Humans and Autonomy Lab

HAL2016-01: Determining UAV/UGV Training Effectiveness as Autonomy Increases Interim Report #1

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Andrew Hutchins, Michael Clamann, Joshua Furth, & Mary Cummings (P.I.)

Humans and Autonomy Laboratory
130 North Building
Duke University
Durham, NC 27708

Abstract

With the increase in both the number of Unmanned Aerial Systems (UAS) used by the Army, as well as the like increase of onboard autonomy for Unmanned Aerial and Ground Vehicles (UAVs and UGVs, respectively), significant changes operations and UAV/UGV operator training methods will be required. Towards this end, the main focus of this effort is to present a framework for predicting changes in training of UAV/UGV operators as the autonomy onboard the vehicles increases. In addition, a modeling framework is needed that addresses the various aspects of UAV/UGV operator training, as well as how increasing autonomy will influence the training rate and requirements.

The current effort has focused on developing a model design using a technique known as system dynamics modeling for simulating training for the RQ-7 Shadow per fiscal year. The current system dynamics model is designed around the three phases of training (Common Core, Simulator, and Live Flight) for an Unmanned Aircraft Systems Operator (15W) trainee in initial training to operate the RQ-7 Shadow. The core structure of the systems dynamics model represents 15W trainees moving through each of the three phases of training with the rates of training progression controlled via capacity and error rate variables obtained from site visits and interviews with subject matter experts from the Unmanned Aircraft Systems Training Battalion (UASTB) based at Fort Huachuca, Arizona. The core structure of the model gives an output within 5% of the actual RQ-7 Shadow trainee throughput for FY 2014.

Ongoing work on the autonomous system training model (ASTM) consists of categorizing training tasks into cognitive reasoning hierarchies (skill, rule, and knowledge-based reasoning), and incorporating the influence of increasing autonomy on each of these skill, rule and knowledge-based (SRK) reasoning tasks. How these SRK tasks are affected by increasing autonomy is both the key to our modeling approach in terms of training time, error rates, and overall trainee throughput and also not very well researched. As a results, we are currently studying past technology implementations that increased the level of autonomy onboard piloted, commercial aircraft and air traffic control and observing what effect increasing technological advancements had on the relevant training programs. In addition, current pilots and trainers are to be interviewed to gain insight into their personal experience with increasing autonomy onboard commercial aircraft and in air traffic control (ATC) towers. Further goals consist of incorporating the SRK cognitive framework into the system dynamics model, along with a metric for increasing autonomy. These variables will first be implemented into the RQ-7 Shadow training model, but will assist in generalizing the system dynamics model for training programs for UGVs.

Introduction

The Department of Defense (DoD) has made significant efforts to increase the number of unmanned systems (US) in the United States Army in an effort to reduce the risk to Soldiers and reduce Soldier workload during routine missions (U.S. Department of Defense, 2014). In particular, Unmanned Aerial Systems (UAS) that are used for information, surveillance, and reconnaissance (ISR) missions are the most widely produced UAS type, with production numbers far beyond other types, including radar decoys and target drones. Production numbers are also expected to increase in the future, as seen in Figure 1, which forecasts a doubling of ISR UAS platforms between 2014 and 2022. This increase in the number of UAS platforms will require a corresponding increase in qualified operators and resources to support future operations (U.S. Department of Defense, 2012). This investment in increasing UAS operations makes the training of new UAS operators critical for DoD budgeting, human-machine coordination, and overall mission effectiveness, particularly as UAS technology evolves to meet new demands. With current advances in the artificial intelligence (AI) community, operators will also need to be trained to manage the vehicles' increasing level of onboard autonomy. It is important to coordinate the training of UAV/UGV operators with evolving interface designs to reduce the risk reduced mission effectiveness due to automation complacency (Parasuraman, Molloy, & Singh, 1993; Singh, Tiwari, & Singh, 2009) and human error due to automation confusion (Leveson & Palmer, 1997; Funk & Lyall, 2000). The term "automation complacency" refers to the notion of human operators over trusting the capabilities of automation and, as a result, not intervening when demands exceed that of automated functions (Parasuraman, Molloy, & Singh, 1997). "Automation confusion" refers to operators not understanding what the capabilities of the automation are and could result in them not knowing how or when to intervene when human input might be required (Sarter & Woods, 1995). The confusion could come from the controls, interfaces, or displays of the system itself. These two potential human induced errors have the potential to become more prevalent as US become increasingly autonomous, unless training programs are altered to cope for new capabilities of automation.

The difference between automation and autonomy should be noted to reduce confusion in this report. "Automation", or automated systems have a prescribed set of capabilities and cannot operate outside of the bounds of the task to which it has been assigned. A good example of automation is a robotic assembly line in a car manufacturing plant. The robots have a discrete task that has been preprogrammed and will repeat that task as long as no uncertainty is introduced into the environment or workspace. "Autonomy", or autonomous systems, on the other hand, have the capability of reacting to scenarios that are unexpected or high in uncertainty. There are some preprogrammed scripts for the system to follow but the system is "self-governing" and allows for information collected from the environment to assist in independent decision making. An example of an autonomous system is the Google™ driverless car. The vehicle gathers information about its surroundings with a series of sensors and reacts based on the collected data without direct human input.

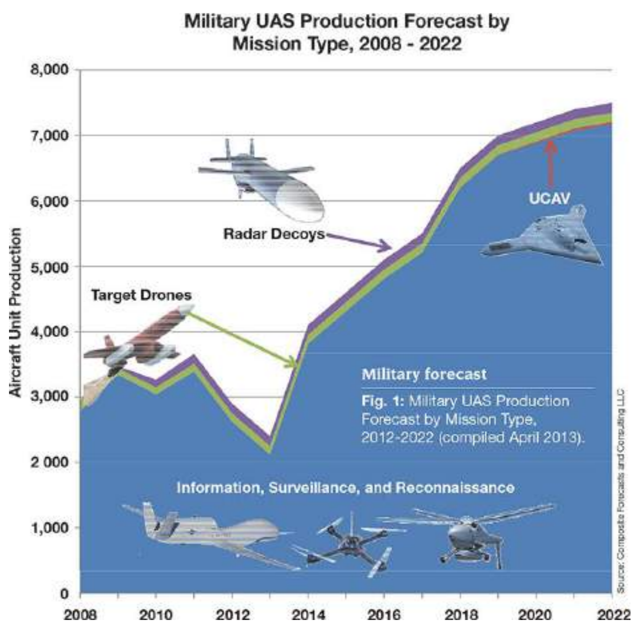
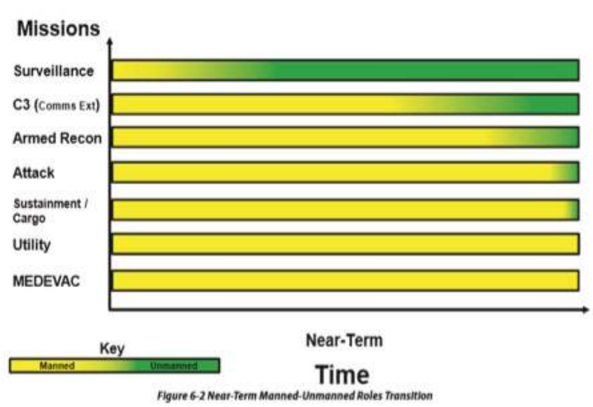
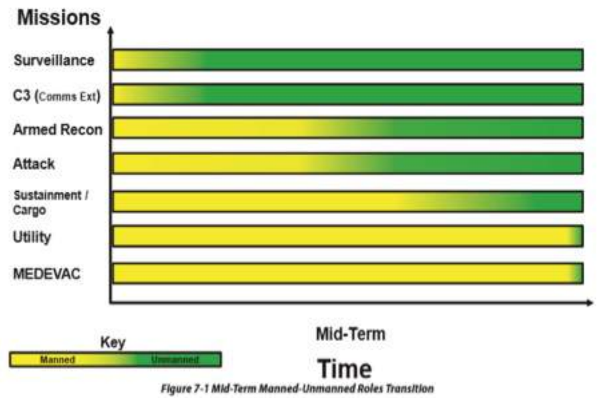


Figure 1: Military UAS Forecast (Red, 2013)

Figure 2, from the U.S. Army Unmanned Systems Roadmap (2010), gives a notional visualization for the U.S. Army's goal of shifting various mission types from manned to unmanned operations. As Figure 2(a) shows, of the seven mission types listed in the roadmap, currently only surveillance missions are predominantly unmanned, with limited unmanned capability in communications missions. These capabilities are supported by current UAS platforms such as the RQ-11 Raven and RQ-7 Shadow. The mid-term (2016-2025) projections show a large increase in the number of comms and weaponized unmanned operations, and through 2035 (far-term) all missions except utility and MEDEVAC are expected to be predominantly unmanned.



