Automated Scenario-Based Training Management: Exploring the Possibilities

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ABSTRACT

Despite the prevalence of software applications that exploit user information to individualize the experience, personalized training systems are still relatively rare. This paper describes changes in technology and standards that may alter this trend. Utilizing these advances, we have developed a standards-based learner model that is updated dynamically during training and that controls content sequencing. We have established the impact of this technology on learning through training effectiveness research. With this core learner modeling capability established, we have subsequently started exploratory studies into ways it might be used to manage scenario-based, simulation training. Specifically, we describe two prototype systems that use this core modeling capability, but that use the information it provides in distinctly different ways. Because of the complexity of simulation training, the root cause of performance issues is seldom apparent. The first prototype addresses this issue by using the learner model to select follow-on scenarios that help to build skill while distinguishing among competing learning needs hypotheses. The second prototype addresses the issue of maximizing learning opportunities within a scenario. It uses the core learner model to modify a scenario during execution in order to provide additional opportunities to achieve specific learning objectives or to adjust the challenge of an exercise. Directions for future research for both efforts are described.

ABOUT THE AUTHORS

Bruce M. Perrin leads the Instructional Systems Operations Support group. He designed and oversaw the original adaptive learning training effectiveness research and was the technical lead for the first prototype described in this paper.

Barbara Buck was the Principal Investigator for the Scenario-Based Training Management project, under which the second prototype was developed. Barb continues the evolution of this technology as part of the Boeing Training Systems and Services Technology Center.

Brandt Dargue is a software engineer assigned to the Boeing Training Systems and Services Technology Center. He was responsible for developing much of the simulation – training integration technology underlying both prototypes and was the lead software engineer for the first prototype.

Elizabeth Biddle was the Program Manager for the first prototype and was instrumental in the development of much of the performance assessment technology on which both prototypes are based. Beth is currently a manager in the Boeing Instructional Systems Operations Support.

Troy Stull is a software engineer assigned to the Boeing Training Systems and Services Technology Center. He was the software lead for the development of the LO Evaluator, a central component of the second prototype. Troy currently supports our C-17 Program.

Curtis Armstrong is a software engineer assigned to the Boeing Training Systems and Services Technology Center. On the second prototype described in this paper, he was the lead software engineer for the scenario planner and provided support for the training devices, threat server, and debrief station.

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Not long ago, the first author was visiting a university where the local email server happened to be named for a popular vacation destination. Lacking the data needed to connect to the server, he searched the school's intranet for this information, without success. Interestingly, over the months that followed, discount travel offers to this vacation spot appeared persistently on Internet websites…where they had never been before.

Clearly, computers can learn about us – sometimes to our benefit, sometimes with humorous results, and sometimes, unfortunately, in ways that annoy or even harm. Computers that deliver training, however, rarely learn about us. Most computer-based training systems seem oblivious to who is using them and every new learner is treated the same as the last.

In the first section of this paper, we discuss factors that have contributed to the lack of personalization of training and describe recent advances in technology and standards that facilitate the modeling of learners. Over the last 4 years, we have been developing methods that leverage this technology and these standards. Standards and enabling technology are of little use, however, if the resulting models cannot be used to facilitate learning. Consequently, we have accompanied our development efforts with testing to verify that the resulting models facilitate learning. This research will be briefly reviewed.

With a basic capability for learner modeling and its effectiveness established, we have subsequently turned our attention to exploring the possibilities for using these methods to adaptively manage scenario-based training. In particular, our focus has been on managing High Level Architecture (HLA) and Distributed Interactive Simulation (DIS) compliant simulation scenarios. Simulation-based training provides a rich environment in which new knowledge can be applied, and skills and abilities can be developed and honed in a safe, controlled setting that approximates actual work. In this paper, we describe two prototype applications, both of which leverage our common learner modeling scheme, but use its data in different ways to manage the scenario-based training process. These prototypes are described in the second major section of this paper.

MODELING THE LEARNER – THE CORE CAPABILITY

Although the modeling of a learner is not commonplace in training systems, as noted above, there are some notable exceptions. Intelligent tutoring systems (ITSs) are one. ITSs commonly include an explicit student model that is used for adjusting the sequence or content of practice exercises or to form hints, coaching, or feedback on performance. Developmental work on ITSs dates back to the early 1970s, with the founding work on SCHOLAR (Carbonell, 1970). Since that time, research on the effectiveness of these systems, while limited, has generally yielded positive results (e.g., Anderson & Reiser, 1985; Koedinger, Anderson, Hadley & Mark, 1997; Shute, Glaser & Raghavan, 1989). But over the same time period, fielded applications of ITSs have been nearly nonexistent. Although there have been some implementations in military organizations and a few in public education, ITSs have largely remained 'hand-crafted' research tools for the laboratory or academia for nearly 35 years.

