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Tactical AI in Real Time Strategy Games

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THESIS

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Abstract

The real time strategy (RTS) tactical decision making problem is a difficult problem. It is generally more complex due to its high degree of time sensitivity. Not only must a variety of unit maneuvers for each unit taking part in a battle be analyzed, the decision must be made before the battlefield changes to the point that the decision is no longer viable. This research effort presents a novel approach to this problem within an educational, teaching objective. Particular decision focus is target selection for a artificial intelligence (AI) RTS game model. The use of multi-objective evolutionary algorithms (MOEAs) in this tactical decision making problem allows an AI agent to make fast, effective solutions that do not require modification to fit the current environment. This approach allows for the creation of a generic solution building tool that is capable of performing well against scripted opponents without requiring expert training or deep tree searches.

The RTS AI development occurs in three distinct phases. The first of which is the integration of a MOEA software library into an existing open source RTS game engine. This integration also includes the development of a new tactics decision manager that is combined with the existing Air Force Institute of Technology AI agent for RTS games. The next phase of research includes the testing and analysis of various different MOEAs in order to determine which search method is most optimal for the tactical decision making problem. The final phase of the research involves analysis of the online performance of the newly developed tactics manager against a variety of scripted agents. The experimental results validate that MOEAs can control an on-line agent capable of out performing a variety AI RTS opponent test scripts.

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. List of Acronyms

AETC Air Education and Training Command

AFIT The Air Force Institute of Technology

AI Artificial Intelligence

BA Balanced Annihilation

ESA European Space Agency

FPS First Person Shooter

HA Hyperarea

HP Hit Points

HV hypervolume

GD Generational Distance

MCTS Monte Carlo Tree Search

MOEA Multi-Objective Evolutionary Algorithm

MOEAs Multi-Objective Evolutionary Algorithms

NFL No Free Lunch

NSGA Nondominated Sorting Genetic Algorithm

NSGA-II Nondominated Sorting Genetic Algorithm II

NSPSO Nondominated Sorting Particle Swarm Optimization

PSO Particle Swarm Optimization

RTS Real Time Strategy

SPEA Strength Pareto Evolutionary Algorithm

SPEA2 Strength Pareto Evolutionary Algorithm 2

TAV Tactical Airpower Visualization

TACTICAL AI IN

REAL TIME STRATEGY GAMES

I. Introduction

This research aims to improve on current RTS Artificial Intelligence (AI) methodologies by introducing the concept of utilizing Multi-Objective Evolutionary Algorithms (MOEAs) to quickly determine tactical actions to take in combat without relying on search trees or expert data [7]. RTS games, along with video games in general, provide an attractive means to test out these new AI techniques due to their broad range of environments and lack of costs that real-world experimentation requires [8]. The current state of an RTS game is also constantly changing, which introduces a level of time-sensitivity which increases the necessity for quick decision making.

1.1 Military Decision Making

The US Military holds the education of its forces as one of its major responsibilities. The Air Force has an entire Major Command dedicated solely to this purpose, Air Education and Training Command (AETC) [9]. One of the roles of AETC is the training and development of officers with regard to strategic and tactical decision making. This decision making training is provided through many means, one of which is to have officers perform various command level roles in a custom built RTS, Tactical Airpower Visualization (TAV) [10]. Officers are taught many problem solving approaches prior to the exercise with TAV. One of the most important of these processes is the OODA loop. OODA stands for Observe, Orient, Decide, and Act,

and was originally developed by John Boyd as a process to aid in decision making [1]. The OODA loop is a four step decision making process which places emphasis on a linear decision making pattern that can be used in many situations. First, the user must Observe, or gather data pertaining to the problem at hand. Then the user must Orient, or determine the potential effects from various decisions that could be made for the problem. Then the best one of these potential solutions is Decided and Acted upon. Once performed the user must go back and examine whether the intended effects took place and if the problem is resolved. The research performed in this thesis investigation replicates this four step process by utilizing MOEAs to make a decision based on immediately available data and with no prior knowledge of the opponents play style or decision making capacity.

1.2 Real Time Strategy Games

RTS games are a genre of video game which "are essentially simplified military simulations [11]." In an RTS game, a player is responsible for developing an economic supply life for his army via natural resources or other means, and then exploiting these resources to produce and maintain a sizable military. The player then uses this military to seek out and destroy enemy players. Each player's approach to the battle can be different, but the end state is based heavily on the strategic and tactical decisions the player makes throughout the campaign.

The decision making required in an RTS game is very complex, as the game state is constantly in flux. There are many segments of decision making in an RTS game as well, which can all significantly affect the player's capacity to win. Initially the player must split effort between economic development and military development. A poor decision at the start can significantly handicap a player's future efforts by affecting how many resources and units are available to repel enemy attacks. Even with a

proper base set up the player must still control individual units in battle. There are A^E potential attack combinations, with A representing the number of units in the player's army and E representing the number of enemy units. This is further compounded by different unit armor, attack power, and ranges. A good RTS player or agent must be able to make sound decisions in each of these environments in order to win.

Strategy in Real Time Strategy Games.

Strategic decision making in RTS games are typically modified by changing the focus of development between military, defense, or economy. Each strategy requires that the player or agent hit various tech levels. Higher tech levels in RTS games allow for the development of more powerful units. For example, a player at tech level 1 may have access to basic infantry units. Tech level 2 may allow for light vehicles and rocket lauchers, and tech level 3 may allow the player to begin constructing tanks. Players and agents enact different strategies by pursuing the requisite tech level for their strategy, and then begin creating armies [12]. AI agents also have the benefit of being able to "cheat", or gather economic more quickly than what a human player is capable of. This modification of resource acquisition capacity allows for an AI agent to counter the human's ability to learn and predict a particular agent's strategy. By improving resource acquisition the agent is more likely to overwhelm a human player before effective countermeasures can be created.

The selection of a good strategy heavily affects the chance of victory between players. Many strategies have distinct counters, and modifying one's chosen strategy to counter the opponent's gives the player a distinct advantage in the long term performance of the game [6]. The rate that a player is capable of building up a base and army also affects the overall outcome of the match. If a player is able to outpro-

duce the opponent the player has a higher chance of winning as a higher production leads to larger, more powerful armies. This production is based on the build order of buildings and units, which, if optimized, can create noticeable improvements over base strategies [5].

Targeting in Real Time Strategy Games.

There are many methods currently used for tactical decision making in RTS games, otherwise known as "micro" for micromanagement of individual units and forces in combat. Some of the fastest decision making tools are scripted attack methods. In a scripted tactic the agent looks for a particular element or statistic of enemy forces and engages the enemy with the most extreme value. This could be proximity (i.e. attack closest), remaining hit points (i.e. attack weakest), or some other value (e.g. attack lowest armor, attack fastest, attack most damaging). Other attack methods rely on in-depth tree searches or other single objective evolutionary algorithm searches with constraints [11, 13]. These methods can require previous training or an amount of calculation time which prevents on-line play. In each of these cases the agent has the potential to fall short in decision making as the focus on a single objective can results in sub-optimal solutions being selected. The research performed in this paper implements a Multi-Objective Evolutionary Algorithm (MOEA) to face against various scripted agents and then compares the results against other tested tactical decision making methods.

1.3 Research Goal

The goal of this research is to develop and test an extension to the currently existing The Air Force Institute of Technology (AFIT) AI agent for the Spring RTS Engine. The AFIT agent has been under constant work, with previous upgrades

improving strategic decision making and build order optimization [6, 5]. This next extension controls the tactical combat maneuvers and firing solutions for individual units in an effort to optimize their outgoing fire and maximize their survivability. The completed tactical agent is expected to be brought into some of the currently existing RTS AI competitions such as StarCraft [14].

1.4 Research Objectives

The research performed in this thesis investigation is based on achieving the following objectives:

1. Develop a custom MOEA RTS AI technique which represents a tactical decision making process

2. Evaluate the offline performance of various MOEAs on this RTS tactical decision making process

3. Evaluate the online performance of an MOEA based agent against various scripted tactical agents on the Balanced Annihilation mod of the Spring RTS Engine

1.5 Research Approach

The research and concept behind implementing MOEAs in a tactical environment are a continuation of the research from another AFIT student, Jason Blackford [5]. In his thesis, Blackford is able to create newer, better solutions for build orders that can outproduce other agents via MOEA analysis. The implementation of an MOEA in the strategic decision making area of the RTS game is proven to have a noticeable positive effect. This research shows that the MOEA can be brought into the tactical portion of RTS gameplay and is a viable option for optimizing unit targeting.

The first step of this research is to integrate this previously developed agent with a freely available MOEA framework. This step is critical in order to allow an agent to access and analyze the results of an MOEA. Once complete, the agent is then able to implement the solution provided by the MOEA in an on-line manner.

After the MOEA software is integrated into the AFIT agent, various MOEAs are selected and tested against each other on the tactical decision making problem. The objective of this portion of the research is to find an MOEA which is capabile of quickly finding good solutions for the tactical decision making problem. Performance is based on speed of solution as well as the analysis of the resulting Pareto front via metric analysis.

The research culminates in an online test between the MOEA controlled agent and a variety of scripted opponents. The goal is to determine how well an MOEA serves as a tactical decision making tool and if it is viable in an online environment. These tests are measured with a performance focus of the army over the conflict length.

1.6 Thesis Organization

The remaining sections of this thesis cover the entirety of the process, analysis, and conclusions relating to the tactical decision making research. Chapter II provides background information that is useful in understanding the processes and purpose behind this research. Chapter III provides an design methodology of the MOEAs being compared, techniques for measuring the "value" of a particular result, and how these MOEAs are expected to react in an on-line performance. Chapter IV contains the design of experiments and states states specifically how the experiment is being performed, with Chapter V providing an in-depth analysis of the results that are obtained. Chapter VI provides an overarching conclusion for the entire development process and also provides feedback on future efforts.

II. Background

This chapter provides a base level of information about some of the major themes in this thesis research, such as decision making techniques, RTS games and platforms, and an overview of strategic and tactical planning. The chapter continues into a overview of past AFIT research papers that investigate new improvements with regards to AI agents for RTS games, as well as a discussion of current tactical RTS agent research taking place. Finally, the chapter ends with an explanation of the purpose of this research and how it progresses the current state of RTS AI tactical decision making techniques.

2.1 Decision Making

Before creating a method to improve AI agent decision making, the individual components of decision making must first be understood. Any decision making method requires two primary components - an input of data and a plan of how to manage the data that has been provided. The generation and utilization of the initial data is important as the analysis of too much data can negatively affect the time required to make a proper decision, while too little information increases the likelihood of a sub-optimal solution being used. Malcolm Gladwell discusses a method of optimizing the amount of information used in making decisions via a technique called "thin slicing" [15]. Once acquired, the information that has been gathered is passed into a decision making process. The decision making process most familiar to Air Force Officers relies on four distinct phases. These phases are Observe, Orient, Decide, and Act; the technique is named the OODA Loop [1]. This methodology is taught in officer training throughout the first years of an officer's career in various training programs[16, 17].

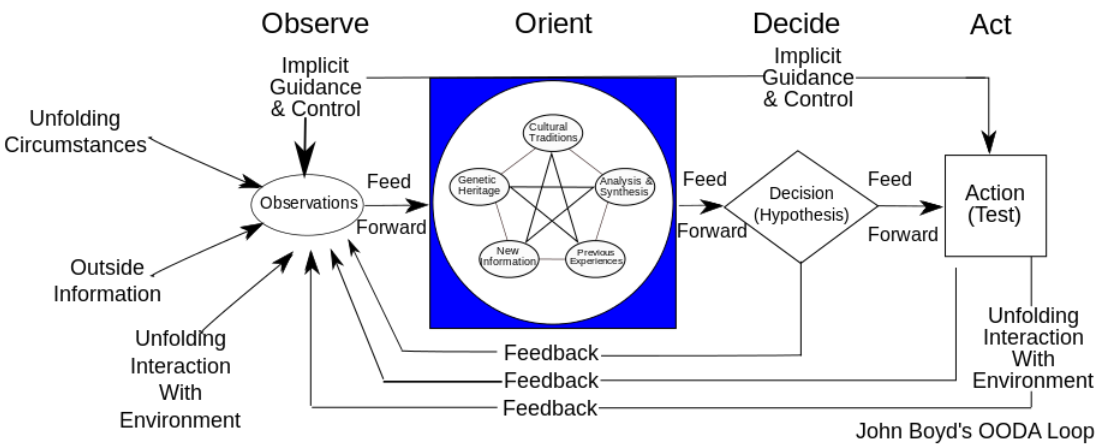


Figure 1. Boyd's OODA Loop [1]

OODA Loop.

The OODA loop is a decision making process that stands for Observe, Orient, Decide, and Act. This process is meant to be a universal decision making process that can be used to choose courses of action in a variety of situations. The overall process can be seen in figure 1.

Observe.

In the observe phase of the OODA loop the user is taking in as much information as possible. For the purposes of an RTS AI agent, this phase represents the computer gathering information about the current game state. This includes map positions, unit statistics, and other information that is readily available. No processing of the data is done at this time.

Orient.

The orient phase analyzes the information gathered from the observation phase. In the AI agent this represents the actual analysis of the battlefield. This is the analysis and prioritization of targets based on their attack power, hit points, and

map locations. Future iterations could include the attack bonuses versus different types of enemy units or even the strategic usefulness of a battlefield. The information from this phase is used to continue to the next phase of the OODA loop.

Decide.

The decide phase is simply to decide on a course of action based on the information from the orient phase. In the AI agent this represents the analysis of a course of action chosen by the evolutionary algorithm. Each member of the population represents a different "decision"

Act.

The act phase is for performing and testing the outcome of the chosen course of action. In the MOEAs used for the agent, the act phase is performed during the objective analysis at the end of each member of the population. The action and testing of each member of the population determines the relative "goodness" of each decision and can be used to reorient the agent for future decisions.

Incomplete OODA Loops.

One of the primary issues of the OODA loop is to get stuck in incomplete decision loops. One of the most prevalent of these incomplete loops is to be stuck in a constant analysis phase without ever making a true decision. This is represented by OO-OO-OO [18]. This problem arises when solving a problem is either too complex or the problem has changed before a solution has been found. In the RTS environment both of these issues can be represented in the same manner. In an RTS game, a battlefield decision must be made quickly in order to be useful. Every second of computation time introduces more potential error into the solution due to the way objectives are

managed. Unit hit points, location, or even the number of remaining units can change over the course of a short amount of time in a RTS game, and these changes can lower the reliability of a solution or even invalidate it. One of the most important things to keep in mind in the development of an AI algorithm is to ensure that it can quickly make decisions in complex environments.

Thin Slicing.

The concept of thin slicing is introduced by Malcolm Gladwell in his book Blink [15]. In this book Gladwell goes into detail on how some decisions are quickly made subconsciously using very little information. He goes further to say that if a person is well trained, these snap judgments can be more correct than if the person in question took the time to perform an in-depth analysis to verify their snap judgment. He defines this concept of making a snap decision using only the most basic, critical information as "thin slicing". The experiment process utilized in this research attempts to replicate this idea for combat situations by pursuing a "good enough" decision based on information currently observable to the player/agent and disregarding information that comes from more in-depth analytic methods. This technique allows RTS games to make better decisions based on information that is readily available, which minimizes the amount of computation required to generate a targeting solution.

Making Decisions with Current State Analysis.

A popular method of decision making in games or battle simulations is to attempt to fully analyze all potential outcomes from a particular decision point before making a choice. The issue that arises from this course of action is that while a simple game such as chess or checkers has a limited number of pieces and a small set of potential moves, the number of pieces and moves can introduce an exponential level

of complexity to the problem. Another problem to consider is that while in chess and checkers the other side cannot move during a players turn, in battle the opponent has no such limitation. This exacerbates the already complex problem by introducing a factor of timeliness to any potential decision making process. This causes issues at larger battle sizes where the time required by an algorithm prevents it from providing solutions quick enough when then makes any potential solution supplied out of date on arrival. The approach of attempting to simulate every outcome in order to choose the best solution is similar to the approach used by the US Armed Forces in Millennium Challenge 2002. In this challenge US forces ("Blue Team") had so many rules and so much knowledge that it prevented them from being able to respond quickly to the much freer enemy forces ("Red Team") controlled by Lieutenant General Paul Van Riper (RET) [15].

RTS games, due to their purpose or role as battlefield simulations can carry over many of the intricacies of actual combat. These intricacies can cause a complex tactic searching method to become bogged down much like the Blue team forces in an actual wargame. The research performed seeks to prevent a slowdown in decision making due to the pursuit of a full analysis for the pursuit of a "perfect" solution and instead aims to generate solutions that steadily improve the AI agent's status in comparison to enemy forces through the battle.

Research Goal.

The purpose of this investigation is to develop an RTS agent that handles tactics and combat quickly and efficiently by only analyzing a few specific metrics in the current battlefield state. The overall goal is to analyze a battlefield in a way similar to the method created by Lee Goldman to manage heart attack patients at the Cook County ER [15, p126]. In his experiments, Goldman found that the best decision

can often be found by focusing on a few objective metrics to determine a patient's heart attack risks. This solution is quick, since it only needs to process a few test values, and more important this solution is effective, with a successful detection over 95 percent of the time. The agent developed for the purpose of this paper aims to mimic this result by taking a quick look at the current status of a battle and using a few objective values to quickly determine the immediate best course of action.

The overall goal of this research is to develop and test the usefulness of MOEAs in tactical decision making by comparing the MOEA agent's performance against more in depth search methods. The battlefield is simplified into a few easy to measure metrics which are then compared against each other in order to choose an optimal solution. This method of search is in contrast to a more intensive search which aims to seek out good choices by measuring the battle's outcome.

One of the critical areas to be wary of when designing an algorithm that quickly evaluates the current state of affairs is that strictly limiting time can have adverse effects on solution quality. This is also brought up in Gladwell's book in the line "When you remove time, you are subject to the lowest quality intuitive reaction" [15, p. 231]. Any analysis performed must be quick, but thorough. There must be enough testing in order to ensure that the objectives result in solutions that are reasonable and feasible.

2.2 Real Time Strategy (RTS) Games

RTS games are a type of war game in which a player needs to simultaneously manage the military and economic requirements of an army in order to use that army to destroy an enemy. RTS games typically require the player to focus on both long-term and short-term requirements. A player that focuses too much on short term gains will likely not have the resources to carry out an extended campaign, while a

player who is too busy laying the foundation for an end strategy without considering short term goals can find themselves vulnerable to a faster opponent.

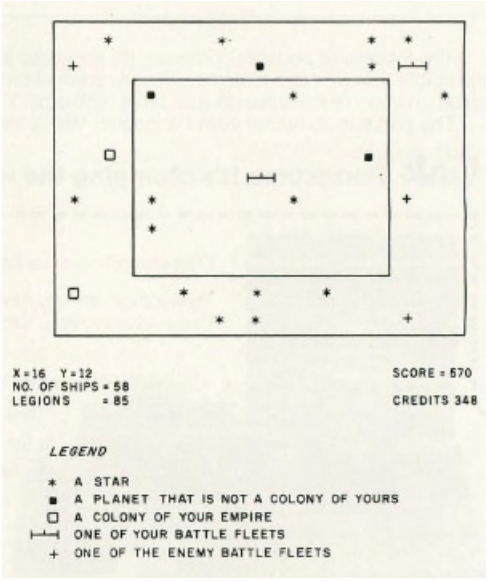


Figure 2. Screenshot of Cosmic Conquest [2]

RTS games have been developed to represent battles in a variety of time lines and locations. One of the first commercially available games focusing on the strategic management of forces used to conquer territory is Cosmic Conquest [2]. Relatively simple by today's standards, the goal of cosmic conquest is to capture more of the known galaxy than the computer opponent. A player needed to split resources between ground legions or space fleets and use these legions and fleets to capture other planets which provided the player even more resource generation over the course of the game. The choice of locations to send forces affected future points in the game, as fleets required traveling distance and planets gave varying amounts of resources. A screenshot of this game can be seen in Figure 2. This relatively simple concept behind a game of strategic decision making eventually evolved to the RTS genre as it is known today. A brief history of RTS games is presented in order to provide the reader with an overview of the progress and capabilities of the RTS genre and how they can be applied to military simulations.

Dune II.

Figure 3. Screenshot of Dune II [3]

Dune II stands as a landmark in the development of RTS games. It is the first game which combined various concepts that became a standard in RTS games for years to come. The game combined optional mission location selection, resource gathering as a means of economic development, base development, technology trees, and multiple playable factions in a way that had not been previously used in the genre. This combination of options became a template for future RTS games for a long period of time and is still seen as the template for a standard RTS game. The Graphical User Interface for Dune II is still used as the standard for RTS games in terms of providing a player with the necessary information to control their forces during a game, and can be seen in Figure 3 [19, 20].

WarCraft.

WarCraft and its sequels WarCraft II and WarCraft III serve as one of the pillars of current RTS games [21]. Located in a fantasy realm of Azeroth, the game initially put two armies against each other, humans and orcs, with each faction having its own set of allies. Later expansions introduced additional races and other fantastic creatures and worked at developing the story of the realm which would eventually

Figure 4. Screenshot of Warcraft [4]

became the World of WarCraft. Through each of the initial games, however, the overall goal of the player is the same. In each game the goal is to build up a base, gather enough resources to maintain an economy, and then construct an army to destroy the opposition. Figure 4 shows a depiction of an orc base. The base setup has become more complex in comparison to Dune II, with multiple forms of currency being required for unit and building construction. A player must balance the amount of gold and lumber they have and also maintain enough farms to feed all of their constructed units.

StarCraft.

StarCraft can be thought of as simply WarCraft in space, with additional mechanics and in a different environment. While humans still exist, they are now known as Terrans and have armies which focus mainly on mechanical support and ranged attacks. The terran army operates most similarly to Warcraft. The player must still balance food (supply depots), and two other resources (minerals, vespene gas). There are two new armies available for players to control as well: the Protoss and Zerg. Each of these new races introduce drastically new ways to manage base construction and management. The Protoss represent a hyper-futuristic race with psionic abilities and

shields. While individually more expensive, the shields of the Protoss units provide a level of survivability and regenerative capacity unavailable to other armies. Their buildings require access to pylons, a dual purpose building which serves as both a supply depot as well as a power plant. The loss of these pylons not only reduces maximum army size but also severely limits the capabilities of any nearby structures. The other new race are the Zerg which are a semi-parasitic alien race that contaminates and consumes neighboring worlds. Their buildings are organic and require a builder unit to evolve into the building which causes the loss of the building unit. This race builds extremely quickly compared to the Terrans or Protoss and can evolve into very role specific organisms. This means that if left unchecked, the Zerg can simply overwhelm enemies in the initial stages of a game. This quick buildup and attack of units led to one of the most iconic strategies in the RTS world, the "Zerg Rush".

Tactical Airpower Visualization.

