Operationalizing Artificial Intelligence in Simulation Based Training

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ABSTRACT

Imagine a synthetic environment that automatically adapts to better achieve the goals of its intended use. A training simulator that understands a trainee's strengths and weaknesses and changes the tasks presented accordingly. The value of infusing Artificial Intelligence (AI) and Machine Learning into simulation-based training systems is undeniable. Previous articles clearly show this, for driver training systems and Live, Virtual, and Constructive (LVC) training environments, as well as for many other applications. Yet, what does it take for Artificial Intelligence and Machine Learning to reach its potential? Rigorous, measured training performance metrics that can be compared to a standard or correct response are necessary for a system to adapt training scenarios to each trainee. For AI to effectively adjust to a student, this assessment needs to provide significant insight into the capabilities and limitations of the trainee and provide metrics that span a spectrum (not a simple binary result, e.g., pass or fail). These metrics need to be measured during training, assessed by the AI system, and then used to dynamically modify the training venue to improve training outcomes. A process to accomplish this for any simulation-based application - beginning with describing the requirement, assessing the simulation's role, deriving associated metrics and success criteria, measuring the metrics, and characterizing how the AI could be used to adapt the synthetic environment - is described. Then, this process is applied to two simulation bookends: simulator-based driving training and LVC-based command, control, and communications training. These proof-of-concept examples provide a means to describe associated insights, lessons learned, and useful next steps. This paper describes and provides the beginning of the technical detail needed to implement AI augmented digital simulation-based training systems capable of adapting to the application's trainee or training audience in ways that make the simulation training system even more effective.

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INTRODUCTION

Training, in any discipline, is essential, expensive, and time-consuming - which is a key cost driver. In many cases, training is a static program of instruction (POI) where a trainee starts at the beginning of the program, successfully completes training modules on all the topics that need to be covered, and at the end is qualified in the task or discipline. Often tasks in the POI are repeated several times to gain proficiency in that task. But what if a trainee is very proficient in some tasks in the POI and deficient in others? If there was a method to have the trainee practice the deficient tasks more and receive feedback while downplaying the proficient tasks (not ignoring them, but practicing them less), training would potentially be more effective, less timely, and more rewarding for the trainee. This is the essence of adaptive training. This paper discusses developing the metrics and associated measures required for a simulation-based training system to adapt in real-time to a trainee's progress, allowing the trainee to receive more training on deficient tasks and less on those highly proficient tasks, thereby reducing training time and increasing training efficiency.

Adaptive training is the ability of a training system to change to the needs of the trainee. Previously, we discussed this idea in the context of simulation-based training, reviewed the literature, and provided an outline of an adaptive training system for Driver Training (DT) and a Live-Virtual-Constructive (LVC) training environment (Oswalt, 2019). This paper is a follow-on which discusses and then presents the next steps needed to field an *innovative adaptive simulation-based training system that adapts on the fly* - during the scenario - and not at the end or within a subsequent event. In order to determine the proficiency level of a trainee a set of metrics to measure the performance are required to be developed and those metrics must be measurable by the training system in real time. The measures of the trainee's performance are evaluated by the training system and the scenarios or activities where the trainee is less proficient are presented for training more often than ones where they perform well. This provides the opportunity for a more highly trained trainee in less time. The following pages will lay out a process for determining the metrics and provide a sample set of metrics for each application; DT and LVC.

DATA AND METHODOLOGY

The approach employed follows well established techniques for decomposing a set of primarily sequential activities for metrics development and measurement (Hubbard, 2014), see figure 1. The first step is to define the training requirements and the basic parameters of its delivery. Overlaid on these are the scenario, learning objectives, and audience/trainee considerations. Then, the focus turns to defining the metrics needed to evaluate the degree of learning achieved relative to specific knowledge, skills, and abilities (KSAs) as well as further specifying both the scenario and the trainee's characteristics. Since the focus of this paper is on training objectives and associating metrics (DT and LVC C^3), these activities are highlighted, along with assuring that metrics are measurable and establishing their types (normally interval or ratio) and ranges (e.g., 0-N), in the lower box. Next, it is important to establish data collection points, which in the case of LVC simulations may vary in type. Finally, the training is conducted, with the simulation system dynamically adapting to the trainee inputs/training results.

