On developing the Intelligent Decision Supporting Technologies for Ground Operations

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ABSTRACT

The concept of operations in future battlefields is undergoing a transition toward mosaic and decision-centric warfare. This situation demands an intelligent decision support system that conducts swift and accurate battlefield analysis and command decisions by utilizing artificial intelligence (AI) technologies. Essentially, the construction of an intelligent command and control system requires the integration of specific technologies that facilitate the development of command decision support using AI. Therefore, to assist the decision-making processes for ground operations involving forces, such as infantry and armored forces, we are developing techniques to make the AI-command decision support for ground operations (AICDS-G). This study presents comprehensive concepts and methodologies of AICDS-G. In the AICDS-G system, the Battlefield Digital Twin (BDT) simulates the battlefield scenarios, including ground forces and behaviors of both enemies and allies, and it is employed for realistic battlefield simulation and as an AI learning environment. AICDS-G is comprised of sequential processes that are designed to aid command decisions for ground operations. Initially, enemy threat analysis anticipates their behavior and evaluates the threat using deep learning models, such as a graph neural network. Subsequently, within the learning environment of BDT, models, such as reinforcement learning, are employed to analyze the optimal assignment or distribution of friendly forces to take action against the assessed enemy threat. Moreover, the findings from the enemy threat analysis and the assigned friendly forces are assessed to determine the optimal placements as a part of a course of action. Finally, the development of operation support and visualization software are undertaken to support users of AICDS-G. In addition to the experimental results, this research proposes the development of specific methodologies, models, and software related to these processes and concepts.

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INTRODUCTION

The concept of future warfare is transformed by mosaic warfare, decision-centric warfare, and the demand for intelligent command and control systems is growing with the emergence of innovative technologies within the Fourth Industrial Revolution, such as artificial intelligence (AI). In other words, intelligent battlefield analysis and countermeasure support technologies are crucial to conducting operations on the future battlefield. This requirement is reinforced by the enhanced precision and sophistication of combat equipment and the increasing uncertainty of battlefield conditions (ARMY, U, 2019).

Consequently, we are engaged in research on the AI-command decision support for ground operations (AICDS-G) to establish intelligent command and decision support technology that can be effectively implemented in ground operations. In this research, we model the Battlefield Digital Twin (BDT) to accurately mirror the battlefield environment and the actions of both enemy and friendly forces. Utilizing AI learning models, we analyze enemy threats and determine a course of action (CoA). Furthermore, we designed tools to facilitate user operations and visualization for AICDS-G. Figure 1 illustrates the comprehensive developmental concept of AICDS-G.

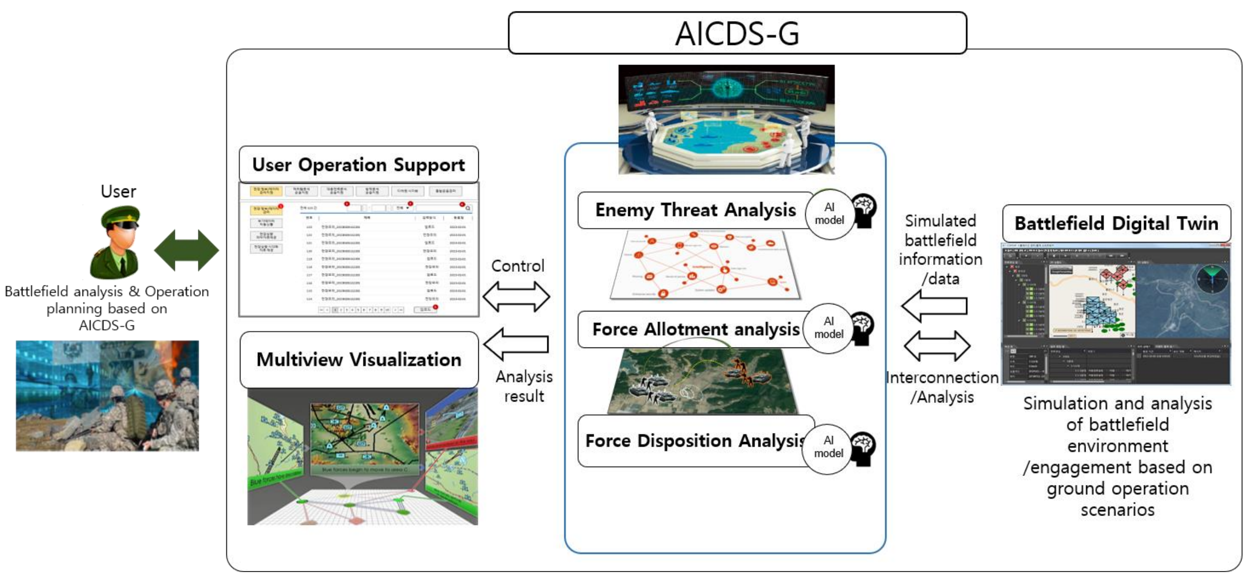


Figure 1. Overall Development Concept of AICDS-G

In the development of an AICDS-G, the BDT simulates the battlefield, including ground forces and the behaviors of both enemy and friendly forces. This simulation provides a realistic representation of the ground battlefield conditions and an AI learning environment. AICDS-G is composed of sequential processes to support command decisions for ground operations.

First, the enemy threat analysis (ETA) foresees enemy behavior and evaluates their threat level using deep-learning models, such as graph neural networks (GNN). Second, within the learning environment of BDT, models, such as reinforcement learning (RL), are employed to analyze the optimal distribution of friendly forces to take action against the analyzed enemy's threat. Third, the enemy's threat analysis results and the allocation of friendly forces are thoroughly examined based on its optimized positions, integrated into the course of action (CoA) for friendly forces. Finally, specific operation support and visualization software are developed to support the functionality of AICDS-G for its users.

The operational configuration and procedural flow based on the integration of AICDS-G are illustrated in Figure 2.