TAV is one of the most current iterations of the Air Force's approach to modeling and simulation of a campaign via RTS gaming [10]. Used throughout the training courses available at Maxwell Air Force Base for officer training, the game has been used in Officer Training School, the Air and Space Basic Course, and Squadron Officer School. Each class considers a different scenario with simulated conflicts spanning the globe and covering a variety of potential situations Air Force officers may find themselves facing in their career. It should be noted that the span of the courses that use TAV cover the initial years and ranks of a junior officer's career. Officer Training School is one of the introductory routes to becoming an Air Force Officer. The Air and Space Basic Course, while no longer available, was the mid-term school for Lieutenants and officers were expected to attend near their two year point in the

military. Squadron Officer School is the Captain school, which officers are expected to attend between their four to seven year point.

The important thing to note about TAV is the fact that it is a completely team based affair. A single player is completely incapable of winning on their own due to the method of control of the units. While most commercial RTS games give a single player complete control of the entirety of their forces, TAV takes a different approach. In order to emulate how the military is organized, each player has command of a group of units focused on a single goal. For example, one player is be given command of all strategic assets to be used for the campaign. This player (often with a second person playing as a counselor/vice commander) has complete control of all bombers used in the campaign. It is this player's job to work with other units, particularly the players responsible for any air superiority fighters in the area, in order to provide a safe ingress/egress routes for their bombers to attack. Failure to perform this planning results in the computer destroying most if not all of the bombers available to the group during this campaign.

In order to facilitate the required level of teamwork, a single player is chosen to be the overall commander. This player cannot give any orders to units in the game, in fact this player does not even have a computer terminal of their own. This player's job is to act as a liaison between the various players and ensure that everyone is working towards the goal. They also have the ability to remove players from play if they are violating current orders, and can force the observer (vice commander) to take over for the now defunct commander.

One of the main issues with this program is that it is heavily scripted. Enemy planes take off at set intervals and perform a specific course of action until a player interferes in some way. This makes it possible for a player to effectively solve the game. If a certain scenario can be played infinitely, with the computer performing the same

thing every time, it is possible for that player to find a way to complete the campaign quickly and efficiently due to the exploitation of the game's AI. Therefore the goal of this research, as well as the research that precedes it, is to create a more "human" AI that can add a level of strategic and tactical thinking to training simulations to provide a higher level of training available to Air Force officers.

Combining First Person Shooters with RTS Games.

One of the newer fields of the RTS genre is the inclusion of First Person Shooter (FPS) themes. In an FPS a player is typically only responsible for controlling themselves, and are expected to work together with a team in order to capture or kill enemies. Some games have been released that combine this aspect with RTS play, the first of which being the Natural Selection modification for the CounterStrike framework. In Natural Selection the FPS action is split between two opposing factions - humans and aliens. While aliens are able to work and act independently, the humans are reliant upon a Commander. This Commander views the game as a RTS, with a top down view of all friendly units. This combination of RTS and FPS play allows for the introduction of interesting mechanics as the Commander is able to issue orders but is reliant upon each individual player to respond and fulfill the order in their own manner. This concept has been brought into other games since then, notably a mod for the Spring RTS Engine which allows players to take direct control of individual units. This combination of large scale warfare with the control of individual units may eventually lead to fully integrated wargaming scenarios where every unit on the field is directly controlled by a human user.

2.3 RTS Platforms

The selection of an RTS platform for agent development can be just as important as the selection of the game mode. The platform can serve as a restriction on future capabilities based on the manner in which it is implemented. Most commercially available RTS games are developed on proprietary platforms, which means that outside developers or modders have a difficult time deciphering specific commands and event flags. This can hinder attempts to have an agent interface correctly with the agent, and can also reduce the effectiveness of trying to change some aspects of the game in order to meet different objectives.

Wargus.

WarGus is a Stratagus based environment for the Warcraft 2 game. This adaptation of Warcraft 2 into the open source Stratagus engine allows for game and environment manipulation unavailable in the original Warcraft 2 engine. It is important to note that many components of Wargus require data from a valid Warcraft 2 installation. Wargus cannot be used as a true stand-alone game environment [22, 23].

SparCraft.

SparCraft is a combat simulation engine for the Starcraft RTS game. It provides users with a way to test and analyze the performance of bots specifically made for the StarCraft engine. Currently the SparCraft environment fully replicates unit damage, armor, hitpoints, and research, but does not account for acceleration, collisions, or area of effect damage [24].

Spring RTS Engine.

The Spring RTS Engine [25] contains many options that are useful to RTS research. Some of the most important of these options are visualization, animation, unit customization, and the fact that it is open source.

Visualization.

The visual capabilities of the Spring RTS Engine are an important factor to consider when creating an agent that is meant to simulate theoretical military battles. Unit models can be changed and the landscape terrain features can be modified as needed. This allows for scenario modification and customization, which in turn allows a user to test potential strategy and tactical outcomes in a simulated environment

Animation.

The animation portion of the Spring RTS Engine, and any RTS engine, provides a visual feedback to the user of how battles progress through time. While simpler simulation programs may be able to provide a numerical analysis of a battles conclusion or state at a specific time, an animated progression allows users to have a direct feel of the flow of battle. This allows a user to learn and eventually hypothesize the outcome of certain situations and change their strategic or tactical decisions as needed.

Unit Customization.

One of the most powerful capabilities that the Spring RTS Engine brings to the table is the ability to generate and implement new unit types. This allows further customization of the battlefield in order to replicate an expected encounter. The capabilities included in the Spring RTS Engine's code go as far as introducing a unit's turn rate, turret turn rate, and attack rating against different types of targets.

This provides a means for planners to input specific unit capabilities based on current intelligence.

Open Source.

The most useful aspect of the Spring RTS Engine with regards to applying an externally generated AI agent is the fact that it is open source. As an open source program, all code pertaining to the program is readily available and once deciphered can be used to improve the application of any agent. The open source factor also includes the ability to create new interrupts or event flags which a user can build to occur at very specific situations - further improving the customization of this software.

2.4 Strategic Decision Making

The concept of strategy encompasses the goal of achieving a set objective or objectives while being restricted by a set of constraints. The decisions made in the development of a strategy are generally higher level, with a leader's choices affecting a large amount of people or resources. Strategy can be used in many environments, be it business management, military engagement, or personal finance. In warfare, strategy can be used to accomplish a military leader or country's goals. The goals of military encounters change based on the strategist, with leaders such as von Clausewitz establishing that victory in a battle should be determined by decisive battles of annihilation or a slower series of battles of attrition, effectively tying victory directly to the remaining military power of the opponent [26]. Other leaders such as Antoine-Henri Jomini focused instead of the geometry of battle, attempting to find a method to compare military strategic decision making to a mathematical formula or ideal series of decisions. In Jomini's approach victory did not require destruction of the enemy - victory can also be gained by sufficient acquisition of territory or re-

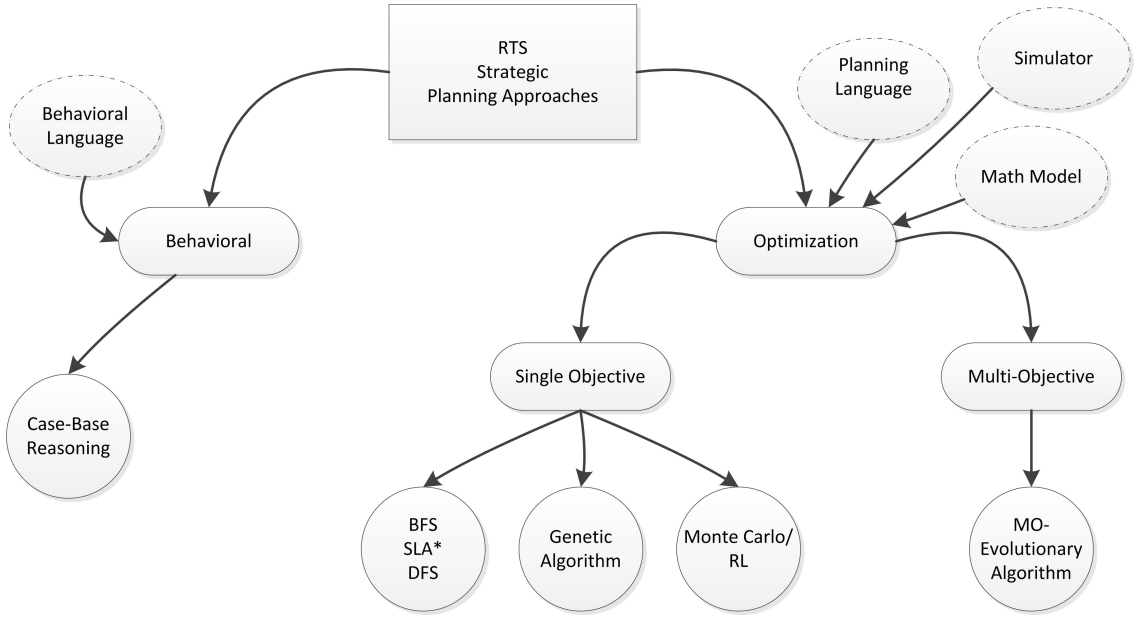


Figure 5. RTS Strategic Planning Tree [5]

sources [27]. In either case, the objective of military strategy can be victory via the destruction of enemy forces or the capturing of enemy territory and causing a rout.

Strategic Planning in RTS games.

The strategic planning of an RTS game covers the same objectives as a standard military confrontation. In most RTS games the objective is complete destruction of the enemy, with some versions describing victory as the elimination of any manufacturing ability or the conquest of a specific portion of the game map. These goals are accomplished through the development and application of a series of construction actions, otherwise known as a build-order [5]. The build-order is responsible for moving a player through various technological development stages and can improve a player's unit construction ability. For example, a technical level of 1 may allow a player to build basic infantry, level 2 may introduce more advanced unit types such as flamethrowers or heavy machine guns. Level 3 may build off this further and allow the player to begin building larger assets such as tanks or other vehicles.

Figure 5 shows a variety of methods used to plan strategies in an RTS game. The first distinction to make is the initial option between behavioral planning or optimization. Behavioral planning is an approach based on either learned or trained courses of action. The expectation for this type of strategic planning is that the agent is provided a set of data that represents expert players decisions on build orders. The agent takes this data, develops a case based reasoning methodology of what to build, and utilizes this to mimic expert players. A potential fault in this method is the fact that "expert" is a very loosely defined term in the RTS world, and that an agent may not be effective against opponents using unknown strategies [5].

The remaining path in figure 5 represents optimization via performance based metrics. The thought on this section of the tree is to ignore the concept of providing an agent with external data based on expert play, and instead to allow the agent to create its own decisions by maximizing or minimizing a series of functions that provide a value to the current state of a game. Given a suitable function an optimization based strategy can play at the same level or better than expert level players, but has the issue of an increased level of computational time [5].

2.5 Tactical Decision Making in Combat Scenarios

If strategy is the overall plan made before approaching a specific problem, then tactics is the series of smaller decisions made to fulfill the strategy. Tactics represent the actions and specific utilization of resources in order to make progress towards completion of a specific goal or objective. Tactics can change based on the situation at hand. In military encounters tactics encompass the formation of units, position of forces, and manner of attack. Tactics can take into account choke points and environmental aspects. In short, if a strategy is to perform a task, the tactics define how exactly that task is performed.

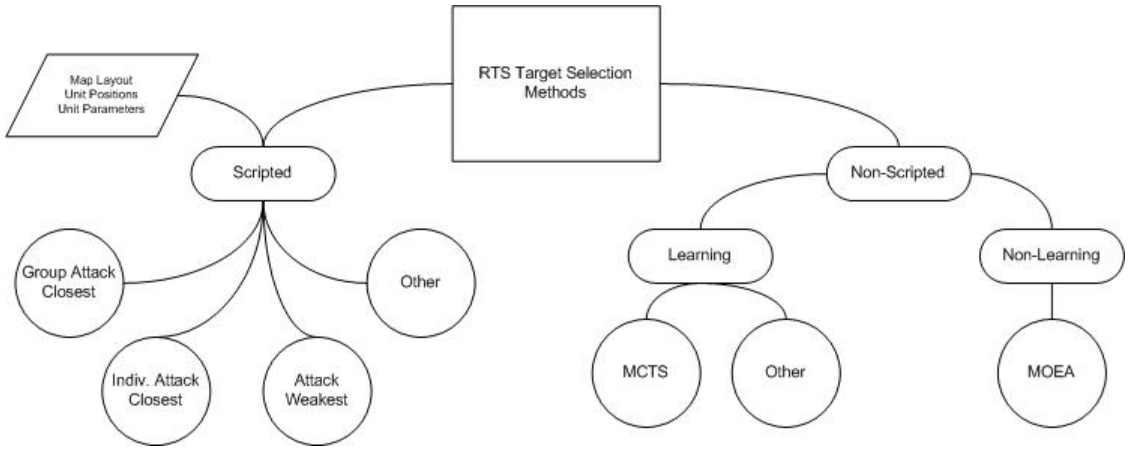


Figure 6. RTS Tactical Planning Tree

Tactical Planning in RTS games.

Tactical decision making in an RTS game focuses on the micromanagement of individual units or groups of units. Micromanagement is an extremely important aspect in competitive StarCraft play, with top earning professional StarCraft player JaeDong stating that in StarCraft: Brood War his ability ability to control the micromanagement "made me different from everyone else in Brood War, and I won a lot of games on that micro alone." . He then continues to say that micro is more important in StarCraft II than it was in StarCraft: Brood War [28]. These statements by one of the top players in the professional RTS world show that the ability to control the micromanagement of units is important, and that future games may increase the requirement of mastering this skill set. Micromanagement includes movement decisions, where to attack, how to attack, and how to maneuver in battle. Movement decisions focuses on the distribution of forces at the beginning of an attack. Units can be grouped tightly together or split up in various smaller groups in order to enable flanking or ambush attacks. The decision on where to attack could be a players decision to wait for enemy units to pass through a choke point which would maximize the ratio of friendly units to enemy units engaged in the fight. How to attack is the

method of choosing distinct targets for each unit participating in combat. Finally the maneuvering during combat references tactical retreats or "kiting", which is when a player moves within range to fire a volley and then retreats out of the opponents range to reload. The research done in this paper seeks to optimize the targeting portion of tactical decision making.

Figure 6 presents a variety of target acquisition methods available to AI agents. The simplest type of decision making tool is a strict scripting method. These types of methods analyze the current status of enemy units and makes a decision based on a single metric. These techniques are very fast, but are open to exploitation by players. The non-scripted methods of attack involve using similar methods to the strategic development options shown in Figure 5. The Monte Carlo Tree Search (MCTS) method analyzes the current state of a battle as if it is a static turn based game such as chess. It takes the time to determine potential outcomes and provides a scalar weight to each option. Another method of using a non-scripted learning method is to provide a set of expert data to the agent or allowing the agent to run through multiple simulations to generate its own data, as in the strategic decision making process. This expert data can be used to have the agent mimic an expert player's decision methods. Finally, an MOEA can be used to create an attack solution based on currently available information that would assign each unit a target with the goal of outperforming the capacities of a human player.

2.6 Previous AFIT Developments

The agent being modified by this research topic has been in development for four years, with Jonathan Di Trapani's work in 2012 and Jason Blackford's additional work in 2013 serving as the most recent improvements. The objective for each step of the development of the agent is to build on and improve a customizable RTS AI

agent that can be used as a means to train military members in strategic and tactical decision making.

Adaptive Response - Weissgerber's Agent.

Weissgerber's work in 2010 created an agent that is capable of reacting to the current situation of an RTS game by analyzing and acting on a subset of "features" which are capable of encompassing the the current state of the game [29]. Weissgerber's research culminated in an agent capable of outperforming the scripted agents that faced it by analyzing those scripted agents' previous performance and developing an active counter strategy. This counter strategy is 100% effective against the tested strategies, quickly analyzing the current state of a game and choosing decision paths which led to "win" states by optimizing the state of the "features" used to represent the game's status.

Strategy Optimization - Di Trapani's Agent.

Di Trapani's agent seeks to develop a means of identifying and countering an incoming wave of enemies [6]. This research is a continuation of the work performed by Weissgerber [29] and works to build a variety of different strategies to determine the effectiveness of each in various scenarios. In his work Di Trapani determines the advantages and disadvantages of each strategy tested against all other tested strategies. The purpose of this initial set of experiments is to determine the counter to each strategy on each tested map. Once these results are compiled, Di Trapani tests various classifiers that can be used to determine the enemy's strategy given a limited set of data. The purpose of this classifier is to allow the agent to hypothesize an enemy's strategy and start building the counter strategy. The result is a distinct

record of advantageous and disadvantageous options to choose based on the enemy's strategy selection.

Build Order Optimization - Blackford's Agent.

Capt Blackford builds on the work developed by Capt Di Trapani by creating a method to optimize the strategic decision making done in the initial stages of a game. His agent, the Build Order Optimization ("BOO" for short) uses a MOEA to optimize the build order for a given side. The MOEA selected has three objective functions. The first function seeks to minimize the number of steps required to transition from a current state to a desired state. For this first objective, the duration of all actions are equivalent. The next objective function used represents the amount of consumable resources required to move from a current state to a desired state. This objective does not have uniform costs like objective 1, so objective 2 is able to generate a more specific solution. The final objective simply takes the time requirements of each action in a solution string and compares them to each other. The goal of this third objective is to minimize the time required to complete a build order, otherwise known as a makespan [5]. The end result of Capt Blackfords research is a MOEA based build order modification tool that is capable of out-manufacturing bots currently available for the Spring RTS Engine.

Tactics Optimization - AFIT Agent Continuing Work.

One of the most difficult problems that has developed through continuous improvement on the AFIT agent is the understanding of the code. As with any project, understanding another person's code can be a difficult endeavor. In the case of the AFIT agent this is exacerbated by the use of multiple managers through the AFIT agent as well as the references to various Spring RTS Engine libraries written in both

Python and C languages. One approach to the current AFIT agent is to begin a cataloging and reference building of how all of the agents work together. Other areas the agent is lacking is the fact that the agent currently requires full battlefield awareness - it cannot be used with any sort of "fog of war", as some of the basic decision making requires the knowledge of the enemy commander location. The agent can also be improved on tactical decision making since it uses a very simple scripted algorithm to determine tactics in a battle. The agent can also be improved in the base construction / manufacturing stage, as it is currently incapable of using multiple construction units. In short the agent can be improved on almost all fields of play, as human techniques and ingenuity create or demand consideration of new tactics or strategies to counter currently used options.

2.7 Current Research in RTS Tactics Optimization

The current research environment for tactical decision making in RTS games is focused primarily on single objective evolutionary algorithms or making decisions based on AI learning techniques. Many researchers also focus heavily on applying their techniques to the game of StarCraft. This is likely due to the widespread knowledge of the game, as well as the availability of AI competitions that a researcher can use to provide measurable metrics to grade their agent's performance. Robertson and Watson describe StarCraft as "a canonical RTS game, like chess is to board games, with a huge player base and numerous professional competitions" [11], in their 2014 analysis of current RTS AI. Chapter 2 of Roberson and Watson's review covers tactical AI in depth, leading to three major tactical decision making techniques prevalent in current AI research. These techniques discussed in this review are Reinforcement Learning, Game-Tree Search, and Monte Carlo Planning [11]. Other methods of RTS tactical decision making include subjects such as genetic algorithms and fuzzy logic decision

making, but these types of methods are typically used in the strategic decision making level [30].

Reinforcement Learning.

Reinforcement learning is the concept of providing feedback to the agent based on the outcome of a specific scenario. One example of this is to have a Markov decision tree with no weights on each decision - every probability is equal. The agent traverses the tree until it reaches an end point. If the end point is a win, the agent provides a positive weight score, if the end is a loss then the agent instead provides a negative weight or a weight of zero. This weight is back-propagated through the chain of decisions the agent used to reach the final point. This back-propagation skews the probabilities for decision points along the tree search, which affects future runs of the algorithm. This action of testing and then skewing the probabilities eventually leads to an agent with a decision tree that is heavily weighted towards winning decisions [31].

Wargus and Case Based Reasoning.

The research performed by Aha et al. is focused on applying the same case-based reasoning approach used in chess and other genres to the RTS environment. The RTS environment used for this research is the Wargus platform, an Strategus based representation of the original Warcraft 2 environment [22]. The result of Aha et all's combination of Case based reasoning to tactics/strategy pairings shows that case based reasoning is capable of performing very well in the realm of RTS games. After 100 games the case based reasoning agent achieves an 82% win rate, a noticeable improvement from the original 23% win rate. Aha et al.'s research shows that learning

techniques are extremely viable in RTS environments as long as enough learning time is provided against specified opponents [32].

Game-Tree Search.

A game-tree is the representation of a game and its future states as a tree diagram. The current state is the root node, and each action available at the root node serves as a branch that goes to a new leaf node representing the result of the action being taken. Game tree search methods seek out ways to exploit this tree comparison to find a good solution by limiting the search area by pruning unnecessary branches and performing different search methods such as depth first search or Min-Max [31].

Starcraft, Sparcraft, and Game-Tree Search.

Churchill has performed numerous experiments into the use of AI techniques for various RTS problem areas, and has also developed the SparCraft simulation of the StarCraft RTS game [24]. He also organizes the AIIDE Starcraft AI competition [14], and has worked with others in order to provide a level of analysis of current generation RTS AI agents used in these competitions [33]. His own research into the realm of RTS tactical decision making addresses the use of modified game-tree searches to optimize the search process [13, 34]. These methods focus on speeding up the search by trimming "bad" decision areas off of the search tree early on, and more searching "good" branches more deeply.

Monte Carlo Planning.

The Monte Carlo Tree Search (MCTS) is an approach to tree search problems by utilizing a Monte Carlo decision making process [35]. A tree search is a search methodology where various states in a problem can be represented as nodes, each

node other than the root node must have a parent, and each parent can have multiple children based on what decision options are available at the parent node. The search evaluates each child and eventually determines an optimal course of action based on the scores. The final solution is the path that leads to the best solution.

The Monte Carlo decision making methodology is a semi-random way of choosing a solution. The idea is that if the average outcome of a decision at a specific point (i.e. parent node) is known, then the better choice should have a higher probability of being chosen. This is not always chosen, however, as sometimes the choice with a lower win probability can have a higher payout at the end. This balance between best choice and still choosing apparently sub-optimal solutions is why this search is semi-random. The choice itself is random but the weight given to each potential solution is weighted by the currently known value of each choice.

The MCTS combines the tree search and the Monte Carlo algorithm in a way that is able to use the benefits of both systems. First off, the tree is started from an initialized root node. This node represents the state of the system before any decisions are made. From this node, a choice is made on the next step according to a Monte Carlo based decision method. At the initial state all perceived payouts are the same so the first decision is completely random. Once a new decision is made, the remainder of the solution string is generated randomly and then the solution generated is scored. This score is back propagated to the decision point, and the payout weight at that point is modified. The search is then reset back to the root node and the next search is performed with the new weight scales affecting the Monte Carlo decision. This process is repeated until the entirety of the search tree is searched or an artificial search interrupt is engaged. When the search ends the path to the best child node found is given as the optimal solution.