While there are undoubtedly many reasons why ITSs and similar adaptive instructional technologies have not been introduced into the mainstream of training, a significant contributing factor appears to be the lack of portability and reuse of the approaches under research. Because each ITS researcher implemented their learner models and other ITS components using their own proprietary methods and metrics, gains in one laboratory have not translated into gains for another or for the training community in general.

Applying SCORM

Although focused on the presentation of web-available, declarative content, the Shareable Content Object Reference Model (SCORM®) enables the implementation of a reusable, portable learner model for a variety of different types of training. In particular, SCORM permits the association of a given student response or behavior to one or more of a training exercise's learning objectives. Thus, correct learner responses increase scores for the learning objectives that underlie the produced behavior. Incorrect behaviors, on the other hand, decrease these same learning objective scores, as well as those scores that are related to the incorrect behavior that was exhibited. This set of learning objective scores represents the state of learning for the individual, or a learner model, that is updated dynamically as the learner responds to the training. Because this model builds on information that is commonly defined for training systems, i.e., learning objectives, it is an approach that can be widely applied across systems and a basis for blending media within a system (Perrin, Biddle, Dargue, Pike & Marvin, 2006).

Changes to the model variables are communicated to a Learning Management System (LMS) using the Computer Managed Instruction (CMI) data model. Figure 1, for example, illustrates a learner model based on learning objective scores from one of the prototype systems we will discuss later. It illustrates a situation in which much of the declarative information on a simulation's controls and displays have been successfully demonstrated, while the later objectives related to tactical skills are yet to be developed.

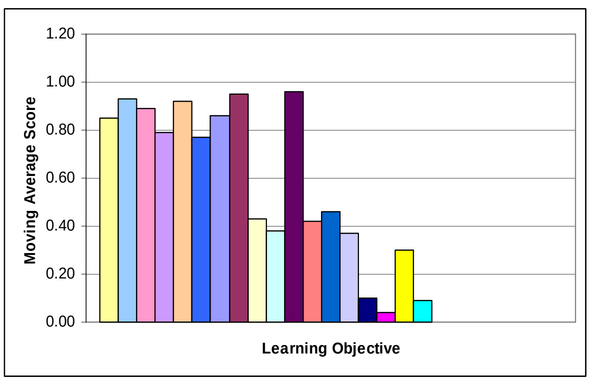

Figure 1. Sample Learner Profile

Effectiveness Research

Although this modeling approach was clearly technically feasible under SCORM, a key question was whether it benefited the learner; that is, could we use this model in ways that increased learning performance? We addressed this question in a training effectiveness study. Specifically, we examined the effect on learning performance of using this model to adjust content sequences during training.

The course involved web-based training on export compliance and used text, graphics, and video clips to cover the relevant rules and regulations, and to provide problem-solving exercises. As such, it included both the presentation of declarative, background information and the application of this information in text-based, problem-solving activities. Responses to these problems were limited to selection from a set of predefined options. That is, it was a problem solving environment typical of content presentations, rather than a more interactive, less constrained simulation.

Figure 2 illustrates the Content Structure Diagram for the course. Declarative knowledge (definitions, regulations, forms, guidelines, etc.) are contained on the left side of Figure 2, while problem-solving exercises are included in the content on the right side of the figure. By default, when delivered by the LMS, a student would study this content from top to bottom, left to right. This default organization, with unlimited opportunities for student initiated review, constituted one of our control treatments (Control-Computer). The second control was classroom training (Control-Class). As the name implies, this control group received equivalent training in a class setting, as part of a standard training program. The two adaptive learning treatments, which used the learner model to adjust content sequencing, are described next.

Mastery Learning Treatment

The first type of adaptive learning treatment that was assessed was Mastery Learning. Under the Mastery Learning training treatment, content under each aggregation was presented, followed by a test for that aggregation. Aggregations are represented as the yellow boxes in Figure 2. If all items on the test were answered correctly, the participant was free to move to the next aggregation. For any items that were missed, the corresponding Shareable Content Objects (SCOs) were displayed again for review, followed by the test on this content. This cycle of presentation-test could be repeated up to 3 times. If the participant could not pass the test after the third presentation, he/she was moved to the next aggregation. The necessity to move a student forward without passing the related test did not occur in our study.