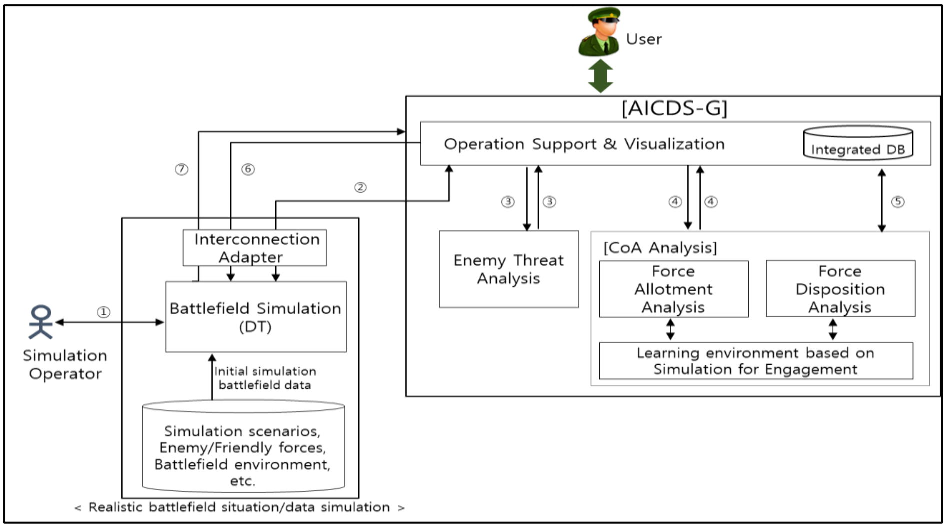


Figure 2. Operational Configuration of AICDS-G

① Operation of battlefield simulation (Setting simulation scenarios)

② Forwarding battlefield simulation data & simulation control

③ Control and Input/Results of ETA

④ Control and Input/Results of CoA analysis

⑤ Decision of optimal CoA

⑥ Input of battlefield simulation for optimal CoA

⑦ Results of battlefield simulation for optimal CoA

The development of concepts, methodologies, and models related to these operation processes of AICDS-G are described in the following sections.

BATTLEFIELD DIGITAL TWIN (BDT)

The BDT is based on modeling and simulation (M&S) and is developed in its main format in the AICDS-G, as illustrated in Figure 3. This consists of two primary components: first, a battlefield simulator that generates virtual battlefield situations using high-resolution simulation models to yield detailed information concerning battlefield engagements; second, as a function that supports AI learning, BDT serves as the learning environment for engagement simulations, applying learning models to analyze the CoA for friendly forces.

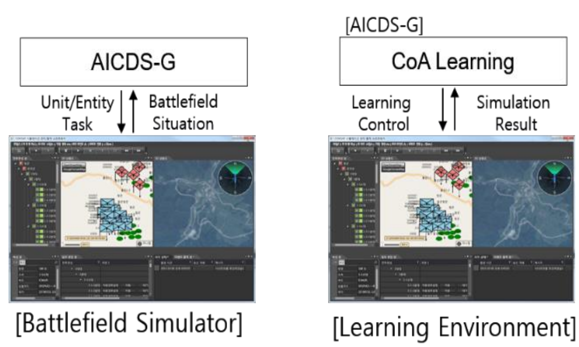


Figure 3. Concepts of BDT Development

Battlefield Modeling and Simulation

In the context of the battlefield M&S of the BDT, simulated battlefield objects are formulated for units and entities, mirroring the requisite capabilities of objects deployed in both current and prospective ground operations. This includes the representation of enemy or friendly forces such as infantry platoons, tanks, and artillery. In these instances, simulated objects are developed using mocking techniques based on semi-automated forces (SAF) (Wittman & Courtemanche, 2002) to enable high-resolution and automated simulation, thereby minimizing user intervention.

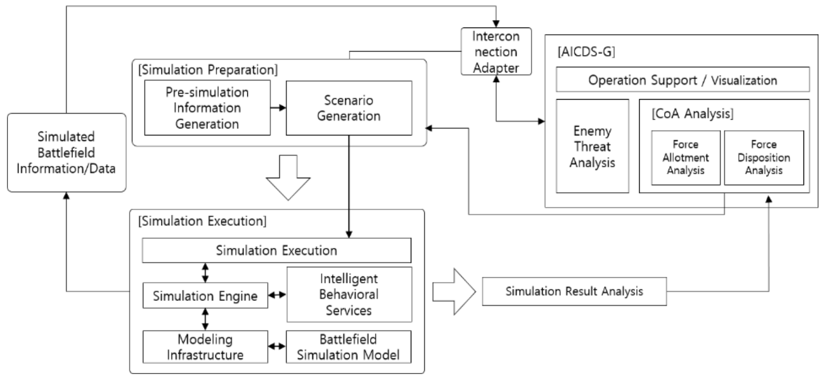


Figure 4. Composition and Execution Flow of Battlefield Simulation

As depicted in Figure 4, the object modeling and architectural framework are structured through ComSAF (Kim, et al., 2014), which is battlefield simulation software developed by the ADD and is currently a benchmark of the U.S. OneSAF. This process involves the design and application of specific tasks and actions for offensive and defensive maneuvers against both enemy and friendly forces, enabling simulated units and entities to emulate real-world battlefield combat. The array of simulated tasks and actions including various operations such as movement, detour, pioneering, fire attack, guarding, seizure, sustainment, and reconnaissance are detailed in Figure 4.

Table 1. Overall Simulated Information/Data of Battlefield

Items	Main Simulated Information/Data
Initial info. for simulated battlefield	Enemy and Friendly Force Status Information for Simulation Scenarios
Unit static info.	ID, Size, Branch, Weapons, Etc. of Units
Unit dynamic info.	Location, Velocity, Combat Power, Current Personnel and Weapon Status, Tasks, Etc.
Unit Detection info.	Detected Units, Detection Distance, Etc.
Unit Engagement /Damage info.	Engaged Units, Target entities, Engagement Distance, Unit Damage Personnel and Weapons, Attacking Units and Entities, Etc.
Entity static info.	ID, Type, Weapon, Equipment, Affiliation, Maximum Detection Distance, Weapon Range and Speed, Etc.
Entity dynamic info.	Location, Velocity, Status, Etc. of Entity
Entity detection info.	Detected Entity, Detection Range, Etc. of Entity
Entity fire/ damage info.	Units & Entities for fire, Target, Damage, Weapon Type, Target & Firing Position, Etc.