Genetic Algorithms.

Genetic algorithms work by generating a population of solutions and analyzing each member of that population with regards to a certain objective function. The top performing members are selected and combined to create a second population which is also analyzed against the fitness objective. The top performing members of this second population replace the worst performing members of the original population and the process is repeated. Each combination of populations is referred to as a generation, and genetic algorithm run times are typically limited by population sizes and generational limits.

Planet Wars and Genetic Algorithms.

Fernandez-Arez et all associate the genetic algorithm against the RTS game Planet Wars in their research towards the 2010 Google AI Challenge. Planet Wars is a simple RTS where a player is assigned a number of planets each with their own starting units. Players must then utilize their fleets to conquer other planets and increase unit production. The game is largely about expansion by conquering neutral planets in the first stages of the game, and then evolves into tactics based combat as the two players battle to take each others territories in the later stages of the game. The results of the research show that a properly attuned genetic algorithm can be used to create a high percentage win rate, but a poor choice of objective can actually work against the AI agent and result in a higher loss rate [36].

Computational Agent Distribution.

Another important factor to consider in the construction of an AI agent is the method the overall framework is built. Many researchers utilize a single agent design that aims to have a single algorithm develop a solution to many aspects of the RTS

game. The AFIT agent is instead built using the modified technique introduced by Weber et al. [37] for their StarCraft EISBot. This type of agent is actually a compilation of many different agents - each individual file responsible for their own area. In his paper Weber discusses that his agent has separate managers for Strategy, Income, Construction, and Tactics. The AFIT agent built off of this initial design plan has its own separate managers: Attack, Defense, Unit, Building, and Economy. Each of these agents are able to prioritize and act on a different set of goals in order to help offset the restrictions caused by the No Free Lunch (NFL) theorem. This theorem states that no algorithm is optimal in all situations. The splitting of an agent into multiple managers allows each manager to be separately customized, which can provide better, faster searches in a smaller domain space.

Hierarchical Control of RTS AI.

In their 2014 paper, Stanescu et. all introduce a method of controlling combat in RTS games by generating a hierarchy of agents to control units on the field according to various objectives. The purpose of this model is to create a situation where some agents are on the "squad" level which control individual units to accomplish a set objective. These units fall under the control of other agents which have a "commander" level of authority which seeks to accomplish an overall strategy by assigning squads particular tasks. This split up of authority and decision making results in many smaller searches being performed instead of a single solution being sought for every unit on the field. This approach to RTS decision making is proven to have its benefits, especially in large combat scenarios where other search methodologies such as tree searches are overwhelmed by the sheer number of potential outcomes [38].

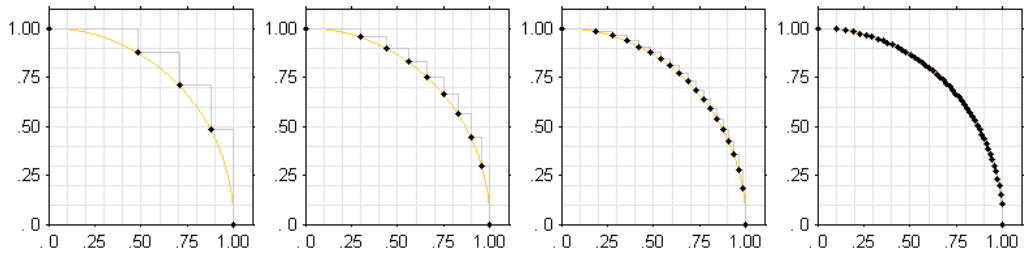


Figure 7. Example Pareto Front with Different Population Sizes (5, 10, 20, 50)

2.8 Multi-Objective Evolutionary Algorithm Tactics

The effort described for this research is a novel approach to the tactical decision making problem area, as it utilizes a variety of MOEA methods to determine the best targeting solutions faster than humanly possible. While current research primarily focuses on single objective evolutionary algorithms or applying various learning techniques and foresight, this research aims to create and test a methodology that is capable of generating a "good enough" solution using data that is currently available. The process involves testing various MOEAs under different parameter settings and then choose the option with the best resulting Pareto front as the example to bring to on line testing. The hypothesis is that a properly programmed MOEA finds an optimal set of tactical targeting decisions that maximizes damage output and minimizes wasted firepower.

2.9 Multi Objective Evolutionary Algorithms (MOEAs)

Multi Objective Evolutionary Algorithms are methods of solving problems by analyzing the potential results with regard to a variety of objective metrics [7]. While a single objective search focuses on optimizing a particular equation or metric within a set bounds, MOEAs are capable of finding multiple solutions that provide a range of outcomes based on the weighting of the objectives used. This range of data points which scale the different resulting scenarios resulting from differently weighted ob-

jectives is known as the Pareto front. The Pareto front consists of a set of optimal solutions that maximize the evaluation of a series of solutions based on which objective is assigned most important, least important, and every objective in between. Each axis of a Pareto front is represented by a separate function. The front serves to provide the user with a visual method of showing how the weighting of each objective value affects the overall outcome of the algorithm [39]. An example of the Pareto front can be seen in Figure 7 [40].

Nondominated Sorting Genetic Algorithm (NSGA).

The first algorithm to be discussed and used in this experiment is the Nondominated Sorting Genetic Algorithm (NSGA). Currently NSGA-II [41] is the most popular version of this algorithm used in MOEA software. The NSGA algorithm works by first randomly generating an initial population of potential solutions. Each of these solutions are then analyzed based on the objective functions set in the problem. Once all members of the initial population are analyzed they are ranked based on their level of pareto dominance. The more dominant members of the population are weighted higher than the non-dominant members of the population. The members of the population are then combined, with the more dominant solutions having a higher probability of being chosen for combination to create new members of the population. Once these new individuals are generated they are also measured against the objective values stated in the algorithm. The new members of the population are then combined with the old, and the best set are maintained for the next generation. It is important to note that there is a crowding factor - multiple individuals with very similar objective values are not saved in order to maintain a certain level of diversity in each generation. This process repeats for each generational instance in the algorithm until a final champion individual is found [39].

Strength Pareto Evolutionary Algorithm (SPEA).

The original version of the Strength Pareto Evolutionary Algorithm (SPEA) was developed in 1999 and aimed to combine many previously popular MOEA techniques into a single new algorithm [42]. The SPEA algorithm stored non-dominated solutions externally, used the concept of Pareto dominance to assign a scalar fitness value to each individual, and performed clustering in order to reduce the number of non-dominated solutions within the current generational solution set without negatively impacting the Pareto front. The algorithm works by generating an initial population P and an empty non-dominated set P'. It then copies any non-dominated members of P into P'. If these new members of P' dominate or are dominated by existing members of P', the dominated solutions are removed. If the number of members in P' exceeds the maximum population size, then P' is pruned. Once the size of P' is less than or equal to the maximum population size, the fitness for each member of P and P' is calculated, members from both are taken and then used to create the next generation. These steps are repeated until the maximum number of generations are calculated.

The unique aspects of the SPEA are the fitness evaluation functions and the clustering function used to trim an overfull P'. The first step in this analysis is to generate the scores for each member $i \in P'$. Each fitness score, or strength is evaluated according to the formula $s_i = \frac{n}{N+1}$, where N is the size of P and n is the number of members in P that the point $i \in P'$ dominates. Once this is accomplished for every member in P', the algorithm then computes the fitness for each member $j \in P$. The fitness of j is evaluated by summing the score of each point $iinP'$ that dominates j, and then adding one. These evaluations are performed in each generational computation, with the consideration that a lower fitness value leads to a higher probability of being chosen for combination to create the next generation.

The final evaluation that takes place is the clustering function, used to trim down the non-dominated set P'. This function works by dividing each member $i \in P'$ apart into a set of clusters. If P' is overfull, the algorithm determines the overall distance between each cluster. The nearest two points are then merged together into a single cluster. This repeats until the number of clusters equals the maximum population size. Once this is done a single solution from each cluster of size larger than one is chosen as that clusters representative on the pareto front, and the other members of that cluster are discarded.

Strength Pareto Evolutionary Algorithm 2 (SPEA2).

The SPEA2 is a continuation of the development used to create the SPEA [43]. The overall process used in each generational computation is largely similar to the one used in the SPEA. First, an initial population set P_0 is created, with a blank set P'_0. An additional variable $t = 0$, which represents the current generation, is also created at this time. Once the set is created then the fitness values of each member of P_t and P'_t are calculated. All non-dominated members of P_t and P'_t are copied into P'_{t+1}. If P'_{t+1} exceeds the current population limit, then it is truncated. If the generational limit has not yet been reached, then the members of P'_{t+1} are combined via binary tournament selection in order to create the next generation. This process repeats until the generational limit is reached.

The first difference in the calculations performed in Strength Pareto Evolutionary Algorithm 2 (SPEA2) is the fact that every point in P and P' are assigned a strength value. In the SPEA, the fitness value of a point in P is simply the sum of the strength values of the members in P' that dominated it. This could potentially lead to numerous points in P having the same value, and a sub-optimal one of these being selected for future combination. SPEA2 fixes this by assigning every point currently

in consideration a strength value, and then following the old process of a fitness value for any given point i being the sum of any points $j \neq i$ that dominate point i. This creates a hierarchy of dominated points, so that a point that is only dominated by the points in P' has a higher chance of being selected for combination than a point in P that is dominated by points in both P and P'. The pruning operator of the SPEA2 has also been modified. The first new capability of this operator is to always maintain the furthest points on the pareto front in order to ensure that the front is always as long as possible. The second modification is to sort through the entire solution set P'_{t+1}, find the closest two points, and remove the point of that pair that does not increase the maximum distance between the pair and adjacent points. These two operations ensure that the resulting pareto front is more uniformly distributed across the entirety of the pareto front.

Non-Dominated Sorting Particle Swarm Optimization).

The Nondominated Sorting Particle Swarm Optimization (NSPSO) algorithm is an application of the Particle Swarm Optimization (PSO) methodology to a multi-objective landscape [44]. This algorithm combines concepts from PSO and Non-dominated Sorting Genetic Algorithm II (NSGA-II). First, an initial population is developed, each member of the population has a randomized starting velocity within a previously set boundary. Each of the members of this population is then analysed, and the non-dominated members are copied into a separate list. Once the list of non-dominated solutions is completed, the algorithm chooses one member from this non-dominated list as the best, and uses this as the global best option for the rest of the calculations in this generation. The rest of the operations of the PSO work as normal, with the other members within the population changing their vector and velocity to move towards the current personal best and global best members in the

population. This results in an MOEA that gradually clusters its solutions near the best solutions, leading to a more intensive localized search while sacrificing the ability to search the entirety of the available landscape.

Other Multi Objective Evolutionary Algorithm Options.

There are numerous other methods of solving multi-objective problems, as any algorithm can be modified to more closely fit a specific problem at hand. This modification limits the use of this now customized algorithm for the purpose of solving other problems so there is a trade-off between having a generic algorithm that can be used on many problems or creating a custom problem suitable for a single problem [45, 46].

Pareto Front Indicators.

The multiple ways of deriving a Pareto front leads to the problem of the comparison of the results of one MOEA to the results of a separate option. For each specific problem, there is an MOEA that works the best, and one that does not work as well. This is known as the "No Free Lunch" theorem, which in essence explains that there are always optimal and sub-optimal algorithms available to solve any given problem. There is no such thing as a universally optimal search algorithm [47]. The goal of any Pareto front indicator is to judge the Pareto result from a given MOEA and provide a means to compare that result to the result from a different MOEA.

Hyperarea / Hypervolume.

The hypervolume (HV) or Hyperarea (HA) method aims to maximize the area or volume covered by a particular Pareto front. This indicator determines the volume of

an objective space that is dominated by any given set A with regard to a designated origin point [48].

R - metrics.

R-metrics operate by using an external utility function to compare the results of any Pareto front. Each point within the Pareto fronts being compared is put through these utility functions and then the results can be used to provide a means to determine which option is better. The results of an R-metric analysis between Pareto fronts is heavily reliant on the metric used for the comparison, and the user should also be aware that a single large outlier can offset numerous smaller differences [48].

Generational Distance.

The Generational Distance (GD) method compares the results of a given MOEA to the known best Pareto front available. Each member of the MOEA's resulting Pareto front is paired with the known best, and the total difference between the two options is calculated. This results in a clear metric that can be used to determine how close any given Pareto front is to optimal. The limitation of this indicator is that the user must first know what the optimal Pareto front is for a given problem [48].

ϵ - indicator.

The epsilon indicator operates by attempting to minimize the value ϵ that causes a set B that is dominated by another set A to instead weakly dominate A. This can be visualized as determining the amount of error that, if added to a substandard option B improves B to perform at least as well as the alternative A. This metric requires two different sets to compare, and can show improved results if the true Pareto front

is known, as it then becomes a metric directly comparing distance away from the true Pareto front [48].

MOEA Software.

The purpose of the MOEA software selection is to serve as a external framework that the AFIT agent can access and use to determine an optimal course of action for the controlled units to take. These frameworks can be accessed in different ways and can come in a variety of coding languages.

jMetal.

One of the most popular MOEA frameworks available is jMetal (Metaheuristic Algorithms in Java) [49]. As expected from the name, this framework is coded entirely in Java and is capable of handling NSGA-II, SPEA2, PSO, and a variety of other algorithms. It also supports numerous quality indicators such as hypervolume, generational distance, and inverted generational distance. This software provides a very robust system with the means to analyze a variety of potential setups with regards to MOEA performance and evaluation.

MOEA Framework.

MOEA Framework is another java library custom built to support MOEA problem solving. This library supports numerous types of MOEAs, including the recently developed NSGA-III algorithm. It also supports numerous metrics to gauge the results and performance of various MOEAs on a specific problem, and includes a pre-built graphical user interface for easy translation of the results [50].

PyGMO.

Another MOEA evaluation framework is the python language based PyGMO (Python Parallel Global Multi-objective Optimizer) [51]. Developed by the European Space Agency (ESA), PyGMO is a powerful tool that takes advantage of python's malleability as a coding language. PyGMO integrates with some other popular python based scientific evaluation software, such as SciPy, NLOPT, and SNOPT. While PyGMO provides an easy to understand structure to determine best results and scoring, it does not have as much breadth as jMetal. Many of PyGMO's built in algorithms are focused on single objective evolutionary searches, and it currently only provides hypervolume as a means to analyze the results of a given search.

ParadisEO.

ParadisEO is a C++ based framework for MOEA analysis that supports many basic MOEAs such as MOGA, NSGA-II, and SPEA2. It also contains the capability of using a variety of built in metrics and quality indicators such as hypervolume and additive and multiplicative epsilon [52, 53].

Borg.

The Borg MOEA is a specifically coded program that utilizes a single custom built algorithm. This algorithm seeks to measure the tradeoffs between different objectives and modifies itself to run optimally for the problem at hand. The Borg MOEA is coded in ANSI C. This MOEA is focused on attuning itself and modifying its own parameters in order to achieve optimal analysis of a new problem. [54].

Others.

The list provided in Chapter 2.9 is only a portion of the software available that has been built to address the analysis of MOEA problems. A much more intensive list is maintained by Dr. Coello Coello which holds many libraries and frameworks built for the analysis of a particular MOEA or problem of interest [55, 56].

2.10 Chapter Summary

This chapter provides a synopsis of many concepts and approaches used to plan and accomplish the experimentation performed for this research. An overview of the decision making process is provided, as well as a link to the analysis and use of this process for its application to the RTS decision making problem. A variety of considered RTS software platforms and MOEA libraries and environments are listed in order to provide an overall view of currently available technology applicable to this research. Finally, a comparison between strategic and tactical decision making is shown, as well as a variety of different approaches to the tactical decision making problem that have already been tested. The following chapters provide an explanation and process of the newly generated MOEA based tactical decision making RTS AI agent that is used to create targeting solutions in online play on an RTS environment.

III. Methodology of RTS Tactical Design

3.1 Introduction

As stated in Chapter I, the goal of this thesis research is to develop a decision making element of an RTS game agent that utilizes MOEAs to make fast, optimized tactical battlefield decisions. The research is segmented to accomplish three primary objectives. First, the research combines external MOEA software with the previously existing AFIT RTS AI agent [6, 5]. Once this integration is complete an offline simulation of combat is developed and used to test the performance of different MOEAs to find which type of MOEA performs best with the RTS tactical decision making problem, and which parameters maximize this performance. The best performing MOEA/parameter set out of the tested options are coded into the AFIT agent and tested against various scripted tactical decision making methods which serve as a comparative basis to test the performance of the MOEA.

This chapter is decomposed in order to adequately describe the methodology of each of the three primary phases. First, a brief high level description of the entire experimentation process is provided, along with an analysis of the new software used to perform MOEA analysis within the AFIT agent. The chapter then goes into detail describing the purpose and process for each of the primary phases, development of the problem, offline experimentation, and online experimentation, and details the selection of the required metrics and analysis tools used to gather data. The chapter concludes with a summary of all actions performed, and leads into Chapter 4. Chapter 4 expands on the information provided in Chapter 3 and provides a more detailed explanation into the actual steps used to perform the research.

3.2 Overview of Research Approach

The purpose of this research is designed to test the capacity of MOEAs for use in solving the RTS tactical decision making problem. To accomplish this task, MOEAs with differing parameter settings are used to solve an offline simulation of a round of combat in order to determine which search method performs the best in the tactical decision making search landscape. This research and experimentation requires analysis of multiple types of MOEAs, integration of MOEA software with the existing AFIT agent and Spring RTS Engine, and final evaluation of MOEA controlled tactical decision making against scripted opponents.

The development in this thesis investigation has three distinct phases. In the design phase, the objective is to combine the currently existing AFIT agent with the PyGMO python library [6, 51]. This requires the development of a new MOEA structure which represents a round of combat in the Balanced Annihilation mod [57] of the Spring RTS Engine. Once completed, this customized structure is used extensively in experimentation phase two, and is maintained in the online decision making of experimentation phase 3. Experimentation phase two consists of testing of various MOEAs and measuring their performance in solving the RTS Tactics problem. Multiple MOEAs are used in this phase, which are chosen based on their differing search techniques. Each MOEA is tested under a variety of population and generation limit parameters in order to gauge parameters' effects on the performance of the MOEA. The resulting performance of each MOEA in solving the RTS tactical decision making problem is decided based on an analysis of the generated Pareto front. The most optimal MOEA should have a quickly expanding Pareto front, which should depict a series of high-performing solutions being generated quickly [58]. Speed is a critical factor in the RTS tactical decision making problem, as solutions quickly become outdated due to a constantly changing battleground. Thus, the best performing

MOEA/parameter set is coded into the AFIT RTS AI agent and used as a test case against a variety of scripted tactics. The performance of the MOEA based tactical agent is tested against a new set of objectives, and the results are used to determine the effectiveness of MOEAs as tactical decision making managers.

3.3 MOEA Software Selection

The PyGMO library is selected as the MOEA software for use in this research [51]. The PyGMO software allows for four dimensional Pareto front analysis while also allowing use of the NSGA-II, SPEA2, and NSPSO algorithms [51]. PyGMO was also coded in the python, which is the same language used to write the AFIT RTS AI agent [6, 5]. Choosing a MOEA library with the same native language as the existing agent allows for easier integration with existing code. Libraries utilizing other languages would require additional development time which would have a questionable impact on the overall performance of the MOEA based tactical decision making manager. The purpose of this research is to prove the usability of MOEAs in the RTS tactical decision making problem - complete optimization of this agent is not within the scope of this research.

3.4 Design Phase 1 - Integrating Spring RTS & PyGMO

Phase 1 of the research includes the redesign of the existing AFIT tactical decision making manager to allow for the integration of MOEA based tactical decision making within the Spring RTS Engine. This phase begins with the analysis of the methods the AFIT agent utilizes to initialize and perform combat maneuvers, and modification of the agent to act on champion solutions resulting from MOEAs. A custom problem representing the RTS tactical decision making problem is also developed and used to test the performance of different MOEAs in Phase 2.

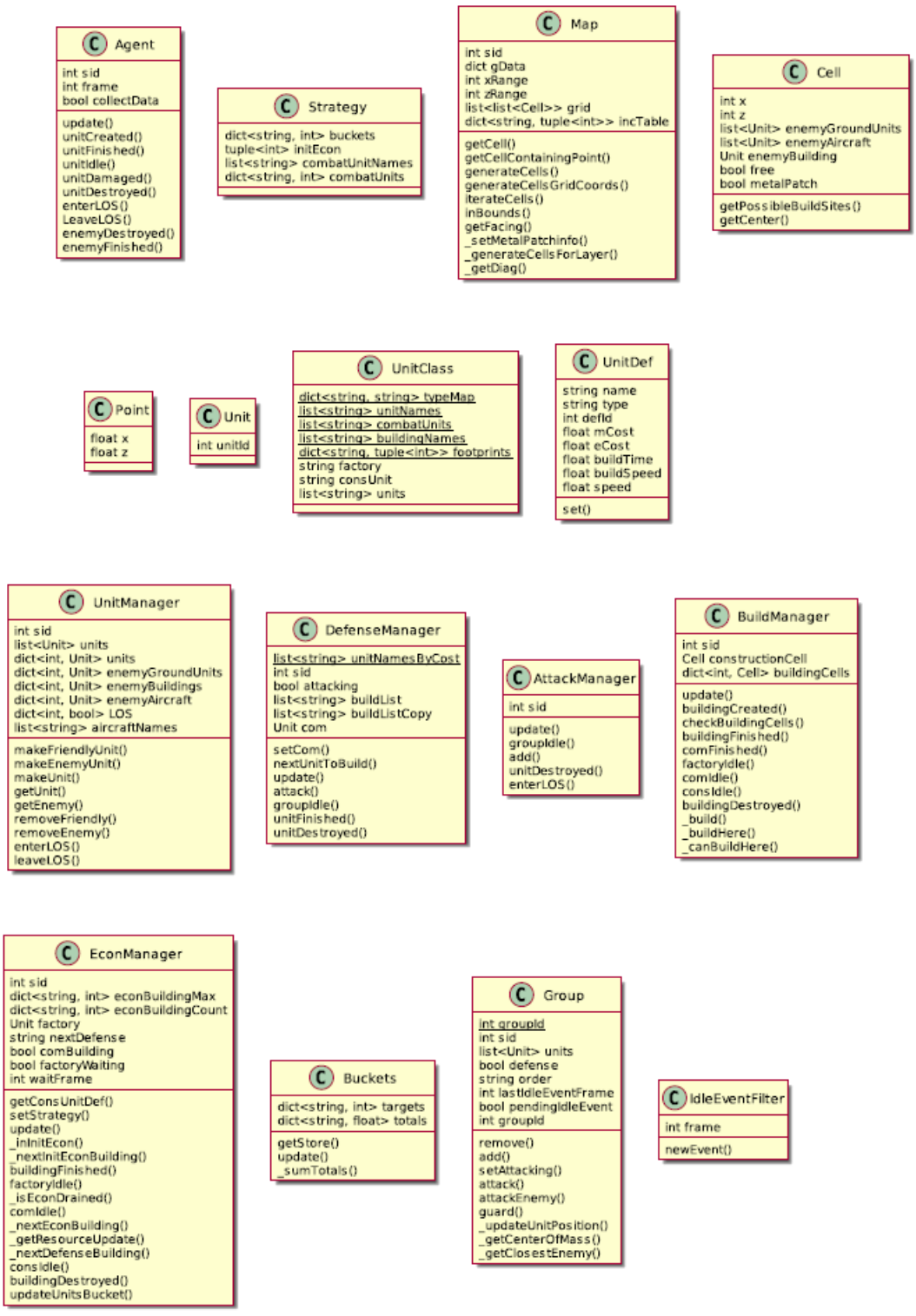


Figure 8. File layout for the Di Trapani (AFIT) Agent [6]

It is important to note that the integration of PyGMO into the AFIT agent is complicated by the nature of the AFIT agent. The AFIT agent is developed by a variety of students, each with their own coding styles. The integration of open-source software into the AFIT agent requires a very methodical approach in order to minimize potential code conflicts or errors.

