Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
April 29, 2021
A Regional Conference of the Society for Industrial and Systems Engineering

Roadmap to Implement Artificial Intelligence in Course of Action Development & Effect of Weather Variables on UH-60 Performance

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Author Note: Cadet Hough, Cadet Hunter, Cadet O'Donnell, Cadet Patterson and Cadet Wilt are seniors at the United States Military Academy (USMA) participating in a year-long capstone under the direction of COL (R) Parrish and LTC Schreiner. They will commission on 22 May 2021 into Air Defense Artillery (Hough) and Field Artillery (Hunter, O'Donnell, Patterson, Wilt). The client for this project is the Naval Innovative Science and Engineering (NISE), with the main point of contact being the Mr. Phil Bond.

Abstract: US military aviator leaders are forced to make challenging tactical decisions with limited intelligence. Our capstone team created a roadmap for AI technology that can assist aviators in making sound tactical decisions. This study explores human limitations and why an AI system would be beneficial, and concepts necessary to implement the technology such as Multi-Layer Neural Networks (MLNN), Multi-Agent Reinforcement Learning (MARL), Stochastic Model, and AI teaming. Specifically, it investigates how the use of multi-layer neural networks along with multi-agent reinforcement learning will provide the optimal path for Course of Action (CoA) success. This roadmap includes a Design of Experiment which will aid in the development of a stochastic environment that assists aviators in CoA development for flying the UH-60 Blackhawk and this will serve as a foundation into further artificial intelligence implementation into military tactical decision making.

Keywords: Artificial Intelligence, Multi-Neural Networks, Multi-Agent Reinforcement Learning, AI Teaming, UH-60 Black Hawk.

1. Introduction

Our team explored *how to use artificial intelligence (AI) to develop viable courses of action for commanders on the battlefield.* Humans, when under the immense stress and time constraints present in the military environment, are often substandard decision makers who fall into the Type 1 category of decision making. That is, decision making associated with one's primal brain and the intuitive, quick, and heuristic-based formulation patterns biological to humans. (Van den Bosch & Bronkhorst, 2018). Generally, when people are faced with difficult questions, they formulate the problem into a simple one where the answer is easily available (Van den Bosch & Bronkhorst, 2018). This is an issue in military decision-making because commanders are constantly presented with extremely complex problems and are expected to make timely and effective decisions under severe duress. This study utilizes system engineering principles to develop a framework for the implementation of an AI system that assists military decision makers.

The Army Futures Command activated the Artificial Intelligence Task Force in 2019 and one of their mission sets is to develop Artificial Intelligence and Machine Learning to reduce cognitive burden on humans and improve overall performance through human-machine teaming (Army Futures Command, 2020). Similarly, this AI system will not be replacing the decisions made by the commander, but rather acting as an Intelligent Decision Support System (IDSS) that supports the commander. While the AI system operates in its stochastically modeled environment, it will be making decisions based on reward functions which the commanders will then assess to make informed decision on the battlefield. The most advanced AI framework for CoA development problem is a Multi-Layer Neural Network (MLNN) learning from a Multi-Agent Reinforcement Learning (MARL) algorithm inside a stochastic environment. After determining the framework artificial intelligence systems should use for CoA development, we determined that the best approach to study the effect different weather variables will have on the UH-60 Black Hawk was to conduct a Design of Experiment (DoE) because DoE allows enables us to assess the magnitude of the main effects and the existence of interaction effects between factors in weather variables in order to provide data to build a stochastic model of the environment.