Development of a Learning Environment for Engagement Simulation

The CoA analysis is dedicated to the optimization of friendly force allocation and positioning to effectively counter enemy threat. The intelligence of the CoA analysis is actualized through AI neural network learning. To this end, the BDT-based learning environment for engagement is developed. This specialized learning environment for engagement simulation provides functionalities for creating and modifying battlefield scenarios, aimed at replicating ground operations. Incorporating techniques such as batch execution, time acceleration, distributed processing, and parallel processing, it enables the mass generation of diverse battlefield scenarios. This optimizes the training duration as well as enhances the generalization performance of AI learning models in battlefield scenarios. Moreover, the learning environment is equipped with an interface referred to as the "blackboard," which communicates with battlefield unit/entity models, behavioral models, and task execution models provided by the BDT to conduct AI training. Each unit or entity of the engagement simulation process is assigned a unique address on the blackboard. Through the Google Remote Procedure Call (gRPC), data including unit status, entity status, action requests, and results are transmitted and received, synchronizing with the AI learning process by accessing information at the respective address.

ENEMY THREAT ANALYSIS (ETA)

ETA utilizes learning models to identify the behavior of enemies and calculates the vulnerability of friendly forces through capability- and relation-based analysis using fuzzy logic. Thereafter, the behavior, vulnerabilities, and acquired information and attributes of the identified enemy are used to infer the probabilities of threat, yielding the degree and ranking of the enemy's threat (Figure 5).

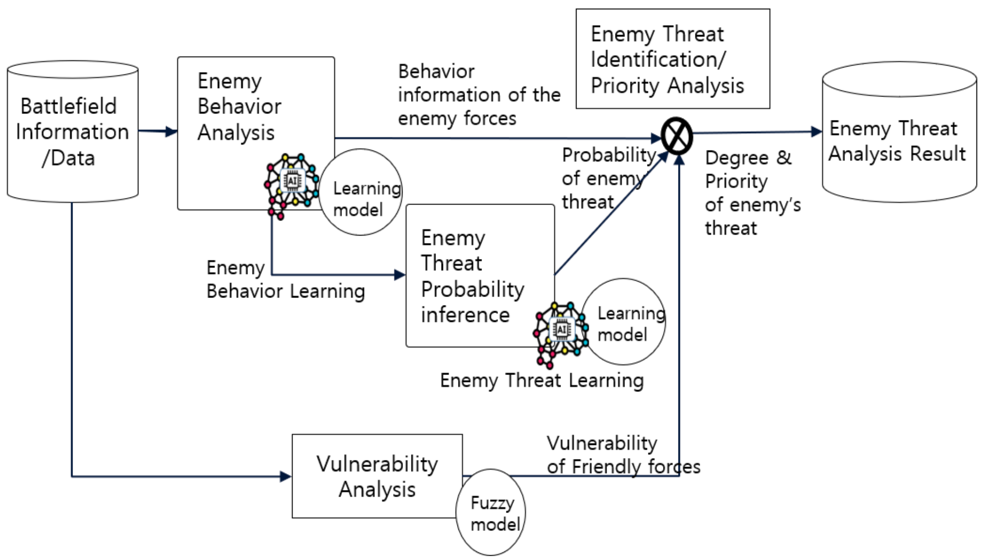


Figure 5. Overall Development Concept of ETA

Enemy Behavior Analysis

Enemy behavior analysis aims to infer the behavioral factors correlated to enemy threats through neural network training, considering the variations in enemy information and data acquired from the battlefield. This analytical model considers the temporal variations in the enemy's information and data, employing a battlefield dynamic GNN (Zhou, et al., 2020; Pareja, et al., 2020) that can learn the interactions between forces. This approach allows a probabilistic deduction of the enemy's tactical behaviors, including strategies such as assault, detour, siege and etc. (Figure 6).

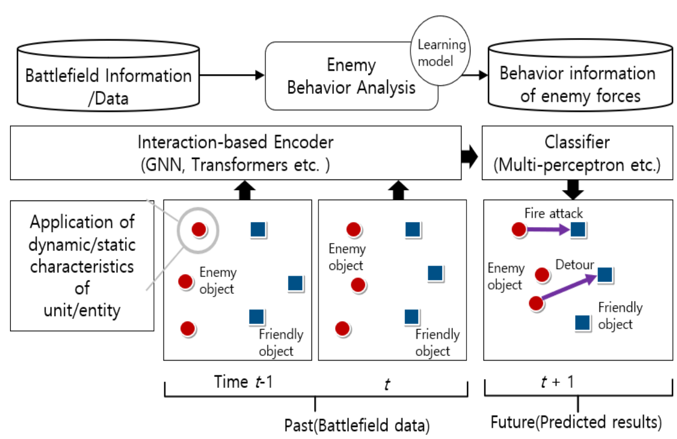


Figure 6. Development Concept of Enemy Behavior Analysis

Vulnerability Analysis

The vulnerability analysis applies capability and relation data to fuzzy models to evaluate the vulnerability of friendly forces to an enemy. Although the capability analysis focuses on the comparative aspects between enemy and friendly forces such as armor and detection, the relation analysis emphasizes the examination of enemy proximity through the consideration of factors including location and distance. Proximity analysis considers the closest point of approach (CPA) and the time for the enemy to reach the friendly force, which is called the time before hit (TBH), as depicted in Figure 7.

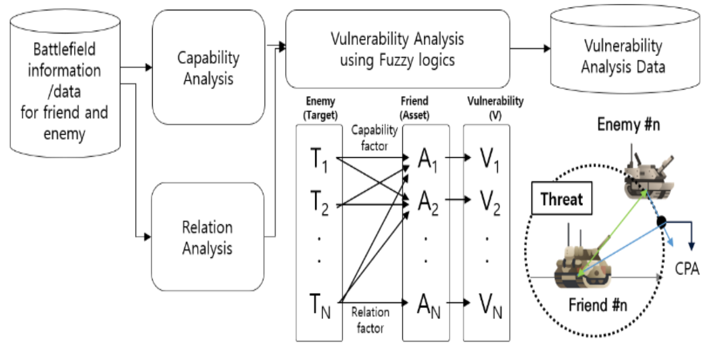


Figure 7. Development Concept of Vulnerability Analysis

Enemy Threat Degree and Ranking Analysis

Enemy threat identification and ranking analysis leverage a dynamic GNN model that is constructed by integrating various facets such as the enemy's behavior, vulnerabilities, information, data, and inherent characteristics. This enables the inference of the enemy's threat probabilities and facilitates the calculation of the enemy's threat level by employing a mathematical model, as represented in Figure 8.