AFIT Agent.

The agent modified for use in this experiment is the one developed by Di Trapani in his 2012 thesis research [6]. His agent is actually a framework of multiple managers that constantly communicate with each other throughout the duration of the RTS game. This inter-dependency allows each individual manager to enact a different decision making process that has been optimized for a specific role. The setup of the original AFIT agent is focused on generation and utilization of series of strategic options chosen through various configuration files. The tactical control exists within the group.py file in the current AFIT agent, but follows very simple scripted commands and is able to make decisions based on a complete knowledge of the current state of the battlefield. A list of the original file structure can be seen in Figure 8 and the inter-connectivity is shown in Figure 9.

As shown in Figures 8 and 9, agent initialization begins with Agent. This file calls on the UnitClass file in order to define all units to be used with a given game type. Once initialized, Agent creates and links AttackManager, DefenseManager, BuildManager, and idleEventFilter. These four files control the majority of systems during gameplay. BuildManager utilizes EconManager and the Strategy in order to generate a series of initial actions for the agent to follow. BuildManager is the primary control system until units are generated. Once units are generated they are added to Group, within DefenseManager. These units are used to defend the base

until they reach the appropriate army size defined within a set strategy. Once the army is "complete", the Group is passed to AttackManager, who presses an attack on the opponent. This process continues until one side participating in the battle is destroyed.

The AFIT agent initializes two files, agent.c and agent.py. These two files serve as the starting points for future calculations - agent.c acts as the first step in the initialization of the AFIT agent, and establishes the connection to agent.py. Agent.py then reads the configuration settings laid out for the system under test and establishes the primary managers - BuildManager, DefenseManager, and AttackManager. The initializations cascade through the various other python files as shown in Figure 9. This co-dependence not only allows for each agent to independently control it's portion of the game, but also allows for the introduction of new managers - a critical trait for the introduction of MOEA analysis to tactical decision making.

AFIT Agent Configuration Settings.

There are two files that drive the initial configuration of decision making methods of the AFIT agent. These files are config.txt and strategyDefs.txt. Config.txt is used in the initialization of the AFIT agent through the cdata.py code, an example of which can be seen in Figure 10. The config.txt file has three sections: The game run number, which game map will be used as the battleground, and the individual player settings. The game run number is the least important of these options as it serves only as a marker for naming the results of automated testing of the agent. The map designation specifies which Spring RTS map should be loaded for a particular experimental run. These maps must be created in order to match the requirements of the Balanced Annihilation mod, which include things such as player start locations and resource patches [57]. The final section in strategyDefs.txt is a number of rows

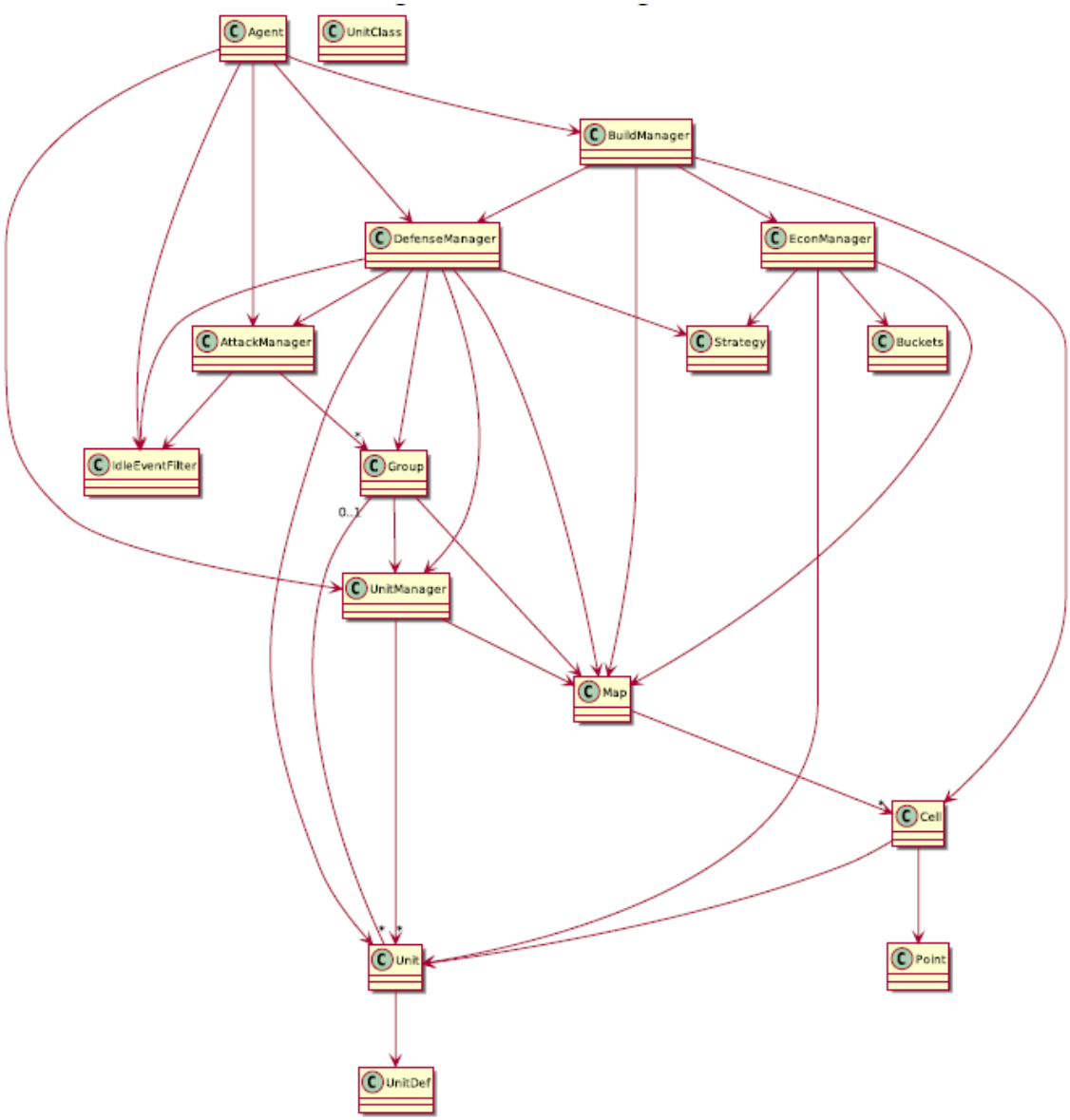


Figure 9. File connection structure for the Di Trapani (AFIT) Agent [6]

```
# Game run number - Used for automated game play
3
# Name of map to be used
ThePass
# Player 1 - Strategy - data collection - Tactics
p1 25v25 on default
# Player 2 - Strategy - data collection - Tactics
p2 25v25 on moea
```

Figure 10. Example for config.txt

Table 1. Layout of a Strategy in strategyDefs.txt

Variable Name	Domain	Description
Build Power	Integer value [0,100]	Percentage of resources for manufacturing capability
Economy	Integer value [0,100]	Percentage of resources for economic development
Defense	Integer value [0,100]	Percentage of resources for defensive structures
Units	Integer value [0,100]	Percentage of resources for units
Group Composition	Non-negative integer for each unit type to be considered	Size and composition of an "attack group"
Initial Economy	2-tuple of integer values	Initial economy required

equal to the number of players on the map. Each of these rows is further split into three sections - a player designator, a strategic method of choice, and a binary data collection variable. The player designator is something as simple as labeling the first player "p1" and second player "p2". The second option sets the strategic methodology for the agent to choose which is further defined by strategyDefs.txt. The final binary variable is a setting to determine whether or not a players actions should be saved in an external file. If true the game saves the current state of a game in an external replay file every five seconds.

Modification of the AFIT agent includes creating a new manager, MOEA, which will be called on by Group in order to provide a series of commands during battle. This new manager will rely on information provided by

The strategyDefs.txt file controls the flags that the agent uses to make building and attack decisions. A description of each of the separate sections of the document can be found in Table 1. In Di Trapani's version of the AFIT agent, this file holds numerous lines of strategies such as tank rush and anti-air [6]. Each line in a strategy tells the agent how to allocate resources, how to construct an attack group, and how to initialize an economy at the start of a game. The initial economy factor is the first segment of the code that the agent carries out, as it establishes a foundation of economic development that provides the resources for future play. The group composition is the portion of the agent that begins an attack. When units are created they are placed in a group under control of defenseManager. When a group is "complete", or deemed equivalent to the string in the group composition value, it is handed from defenseManager to attackManager and set to attack. At this point a new group is created and any newly generated units are again assigned to defenseManager.

Both of the configuration files are modified in order to support the implementation of tactical decision making. Config.txt is changed to manage a choice between various tactical decision making methods as well as strategic options, and new strategic definitions are added to strategyDefs.txt in order to support simulated experimentation. The specific changes and addition of new tactics to config.txt are described in Appendix A

PyGMO.

PyGMO is a python based library which provides the capability to analyze various problems via included optimization processes [51]. Each use of PyGMO requires the initialization of a problem, selection of an algorithm, and evolution by populating an "island". A example is provided via of one of the tutorials on the PyGMO website and is shown in Figure 11a [59]. This example shows how PyGMO solves a 50-dimensional

```
from PyGMO import *
# Initialize Problem
prob = problem.schwefel(dim=50)
# Select Algorithm to Solve
    ↪ Problem
algo = algorithm.de(gen = 500)
# Generate Island for Initial
    ↪ Population
isl = island(algo,prob,20)
print isl.population.champion.f
# Evolve the Population 10 Times
isl.evolve(10)
print isl.population.champion.f
```

(a) Code for PyGMO Example

```
(17643.0955597,)
(0.00063643016983401569,)
```

(b) Output for PyGMO Example

Schwefel minimization problem. As seen from the code any PyGMO initialization has three main components: the problem to be solved, the algorithm used to solve the problem, and the "island" that the population of potential solutions resides on.

In Figure 11a, the first line is responsible for implementing the PyGMO library. The next line which initializes `prob` sets this variable as a integrated problem that has been built into the PyGMO software, with the variable `dim=50` setting the number of dimensions to be implemented in the calculation. The analysis of a RTS game environment requires a customized problem to capture the current battlefield situation. The next line sets the variable `algo` to the differential evolution algorithm with 500 generations. This is made possible by the `algorithm.de` set-up, where the `de` stands for differential evolution. The last step is to build the population's island. The command `island(algo,prob,20)` creates an initial population of 20 members

that is then modified by the algorithm and problem via evolution. The best member of the population can be found at any time via the `isl.population.champion.f` command. The results of the two print commands included in Figure 11a can be seen in Figure 11b. The first line in Figure 11b is the best member of the initialized population of 20 members. The second line in Figure 11b shows the results after the population has been evolved 10 times. Based on the definitions instantiated by the variable `algo`, 10 evolutions of the island is actually $10 * (gen = 500)$ generations, or $5,000$ generations. That is why the algorithm is able to find such a small end result in only ten evolutions.

Custom Tactics Optimization Problem.

The utilization of MOEAs to solve the RTS Tactics Optimization Problem requires the development of custom problem for use in the PyGMO RTS Engine. The problem developed is loosely based on the build order optimization problem developed by Blackford in the previous AFIT agent [5]. For the custom RTS tactical optimization problem, each solution consists of a string with length equal to the number of agent-controlled units in the army. Each position of this string holds a value between 0 and the number of enemies in the battle. The position - value pair represents the target for the agent controlled unit. An example can be seen in Figure 12, and the code for this custom RTS tactics problem solution can be found in Appendix A.

Instantly Spawning Units in Spring.

Typically, unit creation in Balanced Annihilation requires the construction of appropriate factories or barracks. This can require up to 15 minutes for an agent to build up an appropriate number of units to test tactical decision making methods [6]. In order to speed this process, the online testing of phase 3 relies on "cheat" com-

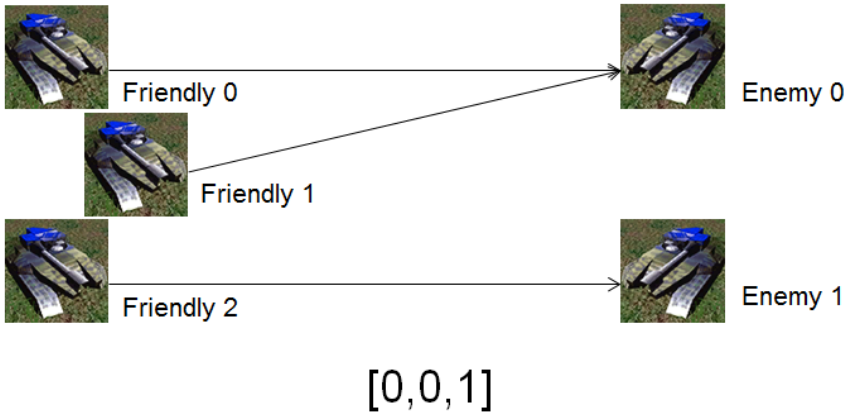


Figure 12. Example Solution for 3 vs 2 Combat

mands built into the Spring RTS Engine. These cheat commands allow instantaneous construction of units so that quick battles can be performed. The utilization of cheat codes drops a single simulation time from 15 minutes to under 2 minutes. This process of instantly generating units is critical for increasing the speed of online testing of the RTS tactical decision making problem. Base development is unnecessary for tactics testing and differing base development decisions between the two tested agents. This may cause armies to be launched at different times, which negatively effects the analysis of tactics performance by affecting battle location or army completion rate.

3.5 Design Phase 2 - Developing Off-line Simulations

Once the custom solution to the RTS tactical decision making problem is developed, it is used to analyze the performance of various MOEAs in an off-line environment. An off-line environment is employed because a typical game of Balanced Annihilation (BA) takes approximately two minutes, even when hastened by the instant generation of units described in Section 3.4. Performing online testing of each MOEA under each parameter setting is time prohibitive, so an offline simulation is created which represents the first round of combat. This truncation is performed un-

der the logic that if a MOEA/parameter set is capable of creating fast, well performing solutions in the first, most complicated, round of combat, then that set also chooses fast, well performing solutions in less difficult situations. Now that the framework has been developed, the next step is to actually choose the MOEAs and parameters to utilize for tactical decision testing.

MOEAs Under Test.

The MOEAs chosen to be evaluated within this research are NSGA-II, SPEA2, and NSPSO. These algorithms are chosen because they represent generic coverage search methodologies in MOEAs. NSGA-II represents algorithms that utilize semi-random combination of seemingly optimal population members. SPEA2 focuses instead on the maintaining the spread between members in a particular generation on the Pareto front. NSPSO gathers its population members towards expected good decisions, which results in a more in-depth search in a small area of the Pareto front. These three methods present a combination of random, spread search, and focused search methods. This provides a baseline approach towards the analysis of different search techniques on the RTS tactical decision making problem. Each of these MOEAs are also readily available for implementation in the PyGMO code, which speeds development time and integration with the Spring RTS Engine [51]. The parameters changed for experimentation are the population and number of generations to evaluate. Population size options are 20, 40, 60, 80, and 100. Generational numbers are 2, 3, 4, and 5. These options are chosen because they provide a "good" coverage of the utility of each MOEA while also providing a range of potential solutions that are calculated within a couple of seconds.

Off-Line MOEA Objectives.

Perhaps the most important decision in setting up an on-line MOEA is the choice and application of the objectives measured. For this research, a four objective MOEA design is chosen due to the desired amount of data required compare each member of the population. Each of the objectives considered for use are discussed in the following sections, as well as their application and refinement in order to make them more applicable for the tactical decision making problem.

$$\text{OBJ} = \sum_{i=1}^{M} \text{status}_i - \sum_{j=1}^{N} \text{status}_j \tag{1}$$

OBJECTIVE: Difference in Number of Units.

The first objective focuses on comparing a total count of units controlled by both sides in a conflict and is shown in equation 1. Fog of war [60] is removed for the analysis of the number of units taking part in battle, which means that the complete number of units available to both sides is visible to the MOEA. In this equation, M represents the total number of enemy units on the field, and N represents the number of allies. The *status* variable is a binary value which is true if the unit is available for use. This objective is initialized to zero and is minimized through the course of generational optimization. The concept behind this objective is that if an army has more units than the opponent, then it has a measurable advantage in how those units can be used. The resulting values of this objective are small in comparison to other objectives due to the limiting factor of the number of units on the field. The maximum number of units potentially lost in a round of combat is equal to the total number of units, which is already much smaller than the hit point or damage capability scores used for other objective analysis.

$$\text{OBJ} = \sum_{i=1}^{M} \text{HP}_i - \sum_{j=1}^{N} \text{HP}_j \tag{2}$$

OBJECTIVE: Difference in Remaining Hit Points.

The second objective considered compared the relative number of Hit Points (HP) available to each side of the conflict. Like in objective 1, M is the number of enemy units and N is the number of allied units. In this objective a pure sum of hit points is taken and the difference between them is measured. The purpose behind this objective is to attempt to measure the future survivability of an army in comparison to enemy forces. If an army has more hit points then it has a higher probability of surviving the next wave of attacks, which means that it is be able to continue firing for a longer period of time and provide more damage to the enemy. This objective is modified by having each unit's HP represented as a ratio rather than a definitive HP total, as some unit's hit points can range into the thousands which skews the objective analysis towards these four or five digit values and away from the smaller objective values. This is represented in equation 2.

$$\text{OBJ} = \frac{\sum_{i=1}^{M} \text{HP}_i}{\sum_{i=1}^{M} \text{status}_i} - \frac{\sum_{j=1}^{N} \text{HP}_j}{\sum_{j=1}^{N} \text{status}_j} \tag{3}$$

OBJECTIVE: Difference in Average HP per Unit.

The objective shown in equation 3 is a combination of the unit number and HP difference objectives. First the total amount of hit points available to each army is calculated, and then divided among the remaining units in that army. The purpose of this objective is to create a glimpse into the survivability of each individual unit on either side. This agent gives more weight to those armies with a higher average

HP value. This increases the optimality score of high HP armies, which have a higher survivability rate in future battles.

$$\text{OBJ} = \sum_{i=1}^{M} \text{damage}_i - \sum_{j=1}^{N} \text{damage}_j \tag{4}$$

OBJECTIVE: Difference in Remaining Damage Capacity.

The objective in equation 4 is a strict measure of the damage dealing capability of the units remaining on the map. This objective is initialized to zero like other difference based objectives. This measure subtracts all potential weapon damage that allies units can perform, and adds damage capability of opposing units. The purpose of this objective is to have allies units focus on destroying hard hitting enemies first, thus reducing the strain allied units need to worry about in future stages of the battle. This also allows allied units to focus on preserving their own heavy damage fighters if mobility commands are implemented in the tactical agent.

```
for each enemy I in combat:
    count = 1
    for each ally J attacking enemy I:
        Subtract count from objective score
        count = count + 1
```

Figure 13. Code Representing Focus Fire Objective

OBJECTIVE: Focus Fire.

The objective shown in the pseudocode of Figure 13 is originally initialized to 0, and decreases with regard to how many friendly units attack the same enemy target. This objective checks each potential enemy in the list and subtracts an increasing amount for each friendly unit attacking that target. The first unit is worth -1, second

is worth -2, third -3, and so on. Five friendly units attacking the same enemy would subtract $5 + 4 + 3 + 2 + 1 = 15$ from the objective. This objective is introduced in order to increase the probability that friendly units focus on the same target. Prior to the introduction of this objective, the MOEA is capable of maximizing damage by spreading attacks randomly across all potential targets, and it is rare to get an early kill due to damage across 5 enemies being equivalent to having 5 units fire on the same enemy. With this objective allied units are able to severely damage, if not kill, more units in each round of combat. This lowers potential enemy damage output and also increases the likelihood of kills in future rounds.

OBJECTIVE: Damage / HP.

This objective is a modified form of the version discussed in Kovarsky and Buro's work [61]. In the original paper, the objective is

$$LTD(s) = \sum_{u \in U_e} HP(u)\dot{d}pf(u) - \sum u \in U_a HP(u)\dot{d}pf(u) \tag{5}$$

where

$$dpf(u) = \frac{\text{damage(w(u))}}{\text{cooldown(w(u))}} \tag{6}$$

This objective is modified to a more generic form in order to take into account a base damage per hp for each unit by changing equation 5 as shown in equation 7

$$LTD(s) = \sum_{u \in U_e} HP(u)\dot{d}amage(u) - \sum u \in U_a HP(u)\dot{d}amage(u) \tag{7}$$

This can be modified in order to achieve the end results from Kovarsky and Buro's paper, but it works sufficiently well in its current form in order to be able to distinguish the importance of targeting low hp high damage units prior to high hp or low damage dealing units. The focus of these equations is to have the agent focus more fire on

dangerous enemies with low hit points. If targets with high attack and low defense are removed first, this not only removes enemy damage dealing capability but also increases the speed and quality of future searches due to the reduced search area.

Objective Selected for Use in Offline Simulation.

The objectives selected for use in the offline simulation are the number of units, the HP total, the damage capability, and focus fire. These objectives are selected due to the uniformity of armies fighting each other - engagements for test are comprised of only one type of unit. With this type of army composition the combination of HP total, damage, and number of remaining units is expected to provide a precise view of the overall health of the two armies after an attack. The focus fire objective is added in order to enable friendly forces to heavily damage a few units rather than distributing fire on many targets. This focus of damage either destroys enemy targets within the first round or enables the search to have better, easier solutions in later rounds of combat due to the existence of heavily damaged enemies.