The performance and effectiveness metric data being gathered and used to assess trainee performance in the two use cases discussed here (DT and LVC) map directly to the simulation's representation as relayed via associated instrumentation.[1] For instance, "identification" in both cases reflects the trainee's categorization of an input (sign or target type), which is known (and reported) by the simulation. The trainee's interpretation (correct or incorrect) is

[1] Measures of effectiveness (MOEs) help to answer if the desired conditions or consequences are being created. Measures of performance (MOPs) reflect if a task is being accomplished relative to a defined standard (JP 3-0, 2017)

reflected in the behavior taken (stop at a stop sign or designate a threat target as a threat), relative to which the simulation then adapts. There are no inferred metrics or cases in which a trainee's action is not directly measurable (which could be true, for instance, in a fire-arms simulator that measures the distance of a round's impact from the bullseye, and then infers the cause - like jerking the trigger which normally causes a round to impact below and to the left of the bullseye).

In any Artificial Intelligence (AI) system, the results are directly correlated to the "goodness" of the input and training data. Certainly, this system is no different and some noise is anticipated. However, in this case, an error in the system response will lead to training that is not as effective as it could be (tasks in the scenario to be repeated are not chosen well), but no worse than the standard scenario as all tasks in the scenario will be trained. Additionally, scenario changes will only occur with multiple instances of the same data (i.e., a trainee would have to be deficient in performing a task multiple times before the system "adapts." The next section provides more detail.)

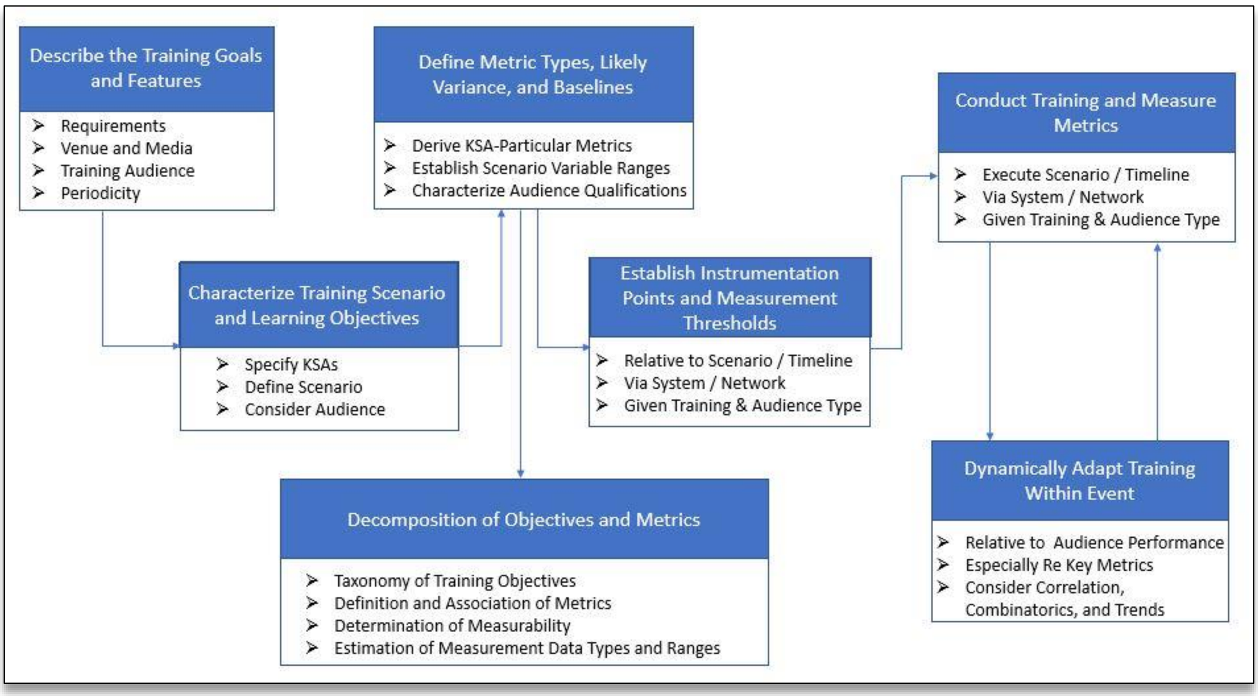

Figure 1 - The Process for Defining Metrics for AI-based Dynamic Adaptation

DRIVER TRAINING SIMULATOR

Driver training in a simulator offers advantages over training in an actual vehicle. Such training is typically performed in a lifelike mock-up of the vehicle with video displays depicting some terrain/scene that places the trainee in an immersive environment (see figure 2). Examples include the US Marine Corps Light Armored Vehicle Driver Trainer and the Operator Driving Simulator (Lara, 2019). The advantages over live vehicles include safety and the ability to train in different and changing weather and road conditions without relying on mother nature to produce the desired weather. The standard training protocol is to have the trainee progress through several scenarios, each one focusing on set tasks and/or skills.