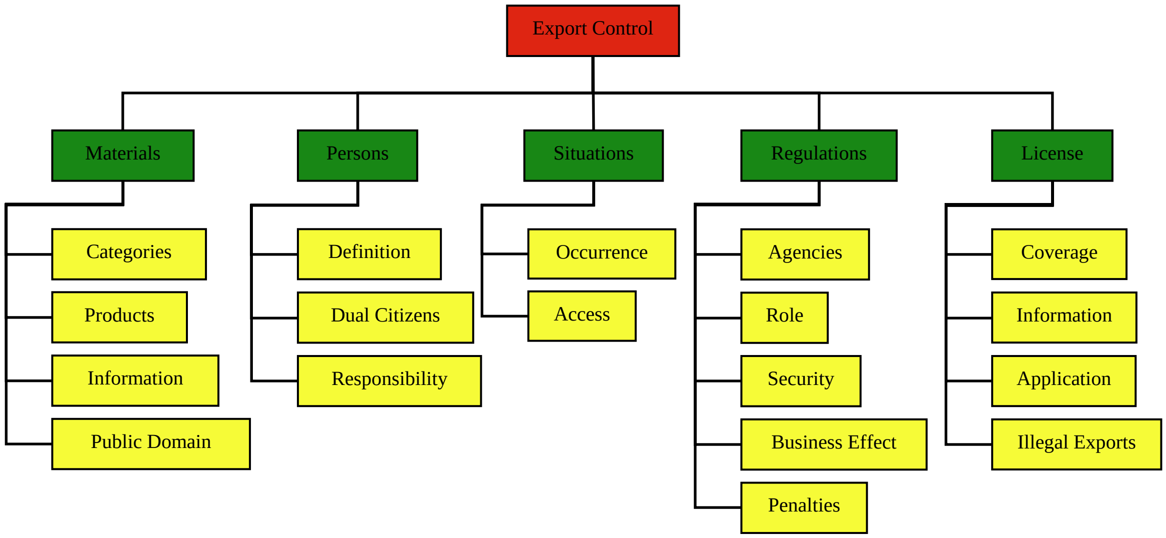

Figure 2. Content Structure Diagram for Adaptive Learning Research

Adaptive Remediation Treatment

A second, more robust type of adaptive learning treatment that we studied was Adaptive Remediation. This training treatment was similar to Mastery Learning, in that content presentation was followed by testing, and errors on the test, in turn, resulted in the corresponding SCO being displayed. The key difference, however, was that each error could be linked to more than one SCO. For example, consider the example of skill A that requires applying a new rule to previously learned facts X and Y. An error in performing skill A could be due to the new information related to this rule. The error could also be from forgetting or misunderstandings of facts X and/or Y, even if the participant had previously passed a test on this information. The student may have forgotten this information or may not have fully understood it initially. Under the Adaptive Remediation treatment, students were returned to all relevant SCOs for further study, even if these SCOs were not part of the current aggregation.

Fifteen individuals were randomly assigned to each of the four training treatments – two control groups and two experimental groups. All participants had taken this export control course approximately two years previously, and this training met their bi-annual requirement for training on this topic. The primary dependent measure in this study was learning performance, which had two components – accuracy on the end-of-course, problem-solving test and speed of completion. To form a stable estimate and to account for tradeoffs between speed and accuracy, we converted both measures to *z* scores, and then averaged them to form a combined learning performance score.

Differences in learning performance between the training treatment groups are depicted in Figure 3. These differences were evaluated using Analysis of Variance (ANOVA). The ANOVA on these data revealed a statistically significant effect ($F(3,56) = 6.30$, $p < .0009$). Using the Dunnett test of mean differences, all control-experimental group comparisons were significant at the .05 level or less. The content sequence provided under both training interventions produced superior learning, compared to student-directed study or class-paced instruction.

The provision of a personalized learning experience, enabled by a SCORM-based learner model in both adaptive learning conditions, improved performance significantly. A more complete review of this research can be found in Perrin, Dargue, and Banks (2003) or Perrin, Banks, and Dargue (2004).

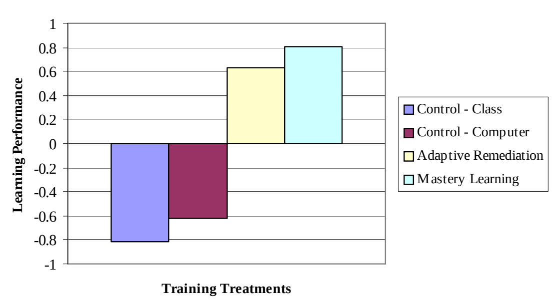

Figure 3. Mean Learning Score by Treatment.

EXPLORING THE POSSIBILITIES

With the demonstrated effectiveness of our basic learner modeling approach, we turned our attention to exploring the possibilities for its use in training that is more complex and dynamic. Specifically, we sought to explore the application of these modeling and adaptation methods to simulation-based training. To do so, we had to overcome two additional technical challenges. Each of these challenges is briefly described below; the interested reader is referred to Perrin, Biddle, Dargue, Pike, and Marvin (2006) for more details.