While the focus fire objective skews the search area due to the fact that it is capable of obtaining much larger values than the other averaged objectives, this offset is mitigated by the inclusion of a variety of constraints within the custom RTS tactical decision making problem. First, any damage dealt that brings an enemy past 0 hit points is ignored, effectively negating the primary effects of that shot. Second any expected damage to an enemy out of firing range is set to 0, which also negates any seen benefit of focusing on enemies too far away. These two constraints work to maximize focused fire while also preventing this objective from creating sub-optimal solutions.

Measuring MOEA Performance.

The performance of each MOEA, population, and generational limit combination is based on the improvement to the expansion rate of the Pareto front's hypervolume [39] over the course of time. This decision is made because the solution to the RTS tactical decision making problem must focus on both speed and correctness. A larger hypervolume provides a better "champion" solution, as the resulting Pareto front is closer to the "true" Pareto front. The speed of solution is important because the state of a RTS battle is constantly changing so a solution must be provided fast enough to still be relevant. The objective of this metric is to determine which combination of attributes leads to the fastest, best solution. In order to accomplish this task, each MOEA is tested with a population of 20 and a single generation in order to serve as a starting point. The hypervolume of these runs is used as the comparative basis against the other MOEA / population / generation tests. For example, if the NSGA-II algorithm is tested to find a hypervolume of x, then each subsequent test uses the formula $\frac{HV-x}{t}$ to determine the score of that combination, where HV is the new hypervolume and t is the time required to complete the test.

3.6 Experimental Phase 3 - Developing On-Line Simulations

The objective of phase 3 is to take the best performing MOEA from phase 2 and utilize it in a series of on-line runs to validate its performance against three commonly scripted options. The MOEA selected for on-line integration is shown to out perform the alternatives due to the results analyzed in phase 2.

RTS Tactic Methods.

There are three scripted tactical target decision making methods used to serve as challengers to the best performing MOEA found in phase 2. These three scripts

are group attack closest, individual attack closest, and group attack weakest. These options are chosen as options because of their use as a starting point of measuring tactical performance in other researcher's work related to tactical decision making [13, 34]. Group attack closest is capable of balancing the number of units firing during a round of combat while also maximizing the extent of focused fire. Individual attack closest instead maximizes the number of units able to fire at the cost of focused fire. Group attack weakest destroys damaged units quickly and removed their damage dealing capacity from the battle as soon as possible.

Group Attack Closest.

The pseudocode shown in Figure 14 depicts the "standard" AI decision making process for the AFIT agent. The entire code can be found in Appendix A The first task the agent performs is to generate a blank matrix based map which holds the data for all friendly and enemy units. This map is populated in the second for loop displayed in the figure. The agent goes through a pre-generated list of enemy positions built by the `cdata.clb.getPositions` command. These positions are assigned a point in the matrix generated at the start of the code. Once all enemy positions have been added to the targeting map, the central point of all allies forces contained in the current group is found by the `self._getCenterOfMass()` command. This command performs a similar task as the previously mentioned for loop, but instead takes all of the X and Z coordinates for every unit in the currently controlled group and averages them. The X and Z coordinates are chosen because the Spring RTS Engine treats the Y axis as the vertical axis to denote altitude. Ground forces ignore altitude in this version of the agent since range is a hard set parameter flying units likewise do not need this axis as they operate at a constant altitude [6].

```
for each cell in map:
    clear cell data
enemyMap = list of enemy units
size = length of enemyMap
unitIds = identification of each unit in enemyMap
enemyPositions = position for each unit in enemyMap
for each unit in enemyMap:
    place enemy and corresponding data on correct position in map
xavg, zavg = center of mass of agent controlled units
if agent forces are flying:
    attack enemy commander
else:
    if enemy commander in line of sight:
        attack enemy commander
    else if building in line of sight:
        attack building
    else:
        attack enemy in Line of Sight closest to (xavg, zavg)
        if no enemies within line of sight
        move towards enemy commander
```

Figure 14. Pseudocode for Default AFIT Agent Tactics (Group Attack Closest)

Once the average allied position and map of enemy locations have been built, the agent begins sorting target priorities. The first task is to search for nearby enemy buildings. If a building is closer than enemies then the building is set as the group's target marked by the `enemy` variable. If no buildings are within range the agent then checks the size of the `enemies` list. If an enemy exists in this list the agent determines the enemy unit closest to the coordinates `(xavg, zavg)` and set that as

the group's target. The last step before firing is to determine if the chosen target is actually within firing range. If the enemy is within range, the group attacks that target. If no enemies are within visual range then the agent defaults towards telling the group to move towards the enemy commander until enemies are encountered. This repeats until the enemy commander is destroyed or the controlled group is completely destroyed.

If a group is comprised of only air units, various if statements check for an "air" designation. If this "air" setting is true, the agent ignores all tactics other than a direct attack on the enemy commander [6].

Individual Attack Closest.

The algorithm for the Individual Attack Closest tactic is shown in Figure 15, with the full code provided in Appendix A. This algorithm is a modification of the default attack code shown in Figure 14, and takes place within the if statement checking if the targeted closest enemy is within line of sight. This code differs in the manner in which it engages the opposing force. Where the default code has every unit in the group engage a single enemy, the individual attack closest tactic performs a sorted search through all enemy locations. This search is performed by first determining each allied unit's location. This location is then saved, and a blank target list is built. This target list is populated by comparing the allied unit's location to every enemy location on the map, with the result being stored as `[distance, enemyId]`. Once the list is completely populated a sort command is used to sort the target list based on the first value, which is the distance. This sort puts the smallest distance first, and then the agent assigns the unit to attack the enemyId associated with that distance.

```
for each cell in map:
    clear cell data
enemyMap = list of enemy units
size = length of enemyMap
unitIds = identification of each unit in enemyMap
enemyPositions = position for each unit in enemyMap
for each unit in enemyMap:
    place enemy and corresponding data on correct position in map
xavg, zavg = center of mass of agent controlled units
if agent forces are flying:
    attack enemy commander
else:
    if enemy commander in line of sight:
        attack enemy commander
    else if building in line of sight:
        attack building
    else:
        for each friendly unit
            attack closest enemy
        if no enemies within line of sight:
            move towards enemy commander
```

Figure 15. Pseudocode for Individual Attack Closest

Group Attack Weakest.

The pseudocode for the algorithm controlling the group attack weakest tactic is shown in Figure 16 and is very similar to the code used in the individual attack weakest tactic (Figure 15). As with the other scripted tactics method, the full code can be found in Appendix A. The selection of a target follows the same basic procedure,

```
for each cell in map:
    clear cell data
enemyMap = list of enemy units
size = length of enemyMap
unitIds = identification of each unit in enemyMap
enemyPositions = position for each unit in enemyMap
weakest = 1
for each unit in enemyMap:
    place enemy and corresponding data on correct position in map
    if unit hit points < weakest hit points
        weakest = unit
xavg, zavg = center of mass of agent controlled units
if agent forces are flying:
    attack enemy commander
else:
    if enemy commander in line of sight:
        attack enemy commander
    else if building in line of sight:
        attack building
    else:
        for each friendly unit
            attack weakest
        if no enemies within line of sight:
            move towards enemy commander
```

Figure 16. Pseudocode for Group Attack Weakest

assigning sort weighting on the enemy's remaining HP instead of the distance between

a unit and potential targets. Once the sorting algorithm is complete, the unit is assigned the target with the lowest sorted HP.

```
allies = []
enemies = []
for unit in friendly units:
    append [ID, hit points, "alive", position, damage, range] to allies
for unit in enemy units:
    append [ID, hit points, "alive", position, damage] to enemies
initialize RTS tactical decision making problem and initialize population
    ↪ size
select algorithm for use with RTS tactical decision making problem and set
    ↪ generation
initialize population
evolve population
select "champion"
for position in champion:
    position (friendly unit) attacks value of position (target)
```

Figure 17. Implementation of MOEA in AFIT Agent

Multi Objective Evolutionary Algorithm.

The pseudocode for the MOEA based tactical manager is shown in Figure 17, with the full code for this algorithm available in Appendix A. The algorithm controlling the agent based on MOEA output is noticeably more complex than with the tactics based on sorting. This method is based on building different arrays detailing information for allies and enemy forces. The first task is to construct the allied array. This array is built by first using Spring commands to determine the health and position for each individual unit. This information is then used to build a line of the `self.allies`

Figure 18. Stumpy Tank

array, which includes the unitId, health points, alive/dead binary indicator, position, damage potential, and attack range of each unit. Constant values are set for damage and range in this research due to the fact that comparative battles are only using a single type of unit, the Stumpy tank [62]. The stumpy tank's model within the Spring RTS Engine can be seen in Figure 18. Once the allied units' array is built the enemy array is built using a similar method.

The arrays are then passed to the custom problem built for the RTS tactical decision making problem discussed in Section 3.4. Once the problem is set, the algorithm, generational limit, and population limit of choice are applied in the `moea`, `gen`, and `pop` fields, respectively. The population is then evolved, and the champion string found. It should be noted that while in the example shown in Figure 11b gives values due to the `champion.f` command, the `champion.x` command returns the actual string that results in the best value. This string has i entries, where `len(i)` is equivalent to the number of allied units on the field. The number at each position $j \in i$ is the target of i. These values can be used to have the attack command associate each unit i with its target `champion.x[i]`.

Measuring Battle Outcomes.

The on-line battles performed between various tactical methods can be used to determine the effectiveness of those tactics. The strategy for each agent participating in the battle is set to one which focuses on the development and construction of 25

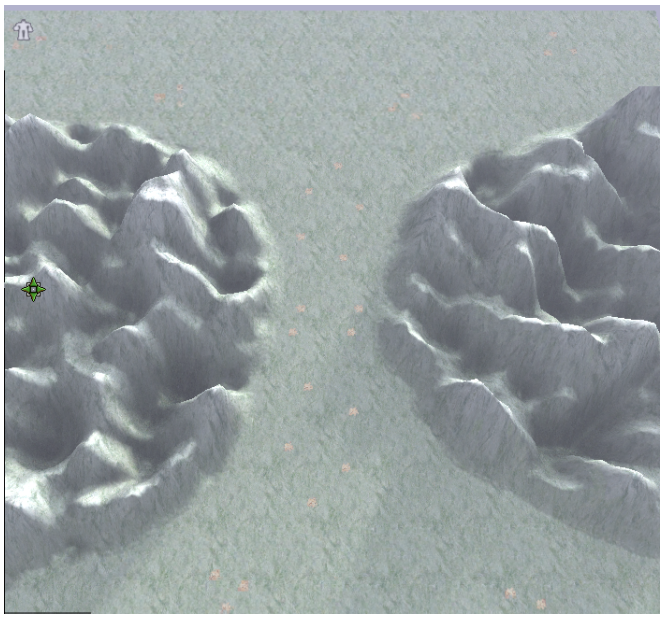


Figure 19. Central Path of ThePass map on Spring RTS Engine

tanks, which are then sent to attack the other army. The map chosen for this is ThePass (see Figure 19), which is a small multiplayer map on the Spring RTS Engine which focuses on driving opposing forces through a central channel. This channel can be used to force opposing armies to encounter and then begin attacking each other, which is ideal for use in testing how different tactical decision making methods perform against each other.

OBJECTIVE: Win Rate.

The first, and most important, metric that determines how well various tactics perform against each other is a simple determination of which agent won the battle. Winning is defined as the team who has forces remaining on the field when the other side is destroyed. This metric can be used as an obvious measure to determine how well an agent performs, but other metrics define the scale of the win based on other factors such as time of battle and army health after combat.

OBJECTIVE: Time of Battle.

The next metric that is used to compare the differences between battles is the overall length of time the conflict takes to resolve. The purpose behind this metric is to determine how long an army is delayed by opposing forces. In RTS games, it can be important to end a battle as quickly as possible in order to free up resources to either return to base to defend against another attack or to continuously provide pressure on the opposing player. This metric is measured in seconds, as that is the smallest unit of time the Spring RTS Engine replay files can measure.

OBJECTIVE: Number of Remaining Forces.

Another important metric to consider is the number of remaining forces. In RTS games, a unit with a single hit point can still serve either as a distraction to enemy units or another platform to damage enemies. For this reason the number of remaining units is used to determine how well various tactics perform against each other.

OBJECTIVE: Health of Remaining Forces.

The final metric that determines the grade of how well tactics perform against each other is the sum of remaining hit points among the forces. This metric is aimed at determining how well an agent has used its forces, and as a measure to determine how useful surviving units are in future attacks. An agent that wins with a number of severely damaged units is not expected to perform well in future engagements with those units.

3.7 Chapter Summary

This chapter provides an overview of the design process and decisions made for the execution of all three phases of this research. The chapter explains the three

phase approach that is used to determine the utility of MOEAs for use in solving the RTS tactical decision making problem. Phase 1 consists of the representation of the RTS tactical decision making problem in a MOEA solvable format, as well as the selection and integration of a MOEA library into the Spring RTS Engine. Phase 1 also details the reasoning behind the selection of MOEAs and the pursuit of covering a variety of search methods in order to be able to determine which search style works best for the RTS tactical decision making problem. Phase 2 includes the selection and implementation of objectives in the off-line evaluation of various MOEAs to determine the performance of different search methods on the RTS tactical decision making problem. Finally, Phase 3 takes the best performing MOEA from Phase 2 and its parameters into an on-line evaluation within the Spring RTS Engine. This MOEA is tested against three different scripted tactics and the performance is analyzed to determine potential MOEA RTS tactical decision making. The next chapter provides greater detail with regard to the experimental steps.

IV. Design of Experiments

4.1 Introduction

This chapter provides more information in the implementation of the steps described in Chapter III. While Chapter III provided a high level view of the processes used to perform the experiments gauging the effectiveness of MOEAs in an online RTS environment, Chapter 4 aims to provide a step-by-step process and analysis into how data is acquired and how selected objectives are implemented.

As in Chapter III, this chapter is split into a separate section for each primary phase of research. The first section analyzes the process used to develop the integration between the selected MOEA libraries with the Spring RTS Engine. This is followed by the procedure, code, and equations utilized to create and perform offline simulation of combat in order to speed analysis of MOEA performance in battle. The data found in the offline analysis is used to create an online tactical control manager that is tested against three generic scripted tactical agents, and the results again analyzed to determine MOEA performance within the RTS tactical decision making problem.

4.2 Experimental Design

As discussed in Section 3.2, the research performed for this thesis effort is divided into three distinct phases. Each phase results in the development of a tool required for the next. These phases are sequential in order to construct an experimental process capable of performing in depth analysis of the custom RTS tactical decision making problem by relying on the output of previous phases.

Phase 1 begins with Di Trapani's AFIT agent [6] and the PyGMO python MOEA analysis library [51]. The objective of Phase 1 is to combine Di Trapani's agent and the

PyGMO code together in a way which allows online optimization of an RTS battlefield using MOEAs. This requires the creation of a customized PyGMO problem which represents the RTS battlefield for on-line analysis. This problem is called within the group.py manager in the AFIT agent by utilizing the PyGMO libraries. There are no metrics associated with this phase as the result is just a code based representation of a round of an RTS battle.

Once the battlefield simulation created in Phase 1 is complete, it can be used to test the performance of the MOEAs of interest. Each MOEA is tested with differing populations and generational limits in order to gauge the landscape of the RTS combat search area. The tested population sizes are 20, 40, 60, 80, and 100. The tested generational limits are 2, 3, 4, and 5. These options are chosen in order to cover the range available to the population and generation limit properties while also constraining expected calculation time to be within on-line time requirements. The metrics used for analysis of MOEA performance are focused on hypervolume maximization over time, as a solution needs to be made quickly but also correctly. A set of objectives are selected from the list in Section 3.5 in order to provide enough description as to the optimality of the results of a battle. The MOEA which is capable of maximizing the rate of hypervolume [39] expansion over time is chosen as the best option for implementation in online testing. This MOEA is then coded into the AFIT agent as a tactical option within the group.py manager.

Phase 3 is the final step of this research. In this phase the previous phases' results are combined to create an online tactical decision making tool which is implemented within the Spring RTS Engine. This tactic is compared against three scripted opponents which are chosen as representatives of basic RTS combat design. Each combat between various tactical decision making methods is statistically analyzed according to the win rate, number of units remaining, speed of combat, and remaining HP.

4.3 Computer Platform and Software Layout

Online experimentation for this research is performed on the Spring RTS Engine [25] version 0.98 using version 8.08 of the Balanced Annihilation mod [57]. The Spring RTS Engine is selected due to the fact that it is open source and capable of heavy modification for future testing. This level of modification allows for manipulation of individual unit characteristics and features, as well as various cheat codes which introduce ways to test very particular features of AI agents quickly through visual simulation. The Balanced Annihilation mod allows for the use of many basic tenets of standard RTS play such as resource gathering and easily identifiable unit types. This mod is chosen as a representative of a generic RTS due to its implementation of two types of resource gathering as well as having multiple specialized unit construction facilities. The unit of choice for this experiment is the Stumpy Tank (see Figure 18, due to its arcing fire pattern, high armor score, and area of effect damage. The tanks also have limited mobility and turn radius, along with a maximum turret swivel speed, which adds complication to the decision making and allows more modification of tactical decision making managers in determining an "optimal" fire pattern.

4.4 Design Phase 1 - Integration of Spring RTS and PyGMO

The integration of the Spring RTS Engine to the PyGMO code is handled through the creation of a new manager in the existing AFIT agent. This new manager, moea.py, is directly responsible for connecting the Spring RTS Engine and PyGMO framework by utilizing PyGMO commands inside of the AFIT agent. The previous version of the AFIT agent made combat decisions by relying on a set script within the group.py manager [6]. The new version of the AFIT agent operates by having group.py call on the custom PyGMO problem held within moea.py. The analysis

```
class ROUND(base):


    def __init__(self, allies=[[0,0,0,[0,0],0,0],[0,0,0,[0,0],0,0]],
        ↪ enemies=[[0,0,0,[0,0],0,0],[0,0,0,[0,0],0,0]]):
        copy allies matrix into self.allies
        copy enemies matrix into self.enemies
        initialize PyGMO for a 4 objective minimization problem, with
            ↪ solution length equal to the number of allied units
        set bounds of output to [0, number of enemies-1]
```

Figure 20. Custom PyGMO Problem Created for Tactic Optimization (Initialization)

performed within moea.py returns a string of commands go group.py which is then implemented within the Spring RTS Engine.

The integration of the AFIT agent and the Spring RTS Engine is accomplished by using the custom PyGMO problem `ROUND` within the moea.py file. The problem is initialized as shown in Figure 20. To begin, `ROUND` requires two arrays of data, one for allied units and another for enemy units. The initialization of the problem also requires that a "base" form of the allies and enemies arrays exist so that some data exists during PyGMO's population island creation. If these arrays are not set within the definition of the problem then PyGMO attempts to deepcopy arrays that have not been initialized, which leads to a program fault. The layout of each line in the array of units is shown in equation 8. The data required by the `ROUND` class includes a Unit ID set by the Spring RTS Engine, the number of hit points remaining for that unit, a binary indicator representing if a particular unit is "alive" or "dead", that unit's position, and finally the unit's damage capability and range.

$$\text{Unit} = [\text{Unit ID}, \text{HP}, \text{Unit Life Marker}, [\text{X Position}, \text{Z Position}], \text{Damage}, \text{Range}] \tag{8}$$

Once data has been passed to the `ROUND` class, the arrays are copied into two local variables `self.allies` and `self.enemies`. PyGMO is then initialized to prepare for a 4 objective analysis of the input arrays, and each member of the output string is bounded to a valid output command. The commands for this version of the RTS agent are limited to attacking different enemy targets, so the number of potential actions available to each unit is equal to the number of enemies on the screen.

Figure 21 shows the next step in the creation of a custom PyGMO problem - analysis of a particular potential solution of a population. At this point within the MOEA analysis, PyGMO has generated a population of solutions according to the restrictions in Figure 20. The analysis of each member within a population starts with the creation of two matrices for allied and enemy forces, `astart/anew` and `estart/enew`, respectively. These matrices represent the initial state and the expected resulting state from the analyzed solution. The values in `anew` and `enew` are modified throughout the analysis in order to create data that is used for objective evaluation.

The first step in analyzing each solution is to check the resulting direct damage from an attack wave. For each attacking unit the code confirms that the target is within range and then reduces the targets HP by the attack value of the attacker. If the target is within range, the target and any nearby enemies are damaged appropriately. If this brings a unit's HP below 0 then the unit is marked as dead by setting their "alive" marker to 0. Once friendly forces fire, the algorithm calculates the expected level of return fire from the remaining enemy forces. Once all damage has been calculated the algorithm is ready to perform objective analysis of the `enew` and `anew` matrices.

```
class ROUND(base): continued


    # Begin objective analysis of solution
    def _objfun_impl(self,x):
        set starting matrices to self.allies, self.enemies
        deepcopy start matrices to create end matrices


        for each allied unit:
            if target is within range:
                deal direct damage
                if other enemy is within area of effect range of shot:
                    deal indirect damage to that enemy
            if enemy HP drops below 0:
                enemy HP = 0
                enemy = "dead"


        for each enemy:
            if enemy is alive:
                select closest allied target
                deal direct damage to allied target
                if other allied unit is within area of effect range of shot:
                    deal indirect damage to that allied unit
            if allied unit HP drops below zero:
                allied unit HP = 0
                allied unit = "dead"
```

Figure 21. Custom PyGMO Problem Created for Tactic Optimization (Calculation)

```
class ROUND(base): continued


    initialize all objectives to 0


    for each allied unit:
        if allied unit is "alive":
            subtract 1 from objective 1
            subtract allied unit HP from objective 2
            subtract allied unit damage from objective 3


    for each enemy unit:
        if enemy unit is "alive":
            add 1 from objective 1
            add enemy unit HP from objective 2
            add enemy damage to objective 3
        count = 1
        for each allied unit:
            if target of allied unit = enemy unit:
               subtract count from objective 4
               count = count + 1


        return (f1,f2,f3,f4,)
```

Figure 22. Custom PyGMO Problem Created for Tactic Optimization (Objectives)

Figure 22 shows the final step of a custom PyGMO problem, the analysis of a set of values and placement into a set of comparative objective values. The first step of objective analysis is to initialize all objective variables to 0. This initialization must be performed for each member of a population in order to prevent the results from a previous member skewing the results for the remainder of the population. Once the initialization is complete the effects of allied units are measured and subtracted from the objectives 1, 2, and 3. As stated in Section 3.5, the objectives used are Units Remaining, Difference in HP, Difference in Firepower, and Focus Fire. Once the allied units' effects on the battle have been computed and subtracted from objectives, the results of the enemy units are similarly summed and added to the same three objectives. The final step is to analyze objective 4, which evaluates the amount of focus fire within a given solution. This objective is calculated by determining how many allied units attack the same enemy. Each unit attacking the same enemy subtracts (1 + number of units attacking that enemy from the objective). When all four objectives have been measures the results are output back to PyGMO for population modification. The entirety of this code can be found in Appendix A

4.5 Design Phase 2 - Offline Simulation

The experimentation within Phase 2 compares the performance of the different MOEAs chosen for analysis, NSGA-II, SPEA2, and NSPSO. Each MOEA has a different search mechanic, and this phase determines which general type of search method is best for the tactical decision making search landscape. A description of each of these MOEAs is given in Section 2.9.