(a)



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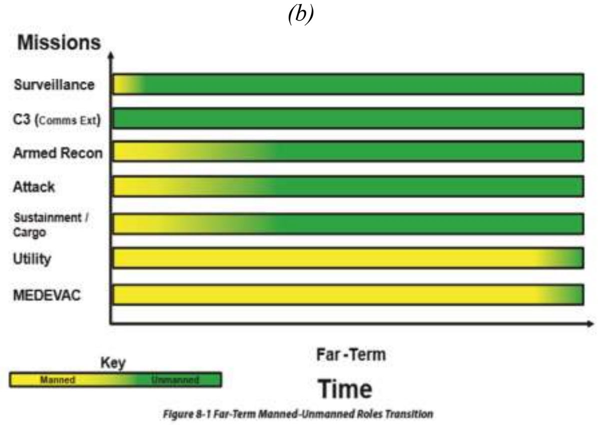


(c)

Figure 2: Transition from Manned to Unmanned Operations. (a) Near-Term, 2010-2015, (b) Mid-Term, 2016-2025, (c) Far-Term, 2026-2035 (U.S. Army, 2010)

The notional forecasts depicted in Figure 2 pose several questions regarding the training methods for UAV/UGV operators. The U.S. Army Training and Doctrine Command (TRADOC) expressed the belief that advances in AI could lead to increasingly autonomous systems used by the U.S. Army. In fact, the 2014 pamphlet goes on to say, “Artificial intelligence may allow robots and automated systems to act with increased autonomy. Robotics will enable the future force by making forces more effective across wider areas, contributing to force protection, and providing increased capabilities to maintain overmatch” (U.S. Army, 2014a, p. 40). In particular, when transitioning weaponized operations from manned to unmanned systems, the operator(s) should fully understand the autonomous capabilities of the vehicle being used and understand how/when to intervene in novel situations. This more advanced knowledge should be obtained during training, but currently the training paradigms in the U.S. Army focus mainly on skill and rule-based tasks introduced in a classroom environment and reinforced with weeks of routine simulator and live flight training tasks, such as hands-on maneuvers and verifying checklists.

This training structure for UAV/UGV operators must change as these vehicles become increasingly autonomous and control demands transfer from hands-on control to intermittent supervisory control. The ability for Soldiers to operate both UAVs and UGVs in uncertain and dynamic (both spatially and temporally) environments is crucial, particularly to prepare for novel situations where skill-based training alone might not suffice. Instead, UAV/UGV operators in the future must rely on higher-order cognitive abilities that are attained only from specific training protocols, such as training for automation intervention, or On-the-Job Training (OJT). However, instead of delaying this important learning component by relying on the Soldier to learn from errors made and corrected in the field during OJT, initial operator training should address the higher cognitive requirements that operators of increasingly autonomous systems must have. These abilities can help improve human-robot coordination, reduce the risk of accidents, and increase training efficiency and effectiveness by decreasing the number of errors made by trainees during Simulator and Live Flight training segments.

Currently, the U.S. Army does not have a method for measuring UAV/UGV training effectiveness or projecting training requirements based on the level of autonomy onboard UAVs/UGVs. The key focus of this work is to develop a training projection that links training requirements to human behaviors using a modeling technique known as system dynamics modeling. Specifically, this report focuses on the RQ-7 Shadow UAS due to its wide-use for U.S. Army unmanned missions, as well its projected use in the future. A core training model structure has been designed and tested for the RQ-7 Shadow using data provided by the Unmanned Aircraft Systems Training Battalion (UASTB) at Fort Huachuca, Arizona. The output from the model falls within 5% of the average Unmanned Aircraft Systems Operator (15W) Soldier throughput of 405 Soldiers when considering just current tasks and educational objectives. Ongoing work involves incorporating the skill, rules, and knowledge-based behaviors into the model, as well as increasing autonomy. Once a validated model for the RQ-7 Shadow UAV has been tested, with the human behaviors implemented, a model of similar structure will be completed for UGVs. The similarity between these models will assist in forming a generalized framework for all US in the United States Army.

Background

Training Emphasis for Increasing Automation

The need for alterations to training methods for operators of automated systems/agents due to increasing levels of automation has also been an important research field for several years (Spettell & Liebert, 1986). Liu (1997) argued that by focusing on more knowledge-based (top-down) training versus skill-based (bottom-up) training, pilots of commercial aircraft will better understand automation capabilities and be able to respond when human intervention is required due to automation failure. Specific problems that Liu found via a combination of observing accident reports and pilot interviews of commercial pilots that were undertrained were automation failure recovery, error detection, anticipating failure modes, and automation complacency, all which potentially could be improved with more knowledge-based training (Liu, 1997). In fact, it was concluded that pilots, or operators, of highly automated aircraft should have *more* training overall due to the increase in the cognitive requirements assigned to the pilot(s), not less. Previous research has highlighted the need for training modifications of pilots/operators specifically as the level of onboard automation on the aircraft increases (Parasuraman et al., 1991; Patrick, 2003; Singh et al., 2009). The introduction of novel automation has the potential to cause confusion, complacency, and an increase in the human footprint with regards to errors made. The risk of each of these potential conundrums occurring can be minimized by refocusing training models from developing hands-on skills to acquiring cognitive abilities.

Skill, Rule, Knowledge Human Behavior Taxonomy

Without linking training requirements to human behaviors and performance, any training model is incomplete. A key component of this work is to determine how to incorporate a human behavior taxonomy with the current training program of UAV/UGV operators to further understand how increasing autonomy affects these behaviors. One well-established model for illustrating human performance is Rasmussen's SRK-taxonomy (Rasmussen, 1983), where the *S*, *R* and *K* refer to skill-, rule- and knowledge-based behaviors, respectively. The classic SRK-taxonomy hierarchy is given in Figure 3. Skill-based behaviors are those that are highly practiced hands-on, psychomotor patterns that occur with little cognitive input required. An example of a skill-based behavior from a UAV operator perspective would be controlling a camera to stay continuously trained on a target. Rule-based behaviors are tasks that require the understanding of stored subroutines and applying the subroutines in a "cookbook" manner (Rasmussen, 1983). An example of a rule-based task from a UAV perspective is following a prescribed checklist prior to takeoff. Highest on the cognitive continuum are knowledge-based behaviors, which are applied in situations where there are few and ambiguous prescribed subroutines (or rules) to follow, and the person/agent must make decisions based on the goal of the task in the presence of uncertainty. The person/agent can apply previously attained skills and/or rules to reach the goal, but there is no specific subroutine of skills that can be applied based on prior experiences. An example of knowledge-based task for a UAV operator would be intervening with an automation failure that they have not seen before.

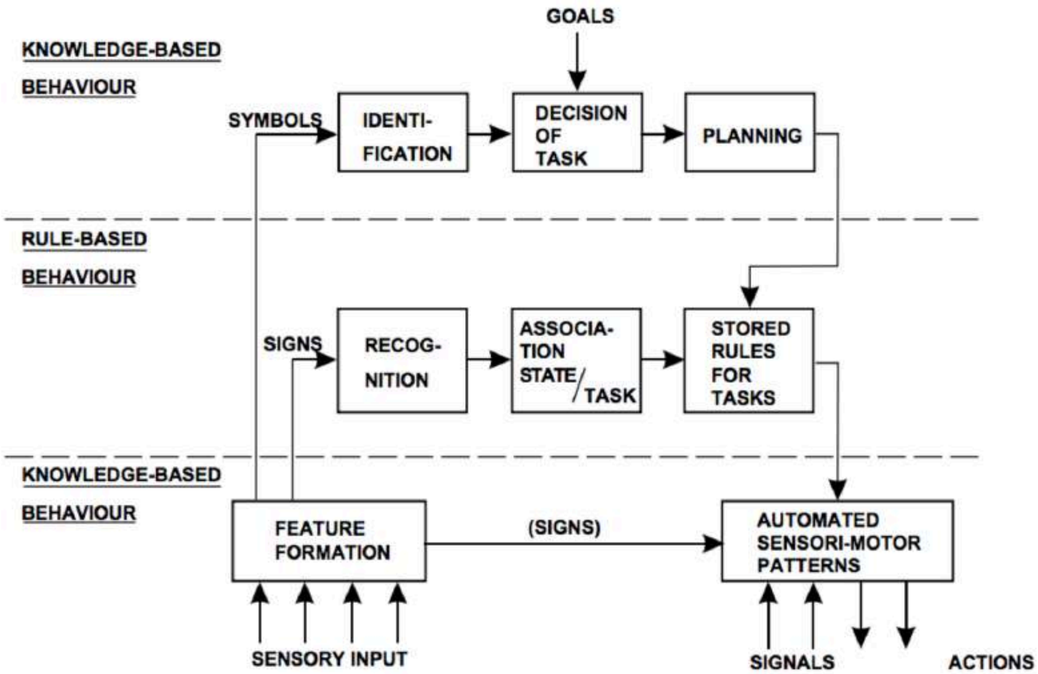


Figure 3: Rasmussen's Skill, Rule, and Knowledge Human-Behavior Taxonomy (Rasmussen, 1983)