2. AI Implementation in COA Development Roadmap

2.1 AI Background: DeepMind’s AlphaStar

StarCraft II is real-time strategy game that’s long-term popularity boasts a highly competitive community of gamers that serve as an ideal sequential challenge to AI application. Prior to developing AlphaStar, DeepMind had utilized their AI techniques to defeat Grandmasters (highest rank Chess/Go player can achieve globally) in both Chess and Go. StarCraft II in comparison with Chess and Go raises important “game-theoretic challenges: it features a vast space of cyclic, non-transitive strategies and counter-strategies; discovering novel strategies is intractable with naïve self-play exploration methods; and those strategies may not be effective when deploying in real-world play with Humans (Vinyals et al., 2019). To address these challenges, DeepMind’s AlphaStar structured their AI as a “Multi-Agent Reinforcement Learning (MARL) algorithm that uses data from both human and agent games within a diverse league of continually adapting strategies and counterstrategies, each represented by deep neural networks (Vinyals et al., 2019).” Through these AI techniques, DeepMind’s AlphaStar was the first AI able to defeat GrandMasters in StarCraft II.

AlphaStar represents the forefront of AI implementation into complex real-time strategy problems. Many of the same challenges that existed in developing AlphaStar also exist in developing an AI to solve CoA development: non-transitive strategies and counterstrategies; discovering novel strategies; and the ineffective of novel strategies when faced against a dynamic enemy. Based on the capstone team’s literature review research, we conclude that similar implementation of multi-agent reinforcement learning algorithms and deep neural networks is an ideal roadmap for a successful implementation of AI in the COA development space.

2.2 Multi-Agent Reinforcement Learning

RL connects the agent to “its environment via perception and action (Emary 2018),” with action defined by the output value produced from the NN. The output action is then evaluated by its effect on the environment. The system then determines if the outcome was optimal and provides feedback to the NN. Depending on how the RL is defined, the feedback provided can be binary, linear, or a custom feedback function. “The goal is to determine the actions that tend to increase the long-run sum of values” from the feedback signal (Emary 2018). Based on the feedback produced, the weights applied to nodes of the NN will be altered to learn from the feedback.

Multi-Agent Reinforcement Learning (MARL) is applicable to our battlefield problem because each member of the enemy squad, or each squad in a platoon, etc. is autonomous. When operating with autonomous, interacting entities sharing a common environment MARL is a suitable way to address the control authority that is distributed between agents (Busoniu et al., 2008).

2.3 Multi-Layer Neural Network

Neural Network (NN) stems from the studying of neuroscience. When the human brain receives information through the five senses, these senses are coded into electric pulses and decoded by neural nodes as inputs (Molnar et al., 2012). These altered inputs are then sent to the next neuron or multiple neurons to decode (Molnar et al., 2012). Ultimately, the initial sensory input data works its way through the NN, getting altered by each neuron, and when it has completed going through the NN an output is returned.

A MLNN is the way NN scientist simplify and represent the complexity of a NN. The layers are used as an organizational tool to separate and distinguish the logical flow of input/output data from one layer of nodes to the next (Figure 1) .