SCORM-Simulation Integration

SCORM must have access to information from the simulation, if it is to manage these exercises in the same way that it manages content sequencing for declarative knowledge training. While the simulation could have been of many different types, most of our simulations conform to the Distributed Interactive Simulation (DIS) and/or High Level Architecture (HLA) standards. Creating a bridge between a SCORM-conformant LMS and HLA/DIS conformant simulations would provide a ready base of reusable, standards-based simulations for training. We demonstrated this capability in a prototype at the Interservice/Industry Training, Simulation and Education Conference (I/ITSEC) 2003. This integration provides the continuing communications from student performance in the simulation to the learner model via HLA and SCORM, as required by our core learner modeling approach.

Automated Performance Assessment

Our approach to performance assessment in the original study was quite simple. Following the description of a problem in text, graphics, and/or video, the learner was given the choice of 4 options – one being the correct response and the other 3 being incorrect distracters. To explore the use of our core learner modeling capability for simulations, more complex, automated performance assessment schemes were required. Independent of this work, we have been designing and developing automated performance assessment tools and methods for some time (Biddle, Keller, Pitz & Nixon, 2005; Biddle & Keller, 2005). These methods provide a ready basis for our learner modeling studies. Learner modeling in the prototype system described next, for example, was based on automatically detecting and measuring 28 different performance metrics, which in turn were used to update 25 learning objective scores.

Testing Competing Learning Need Hypotheses – Prototype 1

With these technical challenges met, we were ready to explore applications of our core learner modeling methods to the more complex and dynamic training environment of simulation exercises. Within this realm, there were a host of ways that learner modeling could be used. Our first exploration was to evaluate how it could be used to identify the root cause of performance difficulties by testing competing learning needs hypotheses.

The basic issue that we addressed in this work can be illustrated by the following example. Suppose that an individual has been trained on both a simulation's controls/commands necessary to implement an action and the situation under which this action should be performed. Suppose further that the learner does not execute this action when the situation arises in the course of simulation-based training. Did the student not understand or forget how to implement the correct response? Or did he/she fail to recognize the situation or not understand what to look for? It is also possible that learner understood and remembered both the situation and action, but was prevented from responding due to workload. Or was the omission simply the result of a momentary lapse of attention. The point is simple. In most cases of dynamic, complex simulation-based training, there are multiple potential root causes for a given learner response. When the response is correct, we are generally willing to conclude that the correct action was the result of understanding and applying the appropriate knowledge and skill. When the response is incorrect, however, there are often several, competing learning needs hypotheses that we are willing to consider.

In the original training effectiveness research, we implemented perhaps the simplest form of logic for remediating learning errors with multiple, potential root causes – we simply scheduled a review of all of the related content. This adaptive remediation capability was implemented by linking the distracters on multiple choice test items to specific, previously studied learning objectives. These objectives, in turn, were linked to SCOs. Overall, 39 test item distracters covering 7 learning objectives referenced not only those 7 objectives, but also 8 other objectives that represented knowledge that was either omitted or used incorrectly in the participant's response.

One might anticipate, however, that this very simple approach to supporting an individual's learning needs will not scale well to longer courses or more complex exercises with many possible root causes. Providing remedial reviews for all of the topics implicated by a single mistake makes sense neither from the perspective of good measurement practice nor the efficient use of training time and resources. What is needed is an approach that distinguishes among the potential root causes for performance errors.

A moving average (a mean score calculated over the last set of a given number of opportunities) is one such measure. A moving average can be expected, over the long-term, to yield an unbiased estimate of the “true score” for each of the learning objectives implicated. That is, over sufficient time, averages based on randomly selected scenario-based training exercises can be expected to differentiate among competing root causes, assuming that the same set of competing hypotheses are not always implicated for each possible error.

Waiting for the random selection of activities to distinguish among potential root causes for learning difficulties may, however, extend training time unnecessarily. By random selection of scenarios, it may be some time before sufficient data are obtained to distinguish among different root causes of an observed error. A more efficient method of diagnosing learning needs may be to actively identify and test learning-needs hypotheses. Conceptually, this amounts to selecting tasks that have the potential to implicate one or a small subset of all of the learning needs that might be the root cause of the performance difficulty. Scenarios that contain those tasks are then selected for execution. As a result, relevant diagnostic data is obtained more quickly than it would be by random exercise selection or by selecting training scenarios based on many common methods such as adjusting scenario difficulty based on performance.