For example, the first scenario may be a simple dry paved road winding through a rural countryside. This may progress to city driving on dry road, then to adverse weather scenarios, and perhaps, if applicable, off-road scenarios. For certification in other countries the mock-up may be configured to right-hand drive and various scenarios presented that challenge the trainee when operating the vehicle in this configuration. At each stage, however, the scenario is set and does not change. If a trainee fails a scenario, subsequent training on that scenario will have the same track, the same turns, the same traffic, and the same weather challenges at the same point in the scenario.

This situation may lead to “gaming the system” where a trainee passes the scenario due mostly to familiarity. Additionally, a trainee is required to complete an entire scenario just to obtain practice on a small portion where they did not perform well. This is an inefficient and time-consuming method.

Certainly, the capability exists today to create scenarios that are similar and yet different enough so that “gaming the system” is mitigated and additional scenarios can be used that present more of the deficient tasks or situations. However, these additional scenarios may also contain many tasks where the trainee is extremely proficient. True adaptable training occurs within a scenario by using artificial intelligence techniques that automatically adapts a scenario to offer more tasks where the trainee struggles and minimizes those tasks where the trainee is proficient. This idea is innovative and has the potential to significantly increase training efficiency.

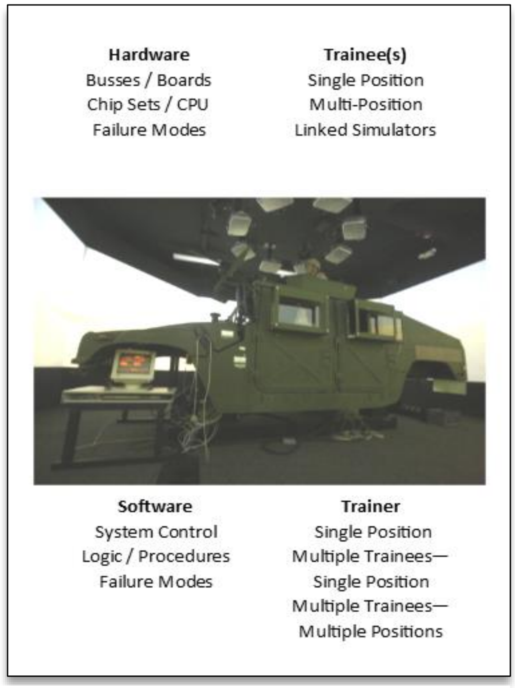

Figure 2 - Components of a Simulator

However, before a system can automatically present scenario tasks, the tasks need to be defined and each task must have an associated metric which can be measured to determine proficiency. For example, suppose the task is to safely drive in heavy rain. First, “safely” needs to be defined. Here we will define it to be staying in the driving lane with the centerline of the vehicle over the centerline of the lane being the goal. The metric then becomes how far the centerline of the vehicle is from the centerline of the road. The system must track simulated vehicle position as well as the road’s centerline. Additionally, given the vehicle width and the lane width the system can determine if the vehicle wanders out of its lane. Leaving the lane could be a failure for the scenario. Different grades could be given depending upon the average vehicle distance away from the centerline over the entire scenario. Developing the metrics is the focus of this paper.

Using the framework described in figure 1 above we first begin by determining the training goal. In this case the training goal is for a trainee to drive from point A to point B in a safe manner. This raises the question as to what is a safe manner? First, the driver must stay on the road and stay in the appropriate lane. Second, they must not travel faster than road conditions (ice, wet, snow, curvature of the road, smoothness of the road, and similar situations) would dictate. Third entails proper interaction with other objects and vehicles. This encompasses safe following distance, avoiding obstacles on the road, proper safety at intersections, and safe passing actions. Finally, there are all the proper driving procedures such as using seat belts, setting mirror position, using turn signals, obeying traffic signs/signals, having headlights illuminated at the appropriate level, etc. Each scenario would have a tailored set of metrics based upon this list of overall categories.[2]

To provide more insight on the associated metrics consider a mountain scenario in the winter driving a medium sized (2.5-ton payload) supply truck. This could have icy/snowy roads, winding switchbacks, situations where passing is not appropriate, rocks on the highway, animals on the highway, plow trucks clearing the highway, and potential rough road. This scenario is an advanced scenario with adverse weather and an approximate length of 20 miles. Estimated training time is 45-50 minutes.