ISBN: 97819384962-0-2

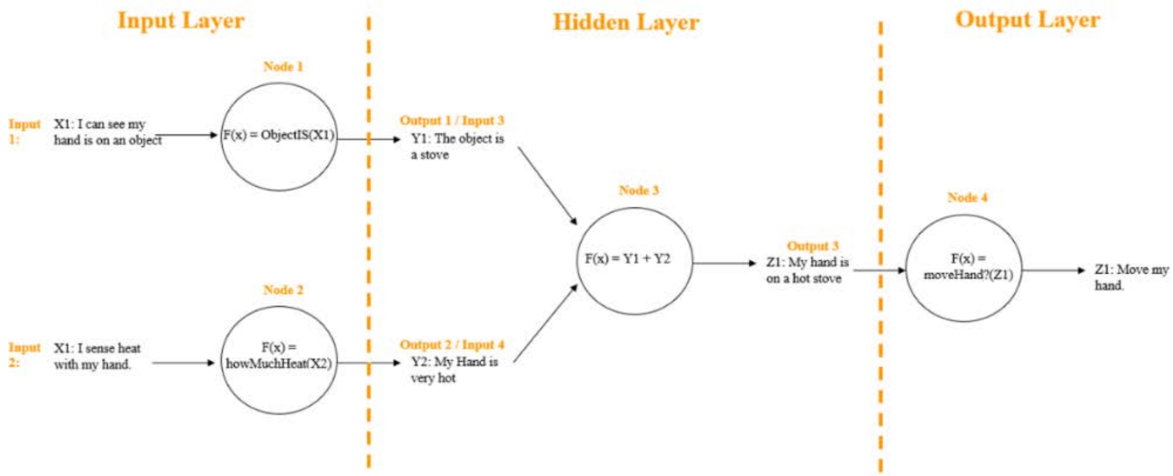

Figure 1. Multi-Layer Neural Network Example

2.4 Stochastic Model

For the NN to produce effective COAs, the environment will need to be accurately modeled. Given the variance that is exhibited in a battlefield environment, a stochastic model of the battlefield is necessary to account for the risks associated with battlefield uncertainty. For example, in a stochastic environment the same execution of a course of action can result in varying rewards to the agent. The degree to which the rewards defer could alter the decision of the NN via the reward function. If the environment were modeled deterministically, the same COA would result in the same reward every time and would not discern between a high-risk COA and a low-risk course of action. Since discerning between the disparity in outcome of a single course of action is needed, our team suggest a stochastic model be used to model the environment.

2.5 AI Teaming

In a perfect world, an AI "should be able to adapt itself dynamically to the decision maker by taking into account his objectives, preferences, and track record (e.g. susceptibility to bias)" (van den Bosch & Bronkhorst, 2018). An Intelligent Decision Support System (IDSS) would provide the ability to counterbalance the heuristics and assumptions which hinder the human decision-making process.

The goal of such a system would be to combine knowledge, such as military aviation tactics, with the ability to propose decisions or diagnose situations. This is accomplished by responding to uncertain situations through functions (intelligent agents) such as intent recognition, machine learning, and data mining that perform the cognitive tasks associated with decision making. In the same breath, a competent AI system needs to be "human aware" with the requirements of "observability, predictability, and (sic) direct-ability" to ensure the credibility of the system and the trust of their human counterparts.

In terms of aviation, the IDSS could potentially identify an unrealized sensitive aviation variable (i.e. vegetation density) due to its superior pattern recognition abilities that has influenced past flight successes (inability to see enemy, LZ, DZ, etc. on the ground) Subsequently, the commander can then make the decision to carry out the planned flight mission given the output, probability of mission success, from the IDSS. Ultimately, the decision made by the commander off of the IDSS would be based on his/her risk profile- whether one is risk tolerant or risk averse.

3. Design of Experiment (DoE)

3.1 Application of Design of Experiment

NN design and implementation for course of action development is many generations away. In recognition of this timeline, the capstone team focused their efforts on contributing data to further research in this area. Mission variables apply to each branch of the army differently. Under this pretense, the capstone team focused their efforts on course of action development within the aviation branch. Specifically, given the assistance of COL (R) Michael Parrish and MAJ Woody (both

Army Aviators), our capstone team decided to advance research in this area by analyzing the effect weather variables have on UH-60 Black Hawk flight performance. Using a MLNN taught through MARL, the data analysis produced by the DoE can be used to build the stochastic environment the NN will operate within by determining the interactions and significance of weather variables on flight performance (measured by mission duration). This will contribute to a portion of the overall architecture needed to create an accurate stochastic model.

3.2 Problem Statement

The purpose this experiment is to utilize the DoE process to conduct a screening experiment to determine the magnitude of the main effects and the existence of interaction effects between factors in weather variables during flight. At the strategic level, if the regression outputted from this design of experiment is significant then this data can be used to aid the stochastic modelers in understanding the effects weather will have on UH-60 Black Hawk and the mission.

3.3 Choice of Factors, Levels, and Half Factorial Design

The five design factors depicted in Table 1 are used as the design factors in this experiment. The effect of the five main effects and their interactions will be found by performing a transformation of variables to create multiple potential regression models.