Consider again the example discussed above – a student has been trained on a simulation’s controls and displays, as well as situations in which specific controls are used. Later, in simulation exercises, when a student fails to use a particular simulation control in a situation that should elicit it, the root cause of the performance error may be in the mastery of the simulation interface or in the understanding of the situation. Assuming that the same simulation control is used in other situations, selecting a scenario or portion of a scenario that presents this second situation will help to isolate the root cause. If the student again fails to use the simulation control, it is more likely that the root cause in the student’s understanding of the simulation interface. On the other hand, if the student produces the expected response in the second scenario, the root cause of the initial performance error is more likely to be a misunderstanding of the first situation.

Implementing the Prototype

These learning needs hypothesis testing methods were implemented in a prototype developed under contract for the Joint Advanced Distributed Learning Co-Laboratory (Joint ADL Co-Lab). The prototype uses the Marine Air Ground Task Force XXI (MAGTF XXI) HLA simulation for its skill practice environment (Figure 4), while providing traditional content presentation for declarative knowledge training. MAGTF XXI is a real-time, tactical simulation developed for the U.S. Marine Corps (USMC) to facilitate expeditionary warfare training under the USMC Program Manager Training Systems (PM TRASYS) Tactical Decision-making Simulation (TDS) program.

Several different roles for the student and several different training tasks were considered before we selected the final alternatives for this study. We selected the role of a commander of a mechanized infantry-tank team. The task we identified was to conduct a hasty breach of a minefield. Additional detail on this prototype and the simulation task are provided in Biddle, Perrin, Dargue, Pike, and Marvin (2006).

For the hasty breach task, we identified 25 learning objectives necessary to perform the skill within the MAGTF XXI simulation. Five dealt with simulation displays and symbols, 7 covered simulation commands and menus, and 14 represented the tactics employed in the various phases of the breach. We also developed a set of 28 behaviors, many representing responses to be completed within a specific timeframe or within given area or both. These 28 behaviors, in turn, were linked to an average of nearly 5 learning objectives each (4.9), with the number of behavior-to-objective links ranging from 2 to 10. For each individual behavior, the learner needed to master the content related to at least 2 learning objectives. In other words, there were always at least 2 competing hypotheses as to the root cause of any individual response error, and usually, several more.

Figure 4. Screen Shot of MAGTF XXI

For the student population, we selected novices, both with respect to their experience with MAGTF XXI and as a team commander. This selection created a situation in which most correct behaviors implicated at least two different learning hypotheses, while errors frequently implicated the same two plus a third. Specifically, most correct student responses provided evidence that the student understood both the MAGTF XXI interface and the correct tactical actions. Errors, on the other hand, implicated the learning objectives in the same two areas – interface and tactical skill – but could also implicate workload, especially for errors of omission. In other words, the failure of a student to act might be the results of a lack of knowledge of the interface, of the correct tactical responses, or simply the lack of cognitive resources to perform the task because the skill was not yet proceduralized.

An initial formative evaluation of this prototype was conducted, specifically examining the following questions:

1. For a given response, did different learners identify different underlying root causes for their actions?
2. Were the underlying root causes that the participants identified the same as those identified by the system?

The data provided by this formative evaluation, although limited, suggested that the answer to both questions was "yes". Some learners identified the lack of mastery of the user interface as the reason why they had not responded appropriately. Others indicated that the basic problem was that they did not understand or had forgotten to implement the tactic. And in some cases, learners suggested that it was the lack of mastery of both the interface and the tactic.

Within the formative evaluation data, there was, however, a definite trend for the learners to cite the interface and workload as the primary root causes of their problems, particularly for the initial trials. It was anticipated that workload would be a factor that would interfere with behavior initially. As a root cause for performance issues, however, workload could be expected to dissipate quickly over trials, following a power function.

The prevalence of interface concerns, on the other hand, most likely stems from the design of this study. Because we wanted to assure that there would be competing root causes from both tactics and interface, we limited the amount of study on the interface. Apparently, the training that we provided on the interface was too limited, with the result that insufficient learning of it was not only a potential root cause, but the primary one.

For a more complete, summative evaluation of the system, we are improving and extending training on the interface. We are currently identifying opportunities to conduct this more complete training effectiveness study.

Adaptive Scenario Modification – Prototype 2

Like the system described previously, this prototype also leverages our basic learner modeling approach. Unlike the previous prototype, however, we have developed this prototype to explore the use of modeling information to dynamically modify the scenario during execution. Using our learner modeling capability, the scenario could be made more or less challenging, depending on student performance to that point. Similarly, additional opportunities to achieve learning objectives could be inserted, increasing the value of the exercise and providing better information on a student's true capabilities. Where the aim of the previous prototype was to efficiently manage the scenario selection process, the objective of this system was to maximize the effectiveness of a scenario during execution by introducing new opportunities to achieve learning outcomes and tailor the level of challenge of the course.