Cummings (2014) extended the SRK human performance taxonomy by adding three components. The first new component is the addition of uncertainty (Figure 4). Uncertainty establishes a hierarchy to the taxonomy that places skills at the bottom of the cognitive continuum. The second component is the additional behavioral layer known as expertise-based behaviors, making the extended model the "SRKE" human behavior taxonomy. Expertise-based behaviors are those that are only attained through experiences under high uncertainty, as designated by the placement against the y-axis. The final addition implemented in the SRKE taxonomy is the computers/humans scale along the x-axis. This scale approximates the level at which computers can perform SRKE tasks. It can be seen from Figure 4 that computers/machines are good at accomplishing skill-based tasks and some rule-based tasks. However, they fail when the cognitive continuum reaches knowledge-based reasoning due to computers/machines failing to operate in scenarios where uncertainty is high. In Figure 2, the need to account for uncertainty will increase as unmanned systems begin assuming more complex roles, such as sustainment and cargo. The ongoing work in the model described below will only incorporate skills, rules, and knowledge-based behaviors since expertise can only be obtained while conducting missions with high uncertainty, which occurs primarily in operations and rarely in training environments.

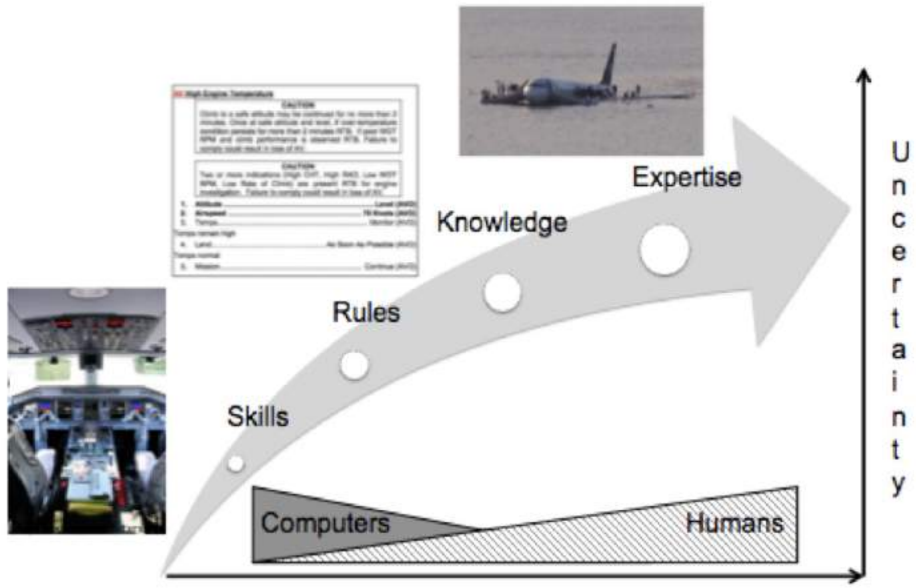


Figure 4: Skill, Rule, Knowledge, and Expertise Human-Behavior Taxonomy (Cummings, 2014)

Model Development

Current RQ-7 Training Program

The RQ-7 Shadow training program that is used today for 15W Soldiers consists of four training segments that each trainee must complete at a satisfactory level. The training segments are as follows: Common Core, Simulator, Live Flight, and Equipment. The model in this report is focused on the first three phases of training, Common Core, Simulator, and Live Flight, due to the discrete tasks that each 15W trainee must complete. Equipment Training will be modeled only as a stock since it is not highlighted as a core component of initial RQ-7 baseline training, and is not broken down into discrete tasks as Common Core, Simulator, and Live Flight Training segments are in TC 3-04.61 (U.S. Army, 2014b). The first segment of RQ-7 training, Common Core, can be thought of as classroom, or lecture-based, training. During Common Core training, Soldiers are trained for 20 weeks, during which they must complete 84 topics at a satisfactory level. Common Core instructional topics include flight restrictions due to exogenous factors, forms of reconnaissance, and tactical airspace coordination.

For Common Core training there are eight classrooms that have a capacity of 20 people/room for RQ-7 training, giving a total capacity of 160 people that can be in Common Core training for the RQ-7 Shadow at any one time. Once trainees have completed the Common Core segment of RQ-7 training, they move into Simulator training. During Simulator training, 15W trainees are exposed to the user interface and controls of the RQ-7 Shadow in a hands-on manner for the first time. The required training time for Simulator training is four weeks, during which the trainees must complete 24 1000-series tasks at a satisfactory level. 1000-series tasks are referred to as base tasks and are those that instruct operators on the "baseline skills, knowledge, and procedures" that are required to operate a specific UAV (U.S. Army, 2014b, p. 2-22). These tasks can vary between UAVs based on aircraft size and mission type. Some examples of these tasks for the RQ-7 include performing system preflight procedures, performing normal takeoff and climb, and tracking a static target. Training tasks are made up of sub-tasks that describe specific requirements that the trainee must complete to progress through training. For example, Task 1048 – *Perform Fuel Management Procedures* is made up of the following four sub-tasks (U.S. Army, 2014b):

1) Verify that the required amount of fuel is onboard at the time of takeoff,
2) Correctly perform an in-flight fuel consumption check after achieving mission altitude and airspeed,
3) Initiate alternate course of action if actual fuel consumption varies from the planning value and the flight cannot be completed with the required reserve, and
4) Monitor fuel quantity and consumption rate during the flight.

The high-level tasks, such as Perform Fuel Management Procedures, vary in complexity with the sub-tasks that are required. The capacity for Simulator training is based on the number of simulators (20) and number of trainees using the simulator at one time (2). Thus the capacity for RQ-7 trainees in the Simulator training segment is 40 at any given time.

The final segment of training that this report focuses on is Live Flight training, which also takes four weeks to complete. During Live Flight training, the 15W trainees perform the same tasks that they were evaluated on in Simulator training but with an actual RQ-7 Shadow UAS. The number of trainees that can be in Live Flight training at one time is limited by the number of runways (2), number of trainees per RQ-7 Shadow (9), and number of RQ-7 Shadows per training group (3). This amounts to a maximum capacity of 54 trainees at any given time in Live Flight training. Once the trainees have met satisfactory requirements for all tasks in each segment of training, they move to equipment training, which takes two weeks. Thus, the total amount of time to finish base training for RQ-7 operators is 30 weeks. This, however, can take longer if errors are made and trainees are forced to repeat tasks, or entire training segments. The capacities and durations listed were provided by the UASTB.

Model Approach

The modeling method that has been chosen to use is known as system dynamics modeling. System dynamics is a causal-loop modeling technique that is made up of stocks/flows and is controlled via embedded equations that are structured based on variables and causal arrows (Forrester, 1961; Sterman, 2000). Figure 5 shows a representation of each modeling component in a simplified system dynamics model for UAS operators progressing from Common Core to Simulator Training. This model contains two stocks, *Shadow Operator Trainees in Common Core Training* and *Shadow Operator Trainees in Simulator Training*, containing the number of personnel currently in the Common Core training segment and the number of personnel currently in the Simulator training segment, a rate that moves personnel that have successfully finished Common Core to Simulator training, and two variables, Common Core Repetitive Error Fraction and Common Core Classroom Capacity, that influence the magnitude of the rate. Common Core Classroom Capacity has a positive influence on the rate and therefore increases the rate of flow from Common Core to Simulator training as the classroom size increases, while Common Core Repetitive Error Fraction has a negative influence on the rate as the number of repetitive errors made by trainees in Common Core increase. It is important to note that the units for the stocks *must* be identical since items are simply being moved from one stock to the next at some rate (in this case the units for the stocks are numbers of people). The rate is the stock unit per time (people/unit of time) and the variables can have any units, as long as they mathematically reduce to the rate units in the embedded equations.

