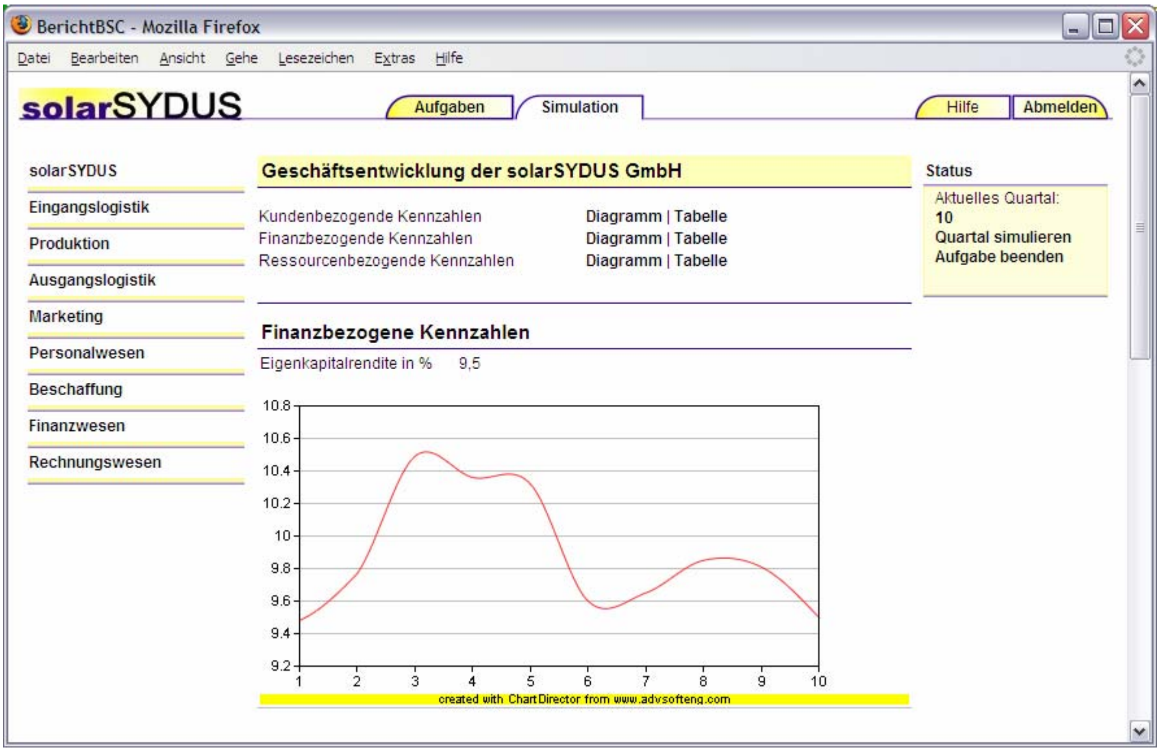

Figure 13 Screenshot of the sample behavior report provided by *solarSYDUS*

The above discussion illustrates the difficulty associated with the design of 'cognitively-efficient' presentation of the underlying SD- model. The other issue that is likely to be problematic in the context of SD-based environments is the overall impression the learners get when faced with a dynamic problem featured by the particular learning environment: Is the problem perceived as a challenge or as a burden? From the CLT-perspective this depends on whether the learners are able to devote some of their cognitive capacity towards germane processing, or whether all the available capacity is consumed by ECL and ICL. In this section we considered how to minimize ECL. In the following section, we discuss how to decrease ICL in the context of SD-based learning environments.

ICL in SD-based learning environments

As indicated earlier ICL is related to the cognitive load induced by the 'subjective' difficulty of the learning material: the more familiar the presented material, the lower the induced ICL, and vice versa. 'Familiarity' with the material is understood as the degree of elaboration of the relevant mental models held by the learners; the more elaborated the mental models, the more complex material may be comprehended (see definition of *Mental_Model_elaboration*, p. 7). As discussed earlier (see p. 12), the CLT research suggests that accurate estimation of ICL is vital for design of an effective learning environment: Overestimating ICL is likely to result in an instruction setting perceived as boring and unchallenging by the learners. Underestimating ICL will produce an instruction setting that will be perceived as too difficult, impeding learners' ability to engage in learning; ICL will use up all the available resources, leaving hardly any available for improvement of mental models – the case illustrated by simulation runs presented in Figure 5, p. 13.

Dealing with ICL in the context of SD-based learning environment seems especially difficult. A number of the SD researchers commented on people's inability to perform well in a simulated dynamic setting even when given full information about the workings of the underlying model (see e.g., Sterman 1987, Paich and Sterman 1993, Diehl and Sterman 1995, Moxnes 2004). Paradoxically, this instantaneous and full access to *all* the necessary information may be exactly what impedes people's ability to comprehend the dynamic settings.