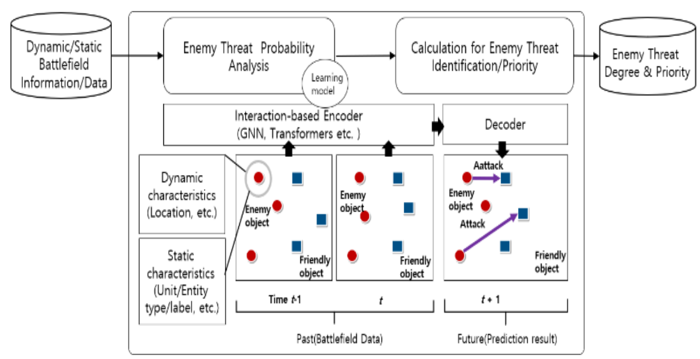


Figure 8. Development Concept of Enemy Threat Degree and Ranking Analysis

Learning Modeling of ETA

The structural configuration of the learning model designated for enemy behavior and threat analysis is depicted in Figure 9. Within this structure, the dynamic graph applied to the learning model is characterized by the information of nodes and edges that undergo temporal alterations. The learning model utilizes GNN, a network adept at analyzing data arranged in graphs, and graph embedding, a technique that can express the entire graph as a vector. Subsequently, a recurrent neural network (RNN) is implemented to comprehend the evolution of the battlefield conditions over time, based on the results associated with each node in the GNN (Shim et al., 2022), as demonstrated in Figure 9.

Learning Experiment and Result

The battlefield simulation data used in the experiments with the training model depicted in Figure 9 were generated approximately 1000 times, utilizing four ground engagement scenarios. Within these scenarios, one task (behavior) was assigned to each enemy unit, comprising tactical movements, siege, and assault tactics. Each simulation contains 30 enemy entities and 24 friendly entities, with 6 units each for enemy and friendly infantry. Moreover, unit- and entity-specific data, such as identification, type, firepower, position, damage status, and attacks, are generated every second for an approximate duration of 20 min. The six enemy force tasks (behaviors) applied in the simulation include garrison occupation, tactical movement, rally point behavior, besiege, assault, and ambush.

Table 2 presents the results of the enemy behavior and threat probability analysis conducted using the proposed model on these simulated data. A comparative analysis using the proposed model and a typical multilayer perceptron (MLP) is provided as well. Moreover, the F1-score of the behavior analysis performance of the proposed model was determined to be 0.94, whereas the area under the ROC curve (AUROC) for the threat probability analysis performance was found to be 0.98, thereby indicating significant learning outcomes. Consequently, we are currently conducting learning experiments in simulated battlefield environments considering various enemy units, entities, and tasks (behaviors).

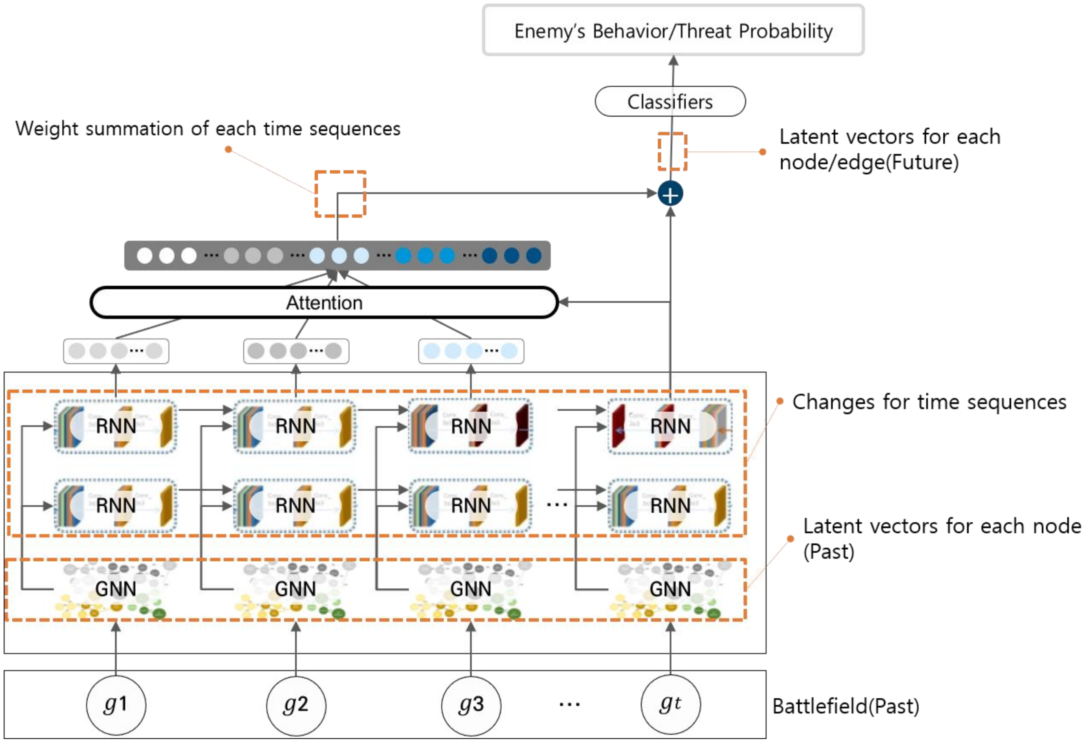
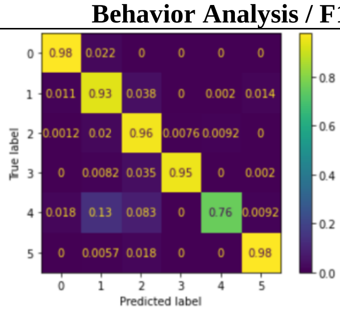
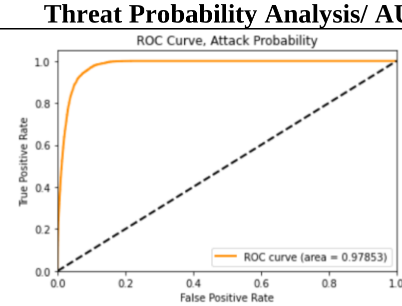
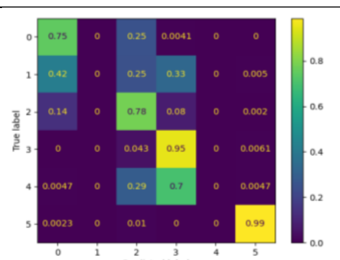
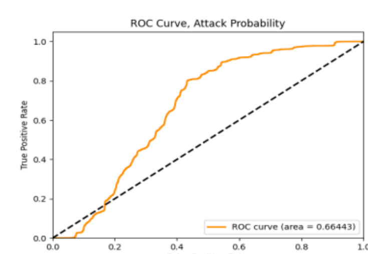