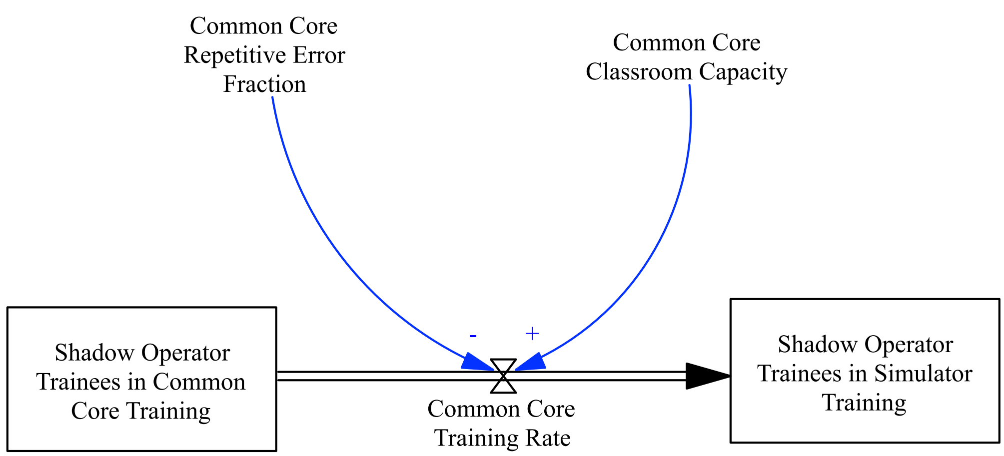


Figure 5: System Dynamics Structure of UAS Operators Progressing from Common Core to Simulator Training

System dynamics models are often used to solve complex problems where non-linear behavior is present. The technique has been used for a wide array of applications, including human performance modeling for scheduling unmanned vehicles (Clare, 2013), project management (Lyneis & Ford, 2007), and product development (Ford & Sterman, 1998). The structure of the baseline model for the RQ-7 Shadow training incorporates facets from each of these three applications. Clare (2013) used system dynamics to model human performance and behavior under various workload levels for a simulated, multi-UAS environment. Modeling human behavior is extremely challenging due to the unpredictable and stochastic nature of human decision-making, but Clare's work demonstrated that it is possible to model human performance with some accuracy. This is crucial for the ASTM, as the only way for trainees to proceed through the training curriculum is to perform at satisfactory levels for each task required in all training segments. Therefore, the number of errors made by trainees at each training segment should be tracked and the rates at which trainees make errors should be modeled as a function of autonomy.

Previous work that uses system dynamics to model human performance and behavior only incorporates training as a single variable (e.g. Akkermans & Van Oorschot, 2005; Block & Pickl, 2014). Jiang, Karwowski, & Ahram (2012) observed how personality affects training using a simple, two-stock system dynamics model, but also categorized training as a single variable ("Training Program"). This modeling effort is different in that a specific training program, the RQ-7 Shadow, will be broken down into discrete segments that will be linked to the SRK human behavior framework. To this end, the ASTM will have two main sections. The first section will model trainees moving through the core structure of the model. This section will have people as the stock variables and will focus on the time of training, the errors trainees make, trainee attrition, and training capacities. The second section will model the SRK in terms of tasks that each trainee is required to complete during each segment of training. After the RQ-7-specific model has been validated with multiple data sets from the United States Army, a UGV model will be constructed that will contain a similar core structure. A general ASTM will then be designed using the validated UAS and UGV models. This general ASTM framework will have many of the same core components as the RQ-7-specific and UGV models and will be adaptable to any autonomous system training program in the United States Army.

Core Structure

The ASTM is structured around a core component that represents the flow of 15W trainees moving through the various training segments. Figure 6 shows the simplified core structure without the balancing loops and variables that control the flow rates.

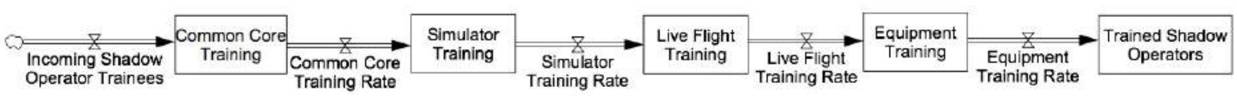


Figure 6: Core Structure of the System Dynamics Model

The core structure begins with an incoming shadow operator training flow that moves 15W trainees into *Common Core Training*. Trainees are then left in the *Common Core Training* stock until the duration of Common Core training is over. Those that complete Common Core training at a satisfactory level move then into *Simulator Training* where they spend four weeks. After simulator training they move to *Live Flight Training* where the same tasks that were performed in the simulator are completed with live flight of the RQ-7 Shadow. This segment also requires, on average, four weeks to complete. Trainees then progress to two weeks of *Equipment Training*. After this final initial RQ-7 Shadow training segment, 15W Soldiers then progress to unit training where mission specifics are learned (this is where the boundary for this model is drawn). The baseline RQ-7 full system dynamics training model, shown in Figure 7, is broken down into two sections, one that contains six components of initial 15W training and the other that consists of the four SRK components. The personnel training portion of the model focuses on Common Core Training, Simulator Training, and Live Flight Training. Equipment Training and Progression to Unit Training are outside of the scope of the current study, as addressed previously. During Unit Training, the 15W trainees are trained on 2000-series tasks, which are mission specific. The model in this paper is only addressing initial training, which ends after 1000-series tasks have been completed. The model is initiated by the incoming flow of 15W trainees (*Incoming Shadow Operator Trainees)* after the preceding class has finished Common Core training. The SRK section of the RQ-7 baseline model will fill stocks of skills-, rules-, and knowledge-based tasks that the operator must complete before completing initial training. The SRK requirements will change with the capabilities, or level of autonomy, onboard the aircraft.