Table 1. Weather Factors and Their Two-Level Settings

Factors Each With Two Levels (High-Low Setting)				
(A) Visability	(B) Turbulence	(C) Icing	(D) Precipitation	(E) Surface Winds
3 miles or 10 miles	None or Light	None or Light	None or Moderate	None or 30 Knots

In many experiments it is not possible to collect all the data points for a full-factorial. Therefore, it is important to understand the implications, and effects reducing data collections has on the results of an experiment. The 2_V^{5-1} half-factorial method will be used to generate the half-factorial for the aviation design of experiment. A design of experiment with a resolution of V has no main effects aliased with two-factor interactions, but two-factor interactions are aliased with three-factor interactions (Resolution of Experimental Designs). This will give us ample data to analyze and will not have confounded main effects.

To create the half-factorial only the sixteen interactions where ABCDE is equal to one were used. Thus, only one pilot was used in this experiment, and no blocking occurred. Although no blocking occurred, the use of only half the interactions produces aliasing among the results (Table 2). Ideally, the regression slope created from two aliased three-factor interaction would follow the equation ABC ≈ ABC + DE, where DE ≈ 0.

Table 2. Half-Factorial Aliases

Half -Factorial Effect	A	B	C	ABC	D	ABD	ACD	BCD	E	ABE	ACE	ADE	BCE	BDE	CDE	ABCDE
Aliases: Generator = ABCDE	BCDE	ACDE	ABDE	DE	ABCE	CE	BE	AE	ABCD	CD	BD	BC	AD	AC	AB	-1

3.5 Procedure

1. **Replication and Randomization**
    a. The capstone team conducted three replications of each data point.
    b. Each replication was based on the half-factorial design where ABCDE is equal to one.
    c. A random number generator was used to determine the order of each interaction/replication.
2. **Pilot and Observer**
    a. The Pilot for each replication was Cadet O'Donnell to eliminate blocking.
    b. The Observer for each replication was Cadet Wilt.
    c. The Observer was responsible for changing the weather factors on the aviation simulator; and recording the duration.
3. **System and Environment**
    a. The capstone team used the ATN flight simulator.

b. For every iteration, the capstone team used the 'introduction to take off and landing' simulated environment. This was a constant environment through every iteration.

4. Methods

a. CDT O'Donnell spent approximately three hours on the simulator gaining a basic understanding of operations.
b. To start the experiment, CDT Wilt added the weather variables that correspond to the first iteration. In this experiment the first iteration was E, where surface winds were place at 30 knots and the other 4 variables were placed on low setting. CDT Wilt then set the scenario to 'introduction to take off and landing' simulated environment.
c. CDT Wilt started the stopwatch when CDT O'Donnell initiated take off. CDT O'Donnell flew the aircraft threw the predetermined flight path (rise slowly, rise rapidly, and descend slowly).
d. CDT Wilt stopped the stopwatch when CDT O'Donnell landed the aircraft in the landing zone. CDT Wilt recorded the time into the CSV file. CDT O'Donnell and CDT Wilt then repeated these methods b through e for all 48 iterations.
e. CDT O'Donnell uploaded the data into a CSV file and performed a half-factorial linear, square root, inverse, and logistic regression on the data in RStudio.

3.6 Performance of the Experiment

The conduct of this experiment followed the three principles of blocking, randomization, and replication. It followed the procedure outlined in section 3.3. Choice of Experimental Design, with three exceptions. The team collected all 48 points in one three-hour period. All the replicates were piloted by Cadet O'Donnell and the trials were all recorded by Cadet Wilt. During the experiment, virtue reality fatigue played a role into Cadet O'Donnell's piloting performance. There were three irregular trials that Cadet O'Donnell contributed to fatigue and crashed the aircraft. These trials were trial 11 (BCD) where Cadet O'Donnell crashed in the landing zone at 74.14 seconds; trial 14 ADE crash outside landing zone at 89.14 seconds, and trial 17 ABD crash in the landing zone at 52.01. These trials were all rerun by Cadet O'Donnell under the same trial number.