Given this scenario the metrics that would be applicable to measure how well a trainee is accomplishing the tasks that represent safely completing the route are listed in Table 1. The metrics include those that reflect how well the student performed the task, the effectiveness of the outcome, and the degree to which the lessons learned were retained (Beaubien, 2015). Note that these metrics are more specific than those listed in the USMC Motor Transport Training and Readiness (T&R) Manual (Dept of the Navy, 2019). Additionally, these metrics are designed to give a gradation of performance and not just a “pass/fail” rating as in many of the training and readiness tasks. For example, one T&R

[2] For the purpose of this paper, we are considering driving trainers with no combat element. We realize there are combat convoy scenarios with vehicles, that is not the scope of this discussion.

task is to conduct a mission brief. It is just a yes/no check with no rating or feedback as to how well the brief was conducted, did it contain the necessary information, was it presented clearly, etc.

Table 1 - Driver Training Metrics

Metric	Type	Range
Staying on established roadway	MOE	On/Yes, Off/No
Distance from centerline of the lane left or right	MOP	0-N Inches
Wheels staying within boundary of roadway	MOP	On/Yes, Off/No
Speed as compared to scenario gold-standard safe speed	MOE	0-N % Deviation
Avoiding potential collisions with objects/animals	MOE	Yes, No
Avoiding collisions with other vehicles	MOE	Yes, No
Following at established safe distance behind a vehicle	MOP	Yes, No
Giving proper right-of-way at intersections	MOP	Yes, No
Giving proper berth to oncoming traffic (includes leaving enough distance from oncoming traffic when passing)	MOP	Yes, No
Obeying traffic signs and signals	MOP	Yes, No
Use of turn signals when turning	MOP	Yes, No
Headlights on and at appropriate illumination	MOP	Yes, No
Training Durability	MOL	Degree change over time
MOE - Measure of Effectiveness, MOL - Measure of Learning, MOP - Measure of Performance		

While this discussion is focused on metrics, a brief examination of how the adaptive training might work is helpful. There are three different training situations that could arise: first time training on a scenario, repeat training due to previous failure, repeat training for sustainment / currency. For first time training, the trainee would be presented a standard snowy mountain scenario with several situations in the first 5-7 minutes. These situations could consist of oncoming traffic, slippery road conditions, slower moving vehicles in front, stopping at intersections, switchback turns, and other similar mountain driving tasks. In this first 5-7 minutes the system would assess which tasks the trainee performs very well and which tasks are either deficient or poor as measured by the metrics above.

For example, suppose the trainee moves well over to the right of the lane every time an oncoming vehicle passes but in one instance was off the roadway. The system would then automatically generate additional oncoming vehicles in the next 8-10 minutes and re-evaluate the trainees progress at that time. Conversely, if the trainee is coming to a complete stop at intersections and utilizing proper right-of-way protocols, the system could change the scenario to remove some intersections which would lead to a quicker training completion. As noted above, performance would be evaluated again after 8-10 minutes, and the scenario readjusted to better match the trainee’s needs.

If this is repeat training, the standard scenario wouldn’t be presented at first. There would be a saved training record of the trainee’s past performance and that record would be used to modify the scenario to provide customized training for the trainee. Particularly, if the trainee failed the previous training, then the scenario would be adapted to emphasize those tasks where the trainee requires more repetition. If the training is simply for recertification or currency training, then the scenario would still be tailored based upon previous performance but would be more balanced in the tasks presented. Currency training would be designed to exercise all the elements of the scenario and those where the trainee was weaker just a bit more.

LVC FEDERATED TRAINING

LVC simulations offer many advantages over other possible training alternatives, some of which are very similar to those found in driver simulators. Compared to employing operational assets on a tactical training range, LVC events are less costly, scenarios can be repeated as needed, and novel and yet potentially dangerous tactics practiced. In addition, LVC exercises can include unusual manned and unmanned concepts of operations using sensors and warfighting plans under development in a way that limits emissions and unwelcome reconnaissance. With the addition of dynamic simulation scenario adaptation based on trainee performance, these LVC-based exercises can become even more effective.