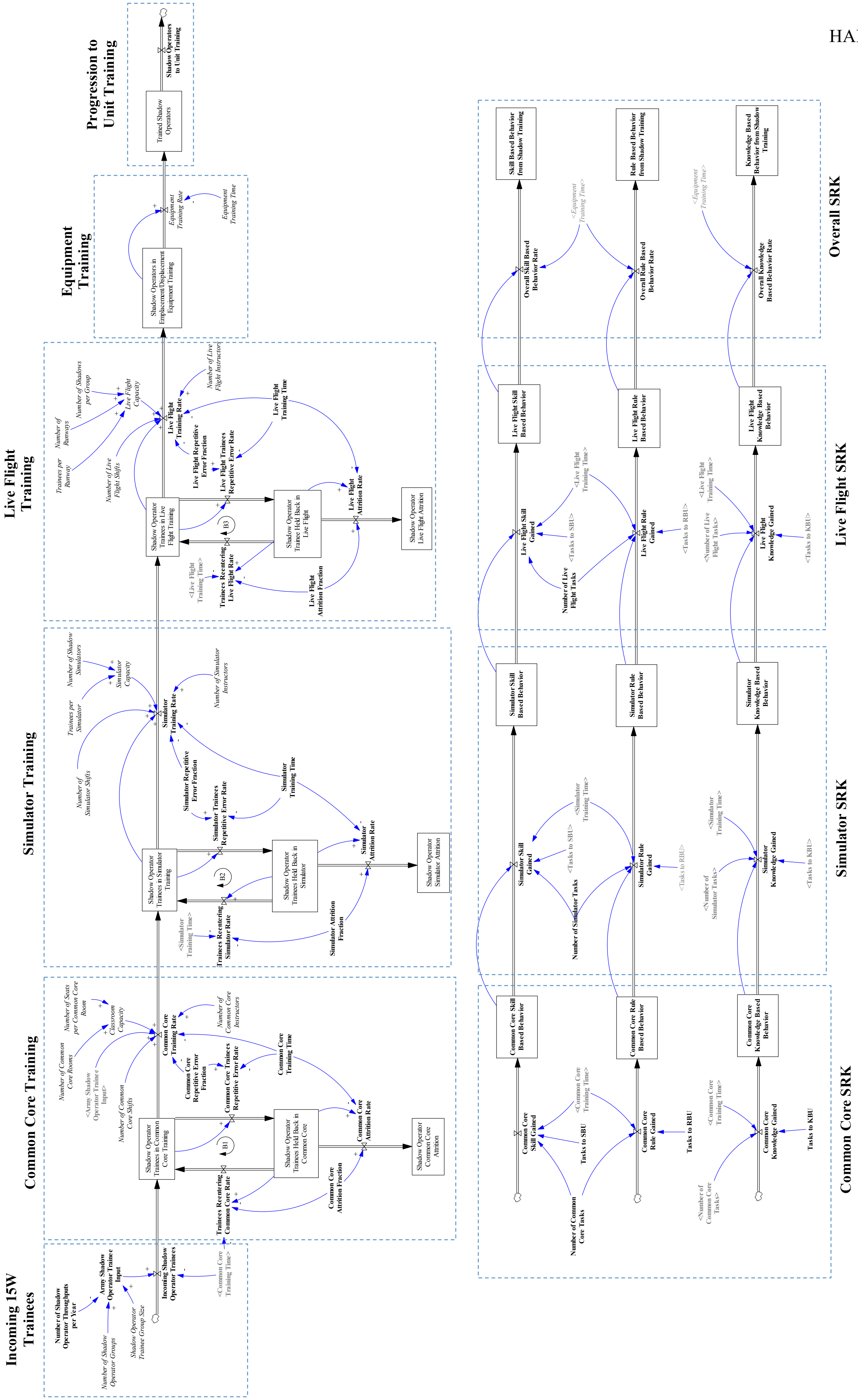


Figure 7: Baseline RQ-7 Training Model

Figure 8 shows this segment of the RQ-7 Shadow baseline training model. This portion controls the initial flow of the model by taking an input of 15W trainees (*Incoming Shadow Operator Trainees)* and moving them into *Shadow Operator Trainees in Common Core Training*. Once the trainees are moved into Common Core training, they are held there for the required Common Core duration. The variables in the training portion of the model are classified into two groups: 1) Those variables that are set by the physical buildings at the UASTB at Fort Huachuca or policy/external decision makers are in italics and will not be altered by increasing autonomy (i.e. they have a fixed value), or 2) Variables that can potentially be influenced by increasing autonomy are bold and will be linked to the four SRK components at the bottom of Figure 7. Examples of variables that could be influenced by increasing autonomy are trainee error rates, number of shadow operators being trained, attrition rates, and training times at each of the training segments. The connection of SRK components of the model across Common Core, Simulator, and Live Flight training will address the notion of increasing autonomy by categorizing tasks into S, R, or K behaviors and determining how these behaviors shift across the SRK cognitive continuum.

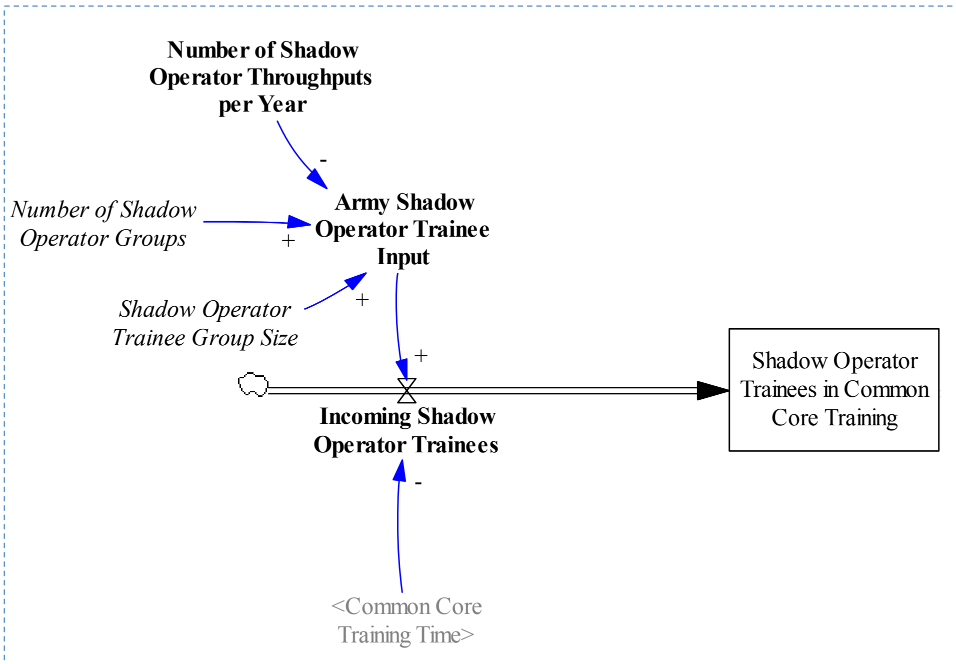
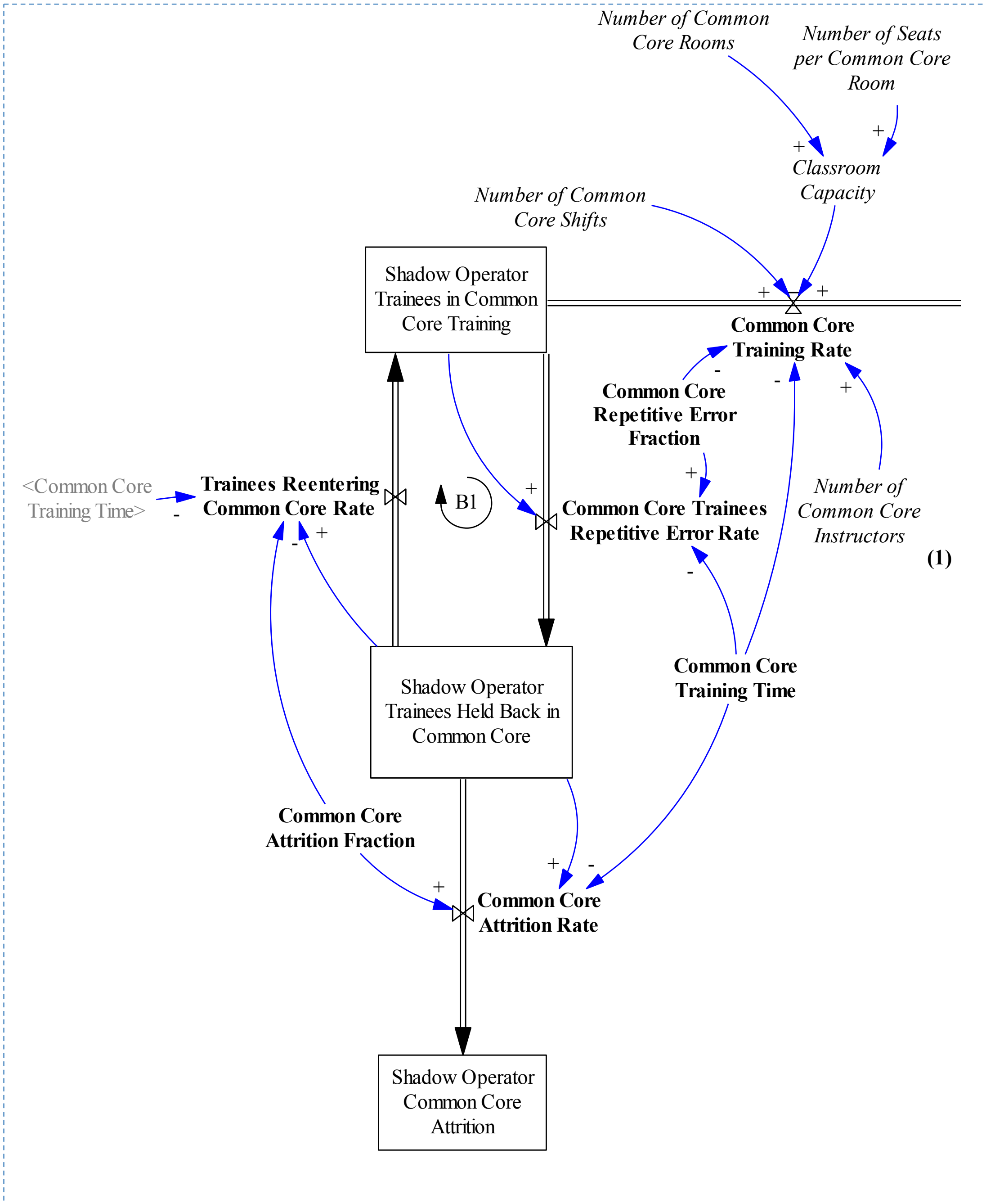