Figure 9. Learning Modeling for ETA

Table 2. Experiment results of Enemy's Behavior and Threat Probability Analysis

Items	Behavior Analysis / F1		Threat Probability Analysis/ AUROC	
Proposed Model		0.94		0.98
MLP (without GNN, RNN, Attention of Proposed Model)		0.61		0.66

COURSE OF ACTION (CoA) ANALYSIS

A battlefield scenario for defensive ground operations under AICDS-G occurs when enemy and friendly forces are arrayed in a line of battle and confronting each other, with an anticipated enemy offense. As illustrated in Figure 10, the simulation initiates with the deployment of friendly forces up to a designated analysis point, after which it pauses to formulate an operational plan to counter the enemy's assault. At this juncture of the analysis, the CoA analysis generates friendly action by employing an AI learning model that operates within the learning environment for engagement simulation based on BDT. The CoA of the friendly forces, i.e., the principal component of the CoA, is created by assessing the allotment and disposition of friendly forces. The formulated CoA is converted to an executable CoA within BDT, and the battlefield simulation proceeds with this CoA after the previously paused analysis point.

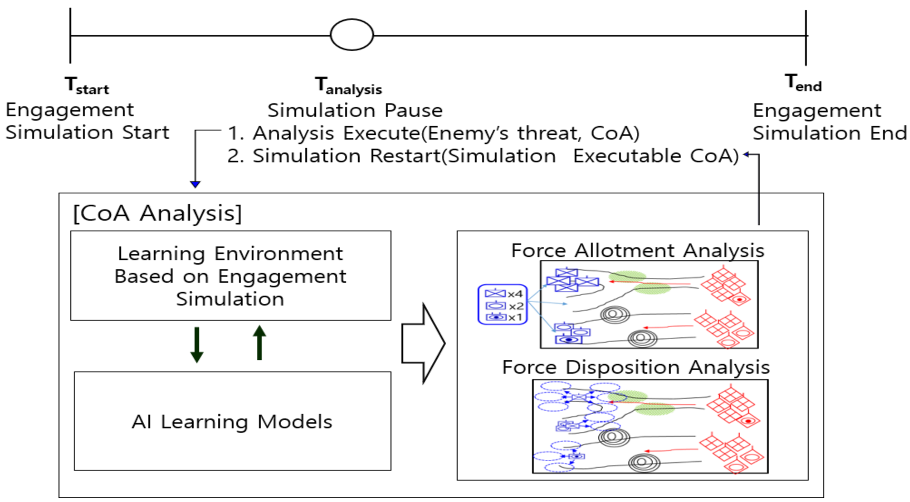


Figure 10. Overall Development Concept of CoA Analysis

Force Allotment Analysis (FAA)

The Force Allotment Analysis (FAA) implements RL models to ascertain the optimal allocation or distribution of friendly forces and counter the identified enemy threats. FAA corresponds to the concept of allotting friendly force in the development of the CoA (Park et al., 2022). In the conventional CoA development process, the distribution of friendly forces is achieved by comparing the tangible or intangible combat power of the enemy and friendly forces based on their primary tasks of evaluation of their relative dominance (FM 6-0, 2015). However, the diversification and sophistication of weapon systems have posed limitations to the effective application of numerical analysis via

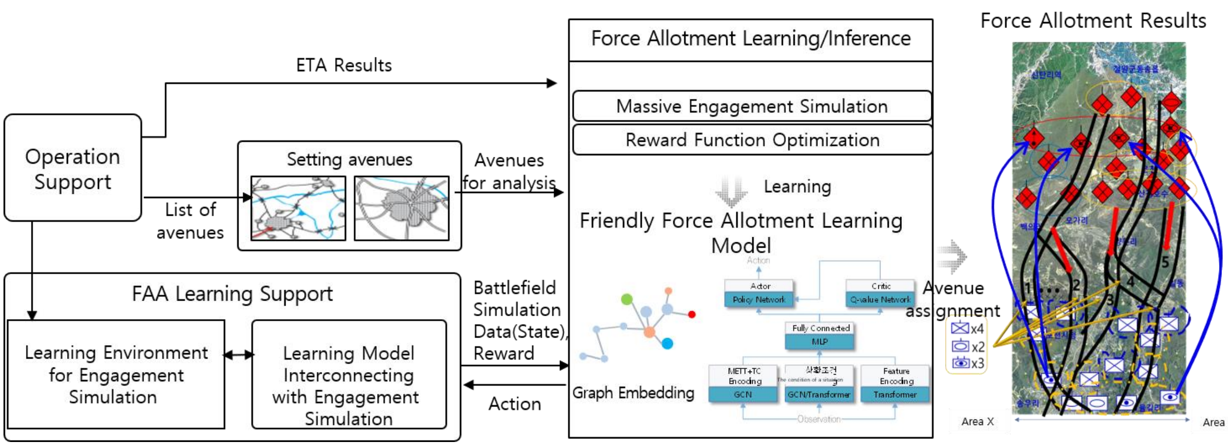


Figure 11. Development Concept of FAA

conventional unit counts, combat power indexes, etc. FAA introduces a methodology that leverages RL to enhance a commander's decision-making regarding force allotment. As portrayed in Figure 11, FAA encompasses learning support, setting avenues, force allotment learning, and force allotment inference. It further guides the distribution and allocation of available friendly units and entities by avenue and target based on the outcomes of ETA, user input data obtained from operation support, and avenue DB.

The learning support feature of FAA facilitates an interconnected environment between the learning environment for engagement simulation and the AI learning model. This integration is specifically crafted to interface the state, an individual agent's observation, action, and reward information, crucial for the structure of the Markov decision process (MDP) in RL. The primary functionality of this integration lies in the distribution of each learning scenario, thereby enabling parallel processing to learn multiple scenarios simultaneously.