LVC events, by design, include interactions between multiple participants and systems striving to achieve a common mission objective. For that reason, LVC-based training exercises normally include as one of their goals teaching participants effective command, control, and communications (C^3) processes and techniques. Such instruction, using LVC simulations was found to "enable enhanced training" in cases that included artillery C^3 (Hannay, 2014). As a result, to describe how to operationalize AI via adaptive metrics within an LVC training event, the use case examined here is instructing effective C^3 techniques to the three operators located within the Engagement Control Station (ECS) of a Patriot air defense missile battery.

Figure 3 - Patriot ECS Vehicle

Patriot is a guided missile air-defense system with long-range, medium-to-high altitude, all-weather capabilities designed to counter tactical ballistic missiles, cruise missiles, and advanced aircraft. The ECS is the command center of the missile battery and contains stations for three operators seated at two radar consoles and a communications station (see figure 3). Operators can see the status of all targets that the system is tracking and can select or deselect targets or set the system run in fully automatic mode. The communication station allows the battery to communicate with other batteries and with the command center for the region. As a result, the operational mission and the training objectives of this use case are to:

- Control the air battle: monitor threats, prioritize targets, and engage targets.
- Communicate with friendly forces: command and coordinate, via messages, with higher headquarters, subordinate, and lateral units.
- Conduct liaison with supported units and other units in the Patriot battery's operating area.

Assessing the effectiveness of these C^3 activities can draw from long history of metrics development and assessment, much of which applies to distributed LVC training simulations. For instance, previous analysis has developed measures of C^2 performance and measures of effectiveness relevant to gunnery and air defense scenarios (Sweet, 1985). This analysis included the ability of the operator to understand the data being displayed (MOP) and then using it to achieve a successful engagement of the target (MOE). It also included decision response time (both elapse and relative (timeliness)) and associated system engagement impact variables and assessment measures.

Table 2 - Patriot C^3 Example Metrics

Metric	Type	Range
Communications Instances	MOP	0-N messages to 0-M Locations
Track Identification	MOP	Known or unknown. Correctly or incorrectly.
Elapse Time	MOE	0-T from unknown to neutralized.
Track Engagement Allocation	MOE	Exploited / opportunities.
Engagement Result	MOE	0-R Threats penetrated. 0-R Threats neutralized.
Training Durability	MOL	Degree change over time.

There has also been previous research into how to assess the effectiveness of C^3 within LVC-based training (Roberts, 2017). In it, four metrics were proposed for evaluating C^2 LVC training effectiveness: observe-orient-decide-act (OODA) time, communications effectiveness, area of responsibility (AOR) familiarity, and communications familiarity. OODA time is the elapse between the estimated earliest entity detection time and when it is classified as suspect, hostile or friendly. Communication effectiveness evaluates an individual's proficiency with communication protocols and brevity codes within the event. AOR and communications familiarity are subjective assessments made by the trainee of how much they learned or increased their knowledge of the region of interest and the required communications procedures, respectively, as a result of the training event.

Considering the particulars of the use case being employed here and these two previous analyses (out of many that could be reviewed and considered), six metrics have been chosen as examples of what could be measured within a C^3

LVC training event to enable the LVC environment to adapt to trainee inputs and actions. They are listed in Table 2 and include key indicators of C^3 proficiency relevant to the Patriot system, ranging from simple message exchanges to engagement allocations, warfighting effectiveness, and learning permanence. These metric types, provide the foundation to estimating baselines, collecting telemetry, determining measurement thresholds, and ultimately to operationalizing them to enable LVC event adaptation.