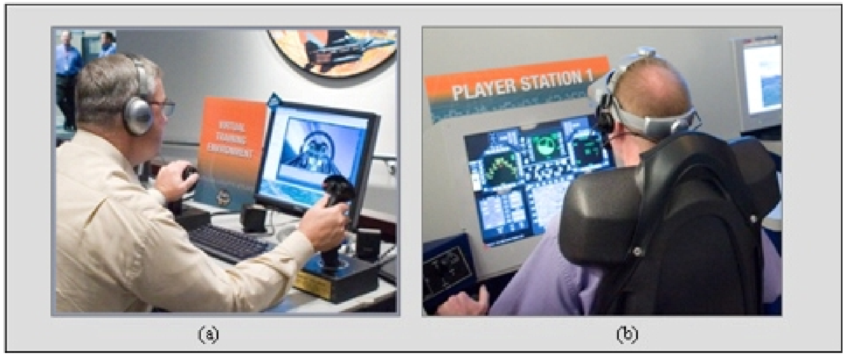

Figure 5. Training for prototype 2: a) Student using interactive IMI; b) Student in the low-cost reconfigurable simulator

In order to adequately explore this use of our core learner modeling capability, we had to carefully select a training scenario. Specifically, we sought one that imposed a fair amount of difficulty for beginning students, but without overwhelming them. A training scenario at this level of difficulty should benefit from the insertion of additional opportunities for practice, for adding opportunities to test skills against learning objectives, and, on occasion, for increasing the scenario's challenges when a given student was found to be particularly adept.

To meet these objectives, we selected a scenario that focused on basic flight maneuvers, e.g., achieving and holding straight and level flight, performing a turn to a specified heading, etc. The selected tasks for this training scenario are at the appropriate level of difficulty for a beginning student. These tasks came with two additional benefits. First, learning objectives were already defined for the basic flight maneuvers we selected, thus providing a ready basis for learner modeling. Second, interactive multimedia instruction on the key interfaces to the training device crew station, as well as the mission steps and procedures, already existed (Figure 5a).

With these training materials, we had the basis for conducting effectiveness evaluations, as well as for training implementations that blended Interactive Multimedia Instruction (IMI) for declarative knowledge presentation and simulation for skill practice under the same learner model (Perrin, Biddle, Dargue, Pike, & Marvin, 2006). The training device we used for this work was our low-cost, medium fidelity reconfigurable simulators (see Figure 5b). These training devices provide a reasonable level of fidelity for training and the appropriate performance metrics to enable real-time assessment.

Figure 6 illustrates an example of the adaptation that is controlled by our learner model for this prototype. The three learning objectives illustrated represent the initial stages of the scenario, as follows: fly straight and level; turn to a specified heading; and climb to a specified altitude. At each stage, performance is assessed against the appropriate learning objective. In addition to visual and display cues, audio feedback was also used to indicate the insertion of new opportunities for learning and practice. For each objective, multiple, specific aspects of performance were measured individually, permitting more detailed assessment and feedback for the modified scenario. Additionally, if the student masters each of these three specified objectives in this segment, there is a more challenging task available; this task requires the student to achieve a specified heading and altitude concurrently.

As Figure 6 illustrates, there are many potential departure points from the expected path, which is shown in green. These departures are marked in red and indicate the various difficulties that the student might have. The yellow paths indicate situations where the student achieved the learning objectives, but with some difficulty. These situations result in the insertion of opportunities for additional practice, i.e., a new target at a different heading and altitude. The blue paths are used when the student has performed exceptionally well and could benefit from the introduction of a somewhat more challenging task. While Figure 6 implies a lockstep progression through these three objectives, and indeed our initial implementation used this approach, more opportunistic methods to insert additional or revised training tasks are also supported.