In FAA, avenues represented in the engagement are assumed to be candidate avenues after the completion of terrain analysis. These avenues are articulated in 2D coordinates as illustrated in Figure 12 and are retained in the Avenue DB of the operation support. They are abstractly expressed in terms of features such as total distance, width, gradient, terrain (mountainous, river, field, etc.), and whether vehicles can traverse, and be applied to the environment for the engagement simulation. Abstract representation of avenues enables users to rapidly identify them, select the desired avenues for each battlefield unit or entity, and request the FAA.

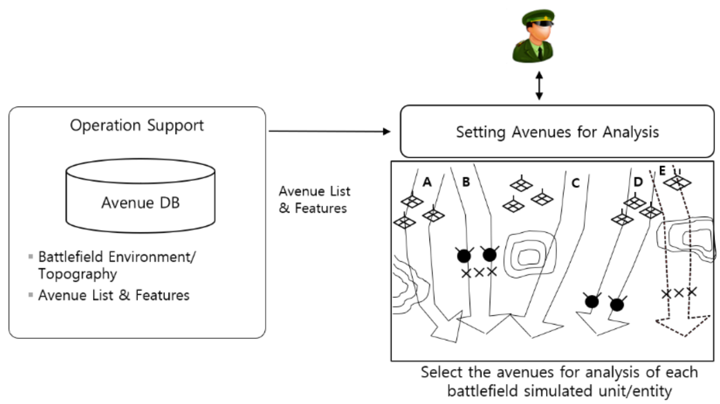


Figure 12. Concept for Setting Avenues

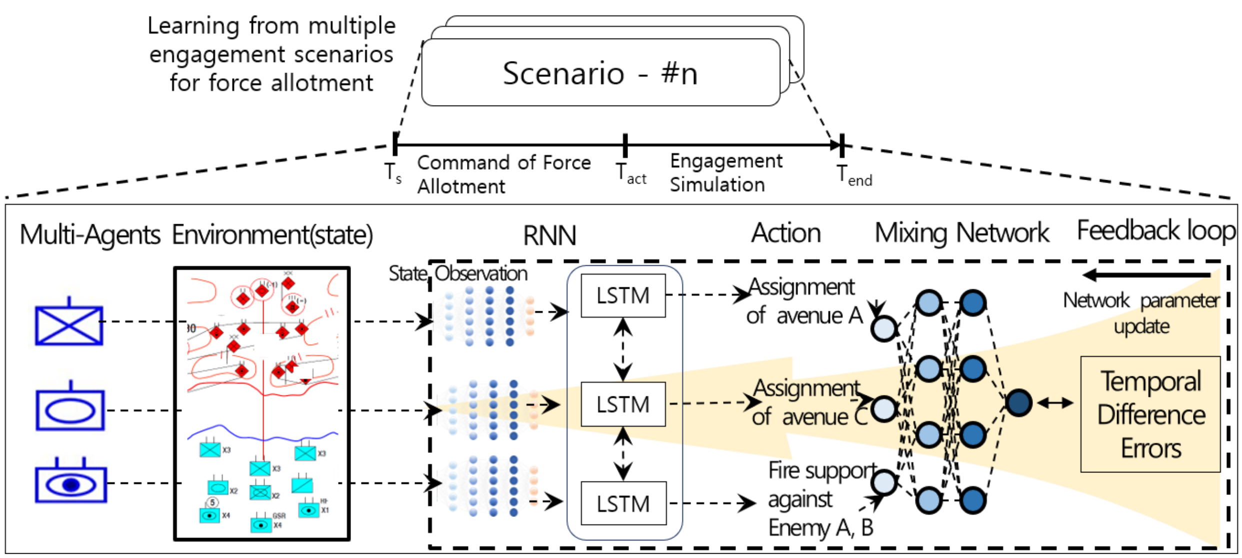
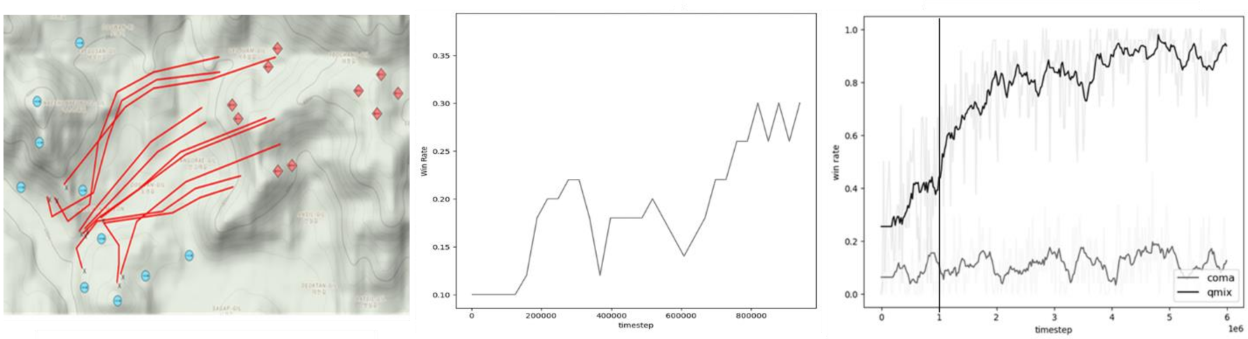


Figure 13. Learning Modeling of FAA

On the battlefield, each unit or entity possesses only a partial view of the entire terrain, mediated through its sensing and communication apparatus. The essentiality of close coordination between units for victory leads FAA to construct the model utilizing multiagent reinforcement learning (MARL) in a decentralized partially observable Markov decision process (Dec-POMDP) environment (Oliehoeck & Amato, 2016). Figure 13 depicts the architecture of the RL model proposed by FAA. By integrating value-based MARL approaches such as value decomposition networks (VDN) and QMIX (Rashid et al., 2020) within the centralized training with decentralized execution (CTDE) paradigm, the model is fashioned to learn cooperative behavior. This learning is achieved through the exchange of parameters among agents representing friendly forces, facilitated by long short-term memory (LSTM) cells. The action space in this model delineates actions as maneuvers by forces like infantry companies or tank platoons along avenues, and the provision of fire support against enemies by artillery units. Continuous updates and training of the entire network minimize temporal difference errors, employing deep Q-networks and defining a reward function predicated on the state information depicted in the engagement simulation environment, along with the outcomes of individual combat, the win/loss scenario, and task accomplishment. Instead of confining the learning network to a single scenario, a structure is designed that permits the network to adapt across various scenarios. The culmination of this process is the optimal allocation and distribution of friendly maneuver and artillery force, calibrated to counter the enemy within specific battlefield scenarios, and additionally, the sequential actions of friendly forces and their contributions to the engagement throughout the learning process.