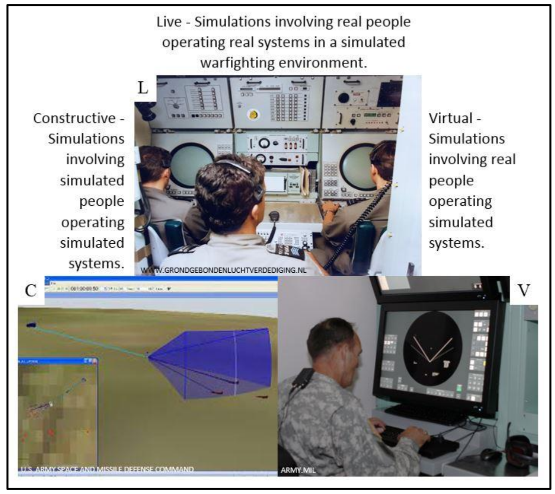

Figure 4 - Patriot C^3 LVC Simulations

When measuring these metrics within an LVC federation, it is important to note that what can be measured, and thus how it will be possible for the system to adapt the training provided to match the needs of the trainees, will vary by simulation type (see figure 4). In a live simulation environment, measurement will rely on range sensors and telemetry recording systems. In a virtual setting, they will be defined by the simulator's interface design specification, which may not include the ability to capture and provide the data needed to assess training performance, effectiveness, or learning retention (Beaubien, 2017). Finally, in constructive simulations, data availability may tip-the-scale in the other direction, providing almost endless amounts for the trainer to convert into useful assessment information.

In the case of a metric like elapse time for instance, it should be possible to measure it within all LVC simulated environments within the first Patriot air defense training event scenario. The result will be compared to both a gold standard and relative to the engagement being examined (i.e., was the decision made quickly enough to engage and destroy the target before it impacted blue forces) since these two values may be different and yet indicate success. Then this data will be used to inform the parameters of the next training scenario that immediately follows. Such adaptation will occur until the training objectives are met or the training event has to end for previously defined reasons.

Such a dynamically adaptive LVC simulation-based C^3 training can be extended to other training types, like force employment, which are likely to benefit in similar ways. While the complexity of measuring performance, effectiveness, and especially learning will require a comprehensive, rigorous, and long-term approach, the results should be promising enough and the technology available – especially given the increasing sophistication of machine learning, particularly in those simulations that employ generative adversarial networks – to make the approach discussed here scalable. Describing how simulation-based training can incorporate of machine learning and then defining the metrics needed to operationalize the approach, brings us a step closer to deploying an effective adaptive learning simulation.

TRAINING PARADIGM

There are important trainer/training considerations with the adaptive training system described above. There are some that say the adaptive training will replace the trainer. While the role of the trainer will change, the trainers are a key component and critical to the success of the system. It is envisioned that the trainer will become more of a coach, providing guidance as the trainee moves through the training scenario. In this role, they advise and mentor the trainee in those tasks where they are struggling. Critical to any training is feedback. Practice doesn't make perfect, it makes permanent, and practicing a task incorrectly only leads to the continuation of incorrect performance. Therefore, the coach is there to provide the guidance and changes to perform satisfactorily in all the tasks. To complement the real-time feedback, after action reports would be generated which would provide more detailed statistics (average deviation from centerline, braking reaction time from when an object was first presented in the path, etc.) which would allow the trainee and coach even more insight into the trainee's performance.

CONTEXT AND EXTENSIBILITY

There are several systems and capabilities within the adaptive instructional system (AIS), intelligent tutoring system (ITS), and artificial intelligence in education (AIED) communities that enable the efficient development, deployment, and interoperation of dynamically adaptive simulations (Julian, 2018). For instance, the Generalized Intelligent

Framework for Tutoring (GIFT) simplifies development, enables adaptive instruction, and provides integrated evaluation tools (U.S. ARL, n.d.). These capabilities are very valuable and will be even more so when LVC Federations become persistent, or persistently available, and thus are able to take full advantage of its features that encourage self-regulated learning.

In other cases, dynamically adaptive simulations are one way to achieve certain AIS goals, while benefiting from associated insights, techniques, and products. For instance, "how a range of simulator fidelity can be introduced into a progressive training program" is discussed in (Edmond, 2020). The advantages of using a simulation environment instead of a "collection of practice simulators" that progress from lower to higher fidelity representations is made clear, along with the value of templates and frameworks. Dynamically adaptive simulations enable a set of simulators to be replaced by one that increases in fidelity and scenario complexity in response to trainee inputs while meeting the same andragogical objectives.

Templates and frameworks extend this capability by allowing, say a unit-level simulation, to be integrated into a mission level scenario in a seamless and efficient manner. One example of this is PM Engine™ (Aptima, 2016) which assesses and calculates performance measures (PMs) from data generated during simulations using the human performance markup language (HPML) to ingest data from a variety of sources. HPML is an XML schema that is both system neutral and human/machine readable and that has been successfully employed in LVC simulations (Beaubien, 2017). Another valuable AIS approach is the Methodology for Annotated Skill Trees (MAST), a skill-modeling framework that facilitates the creation of descriptive and rule-based content that supports skill acquisition learning described in (Bauchwitz, 2018).