Under CLT the experienced intrinsic difficulty of a particular learning material depends on availability of appropriate mental models. Given no relevant mental models, a problem, deemed as 'simple' by people, who have even only very basic knowledge of the domain, might turn out too difficult to deal with for complete novices.[12] The recommended solution in such case is to expose the learners to the problem gradually.

It is not difficult to envision simplification in case of elaborated models. Many authors recommend a segment-based approach, providing more and less aggregated views of a complex model (see e.g., Peterson 1994, Sterman 2000). Such sector-oriented fragmentation of the model is also used in case of the *solarSYDUS* simulator. As indicated before, the underlying model consists of over 100 interconnected variables. Most of novice learners when presented with the model at once would probably experience a cognitive overload. To prevent this from happening, the *solarSYDUS* learning environment is structured into a number of sections were specific aspects of the *solarSYDUS* enterprise and the enterprise as a whole may be examined (see Figure 11, p.21, and Figure 12, p.22). Providing both views is essential in the context of complex problems, where the detailed aspects need to be understood in the context of a greater whole.[13]

Various forms of segmentation and aggregation might help to reduce ICL experienced by novice learners confronted with a particular SD-based learning environment. However, how to deal with excessive ICL when the problem seems to be in its most basic form? A number of recent studies indicate that people have difficulties when dealing even with simplest SD building blocks (Sweeney Booth and Sterman 2000, Moxnes 2004, Jensen and Brehmer 2003). The accumulated observations suggest that people frequently disregard the fact that they deal with a dynamic problem and tend to approach the problem with generic schemata suited for static and linear rather than dynamic and nonlinear situations. One of the possible explanations for the observed misperceptions might be that most people do not hold schemata that would allow them to deal with even the most basic dynamic structure. Consequently, they experience excessive ICL and are not able to deal with the situation effectively. Further research is needed to determine which SD-building blocks might be considered as 'understandable' by a given audience, and which would have to be understood only in the course of the

[12] Sweller, van Merrienboer et al. illustrate the situation with the following problem: *Given that a/b=c, what is a=?* The point out that most of the readers of their paper would not have any difficulty in perceiving all the elements of the problem at once along with performing the required transformation. Still, algebra adepts might require two or more steps to solve the problem.(see Sweller, van Merrienboer et al. 1998, p. 261)

[13] See also footnote no. 6, p. 14

interaction with a given learning environment.[14] The next step in this research effort should concern identification of ways in which such understanding could be stimulated, i.e. how to induce the desired GCL during the interaction with SD-based learning environments. This issue is discussed in the following section.

GCL in SD-based learning environments

GCL refers to the cognitive processing that leads to development of mental models. Improvement of mental models is among the primary objectives of any SD intervention: *"System dynamics models have little impact unless they change the way people perceive a situation."* (Forrester 1991, p. 19)

Still, there are relatively little guidelines in the SD literature as to how to stimulate acquisition of appropriate mental models. One common argument has been that mental models will not be improved unless structure of the relevant SD model is revealed. As indicated in our earlier discussions, seen from the CLT perspective revealing the model structure, when done at an appropriate pace, might reduce the experienced ICL, making more resources available for germane processing. However, the exercise in itself might not directly stimulate mental model development.[15]

The CLT research advocates active and direct engagement of the learner in GCL-inducing activities. Germane-intensive activities involve elaborations, abstractions, comparisons, inferences, etc. (Gerjets and Scheiter 2003). These germane-intensive activities are identified by conducting systematic experiments in which different groups of learners learn something by performing a specific activity. Next, they are asked to assess the amount of invested mental effort. Following, their newly acquired abilities are tested in a transfer task. Improved performance on the transfer tasks coupled with reports of high mental effort in the initial, training phase, suggest that germane processing occurred.

While there have not been any studies of this type conducted with SD-based learning environments, the studies conducted by Bois (2002) indicate that greater effort indeed leads to a better performance and understanding of the problem. The apparent relationship between the performance and effort was also noticed by Jensen and Brehmer (2003). These observations suggest that a greater mental engagement on the part of learners is likely to improve performance within the SD-based learning environments. However, it is still unclear which aspects of the instructional design might stimulate such mental effort and induce the desired germane processing. Indeed, the degree of invested effort in the studied by Bois (2002) seemed to be independent of the instructional context within which the learners were embedded.

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[14] Tools for comprehensive assessment of understanding of a complex domain are still not well developed. One of the reasons for this might have been that the taxonomy of the knowledge necessary to deal with a complex phenomenon remained rather unclear. A notable contribution to clarify this question was recently made by Hillen (2004, 2004).

[15] Revealing model structure might be considered as analogous to providing students with a range of examples for problem solutions in other contexts. Studying these examples is not likely to be an activity that produces a high cognitive load. Still, it was observed that students often skip those examples (van Merrienboer and Paas 1990). Hence, presenting such examples in itself not always will induce germane processing. It is only the instructional procedures such as *"asking questions about the examples or making the examples incomplete so that students have to complete them, may (…) help students learn by increasing germane cognitive load"* (Sweller, van Merrienboer et al. 1998, p. 265).