Testing MOEA Parameters.

The Phase 2 experimentation is performed by comparing the results from NSGA-II, SPEA2, and PSO MOEAs against each other in order to determine which search method performs best in the RTS tactical decision making problem. These three MOEAs are selected because they cover a variety of generic search procedures. NSGA-II performs a semi-random search of the problem domain by combining the current best performing members of the population in order to generate new populations. SPEA2 follows a similar search method, but discards potentially better scoring individuals in order to ensure an even coverage of the Pareto front. NSPSO focuses entirely on migrating the members of its population towards local and global optimal performing members of the population. These three MOEAs therefore cover the random, spread, and focused search processes. The parameters tested for MOEA optimization are population size and numbers of generations to test through. The population sizes tested are 20, 40, 60, 80, and 100. Generational sizes scale from 2, 3, 4, and 5. Altogether this gives 20 different experiments per MOEA, or 60 different experiments total for Phase 2. Each experiment is performed ten times in order to create a statistical baseline for analysis.

Measurement Metrics.

There are a variety of different metrics available for testing the usefulness of a particular MOEA on a problem. The metrics are known as Quality Indicators, and can be Pareto compliant or non-compliant. If a solution set A better than a different solution set B by weak Pareto dominance, then any metric that states A is at least as good as B is Pareto compliant. Metrics that fail to maintain the relationship between A and B are known as Pareto non-compliant [39]. A quick synopsis of many possible options is listed below:

Error Ratio (ER).

The Error Ratio metric gives the ratio of members of the currently known Pareto front vs. the members of the true Pareto front [39, p.255]. In other words, this metric determines the percentage of PF_{true} that has been found in the current generation. A mathematical representation is available in equation 9 [39]. An ER of 0 signifies that the current PF_{known} is the optimal Pareto front. An ER of 1 shows that there are no current matches between any points in PF_{known} and PF_{true}.

$$ER = \frac{\sum_{i=1}^{|PF_{known}|} e_i}{|PF_{true}|} \tag{9}$$

An issue with this quality indicator is that it requires PF_{true} to be known, and as such is not applicable in the problem discussed in this paper. The constantly changing search landscape makes it impossible to nail down the exact optimal Pareto front.

Generational Distance (GD).

Generational Distance is another quality metric that compares PF_{known} to PF_{true}. This method compares the overall distance between the true Pareto front and the currently available Pareto front. A mathematical representation is shown in equation 10 [39].

$$GD = \frac{(\sum_{i=1}^{n} d_i^p)^{\frac{1}{p}}}{|PF_{known}|} \tag{10}$$

An issue that arises from the use of this indicator is that it is not Pareto compliant. A Pareto non-compliant indicator can potentially mistake option B as being better than option A in cases of weak Pareto dominance. Therefore generational distance has the chance of showing incorrect optimal Pareto fronts due to the inherent method of comparison.

Hyperarea / Hypervolume.

Hyperarea, otherwise known as hypervolume for Pareto fronts involving more than two objectives, attempts to equate the multidimensional area or volume covered by a given population of potential solutions. This is a Pareto compliant indicator, as a solution with a higher area or volume is always preferable to one which is smaller. In order to generate this measurement, an origin point must be designated. The area consists of the total volume covered by the area generated by all members of the population and this origin point. For example, a two objective problem would generate a triangle when combined with the origin point. The area of this triangle would be the effective hyperarea of that Pareto front. A mathematical representation of this indicator can be found in equation 11 [39].

$$HV = \left(\bigcup_i area_i | vec_i \in PF_{known} \right) \tag{11}$$

While this method does not require PF_{true} to be used as a population can be directly compared to another population of solutions based entirely on covered area or volume, the availability of PF_{true} allows the use of the hyperarea ratio metric. This metric is very similar to the generational distance method as it compares the currently covered area with the area covered by the true Pareto front. Its mathematical representation is provided in 12 [39], where H_1 is the area covered by PF_{known} and H_2 is the area covered by PF_{true}.

$$HR = \frac{H_1}{H_2} \tag{12}$$

ϵ - indicator.

This method finds the smallest amount ϵ that, if added to option b (a solution set pareto dominated by option a), causes b to cover a. This can be seen as another

quality indicator in the same thought process as Generational Distance or some of the other ratio-based indicators. Its purpose is to find the minimum error between sets a and b, and use this minimum error as a grading scale to determine which set of solutions is the better option. Due to the manner of determining the amount of ϵ, this indicator is pareto compliant. This indicator can also be used either with or without knowing PF_{true}, as two or more populations can be compared to the current "best" population.

Indicator Used In Experiment.

The hypervolume indicator is used in this experiment because it is Pareto compliant and usable without knowing the true Pareto front. The hypervolume metric is also included within the PyGMO library, and is pre-set to allow for four dimensional objective analysis. The rate of expansion of a population's hypervolume over time will be used in order to determine how quickly an algorithm generates good solutions. The concept behind this metric is that a "good" decision in a short amount of time is better than arriving at the "best" solution after it is no longer useful. Hypervolumes are expected to expand rapidly after the first couple of generational cycles. This expansion will be used to determine which type of search approach best fits the RTS tactical decision making problem.

In order to calculate the rate of hypervolume expansion, the hypervolumes for each experiment parameter set is averaged. In order to create a measurable comparison between very different starting positions, the rate of increase of the hypervolume is chosen as the comparative metric. First, the hypervolume for a particular experiment is found. Then the hypervolume for a series of single generation solution sets with the currently tested number of population members is found and set as the initial state for the experiment. This initial hypervolume is subtracted from the current

hypervolume in order to find the net increase of hypervolume over the generations of the MOEA. Finally this increased amount is divided by the total amount of time required to complete the set number of generations under the currently tested MOEA. This results in the metric shown in equation 13.

$$\delta = \frac{HV_{increase}}{time} \tag{13}$$

4.6 Testing of Phase 3 - Online Simulation

The third phase of the investigation includes the integration of the best performing MOEA option from Phase 2 into the custom RTS tactical decision making problem developed in Phase 1. This section is very straight forward, and uses the "cheated" units in order to remove more variables from the combat. Performing full scale RTS game simulations is both time consuming and introduces many more sources of potential error, such as the location of resource generators and factories. initial trials show that a small amount of difference in army construction time can result in one side completing their army and launching an attack before the other side is ready. Therefore, online simulation of battle is performed by instantly generating two separate armies of 25 tanks at opposite ends of the battlefield and placing them into attack mode. The initial start point can be seen in Figure 23. The two lines at the top and bottom of the figure are the instantly generated armies which are programmed to use the tactical decision making methods under test.

Once placed into attack mode, the two armies find the center point of the opposing forces and move towards that point. Once enemies come within visual range, the tactical decision making methods for each army are implemented.

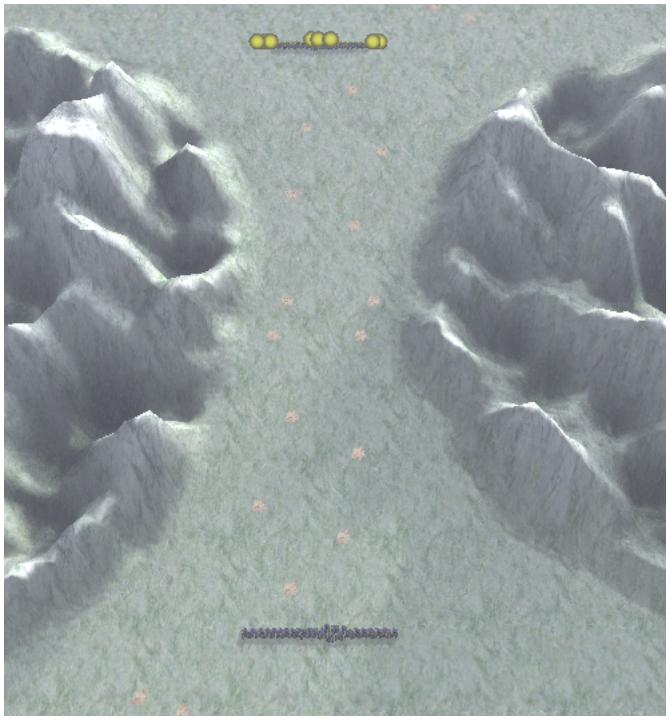


Figure 23. Starting Positions for Online Simulations

Tactical Methods to be Tested.

Four different tactical options are tested by live simulation in this experiment. The first three are purely scripted options, which take the current battlefield into account and choose targets based off of a single objective. The fourth option is the best performing MOEA determined in the experimentation in Phase 2 of this experiment.

Default - Group Attack Closest Tactic.

The first option is the default version developed by Di Trapani [6]. This series of actions first finds the center point of all selected allied units, and then finds the enemy that is closest to this point. All allied units then attack this unit because it has the highest chance of being the closest to more units. This tactic can be seen in Figure 24.

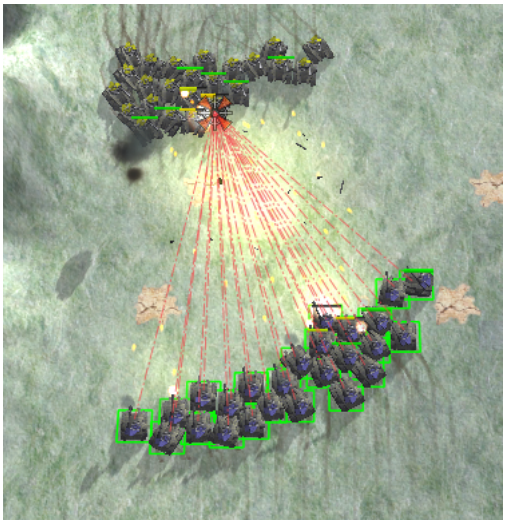


Figure 24. Default Tactic in Use

Figure 24 shows how the entire army is aimed at a single unit which, at the time of target selection, is the enemy closest to the center point of the friendly force. This type of tactic is very good as quickly removing threats as they come within range.

Individual Attack Closest Tactic.

This option is very similar to the default option, but it makes attack decisions based on individual units' locations, rather than the group of units as a whole. It iterates through each allied unit, checks the unit's current location, and then determines which enemy is closest. The selected allied unit is then ordered to attack that enemy. This results in a wave of fire, with each allied unit potentially attacking a different enemy target. The purpose of this objective is to allow as much firepower to be launched on each round of combat instead of wasting time moving to attack a more centrally located target.

Figure 25 shows the proximity tactic being used. In this figure there are four enemy units that are closest to the selected army, so the selected army's fire is split among all potential targets. This type of tactic is very good against numerous weak

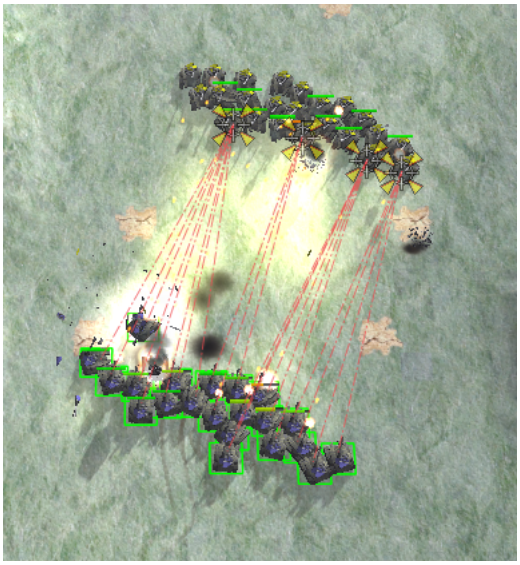


Figure 25. Proximity Tactic in Use

units who are encroaching on a position due to its spread of fire. This tactic reduces potentially wasted shots by minimizing overkill.

Group Attack Weakest Tactic.

This option uses a different parameter as its selection method for attack. Rather than trying to attack the closest target, this method seeks to kill the enemy with the lowest remaining hit point value. As a group, allied units seek enemies within visual range and find the one with lowest remaining hit points. All allied units then target this unit. Once this unit is destroyed the next weakest unit is targeted and destroyed. The purpose of this method is to quickly remove as many enemy units as possible, and by doing so, eliminate their incoming damage as well.

The group attack weakest tactic is shown in Figure 26. This figure shows how targeting prioritization has been moved to the left side of the enemy army due to those enemy units having a lower hp total, as shown by their red hp bars. This tactic is useful against a few strong enemies as it encourages friendly units to take down targets one at a time, slowly whittling down enemy forces.

Figure 26. Weak Tactic in Use

Selected MOEA.

The fourth tactical method tested is the best performing MOEA based off of the data found during Phase 2. The optimality of a particular MOEA is based off of its calculation time as well as the hypervolume found. As stated in Section 4.5, the metric used to analyze the performance of each off-line MOEA is hypervolume expansion over time. In each case the average hypervolume achieved by a MOEA/parameter set is divided by the average time it took that set to complete. These new metrics are compared in order to determine which MOEA has the fastest expanding search. The utilization of this metric follows the logic of stating a quick but poor solution is just as useless as a good solution that takes too long to evaluate. The ideal solution is the best performing within time constraints.

The MOEA tactic shown in Figure 27 works by maximizing potential damage according to the objectives chosen. This tactic's decision making can be seen in the figure by noticing how many units are set to directly attack a specific opponent while other units attack units that are nearby. This spreads out the total damage dealing capabilities of the selected army so that many enemy units are damaged instead of

Figure 27. MOEA Tactic in Use

focusing completely on a single target. The selected units who are attacking enemies near to the main enemy target are expecting to deal a certain amount of area of effect damage which kills the primary target through indirect fire.

Online Simulation Measurement Metrics.

The metrics used for measuring and comparing Phase 3 are based on the speed and efficiency of gameplay. The objective of the tactics algorithm is not just to win, but to win effectively. The efficiency of the win can be based on the following factors:

Win/Loss Ratio.

The most important aspect of measuring the efficiency of a win is first to actually win. The first metric measured in Phase 3 is the Win/Loss ratio between each of the potential tactics options. This metric is binary - if an agent wins a specific match it is given a 1, otherwise it is given a 0. The total result provides an average win rate against opposing tactics options which are derived by summing the total outcomes of an agent and dividing by the total number of runs.

Time of Battle.

Another objective of an agent is to win as quickly as possible in order to free up an army for other use. If an army is kept in one place for too long then it cannot be used as reinforcements or it could allow the opposing player to fortify their base in expectation of the upcoming attack. For this reason the time of battle is an important metric to track. The start time of battle is when the two armies are aware of each other and the simple movement command becomes an attack command. This can be tracked in game by watching the movement marker for each unit in an army. A green marker means that a unit is passively moving towards a destination. A red line shows that a unit is engaging a target. Combat start time is when the first red targeting line appears in a simulation. Combat ends when one side's forces have been completely eliminated.

Remaining Units.

Another important consideration in battle is to minimize the number of losses suffered during a conflict. This metric measures the number of units remaining at the end of battle, and uses it to determine the effectiveness of a specific tactic. A tactic that wins with an 80% success rate but with high losses may not be as useful as a tactic with a 70% success rate with low losses.

Average Remaining Health of Units.

The final objective builds off of the concept built with the Remaining Units metric. The summation of the remaining HP of all units is taken and then divided among the number of remaining units. The purpose behind this objective is to gauge the usefulness of the remaining units. An army of numerous heavily damaged units are not as useful in later conflicts as a smaller army of stronger units. This metric is used

to gauge how a tactic performs against others and how that tactic acts to preserve its units in battle.

4.7 Chapter Summary

This chapter provides a more in-depth review of the design process used to perform the experimentation testing the viability of MOEA controlled RTS AI agents with regard to the RTS tactical decision making problem. This chapter continues from the initial framework discussed in Chapter 3, and provides additional information on the specific layout and function of each part of the experiment. The processes described in this chapter lead to the acquisition of the data in Appendices B, C, and C, which are then used to perform the analysis in Chapter 5.

V. Results and Analysis

5.1 Introduction

This describes the results achieved by completing the processes defined in Chapter IV: Design of Experiments. It also provides analysis of these results to determine the links behind decisions made in the experimental design and the overall outcome. The analysis begins with the evaluation of the integration of the PyGMO MOEA code with the Spring RTS Engine. Once the initial integration has been completed, an offline simulator is used to test the capabilities of three different MOEAs: NSGA-II, SPEA2, and NSPSO. These three MOEAs are tested under different generational limits and population sizes in order to determine the effects of modifying their base parameters. Once the best MOEA has been found via offline testing, the AFIT agent's tactical control manager is modified in order to use the best performing MOEA as an online tactical decision making tool. This tactical tool is then tested against various scripted tactics in order to evaluate the MOEA's online performance.

5.2 Design Phase 1 - Integrating Spring and PyGMO

The first phase of this experimental design is the mapping of combat between two armies composed of 25 tanks each into a grid layout, and the conversion of that grid into an array usable within the PyGMO code. The first analysis of the default attack formation for this layout is performed by creating 25 stumpy tanks in game, and watching how they position to attack a specific point. The results for this test are that the tanks line up in a roughly semi-circular shape and are 4-5 units deep at the center point. A screenshot of the animation is shown shown in figure 28.

Once this initial test is complete, the next step is to ensure that in an actual battle, the tanks are given enough time to position themselves in the same manner they use

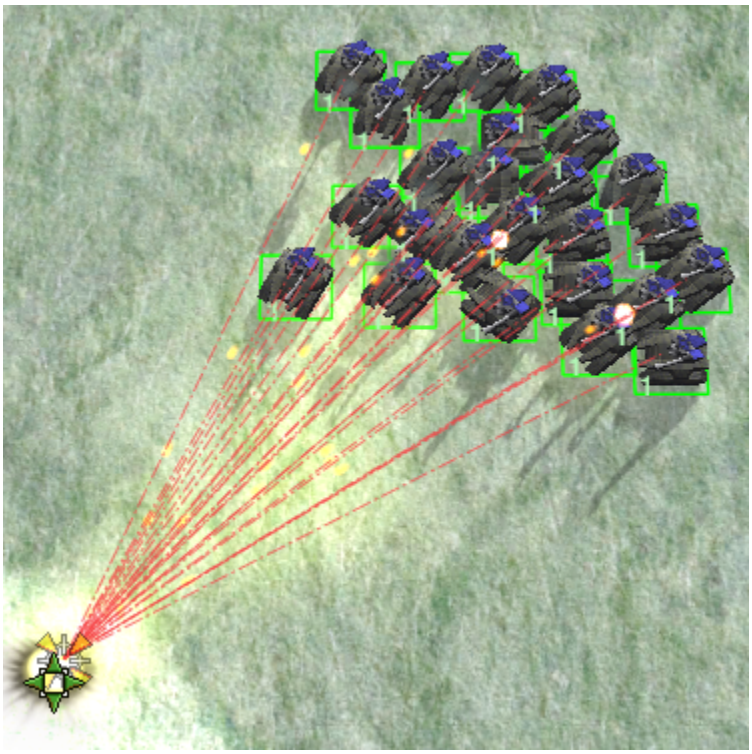


Figure 28. Simulation of 25 Tanks Attacking a Single Point

Figure 29. Two Examples of 25 vs 25 Tank Battles

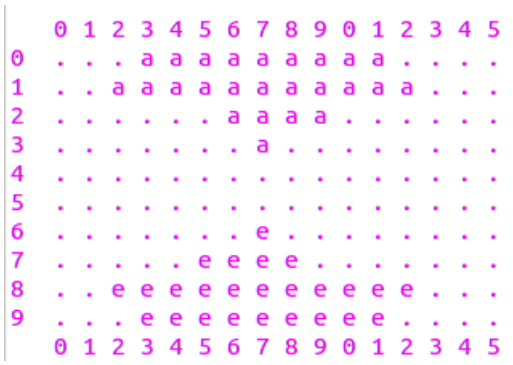


Figure 30. Code Layout of the Initial Round of Combat

to attack a specific point. The pseudocode for this advance to attack procedure is shown previously in Section 3.6. The agent is able to replicate the layout due to the fact that the agent's code is set to designate a lead or scout unit and the other units in the attack group are set to defend that lead unit. This creates a situation where one unit is far ahead of the others, with the remaining 24 tanks following in an unorganized huddle. This lead unit draws the fire of the opposing forces, which allows the other 24 tanks to line up in an attack formation before beginning an attack. Screenshots of two test cases of these battles are shown in Figure 29.

The results from Figures 28 and 29 indicate that a similar formation is created for both instances. As seen in Figure 28, the formation is still roughly semi circular with units positioning three to four units deep at the center point. This layout is duplicated in python code by creating an array which represents the starting positions for each unit participating in battle. The grid representing the array used to simulate this combat is shown in Figure 30, with "a"'s representing agent controlled units and "e"'s representing enemy units. The code version of the battle has many simplifications required to allow the scene to be emulated in python. First, the actual position of the units has to be made much more uniform. In BA, each unit takes up more than one positional unit. Even the basic infantry unit requires a 2x2 positional square which allows it to maneuver around other units. Tanks similarly take up more than one

block due to their size. Limiting tanks to taking up a 1x1 square allows them to be positioned in such a simply designed array. The actual locations of each unit is also restricted to directly match Figure 30. This is done to create a uniform "first round of combat" that can be used to compare MOEA performance. Online testing will allow positions to be updated in real time. Another simplification required for the array construction is ignoring tank and turret direction. In the Spring RTS engine, units are restricted to only firing in the direction they are facing. Stumpy tanks, and other turreted units have an independently controlled turret that can turn faster than the main body, but this aiming still requires time that is not accounted for in the python representation of combat.

Once the units are placed and x and y coordinates are assigned to each, the next step is to apply the other attributes that define a stumpy tank. The actual hit point scores of the units are able to be maintained - each unit has 1530 hit points. The damage can also be carried directly over from the balanced annihilation mod info page [63]. Stumpy units do 97 damage per direct damage hit, and 48 damage via indirect fire. The range for this indirect damage is modified to only apply to adjacent targets. For example if the enemy unit at position (7,6) is hit, then the units at (6,7), (7,7), and (8,7) take a fraction of the primary weapon damage as indirect splash damage. The extent of this indirect damage is modified by the proximity of adjacent units to the primary target. Due to the simplification of the map to a simple grid pattern, the distance for each of these adjacent units are the same.

Once the model has been constructed in can be used to begin Phase 2 testing. Phase 2 testing uses the three different MOEAs to be compared and determines how well they perform in the RTS tactical decision making problem.