Within ITS design, development, and implementation, systems often fall into one of two categories: expert model or error library. The first focuses on developing a gold standard and then comparing training outcomes to that benchmark. The second concentrates on identifying things not to do and on avoiding or correcting those mistakes as training occurs. Dynamically adaptive simulations, as are described here, fall squarely into the first category.

In terms of extending the operationalization of AI in simulation-based training, two sets of standards are most relevant. The first are those associated with AISs, generally discussed above, but in particular to LVC it is important that performance assessments employ standard protocols and are shared to support reuse (Beaubien, 2017). The second are those that enable the federation of simulators and simulations, centered around the distributed interactive simulation (DIS) protocol, high-level architecture (HLA) and associated federation object models (like the real-time platform federation object model), the test and training enabling architecture (TENA), and similar. For adaptive simulators and adaptive simulations to be integrated into, or interoperate with, other M&S environments the application of both sets of standards would be valuable.

FINDINGS AND NEXT STEPS

There are several findings from this research and next steps. First, innovative ability to adapt to a trainee's performance to provide more training on less proficient tasks and less training where the trainee is competent is achievable in both an individual training simulator and a team or staff trainer and will reduce the training time for most trainees. This requires a set of metrics and a correlated standard to compare the measures of the metrics within the simulation. While this isn't an intelligent tutoring system (it does not provide immediate and customized instruction or feedback to the trainee), it has many links to them and both this idea and intelligent tutoring would likely benefit from an information exchange between the two.

This is the second in a sequence of papers that examine how artificial intelligence can be incorporated into training simulations. Next steps include:

- The development or compilation of gold standards for the metrics measurements. In some cases, this is handled in the physics of the simulation model, in others it may be average historic values collected from live exercises or simulator performances, or even best practices from the community.
- As noted above, this adaptive training instantiation requires saving performance data from previous training. This will require an identification method for every trainee across a service or even across DoD. If that method contains any Protected Personal Information (PPI) then appropriate security solutions will be

required on the system. One solution would be to develop a training ID for every trainee; however, this is not the current model.

- Coupled with the security challenge above is the fact that previous training data will need to be available to the training system. This requires the training systems to have worldwide connectivity, local connectivity to a database and then records are transferred with permanent change of station or even when a unit temporarily travels to another site for training, or a digital storage medium that a soldier/sailor/airman carries with them any time they perform training. The last option is a fantastic opportunity for lost training or perhaps PPI data!
- There will be technical challenges (some substantial perhaps) to implementing the real-time training adaptation and scenario generation/change. These will be the focus of future papers; however, careful choice of the change point (where in the scenario) will be required. Specifically, points where the scenario is at a lull, or a pause would be required.
- Note this conclusion specific to simulators from an I/ITSEC 2017 paper (Beaubien, 2017): "While procurement guidelines routinely specify the desired fidelity cue characteristics - such as pixel density, contrast ratios, field of view, and the like - of simulators that are to be acquired, they rarely specify the capacity to measure and track learner proficiency over time." While specifying this capability in a procurement request for proposals and statements of work can be somewhat challenging, it is starting to happen. To implement this real-time adaptive AI system, spelling out the metric requirements will need to become common practice.
- "Real-time performance assessments can and should be used to alert instructors about the existence of unplanned training opportunities" (Beaubien, 2017). This could include adding non-intrusive bio-metric and stress sensors that reflect how the trainee adapts to stress in a driver trainer, LVC-based synthetic environment, or other types of simulation. Such instrumentation is one more reason that a real-time adaptive simulation training system is valuable but does not replace the human trainer. The trainer will need to be capable and well qualified in every task to determine the trainee's status, why the trainee is deficient, and how to remediate the deficiency.

The intent is to continue this line of investigation, from describing how simulation-based training can incorporate of machine learning, to defining the metrics needed to operationalize the approach, and then next to considering specific AI algorithms that could be employed, what other supporting infrastructure or adaptation elements could be included, and, importantly, defining and implementing a proof of principle simulation test case that demonstrates the viability and value of this endeavor.

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