As indicated above, the CLT-research suggests that activities such as comparisons, abstractions, etc. are likely to induce germane processing. In the context of the research conducted with the *solarSYDUS* simulator some initial efforts are made to stimulate this type of activities by providing continuous feedback to the learner. To facilitate this, an additional component that records the activities of each learner is introduced into the *solarSYDUS* simulator. This activity record will enable a continuous diagnostics of the individual problem solving behavior. The continuous and automatic analysis of the individual information-seeking and decision-making behaviors will allow to diagnose elaboration of the particular learner's mental model and to provide each learner with a customized, 'just-in-time' feedback stimulating further improvement of mental representations of the problem-space. Implementation of such instantaneous and automatic learning-assistance is now in the centre of the research activities related to the *solarSYDUS* simulator.

Much research is needed to clearly understand what aspects of the instruction are likely to stimulation germane processing. GCL is arguably the least-well developed area of CLT (Valcke 2002). Also within the SD-based learning environments further research seems warranted to understand better what aspects of the instructional setting are likely to stimulate germane processing.

Conclusions

CLT provides guidelines on how to circumvent limitations of the limited capacity of the human mind in training situations. First, it postulates decrease in ECL – the cognitive load irrelevant to learning. Second, it warns against imposing high ICL on learners – the situation occurs when complexity of the presented material surpasses the learner's ability to deal with. Third, it encourages increase in GCL – the cognitive load directly relevant to learning.

In this paper we developed a system dynamics model of the theory. The model facilitates explorations of the interplay between the various types of cognitive load and the characteristics of the instructional design. Using the model we reviewed how the various instructional choices might impact effectiveness of the learning process. Drawing on these discussions, we considered how CLT might inform design of the instructional overlay in the context of SD-based learning environments.

Although limited, the existing research results indicate that instructional design is likely to impact both understanding and performance in the context of SD-based learning environments (see e.g., Howie, Sy et al. 2000, Bois 2002). Still, specific guidelines as to how to design an effective environment for learning with SD models are scares. Our analyses indicate that some of the CLT guidelines may be applied instantaneously. For example, SD researchers developing SD-based learning environments may try to reduce ECL induced by their environments by incorporating multimedia elements to support cognitive processing within both visual and auditory channels. Or, when featuring a large SD-model, the structure may be presented in a gradual manner so to avoid excessive ICL. However, much of recommendations coming from the broader CLT-research, to become operationally useful for SD, require further investigations in the specific context of learning environments that feature SD models.

The need for further research may be illustrated for example by the issue of how to deal with the split-attention and redundancy effects in the context of presentation of the SD model structure and behaviour: Does separate presentation of the model behaviour and structure cause a split-attention effect? Is such presentation detrimental to the learning process – i.e., acquisition of appropriate mental models? On the other hand, should the behaviour be embedded in the model structure, would it not lead to redundancy effect? Another issue pending clarification is the question of appropriate level of ICL for novices who are to learn about implications of a SD model. Should the SD-based learning environment support development of generic schemata necessary to deal with dynamic settings before it faces the learners with more complex aspects of the situation featured by a particular SD model? How should the germane processing leading to development of these basic schemata be induced by the instructional overlay?

While the CLT research results do not translate directly into a complete set of guidelines for improvement of SD-based learning environments' effectiveness, we see the theory as an attractive framework for facilitating the research in this direction. One reason for this is that CLT explicates the learner-instruction relationship – the relationship that has been shown to be critical to learning with SD models and that is still little understood. Furthermore, CLT – being an acknowledged theory of cognitive system within the instructional design and psychology of learning communities – may facilitate exchange of ideas between these communities and the SD community. Such interdisciplinary cooperation seems warranted and is likely to be beneficial for all the involved parties, with SD providing challenging learning material, and the other communities providing guidance on how to effectively design its dissemination.

The work reported on in this paper is a result of a collaborative research effort between the research groups from Agder University College, Norway, led by Professor Jose J. Gonzalez,[16] and from University of Mainz, Germany, led by Professor Klaus Brauer.[17] It contributes to the research project conducted by one of the paper authors (René Molkenthin) on development of diagnostic tools for assessment of the learning process and provision of feedback that would stimulate the learning in the context of SD-based learning environments such as *solarSYDUS*. It also represents some of the first results of a research project conducted by the other author (Agata Sawicka) that aims at identifying a set of guidelines that would help to improve capability of SD researchers to communicate insights of our models to a broader audience.[18] The initial framework proposed in this paper will be developed further within this research project through a series of follow-up empirical and theoretical investigations conducted to clarify some of the questions formulated above.

We hope that other members of the system dynamics community find the results of our investigations interesting and will be willing to join in the discussion regarding the need for generic guidelines for design of effective environments for learning about insights of SD models as well as the relevant research agenda.

[16] See http://ikt.hia.no/sqo

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