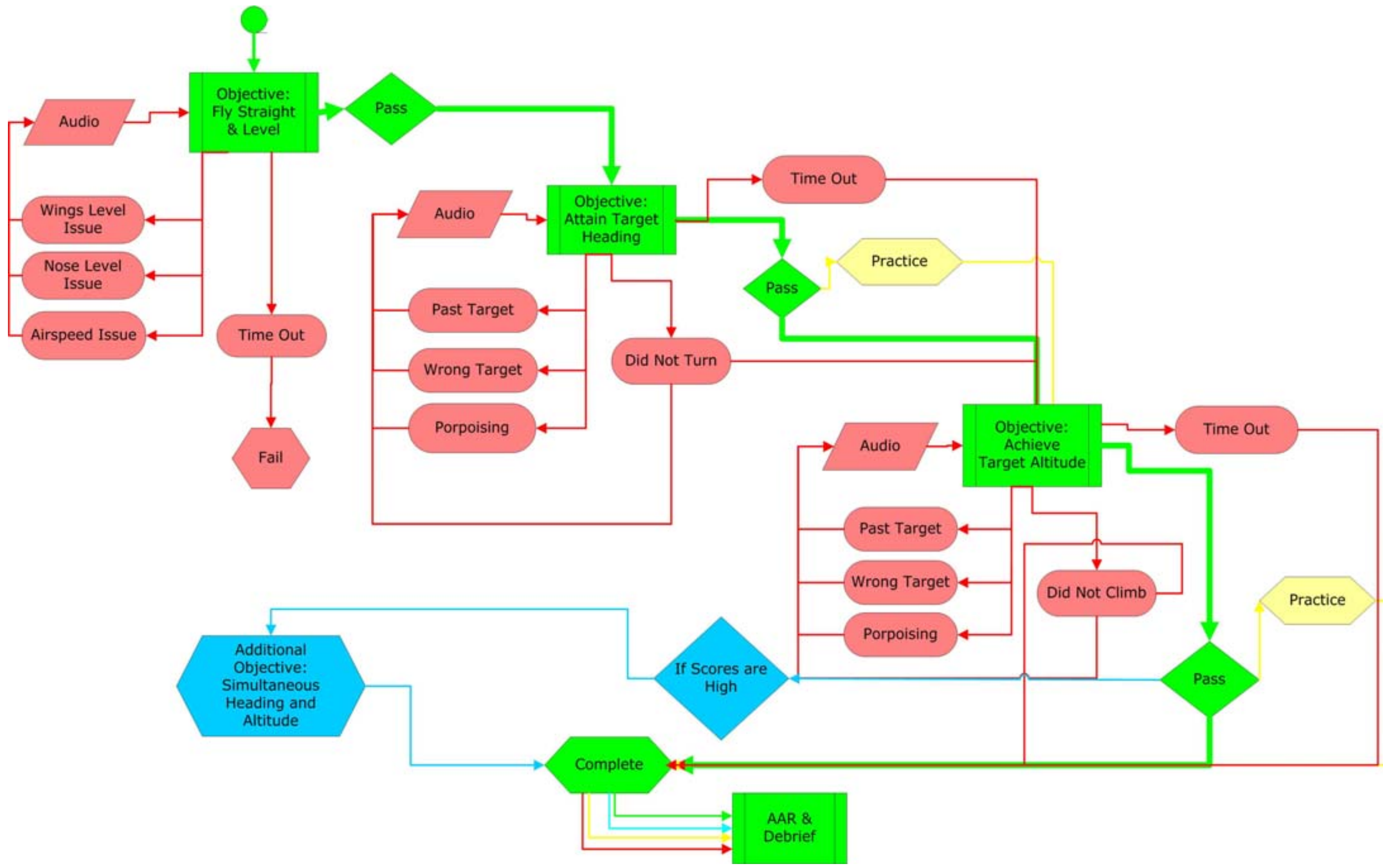

Figure 6. Sample Dynamic Scenario Adaptation Based On Student Performance

Functional Architecture

The prototype described above is part of a more general, scenario-based training management (SBTM) capability that we are developing. The functional architecture for this SBTM capability is illustrated in Figure 7. The actions/processes in yellow are those we have developed specifically in support of SBTM. The remaining actions/processes involve the use of technology developed separately. The Perform Training Mission activity, for example, involves the reconfigurable simulation trainers mentioned previously. Of particular relevance in the current paper is the description of the capabilities of the Learning Objective (LO) Evaluator, which builds and manages the dynamic learner model, and scenario modification as performed by the Scenario Planner.

LO Evaluator

The LO Evaluator is responsible for building and managing the learner model and for determining how best to maximize the student's time within the simulation exercise. The LO Evaluator accepts inputs from the simulation on the student's actions and compares these behaviors against the standards for performance on the learning objectives. These data provide the basis for estimating the student's current understanding and learning needs.

For this prototype, several factors figure into determining learning needs, including the student's past performance, the current importance of various objectives being trained, and the amount of help and the number of opportunities for performance that have already been given. When the LO Evaluator determines that new opportunities for practice or advanced challenges are warranted, it determines the modifications to the environment, visual and audio cues, or the tasks that are to be implemented. It then sends this information to the scenario planner, so that it can modify the scenario.