3.7 Linear Regression and Transformation of Variables

Table 3. Linear Regression and Transformation of Variables

	Linear Regressior	P-Value	Square Root	P-Value	Inverse	P-Value	Logistic	P-Value
Intercept	77.047	0.00	8.751	0.00	0.01330	0.00	1.881	0.00
A	0.000	1.00	-0.004	0.97	0.00005	0.86	-0.001	0.94
B	0.187	0.94	0.010	0.94	-0.00004	0.92	0.001	0.94
C	2.713	0.13	0.156	0.12	-0.00049	0.12	0.016	0.12
D	3.077	0.09	0.167	0.10	-0.00044	0.15	0.016	0.11
E	1.192	0.50	0.061	0.54	-0.00012	0.71	0.005	0.59
ABC	0.761	0.66	0.039	0.69	-0.00008	0.80	0.003	0.73
ABD	2.467	0.16	0.136	0.17	-0.00040	0.20	0.013	0.18
ABE	-0.344	0.84	-0.021	0.83	-0.00007	0.82	-0.002	0.82
ACD	2.107	0.55	0.116	0.56	-0.00033	0.59	0.011	0.57
ACE	1.330	0.45	0.081	0.42	-0.00030	0.33	0.009	0.38
ADE	4.689	0.06	0.257	0.07	-0.00070	0.11	0.025	0.08
BCD	0.596	0.73	0.019	0.85	-0.00008	0.80	0.000	0.97
BCE	1.914	0.44	0.108	0.44	-0.00032	0.46	0.011	0.45
BDE	2.369	0.18	0.135	0.18	-0.00042	0.17	0.013	0.18
CDE	2.369	0.20	0.120	0.23	-0.00030	0.33	0.011	0.26
ABCD	NA	NA	NA	NA	NA	NA	NA	NA

For this design of experiment, the capstone team used RStudio to conduct a linear regression on the data. In addition, the team transformed the data set by performing a square root, inverse, and logistic regression. Upon analysis of the P-Values for the linear regression and the transformation of variable, the weather variables and their interactions were all insignificant. Therefore, for this design of experiment, the capstone cannot reject the null-hypothesis and cannot say with significance that these weather variables impact flight performance measure using flight time (Table 3).

3.8 Discussion

The U.S. Army has regulations and standards of procedures that constrains a pilot's ability to fly in adverse weather conditions. The capstone team created their two factor half-factorial analysis based on recommendations that Army Aviators identified as extremas of operation. Since the Army has identified the two factors the capstone team used as operating extremas, the capstone team believes that the insignificance in the dataset, and the inability to reject the null hypothesis is a result of an error in the DoE and suggest that a larger design of experiment is needed. The first possible alibi the capstone team identified is the operator (CDT O'Donnell) had limited experience on the ATN simulator and was not an Army aviator. Another alibi the capstone team identified is the ATN simulator scenarios are not comprehensive enough to provide adequate depth of scenarios and as a result the team was limited to a specific scenario based on CDT O'Donnell's experience. The lack of robust scenarios did not allow the team to incorporate aircraft maneuverability as a possible performance metric because the ATN simulator could not handle changing weather variables on prebuilt scenarios. Lastly, the team acknowledges that a consequence of doing a repeating scenario is the existence of a learning curve. The learning curve and the human fatigue experienced by repeating the same action with no personal risk, consequently influenced the team's dataset. Based on the described failures within the DoE, the capstone team recommends a more in-depth DoE to ensure the null results are accurate. The capstone team recommends using 2nd year test pilots at Fort Rucker and a ATN simulator scenario that specifically test maneuverability of the aircraft to acquire larger data sets from tactically proficient pilots. The scenario should include tactically difficult maneuvers, so that the dataset can accurately assess weathers effect on maneuverability and mission success.

4. Conclusion

Although the design of experiment did not draw any data of significance, it sets the stage for future research and development into integrating a decision-making artificial intelligence system into aviation. The team has made recommendations in terms of AI structure, application, and how it should interact with human users. Implementation of MLNN will require high-level strategic focus. To capture the caliber of decision necessary on the battlefield, the military needs to focus on collecting data for METT-TC variables categorized by mission set. This will allow future NN scientist to construct stochastic models that accurately assess the environments on mission success.

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