5.3 Testing of Phase 2 - Offline Simulation

Phase 2 testing begins with running the code generated in Phase 1 against various MOEAs with different parameters. As stated in Section 3.5, the MOEAs under test are SPEA2, NSGA-II, and NSPSO. The parameters tested are population capacity and generation limit. Population sizes used are 20, 40, 60, 80, and 100. Generational limits are 2, 3, 4, and 5. Each combination of generation limit and population size are tested 10 times. The analysis of the performance of each MOEA over the given problem domain are discussed in the following subsections.

Analysis of MOEA Performance in Tactics Optimization.

This section provides the data and analysis for phase 2 testing. This data includes a compilation of average data values with regards to the metrics used to analyze MOEA performance with regards to parameter changes and MOEA performance. This raw data is then used to build a series of box plots which visually represent the performance of MOEA parameter combinations. The raw data used to create both the tables and the box plots can be found in Appendix B. The analysis of each population of solutions is performed by measuring the hypervolume of the pareto front generated by each individual population. The solutions contained in each population each build a separate Pareto front which represents the effectiveness of that population. Each member of the population represents a single point in four dimensional space, due to the use of four different objective values. The volume of the four dimensional space bounded by all members of the population can then be used as a metric to judge the optimality and performance of one MOEA combination over another, as more ideal solution sets are closer to the "true" Pareto front and farther away from the point of measure.

Table 2. HV Gain per Second for NSGA-II

(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T		(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T
(20,2)	0.18	108791	9888	54004		(20,3)	0.26	114784	15881	61943
(40,2)	0.38	113352	3799	10176		(40,3)	0.52	127782	18229	35314
(60,2)	0.56	122477	11572	20961		(60,3)	0.77	126316	15412	20157
(80,2)	0.75	128913	16430	21860		(80,3)	1.06	129359	16877	15998
(100,2)	0.93	127300	8293	8851		(100,3)	1.31	133821	14814	11288

(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T		(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T
(20,4)	0.33	117808	18906	57661		(20,5)	0.41	126496	27593	67794
(40,4)	0.66	137682	28128	42555		(40,5)	0.81	149829	40276	50042
(60,4)	0.98	143985	33081	33694		(60,5)	1.21	155515	44611	36805
(80,4)	1.39	145656	33173	23986		(80,5)	1.63	162476	49993	30597
(100,4)	1.70	161917	42909	25291		(100,5)	2.06	179696	60689	29401

Analysis of NSGA-II.

The averaged data of the NSGA-II algorithm can be seen in Table 2. This table shows the average time, hypervolume (HV), hypervolume minus the initial hypervolume of a single generation (HV-1G), and the overall hypervolume gain over time ((HV-1G)/T). The table shows that for the case of NSGA-II, the increase of population size does not improve the overall hypervolume increase over time. In fact increasing population from 20 to 100 decreased hypervolume per second rate by 84% in 2 generations, and caused a 47% decrease in 5 generations. This decrease of performance is caused by the NSGA-II algorithm's approach to population generation. The NSGA-II's method of randomly combining high scoring members of the population results in a semi-random search of the search landscape that is just as likely to decrease the potential solution's value as it is to increase due to the build of optimal solutions[41]. The optimality of solutions on the custom problem created for this research is based heavily on having multiple units fire on the same enemy unit. A

random search has no way to generate solutions that focus fire on enemies, and these solutions are necessary to create good objective scores.

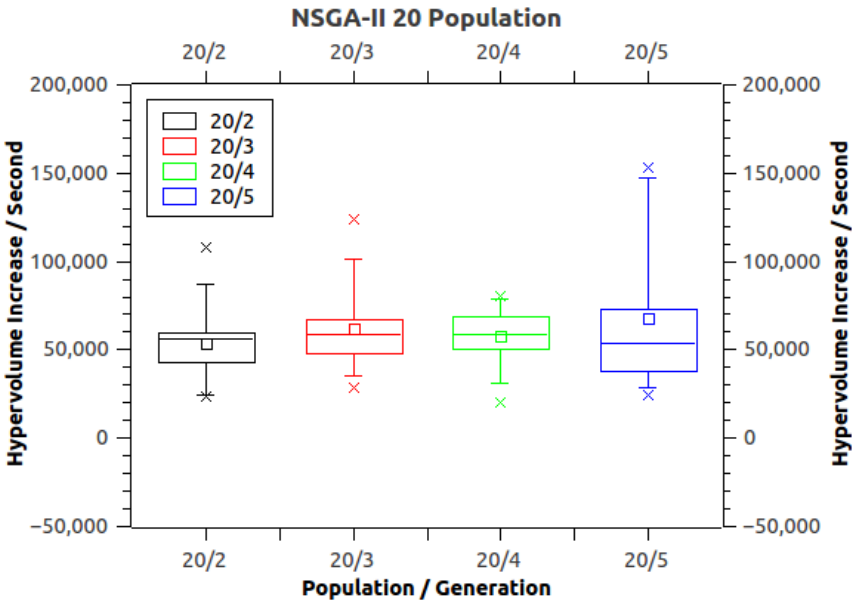


Figure 31. Box Plots for HV Increase Over Time for NSGA-II 20 Population

The NSGA-II performed best with a population of 20. The statistical analysis for this evaluation is shown in Figure 31. This box plot shows that over the course of five generations the NSGA-II algorithm maintains a high level of variance, while showing only a slight increase in effectiveness. The mean value throughout each generation stays between a score of 50,000 and 75,000. The other population tests, shown in Figure 32 show even worse results, with the majority failing to obtain a score of 50,000.

Analysis of SPEA2.

The results of the SPEA2 algorithm are shown in Table 3. The SPEA2 algorithm performed 17% to 35% faster than the NSGA-II algorithm, but it is not able to consistently outperform on a hypervolume per second basis, as shown in Figures 33 and 34. For the combination of 20 population and 3 generations, the NSGA-II

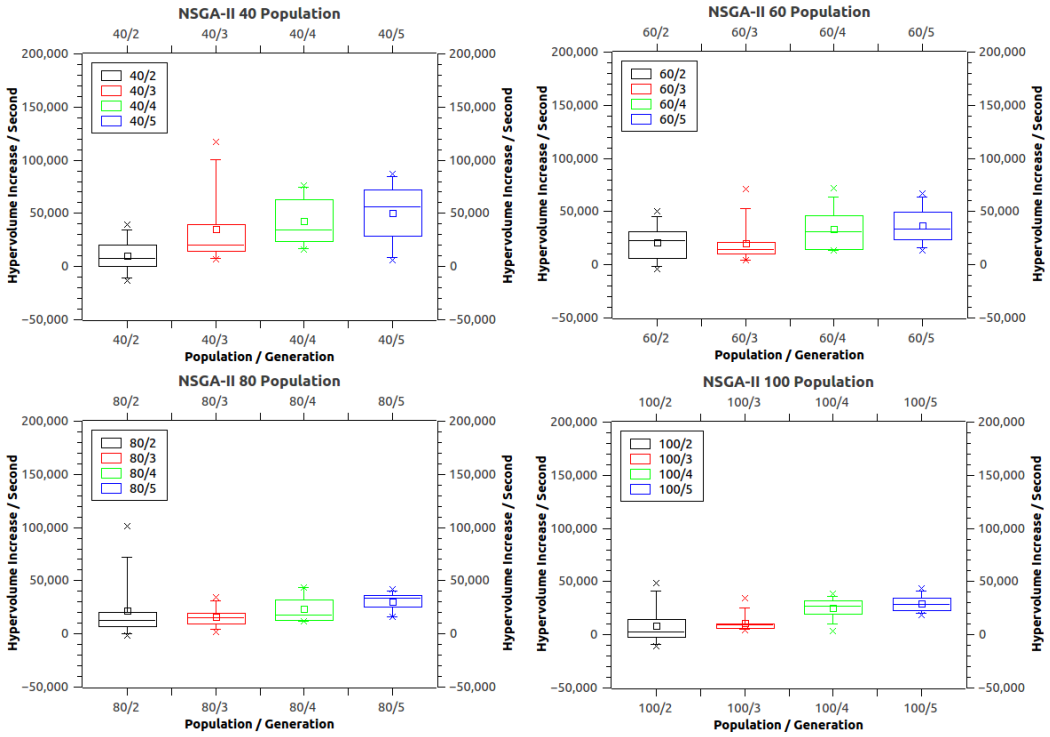


Figure 32. Box Plots Showing HV Increase Over Time for NSGA-II Algorithm

Table 3. HV Gain per Second for SPEA2

(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T		(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T
(20,2)	0.15	110446	4732	32081		(20,3)	0.18	111660	5946	32046
(40,2)	0.30	113061	415	1384		(40,3)	0.37	120926	8280	22073
(60,2)	0.46	123641	14283	30907		(60,3)	0.58	125101	15742	26971
(80,2)	0.62	120785	6007	9647		(80,3)	0.79	132537	17759	22342
(100,2)	0.77	120852	2033	2626		(100,3)	0.96	139219	20400	21176

(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T		(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T
(20,4)	0.22	120426	14712	65799		(20,5)	0.26	131388	25673	100252
(40,4)	0.45	141023	28378	62851		(40,5)	0.54	154609	41963	78146
(60,4)	0.69	146389	37030	53962		(60,5)	0.81	172041	62682	77386
(80,4)	0.94	152152	37374	39801		(80,5)	1.08	162475	47697	44082
(100,4)	1.19	156868	38049	32086		(100,5)	1.40	180566	61746	44215

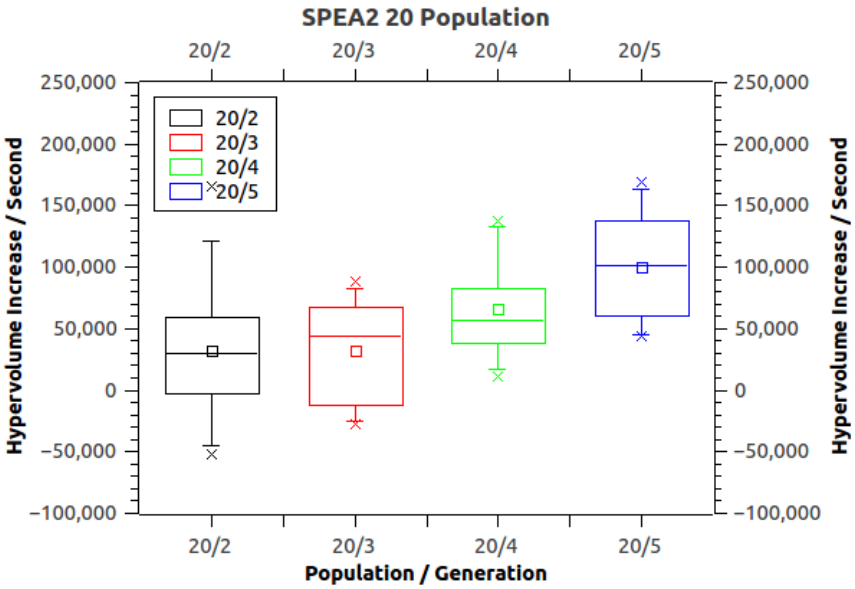


Figure 33. Box Plots for HV Increase Over Time for SPEA2 20 Population

algorithm doubled the SPEA2's score, but on the 100 population and 3 generation test SPEA2 outmatched NSGA-II. This lack of consistency is caused by the SPEA2's search process. The SPEA2 forces a certain degree of separation between each solution on the Pareto front, which could remove a potentially better solution from being used in the next generation [43]. This forced widening of the search area via Pareto front manipulation prevents the SPEA2 from providing consistent results.

The 20 population SPEA2 experiments performed the best according to statistical analysis, as shown in Figure 33. While the algorithm has a slow start in comparison to NSGA-II, with a score of less than 50,000, at 5 generations the algorithm is able to reach an average score of 100,000. This score is achieved with a higher degree, of variance, however, as shown by the increased scaling of the Y axis. The other population options for the SPEA2 algorithm which are shown in Figure 34 show that the SPEA2 algorithm's performance follows the same track as NSGA-II. Increased population size does not have a positive effect on the rate of hypervolume expansion.

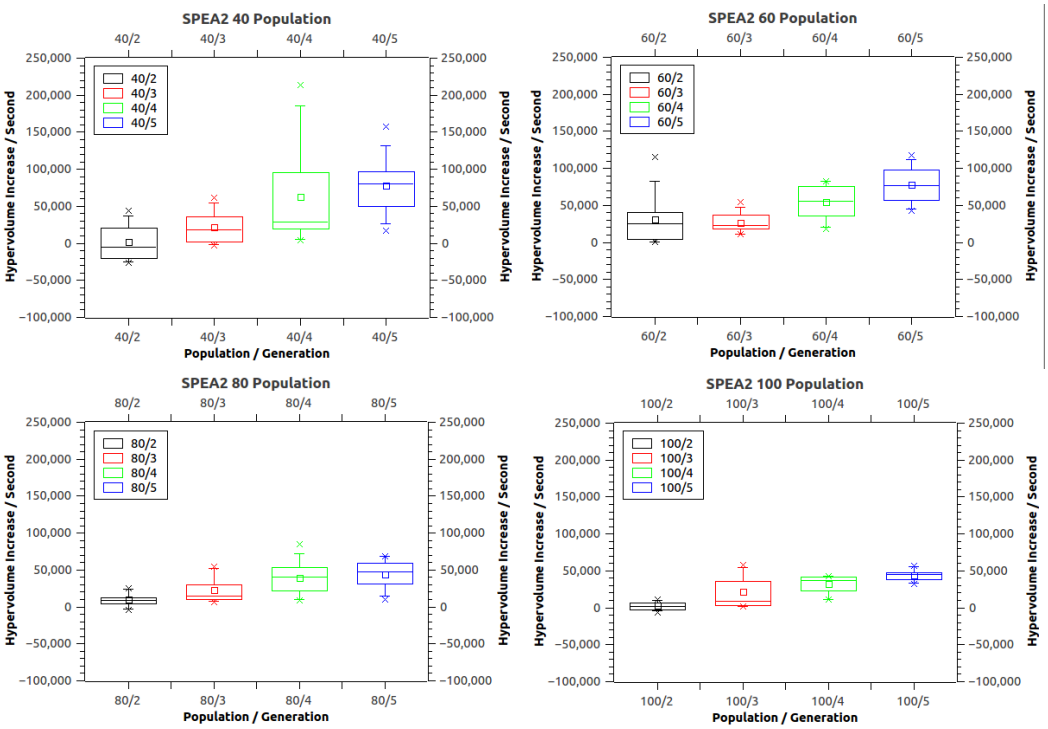


Figure 34. Box Plots Showing HV Increase Over Time for SPEA2 Algorithm

Table 4. HV Gain per Second for NSPSO

(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T		(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T
(20,2)	0.15	133039	23486	156573		(20,3)	0.19	161719	52165	276901
(40,2)	0.30	146446	29968	99892		(40,3)	0.38	193610	77132	203603
(60,2)	0.46	150673	26351	57098		(60,3)	0.57	251850	127528	223943
(80,2)	0.62	155263	31266	50365		(80,3)	0.77	225272	101276	132153
(100,2)	0.79	166060	42336	53845		(100,3)	0.97	313424	189700	194767

(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T		(Pop,Gen)	time(s)	HV	HV-1G	(HV-1G)/T
(20,4)	0.23	207710	98156	437031		(20,5)	0.26	257180	147626	567792
(40,4)	0.45	271242	154764	343238		(40,5)	0.52	398017	281539	539559
(60,4)	0.69	313963	189641	276168		(60,5)	0.80	525404	401082	498732
(80,4)	0.93	345348	221352	238989		(80,5)	1.10	447954	323957	296122
(100,4)	1.17	512206	388482	332127		(100,5)	1.37	577163	453440	330037

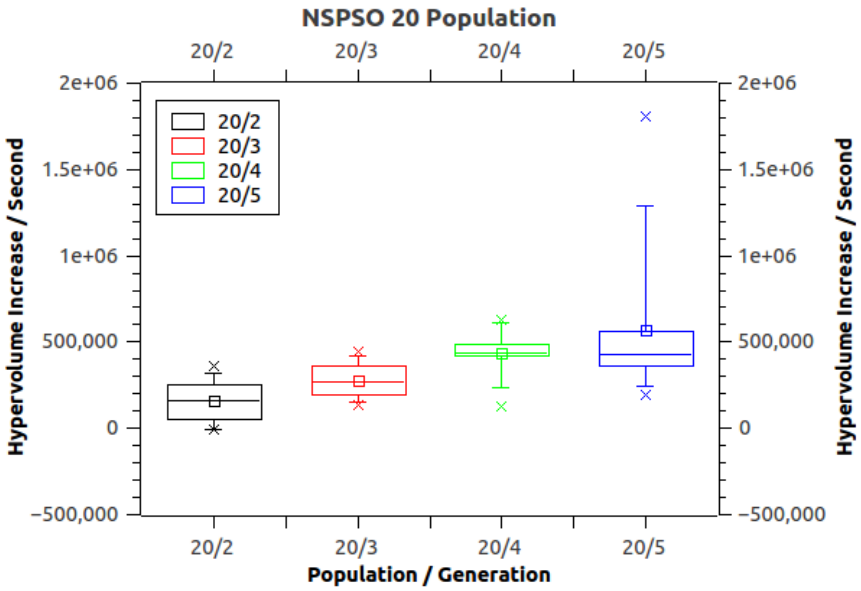


Figure 35. Box Plots for HV Increase Over Time for NSPSO 20 Population

Analysis of NSPSO.

The NSPSO algorithm performed the best out of the three tested MOEAs, the average results of which are shown in Table 4. The NSPSO algorithm completes its search faster than both the NSGA-II and SPEA2 algorithms, and is also able to cover the most hypervolume during its search. This leads the NSPSO algorithm to obtain to a much higher hypervolume per second increase than the other two MOEAs.

The top performing combination of NSPSO parameters is 20 population members with 5 generational evolutions. This result matches with the best performing parameter sets of NSGA-II and SPEA2, although the NSPSO algorithm's output is much better than either of the other two tested MOEAs. While the NSPSO algorithm shows a lot of variance in Figure 35, the worst population member found is equivalent or better than the best members found in either NSGA-II or SPEA2. The best performing member within the NSPSO population set for 20 population and 5 generations almost reaches a score of 2 million. This difference in performance be-

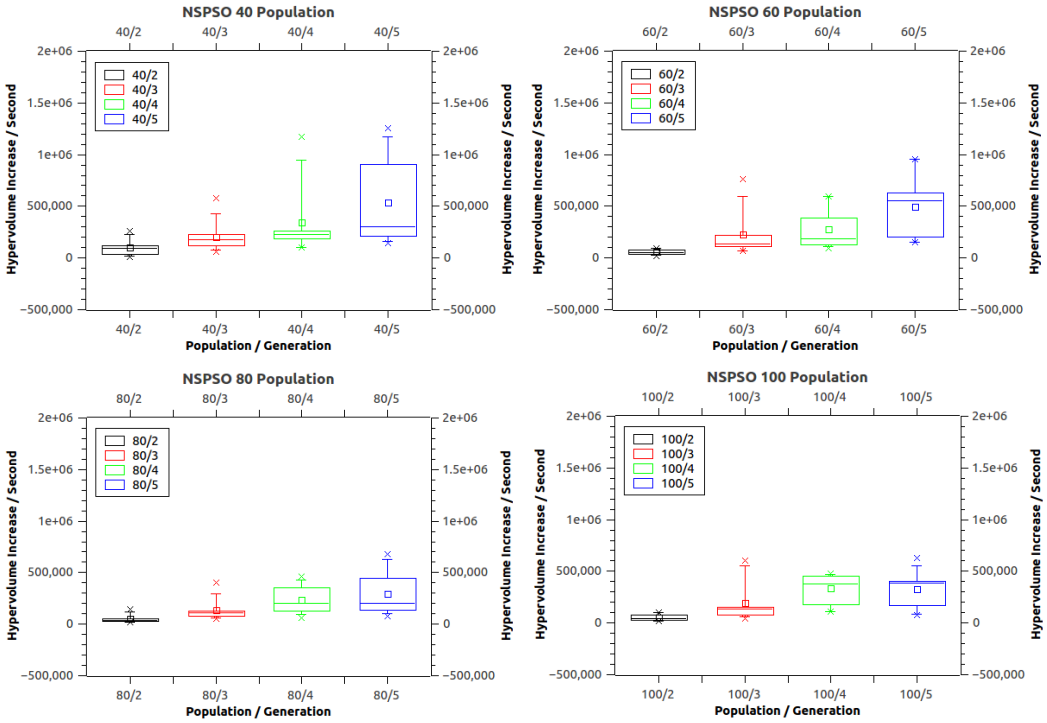


Figure 36. Box Plots Showing HV Increase Over Time for NSPSO Algorithm

tween MOEAs clearly shows that the NSPSO algorithm outperforms the alternatives with regards to the RTS tactical decision making problem.

While the best selection of parameters for the NSPSO algorithm shows a 500% improvement over alternatives, the remainder of parameter settings in Figure 36 show that experiments with higher population also outperform any results from NSGA-II or SPEA2. These results also show a faster slope increase over the course of more generations, showing that the NSPSO algorithm is capable of continuing to improve.

The high level of performance generated by the NSPSO algorithm is made possible by the overall search landscape for the tactical decision making problem. In this problem a certain number of units are required to fire on an enemy in order to destroy it. The NSPSO is able to create a random initial population, and have the other 19 members of the population slowly migrate towards the best solution. This ensures that the best member of the population is maintained while other members

of the population search the nearby area for the "peak", or where the exact number of friendly tanks fire on a single enemy in order to destroy it. This ability shows that the 20 population - 5 generation search using NSPSO is the best performing option out of all MOEAs that are tested.

Conclusions of Offline Simulation.

The offline testing of the three MOEAs: NSGA-II, SPEA2, and NSPSO ended in a clear differentiation between the performances of each option. NSGA-II required the longest amount of time to calculate and had a wide margin in resulting champion solution values. This poor performance is based on the mechanics behind the NSGA-II algorithm itself and shows how a random selection of population members and combination is not suitable for the tactical decision making problem at hand.

The SPEA2 algorithm, while fast, is not able to achieve consistent high quality results through testing. The SPEA2 algorithm's requirement of forcing a maximum amount of space between members of a population is a detriment when attempting to analyze the given search landscape. In the tactical decision making search landscape a "more optimal" solution is most likely next to the currently most optimal population member. This "more optimal" solution can typically be achieved by modifying the current best solution to have a few more units focus on the primary target in order to destroy that target this round. By forcing individuals to be a certain degree apart the SPEA2 search prevents these potentially useful neighbors from being explored, which results in a lower quality solution than what other MOEAs can find. In the search landscape of the tactical decision making problem, the entirety of the SPEA2 algorithm's search methodology works against it when it comes to finding solutions.