Scenario Modification

The scenario planner adjusts the scenario according to the instructions of the LO Evaluator. It accepts commands from the LO Evaluator, translates them, and sends them to the training device so that the prescribed changes can be implemented. In many ways, this function of the scenario planner is similar to an instructor using an instructor/operator station (IOS) to implement changes in a scenario to increase the effectiveness of training. With the scenario planner, however, the modifications originate with the computer, rather than a human instructor. Currently, the available modifications that can be implemented by the LO Evaluator via the Scenario Planner include the following:

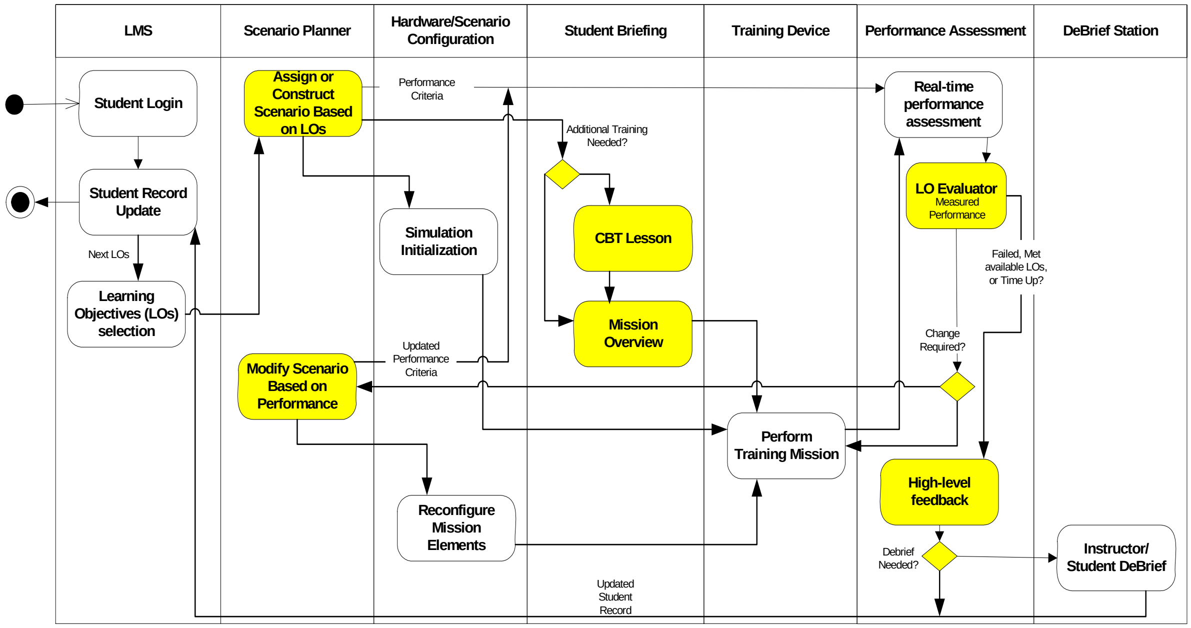

Figure 7. Functional Architecture for Scenario-Based Training Management

- Starting or stopping a training scenario
- Activating or deactivating a simulated threat entity
- Moving a simulated threat entity relative to another simulation entity
- Moving a simulated threat entity to a specific latitude and longitude
- Changing the speed, heading, or altitude of the trainee
- Changing the speed, heading, or altitude of a simulated threat
- Playing audio cues for the student

We are continuing the exploration of this adaptive scenario modification capability by implementing a more complex tactical scenario for this prototype. We are currently integrating this technology onsite at the Naval Air Warfare Center Training Systems Division (NAVAIR TSD), as part of an ongoing Cooperative Research and Development Activity. Because the research base on the training effectiveness of learner-model driven dynamic scenario modification is extremely limited, a primary product of this activity will be to study the overall effectiveness of these techniques for scenario-based training management.

CONCLUSION

By leveraging mechanisms provided by SCORM, we have developed a standards-based, reusable learner model that is updated dynamically during training and can be used to adaptively sequence training activities. This model builds on information that is commonly defined for training systems, i.e., learning objectives, making it a technology that is widely applicable across systems and a basis for blending media within a system. Through training effectiveness research, we have established the benefit of these modeling methods on learning and we have developed a production-ready authoring capability to support programs such as the US Marine Corp’s Expeditionary Fighting Vehicle (EFV).

We have subsequently started a series of explorations into the use of this technology for managing scenario-based, simulation training. In the first of two prototype applications, the user model is applied to the task of selecting follow-on training exercises that build skill while providing information to isolate an individual's learning needs. In the second prototype, learner model data provides the basis for modifying the scenario during execution, in order to provide additional opportunities for achieving learning objectives or providing new challenges. Initial formative evaluations on both prototypes have provided encouraging results, and we are currently undertaking more complete summative evaluations of these capabilities.

ACKNOWLEDGEMENTS

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