As a prototype to test the proposed methodology, we constructed a simulator of enemy and friendly engagements to perform MARL. To simulate a battle, enemy and friendly forces have the same speed, detection, and weapon ranges, and an attack is automatically triggered when an enemy is detected within weapon range. To define the MDP structure of RL, we define six elements of action: moving east–west, north–south, maintaining previous behavior for pathfinding, and no action (when the object is destroyed). The fundamental elements of the state are defined as latitude, longitude, altitude, velocity, and damage.

Figure 14. (a) illustrates the test battle scenario, staging a situation where two enemy tanks traverse the road in a formation, followed by the representation of MARL's outcomes on the planned path and collaboration of scattered friendly tanks in the vicinity of the enemy tanks (Figure 14. (b)). A total of 1 million timesteps of training were conducted, and 10 battles were engaged with the trained agent to compute the win rate. Observations thus far indicate a trend toward an elevation of the win rate to approximately 30%. This finding aligns closely with the outcomes of training the QMIX algorithm for 1 million timesteps within a simulated engagement of StarCraft II (Figure 14. (c)). Such results underscore that future enhancements in training will potentially engender a learning agent proficient in optimal path planning and allotment.



(a) Test Battle Scenario (b) Win Rate for Test Battle Scenario (c) Win Rate for StarCraftII 2s3z Scenario

Figure 14. (a) Test Battle Scenario, MARL Learning curves for (b) Test Battle Scenario and (c) StarCraftII

Force Disposition Analysis

Force Disposition Analysis is designed to optimize the movement of friendly units and entities from a designated analysis point to a specified temporal juncture. The conceptual realm of the disposition space is infinitely vast, compounded by computational resources and temporal constraints in executing engagement simulations for each decision, and subsequently reflecting the outcomes. To address this complexity, we employ a Bayesian optimization technique founded on Gaussian process regression (Snoek, Larochelle, & Adams, 2012). This approach is capable of achieving adequate effectiveness by utilizing an adaptive quantum of training data and an uncertain distribution characterizing the battlefield. Constraints are instituted regarding the extent to which a unit or entity may be mobilized over a defined time frame, along with pre-established candidates for displacement.

The specific intent and objectives as defined by a commander in a given scenario necessitate the formulation of an objective function. This function articulates a quantifiable outcome, such as the count of enemy forces arriving at a target location or the number of enemy forces neutralized by friendly units. The application of Gaussian process regression requires the estimation of a surrogate model or response surface containing a covariance matrix. This estimation is carried out by conducting an engagement simulation, in which friendly force disposition is treated as a variable while other information, including enemy force disposition and avenue information, remains fixed. Based on the probabilistic estimation of the objective function by the surrogate model, the acquisition function, which recommends candidate dispositions for upcoming examination of the function, can produce the disposition and uncertainty of the friendly forces that are expected to yield the best objective function value.

OPERATION SUPPORT AND VISUALIZATION

The operation support and visualization of AICDS-G integrates, processes, and visualizes battlefield information and data provided by BDT's battlefield simulation and analysis results of the enemy's threats and the friendly force's CoA to provide forms and schematics to users. The user operation support plays a role in operating and controlling each analysis software, building and managing the battlefield information and data provided by BDT and the results of each analysis into a database, and providing the data required by each analysis, as shown in Figure 15.

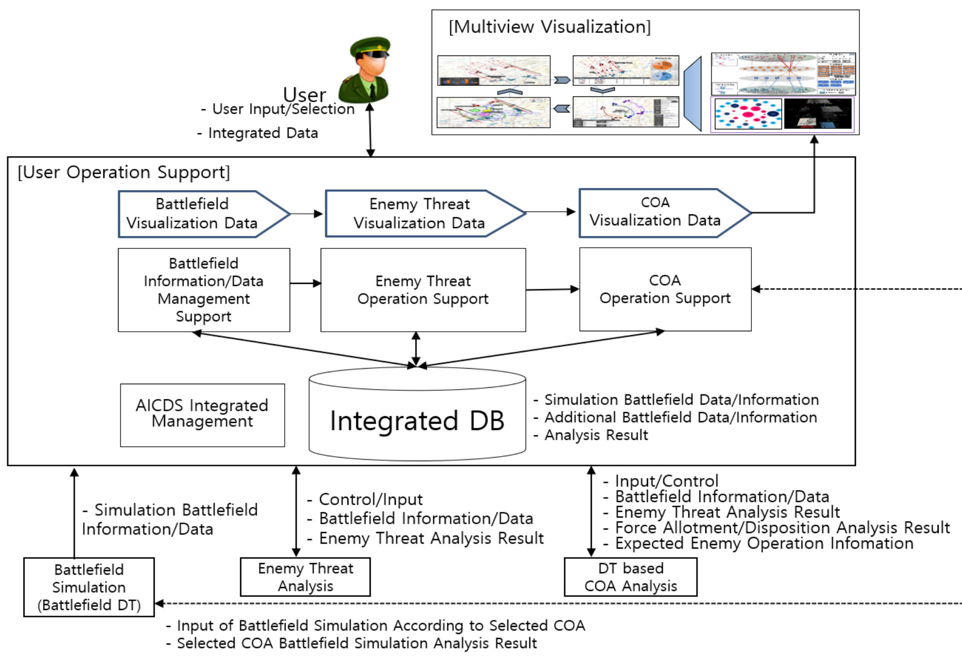


Figure 15. Overall Development Concept of Operation Support and Visualization

User Operation Support

The following is a description of the main configuration and features of user operations support. First, the battlefield information and data management support function accepts simulated battlefield data from BDT and organizes it within a database. It generates additional data, such as the motion or relocation status of units based on simulated battlefield data, and provides battlefield situation visualization and a battlefield data list. This enables users to comprehend the battlefield context.

Second, the ETA operational support exploits the battlefield information and data stored in the database and the results of the ETA. It furnishes the user with fundamental details, such as the position, mobility, weapon range, etc., of the enemy force. Moreover, it supplies information concerning enemy threats, including enemy activities, such as movement and assault, the vulnerability of the friendly force to the enemy force, and the threat degree and ranking of the enemy force. These details are presented in schematics or forms to the user (Shim et al., 2022), as illustrated in Figure 16.