Figure 8: Incoming 15W Trainees

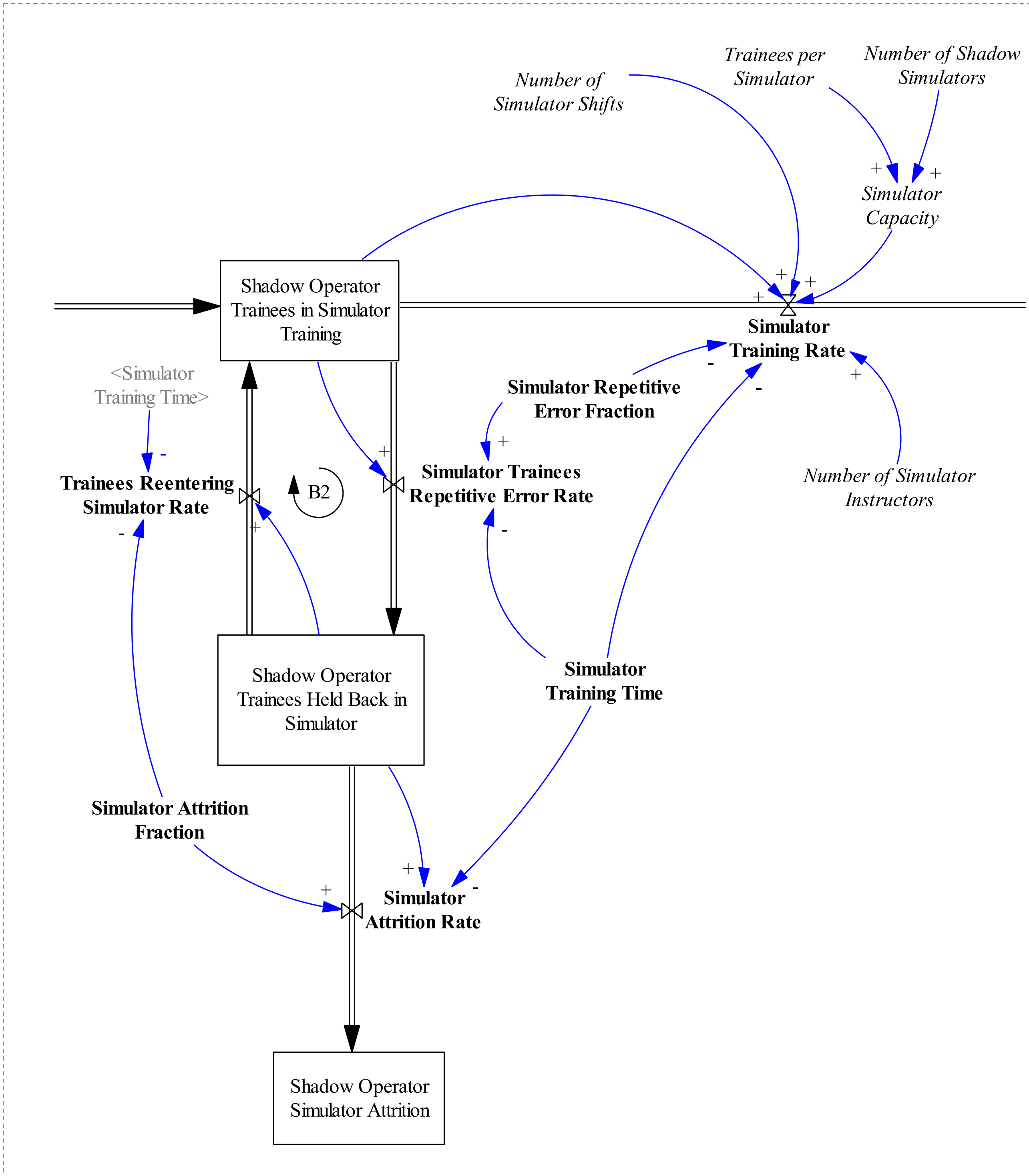
Training Segments

The three main training segments of the baseline RQ-7 training model are shown in Figure 9. The structure of each of the three segments is very similar, with the main portions of the segments represented by a stock for personnel, personnel who make errors, personnel who attrite due to errors, and exogenous capacity variables (e.g. Number of Seats per Classroom, Number of Common Core Instructors, Number of Common Core Shifts, etc.) that drive the flow rates between the training segments. Figure 9(a) shows the portion of the model that simulates Common Core training. There are two ways for 15W trainees to leave the Common Core training stock. The first is to complete Common Core training and progress to Simulator training, which is controlled by the flow that exits the right side of the stock, as indicated by (1) in Figure 9(a). The other output method is for those trainees who commit excessive errors and are not permitted to continue to Simulator training. While this percentage of trainees is low, it is vital to model since modifications of training could increase or decrease this rate. Once in the *Shadow Operator Trainees Held Back in Common Core* stock, 15W trainees either attrite or cycle back into Common Core training for retraining with the proceeding class. The cyclic process creates what is known in system dynamics modeling as a *balancing loop*. Balancing loops decrease or hinder the flow throughout the main core of the model.

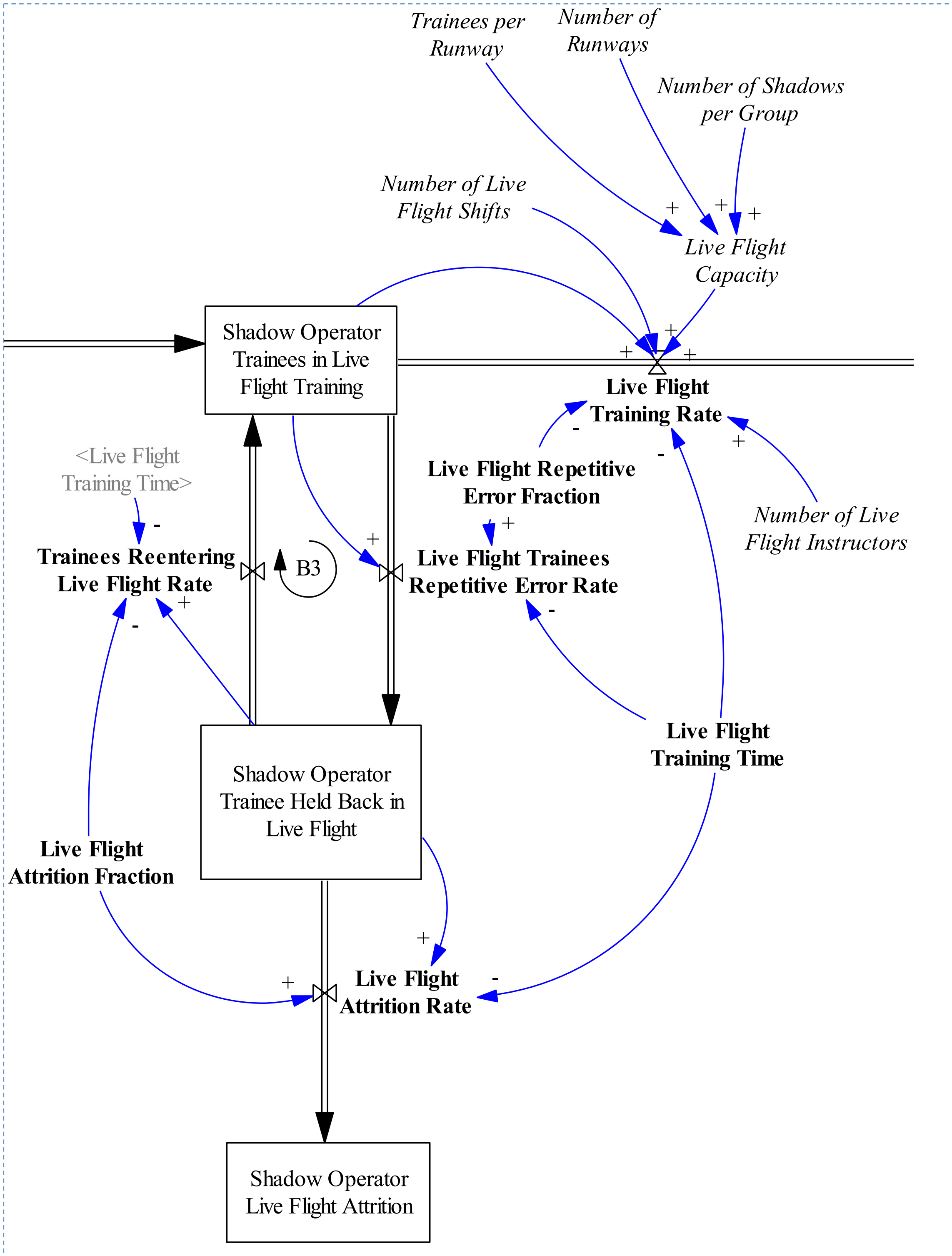
The flow rates between all of the stocks are controlled by the length of time that the 15W trainees are required to spend in that training segment, the capacities for each training segment (classroom size, number of simulators, number of systems available for live flight training, etc.), and the error rates. Each of the flow rate variables contain pulse functions that take each of the capacity variables and permit only the flow from one training segment to the next by using the minimum capacity. The errors that are made by 15W trainees are driven by an error rate multiplied by the number of people in that particular training segment. The error rates that are in the RQ-7 baseline training model are percentages (5%) that were acquired from personnel at the UASTB at Fort Huachuca, Arizona. As the model develops for increasing autonomy, the error rates will become functions of autonomy and SRK. This method of moving trainees through the model is continued for each of the three segments of training using a similar framework.