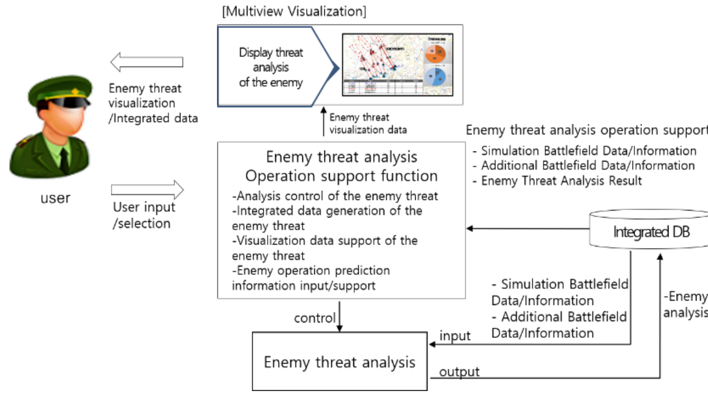


Figure 16. Operation Support Concept for ETA

As depicted in Figure 17, the CoA analysis operational support utilizes simulated battlefield data and ETA results stored in the database to furnish users with the allotment and displacement analysis outcomes of friendly forces obtained from the CoA analysis. In the case of the FAA, the stored terrain and environmental data are employed to generate a list of avenue candidates along with their attributes, which are subsequently visualized and presented to users. According to the avenues chosen through the FAA, the unit symbols and essential attributes of the corresponding friendly forces are rendered in schematic and format for each enemy force. Furthermore, it also visualizes and provides candidates with the friendly force displacement analysis and the optimal displacement results of friendly forces, as calculated through Bayesian optimization techniques.

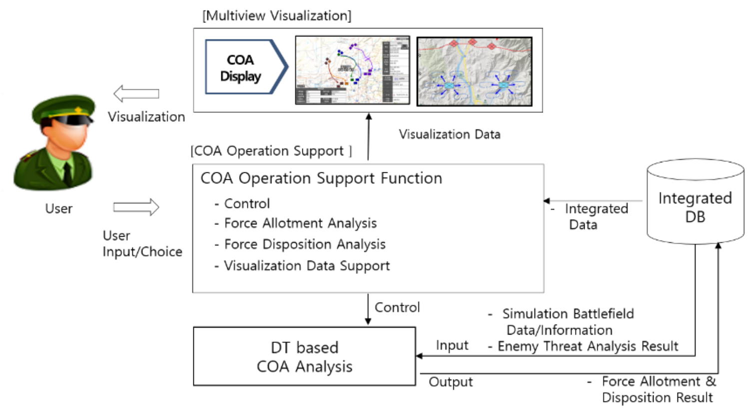


Figure 17. Operation Support Concept for CoA Analysis

Multiview Visualization

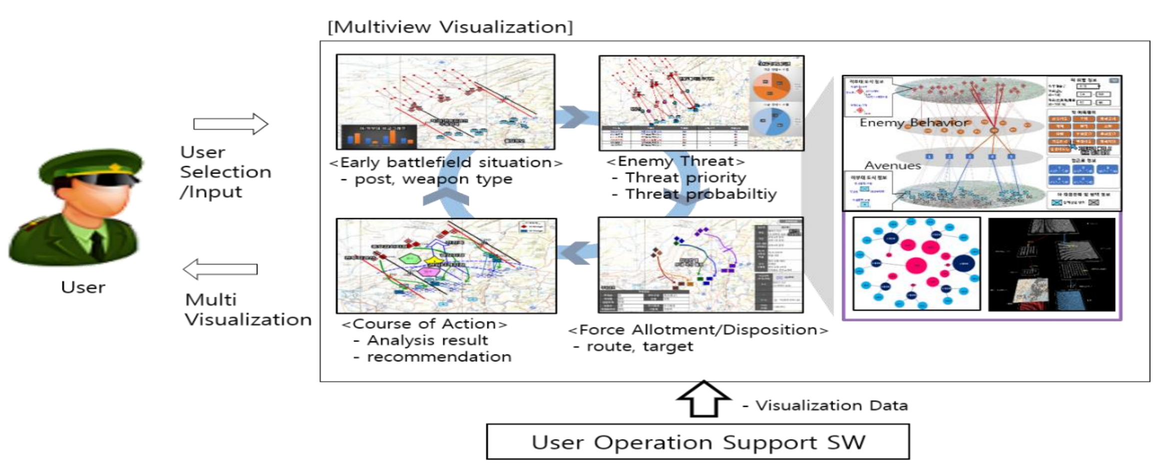


Figure 18. Multiview of AICDS-G

The development of multiview visualization is developed to support command decisions by furnishing commanders with sequential diagrams at pivotal decision junctures utilizing simulated battlefield data, ETA, and CoA analysis results (Ryu, Shim, & Park, 2022). As presented in Figure 18, this approach amalgamates the visualization elements of the battlefield situation, enemy threat circumstances, and force allotment and displacement for each stage of AICDS-G. Furthermore, it interweaves these visualization components with the data generated during the analysis process of the learning model, thereby constructing a multiview visualization screen. To this end, multiview visualization employs an array of temporal, linked, and geospatial visualization representation techniques (Park & Yun, 2021).

CONCLUSION

To build an intelligent command and control system, the command decision support technology must be developed using AI. Therefore, we are developing AICDS-G technology with the capability to support command decisions during ground operations. Herein, we developed the concept, methodology, model, and architecture of the AICDS-G technology.

For developing AICDS-G, we examined the evolution of the BDT and simulated battlefield conditions, including enemy and friendly forces and their behaviors, to generate realistic simulation data that can serve as a learning environment. Furthermore, we proposed the development of an ETA module that forecasts the behavior and threats of enemy forces using GNN and RNN models. Subsequently, we discussed the development of an optimal force allotment and disposition methodology via AI learning models, such as reinforcement learning and Bayesian optimization, synergized with the environment of the engagement simulation. Finally, we presented the development of user operation support and multiview visualization for AICDS-G.

In future, through the integration of these AICDS-G development concepts and methodologies, we plan to verify each developmental function and performance by implementing them into application software that can be adeptly utilized by users.

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