(a)


Number of Simulator Shifts
Trainees per Simulator
Number of Shadow Simulators
Simulator Capacity
Shadow Operator Trainees in Simulator Training
Simulator Training Rate
<Simulator Training Time>
Simulator Repetitive Error Fraction
Trainees Reentering Simulator Rate
B2
Simulator Trainees Repetitive Error Rate
Number of Simulator Instructors
Shadow Operator Trainees Held Back in Simulator
Simulator Training Time
Simulator Attrition Fraction
Simulator Attrition Rate
Shadow Operator Simulator Attrition

(b)



(c)

Figure 9: Training Segments of the Model for (a) Common Core (b) Simulator (c) Live Flight

Model Output

The baseline model shown in Figure 6 for the RQ-7 Shadow will currently output the results seen in Figure 10. The model is validated using a 52-week cycle, representing one year of training classes. The model can be run beyond 52 weeks (e.g., 60 weeks in Figure 10); however, the present version of the model is intended only to represent one fiscal year. Therefore, the number of trained Shadow operators at 52 weeks is used for model validation. As can be seen from Figure 10, the baseline model outputs 397 trained Shadow operators after one year. The true value for FY 2014 was 405 Shadow operators, as reported by UASTB. This accuracy (>95%) validates the basic models' output (trained RQ-7 operator throughput) for the FY 2014 baseline case. We highlight that this is the basic model since it only looks at capacities and temporal constraints, and in Figure 10, does not yet have a link to autonomy and its impact on training.

The jumps in the model at ~30 weeks and ~50 weeks represent instances where classrooms of Soldiers are completing training. This biannual training completion will be further verified with UASTB as a part of the ongoing work. However, the flexibility of the system dynamics structure permits for adjustments of rates of training progression if more than two classes complete 15W training per year. The reasoning behind the non-linear increases at the ~30 and ~50 week marks are due to two factors: (1) Simulator and Live Flight capacities limiting the number of trainees going through training at one time and (2) a small percentage of the 15W trainees making errors at one or more of the three training segments (~3-5% as stated by UASTB). If capacities and errors were not a factor in training, the trends would be a step function with the Trained Shadow Operator number matching that of the *Incoming Shadow Operator Trainees* flow at the start of the model. However, we know that these two variables are critical in the RQ-7 training paradigm and must be modeled as such. The results show that the current system dynamics model baseline is representative of present-day training throughput and therefore a suitable platform for representing future changes to the training curriculum.

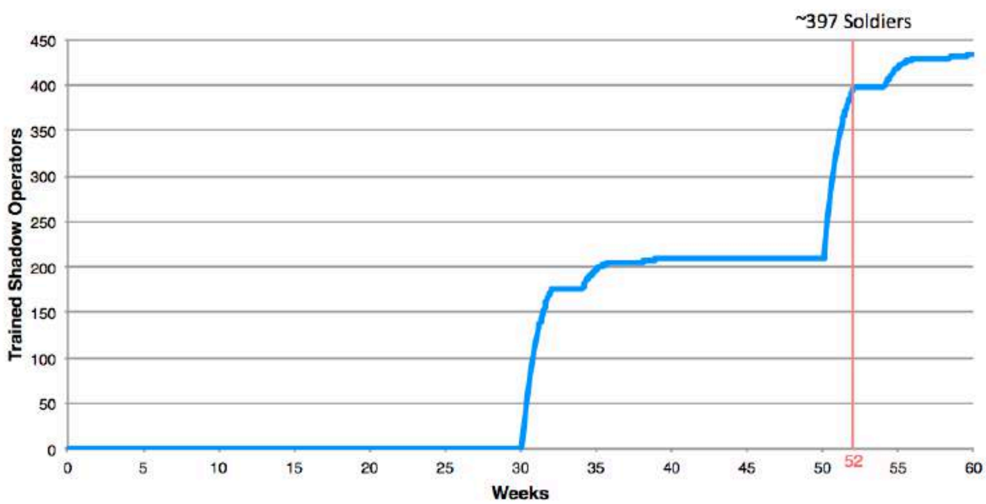


Figure 10: Current Model Output for FY 2014

Ongoing Work

The next steps are to link the layers of cognitive reasoning (skill, rule, and knowledge-based reasoning) into the baseline training portion of the model, along with representations of increasing autonomy. To this end, the SRK framework will be linked into the baseline model through the individual tasks that are instructed during each segment of training for the RQ-7 Shadow. Each of the tasks have been categorized, based on descriptions and current RQ-7 autonomous capabilities, as skills, rules, or knowledge-based, or as a combination of multiple behaviors. How these tasks are categorized will change as the autonomy "dial" is turned to represent increasing autonomy. However, before the autonomy "dial" can be implemented into the ASTM, the baseline RQ-7 model tasks should all be categorized and modeled to determine how the current SRK task breakdown can be structured. As an example of how these tasks are broken down into the SRK-based tasks, take Task 1048 – *Perform Fuel Management Procedures*, which was discussed previously in the *Current RQ-7 Training Program* sub-section. Table 1 gives a breakdown of Task 1048 with the sub-tasks categorized into SRK.

Table 1: Task 1048 – Perform Fuel Management Procedures SRK Sub-task Categorization (U.S. Army, 2014b)

Sub-Task	Skill	Rule	Knowledge
Verify that the required amount of fuel is onboard at the time of takeoff		✓	
Correctly perform an in-flight fuel consumption check after achieving mission altitude and airspeed	✓	✓	
Initiate alternate course of action if actual fuel consumption varies from the planning value and the flight cannot be completed with the required reserve		✓	✓
Monitor fuel quantity and consumption rate during the flight	✓		

The sub-tasks in Table 1 were categorized based on the descriptions of each sub-task from TC 3-04.61 (U.S. Army, 2014b). Sub-task 1, *Verify that the required amount of fuel is onboard at the time of takeoff*, was categorized as a rule-based task since there is not physical interaction with the UAS and the operator is only following a checklist. The second sub-task, *Correctly perform an in-flight fuel consumption check after achieving mission altitude and airspeed*, was categorized as both a skill- and rule-based task. This sub-task was grouped as such since the operator must physically interact with the UAS and follow a checklist. Sub-task 3, *Initiate alternate course of action if actual fuel consumption varies from the planning value and the flight cannot be completed with the required reserve*, was categorized as a rule- and knowledge-based task. The rule categorization is due to the operator continuously referring to a checklist for fuel monitoring, and the knowledge categorization refers to the operators being required to re-plan due to unpredicted shortage of fuel. Finally, sub-task 4, *Monitor fuel quantity and consumption rate during the flight*, was categorized as a skill-based task since monitoring is a physical interaction with the system.

Currently, most of the tasks throughout the RQ-7 Shadow training program are either skill or rule-based due to many of the tasks being hands-on or a manner of following discrete steps. However, as the level of autonomy onboard the RQ-7 Shadow increases, tasks related to the increasing autonomy that are taught in both the Simulator and Live Flight segments of initial training should be instructed in such a manner that the 15W trainees gain a greater understanding as to when to intervene when the system requires operator input and how to fly missions in uncertain environments (i.e., rule and knowledge-based training). This shift in how the tasks in the Simulator and Live Flight are trained can have multiple implications to trainee throughput, i.e., (1) skill-based tasks and some rule-based tasks that are not necessary for operators to be proficient at due to increasing autonomy could be eliminated from training or (2) tasks that were once skill or rule-based that become rule and knowledge-based tasks could require much more training. Figure 11 illustrates the second of these two competing hypotheses. The progression throughout the training model is based on how rapidly trainees can perform the required tasks at a satisfactory level. It is expected that the number of simulator and live flight knowledge-based tasks will grow as autonomy increases and the skill and rule-based tasks are shifted over to knowledge-based tasks.

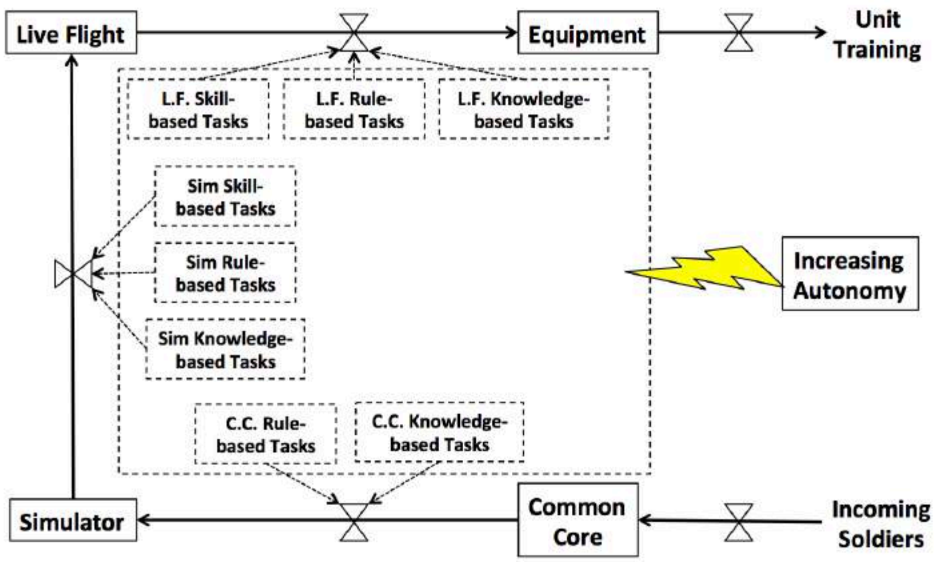


Figure 11: Skill, Rule, and Knowledge Tasks Influence on RQ-7 Training Progression

Figure 12 shows one of the four SRK portions of the full ASTM in Figure 7. The structure of the four SRK portions emulate that of the personnel in training portion in that each of the three training segments, Common Core, Simulator, and Live Flight, all have their own SRK stocks. The variables that affect the flows into the SRK-Based Behavior stocks are influenced by the number of tasks in each segment of training, the training time for each segment, and what percentage of tasks are either skill-, rule-, or knowledge-based behaviors. The structure across the Simulator and Live Flight segments of the SRK portion of the ASTM is similar to that of the Common Core shown in Figure 12.

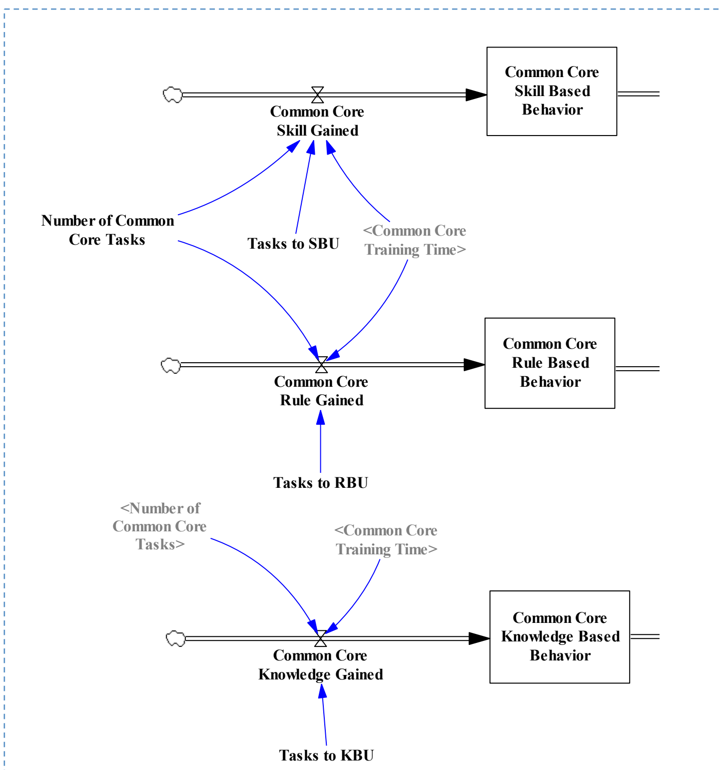


Figure 12: Common Core Training Breakdown to SRK-based Tasks

Historical Validation

Beyond analyzing current RQ-7 training tasks, a review of the influence of existing technologies/autonomy on pilot performance in both commercial and military aviation is also being conducted. Since the overall goal of this work is to formulate a general model for how increasing levels of autonomy will influence UAS/UGV training, it is useful to survey what technologies *have* been implemented in the cockpit, as well as what changes those implementations had on the training program at that time. Changes that we are interested in from former training modifications are overall training time, tasks taught in training, numbers of errors made by trainees, and trainee attrition rates.

Our initial work in this area is looking at RQ-7 training in its early years and identifying what SRK behaviors were formally trained at that time, as well as the length of the training program. Using this historical data will allow us to validate many core assumptions of the model. In addition, we are examining cockpit/air traffic control (ATC) technologies since 1970, (Table 2). In addition to the technologies and dates of implementation (labeled "Start Year"), a proposed breakdown of how the pilot and/or air traffic controllers' tasks were altered from an SRK human behavior point-of-view is presented. The *Pre-Implementation Task* column lists the tasks that could have been affected by the implementation of each technology and the *Post-Implementation Task* column lists the proposals for *how* each of the technologies affected the required SRK-based reasoning for the pilot or air traffic controller. For example, the implementation of the electronic checklist could influence the pilots' rule and knowledge-based reasoning requirements through the automation of select procedures and from the conversion from paper to digital displays. We hypothesize that with the implementation of this technology in 1996, commercial aviation pilots needed less rule-based training and more knowledge-based training due to the checklist being moved from paper to computers with additional automation assisting the pilot(s). Finally, a column of the hypothesized change in overall pilot/air traffic controller training time is given. These hypotheses are taken from the pre and post-implementation of the technologies' effects on the pilot/air traffic controller tasks. An example from the change in training time column is the introduction of simulators in 1970. While simulators did allow for better training, they did increase the training time since they introduced an additional training component.

Table 2: Overview of Cockpit Technologies and Influence on SRK Tasks (↓ means decrease in S, R, or K and ↑ means increase in S, R, or K)

Technology	Year	S	R	K	Hypothesized Change in Training Time	Hypothesized Change in Trainee Errors
Simulators	1970	-	-	-	Increase	Increase
Glass Cockpit	1979	↓	↓		Decrease	Decrease
Flight Management System	1981	↓	↓		Decrease	Increase
GPS	1983	↓	↓		Decrease	Decrease
Fly-by-Wire	1987	↓	↓	↑	Decrease	Increase
Electronic Checklist	1996		↓	↑	No Change	No Change
Advanced Weather Interactive Processing System	1998		↓	↓	Decrease	No Change
Digital Airport Surveillance Radar	1999	↓			Decrease	Decrease
Standard Terminal Automation Replacement System	1999-2020	↓			Decrease	Decrease
Airport Surface Detection Equipment, X	2007		↓	↓	Decrease	Decrease
En Route Automation Modernization	2008-2015	↓	↓	↓	No Change	Decrease
System Wide Information Management System	2009-2017	↓	↓		No Change	Decrease
Terminal Automation Modernization and Replacement	2010-2020	↓		↓	Decrease	Decrease
Traffic Flow Management System	2011-2014	↓	↓		Decrease	Decrease
DataComm/NexComm	2012	↓	↓	↓	Decrease	Decrease
National Airspace Voice System	2014	↓	↓		Decrease	Decrease
ADS-B	2014-2018			↓	Decrease	Decrease

The next steps will involve investigating the trends in training time for commercial and military pilots and air traffic controllers since 1970 as a function of increasing automation and interviewing personnel from both the commercial and military sectors to determine if the hypotheses given in Table 2 are accurate., These results will help provide data for validating the SRK component of the ASTM, particularly as they relate to determining rate functions that represent how increasing autonomy affects training time across various skill, rule, and knowledge-based behaviors.

Currently, the overall model stands as two isolated models, but work is currently being done to link the SRK and personnel training portions with an autonomy variable that can thought of as a dial. The autonomy "dial" will influence the tasks that are categorized in the SRK portions that trainees should learn during initial RQ-7 training. The challenge with modeling SRK in a system dynamics structure is that SRK-based behaviors are typically qualitative, but should be used as quantitative variables/stocks. To do this, rate functions are going to be developed for two purposes: 1) To link skill-, rules-, and knowledge-based behaviors that are learned at the three segments of training and 2) To model how the values of the SRK stocks shift with increasing autonomy.

There are several implications of the ASTM for United States Army training operations. One such usage of this model is to analyze and project how much time is required in the various training segments. This can be accomplished by looking at past models that have been validated with actual United States Army data and projecting how new and developing technologies will impact the future of training for that particular UAS or UGV. The benefit of moving to a generalized model for increasingly autonomous systems is that it can be easily adapted to many different platforms. A generalized model will also provide insight into how operator trainee errors can be minimized. By modeling the error rates of trainees based on past fiscal year trainee throughputs, trainers will have the ability to forecast what errors are likely to occur based on past trends from technologies that require tasks with a similar SRK-based task breakdown. The transitions between SRK-based tasks are also fundamental. For example, a technology that required more knowledge-based tasks and less skill-based tasks will provide insight into future technologies that might require a similar transition. The RQ-7 Shadow model will continue to be used as the baseline model but will assist in constructing a UGV model that is expected to have many similarities in both structure and logic. These similarities will establish the basis for a generalized modeling framework for training of future operators of increasingly autonomous systems in the United States Army.

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