The NSPSO algorithm is the most optimal solution found through this series of experiments. NSPSO achieves the best solutions in the fastest amount of time due

to the process that it uses to create the next generation. This constant moving of the population members towards the currently "most optimal" member provides extensive coverage of a very localized portion of the search landscape which means that an in-depth analysis of a small set of solutions is performed. This in-depth analysis of a small area works very well with the focus fire objective used in the PyGMO problem, which is why the NSPSO MOEA is capable of easily reaching six figure hypervolume per second rates while NSGA-II and SPEA2 struggle to break 100,000. This focused search provides very good solutions with small populations, and the addition of population members does not seem to be worth the additional computational time required.

The most optimal setup found through this series of tests is to use the NSPSO algorithm with 20 population and a 5 generation limit. This option is able to achieve an average of the top rate of hypervolume increase per second within a quarter of a second. The NSPSO algorithm appeared to perform at a similar rate with a 40 population and a 5 generation limit, however this doubled the required calculation time. The 20 population option is chosen in order to allow the AFIT AI agent to more quickly respond to battlefield changes and minimize the amount of computation required to adapt to new situations.

5.4 Phase 3 - Online Simulation

This section describes the overall results of the on-line simulation between the four tested tactic methods. The comparative results can be seen in the bar graphs found in Figures 37, 38, 40, and 42. For these graphics, each tested tactic has its own color, and data related to that tactic is only used if that tactic won. For example, the "weak" tactic did not receive any victories in 20 attempts when facing "MOEA" and "proximity", so very little green shows in any of the graphics. Each of these matchups

Table 5. Results of Default Tactic VS Other Tactics

Default VS:	Win Rate	Time	Units	Average HP
Proximity	60%	0:43	6.42	940.89
Weak	90%	0:37	6.72	1265.6
MOEA	20%	0:35	10	827.13

are performed twenty times, with each army starting at the top of the screen ten times and at the bottom of the screen ten times.

Analysis of the Default Tactic.

The results of the default tactic can be found in Table 5. This table only includes data from when the default tactic won its matchup. The default tactic achieves an overwhelming 90% win rate against the weak tactic, and a 60% win rate against the proximity tactic. This tactic did not perform well against the MOEA tactic, as it achieved only a 20% win rate. The default tactic's method of having the entire group focus fire on the closest enemy unit results in additional area of effect damage to nearby enemy units. This focused damage not only quickly destroys the unit, but it also causes the outgoing fire to sweep across the enemies as they approach which results in very little wasted fire. This is an advantageous method to use when fighting in a confined area, but loses a lot of potential if they enemy is spread out since there is less area of effect damage and more wasted shots.

Analysis of the Proximity Tactic.

The proximity tactic operates by ordering each individual unit to attack the closest enemy relative to that unit's position. The results of this tactic can be found in Figure 6. This tactic causes the group to fire on a few enemy units at a time, which

Table 6. Results of Proximity Tactic VS Other Tactics

Proximity VS:	Win Rate	Time	Units	Average HP
Default	40%	0:39	5.87	1017.65
Weak	100%	0:42	8.42	1229.54
MOEA	30%	0:42	6.83	736.43

Table 7. Results of Weak Tactic VS Other Tactics

Weak VS:	Win Rate	Time	Units	Average HP
Default	10%	0:42	7	1106.29
Proximity	0%	N/A	N/A	N/A
MOEA	0%	N/A	N/A	N/A

is detrimental in the short term, but helps in a longer battle. This is because a more focused fire in the beginning stages of a battle destroys enemy units faster, which significantly reduces the amount of incoming damage. Spreading out targets slows down the rate of the initial kills. Conversely during the last stages of a fight enemies are all typically damaged to some degree. Spreading out fire on different targets minimizes the damage wasted at this point in the battle, and helps destroy the remaining enemies.

Analysis of the Weak Tactic.

The weak tactic operates by constantly targeting the enemy with the lowest remaining HP. This results in a random initial target, followed by a sweeping motion across the battlefield. After the first enemy is destroyed, nearby enemies have been weakened by the area of effect damage. The weakest of these damaged units is se-

Table 8. Results of MOEA Tactic VS Other Tactics

MOEA VS:	Win Rate	Time	Units	Average HP
Default	80%	0:33	8.87	1051.37
Proximity	70%	0:39	8.86	930.92
Weak	100%	0:33	9.6	1283.07

lected as the next target, which again damages the enemies nearby. The effects of this tactic initially seem useful, but the process of having the entire group attack these weakened units ensures an overall location of fire, which slows down the overall damage capability of the weak tactic. This usually results in the weak tactic losing, as seen by its 10% win percentage against the default tactic and complete lack of wins against both proximity and the MOEA.

Analysis of the MOEA Tactic.

The MOEA tactic, based on the 5 generation, 20 population NSPSO algorithm, is the best performing option out of the four tested tactics. It has a win percentage of over 50% against every other option, and is also the fastest victory for each option. The MOEA tactic also has the highest average of remaining units, with almost two more units surviving per matchup. This combination of statistics shows that the MOEA agent is the fastest and most survivable out of all tactical options.

Comparison of Tactical Results.

A more definitive analysis can be performed by directly comparing the numerical results acquired through experimentation against each other by means of bar graphs and box plots. The scaling of each box plot is scaled to match each other box plot within the same objective, they are not universal. The data used in each analysis is

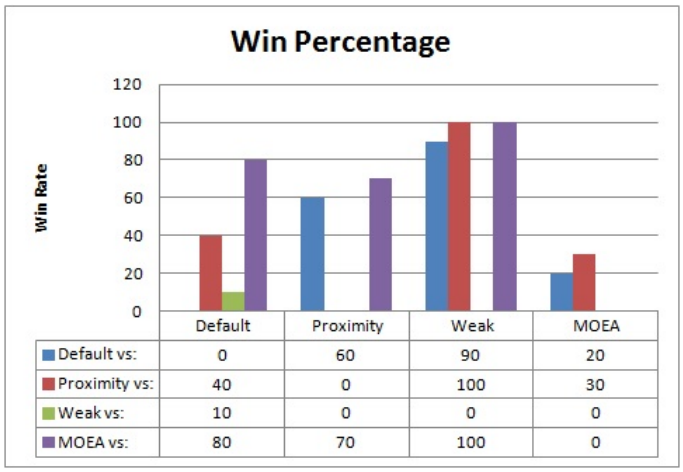


Figure 37. Comparison of Win Percentages Between Tactic Options

only allowable when a particular tactical method wins. The Weak tactic, having only two successes throughout all experimental runs, has its data based on two distinct data points. The remainder of the data is compiled in a similar method.

Win Rate.

Figure 37 shows that the MOEA tactic (shown in purple) is capable of matching or outperforming alternatives against each opponent. The MOEA tactic has an 80% win rate against the default tactic vs. the proximity tactic's 40%. The MOEA tactic also outperforms the default tactic when facing the proximity tactic by maintaining a 10% higher rate of success. Both the MOEA and the Proximity tactic achieve a 100% win rate against the group attack weakest tactic. The data shows that the Default tactic has a slight advantage over the Proximity tactic. The Proximity tactic has a slight advantage over the otehr scripted methods when attacking the Weak tactic. The MOEA based tactic outperforms all scripted alternatives against all opponents.

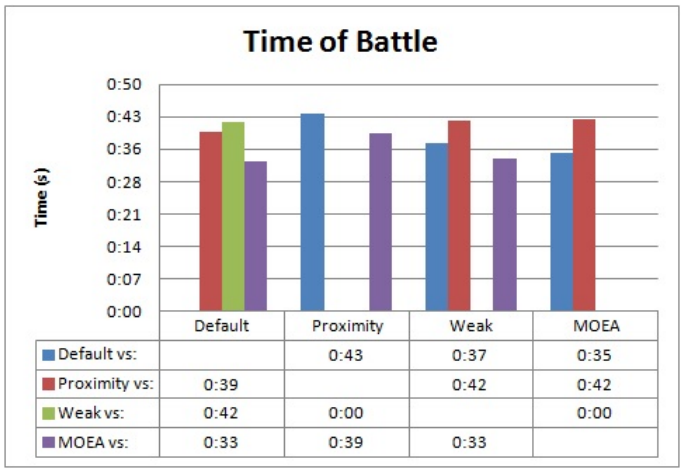


Figure 38. Comparison of Battle Duration Between Tactic Options

Battle Time.

Battle time is used as an objective in order to determine how long an army is held up by an opposing army. The best performing decisions complete the battle quickly and successfully in order to allow remaining forces to be used in other areas as soon as possible. Figure 38 shows that the MOEA tactic, shown in purple, is capable of completing combat faster on average than all alternatives in against every opponent.

The average data from Figure 38 is expanded on by the statistical information in Figure 39, which shows a very similar statistical range for each opponent. The largest variation of battle times occur when the Default tactic and the MOEA tactic face against the Proximity tactic. This similarity shows that there may be some instances where the Default tactic's method of attacking the closest enemy may be faster than attempting to spread fire against all opponents. The data for each tactic facing the Weak tactic shows a very small variance, which means that each method consistently achieves the same results through experimentation.

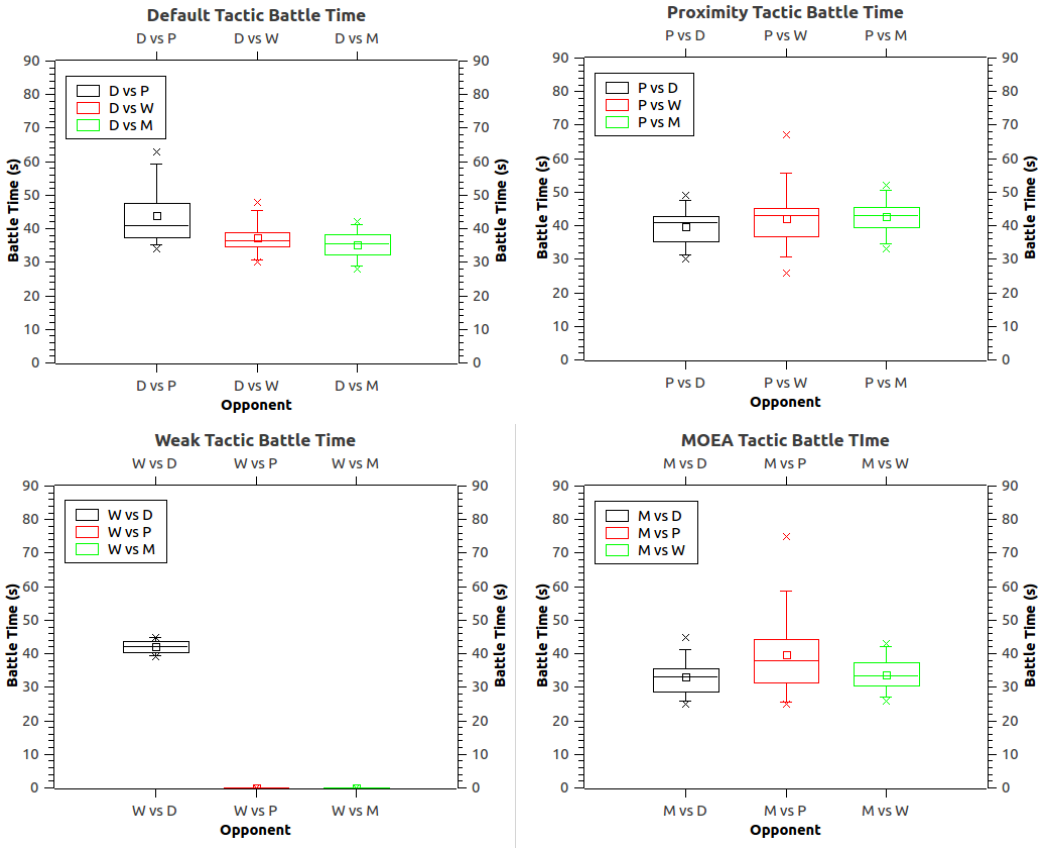
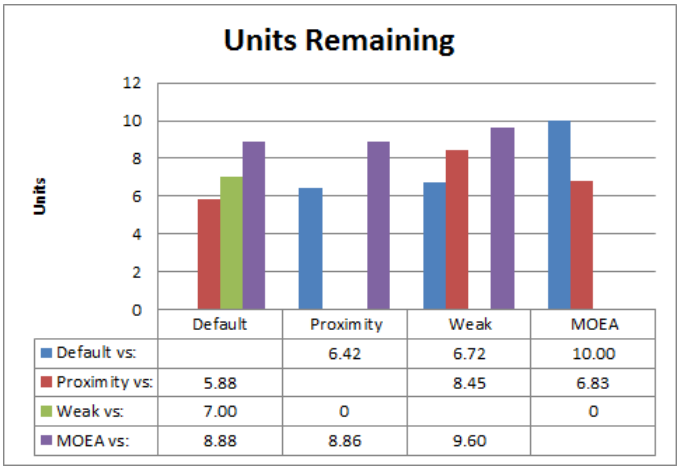


Figure 39. Box Plots For Online Battle Duration



	Default	Proximity	Weak	MOEA
Default vs:		6.42	6.72	10.00
Proximity vs:	5.88		8.45	6.83
Weak vs:	7.00	0		0
MOEA vs:	8.88	8.86	9.60	

Figure 40. Comparison of Units Remaining After Battle Between Tactic Options

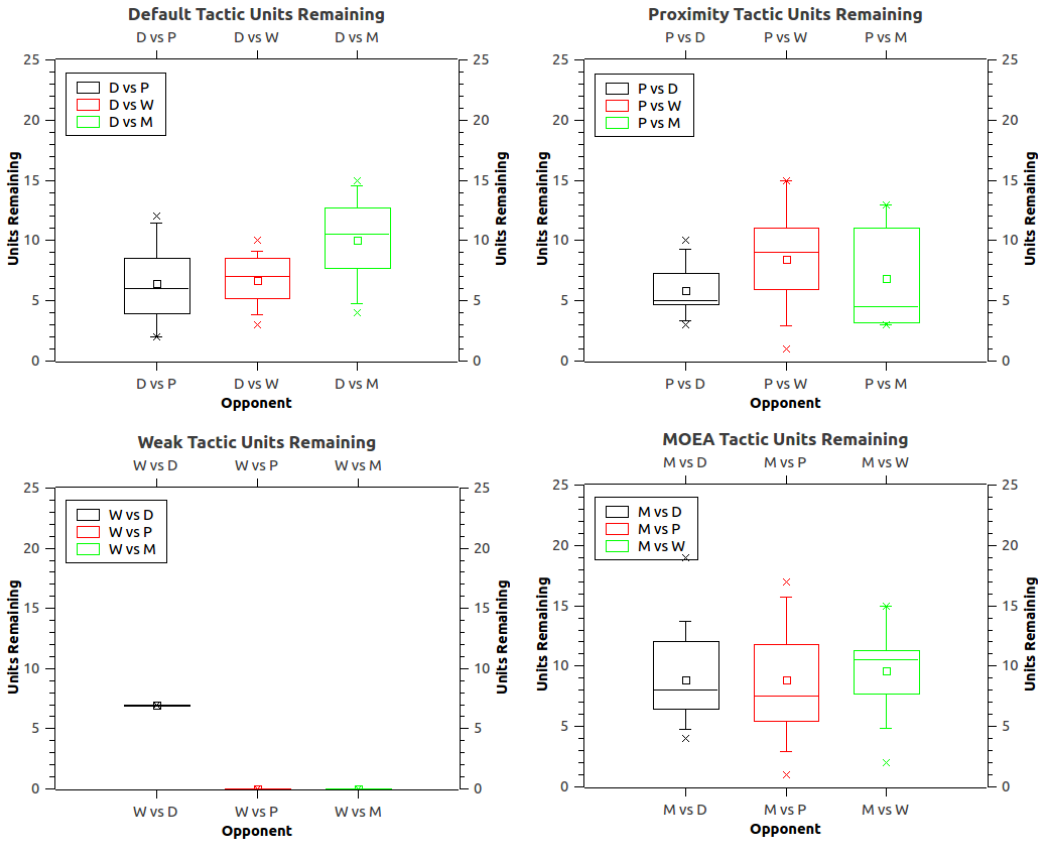


Figure 41. Box Plots For Number of Units Remaining

Remaining Units.

Another important metric of grading the optimality of a battle's outcome is to measure the number of units remaining. While winning a battle is good, winning that same battle with a larger number of forces remaining is better. 40 shows a comparative bar graph between the online performance of each tested tactical decision making method. As in the previous objectives, the MOEA tactic continues to outperform every other tactic tested. Therefore current results show that the MOEA tactic has the highest win rate, completes battles the fastest, and has the most units remaining after combat on average.

The statistical analysis of each tactical method's performance is shown in Figure 41. These box plots show that the MOEA tactic has a larger variance than the other

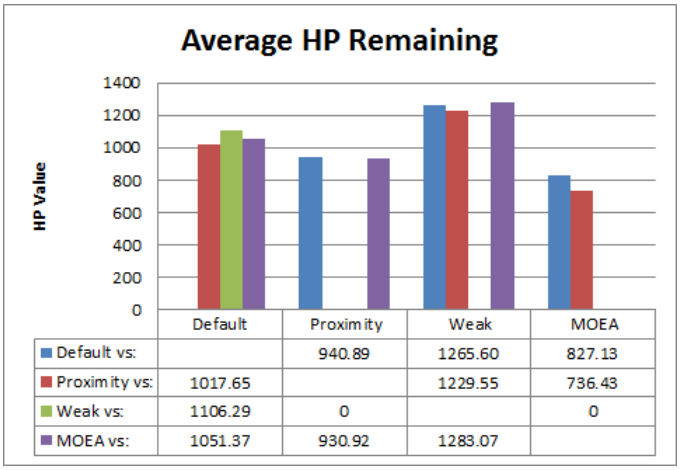


Figure 42. Comparison of Average Remaining HP After Battle Between Tactic Options

metrics when facing the Default Tactic or Proximity tactic, but it maintains a smaller variance against the Weak tactic. It is also important to note that while the MOEA tactic has a larger variance than alternatives, the mean of its variance is much higher than Default or Proximity, which shows that the MOEA tactic has a high probability of continuing to outperform any tested alternative.

Remaining Hit Points.

The final objective used to grade the performance of a winning battle is the average remaining HP of all remaining units. This objective is used in order to determine the future survivability of each remaining unit in future battles. The comparative results of this objective can be seen in Figure 42. Unlike the previous objectives, the MOEA tactic was not the best performing metric on average. However, the discrepancy between the MOEA tactic's performance and alternatives is much smaller than in earlier metrics. Where previous differences were in the range of 15% to 20%, the difference in the average HP remaining is less than 5%. This shows that the MOEA tactic still performs well with regards to the other tested tactics.

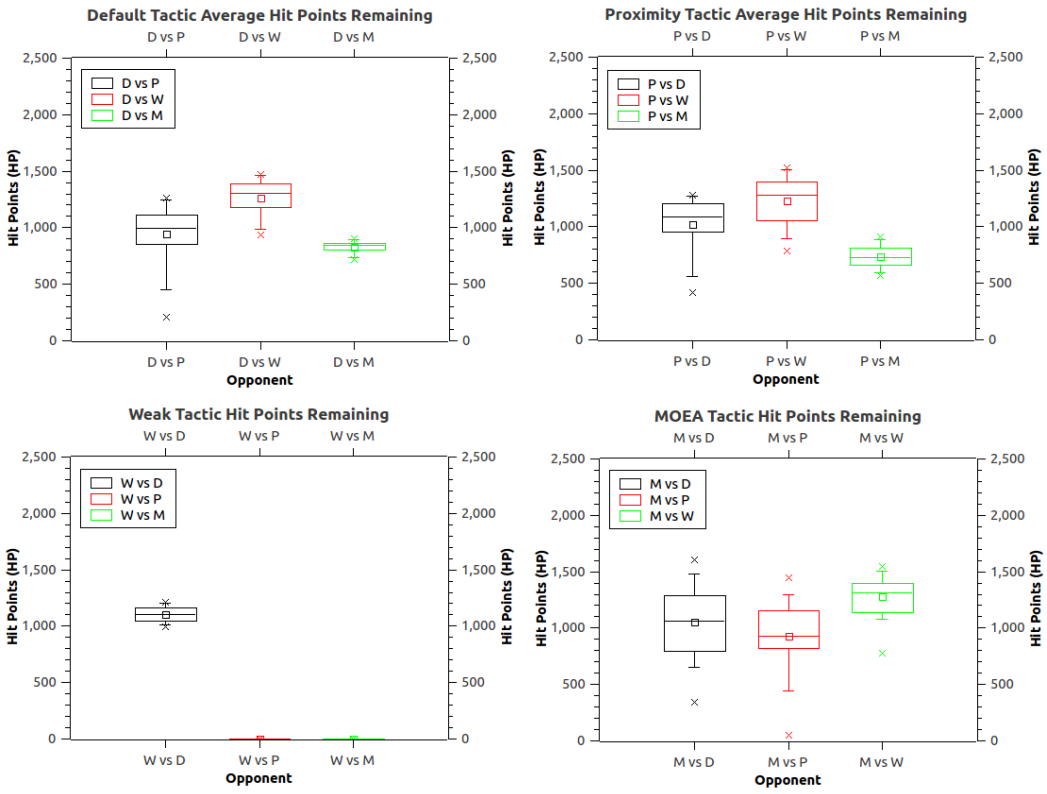


Figure 43. Box Plots For Average HP Remaining

The statistical analysis of the various tactics' performance with regards to remaining HP values can be seen in Figure 43. The MOEA tactic has the highest variance in the majority of battles, with only the Proximity vs Weak coming close to the range of variance. These results show that remaining HP after combat is very difficult to converge to an absolute expectation.

Conclusions of On-Line Battles.

The on-line simulation shows a clear distinction between the performance of the various tactical options. The MOEA option is the clear winner, with the best results in each of the obtained metric scores. The majority of the losses suffered by the MOEA agent are caused by choosing an edge unit as the scout, which caused the entire army to group against the side of the pathway. This bunching up prevented many tanks from spreading out, which reduces outgoing fire and ensured that more friendly units are hit by the enemy's area of effect damage.

Another consideration in the performance of the battles is the speed at which armies moved into position. Most armies are able to move relatively quickly, but the MOEA tactic's constant readjustment of targets during approach all but ensured that its tanks would arrive and form up slower than the opponent. Also, the army located on the lower section of the map appears to have a distinct advantage due to very small details about the map's design. The map has a slightly smaller area directly above the standard battlefield, which means the upper army is more constrained in how they move which sometimes leads to reduced effectiveness in combat.

5.5 Comparison of Results to Previous Research

While not directly comparable to the research performed in the RTS tactical decision making world due to the difference in approaching the base problem, some

preliminary comparisons can be made based off of the effective methods results. In Churchill's paper utilizing a modified Alpha-Beta script considering durations [13], he is able to achieve a 91% to 92% win rate against scripted opponents within 5 ms. The MOEA agent is not capable of reaching the same level of performance, but is also analyzing a much larger battlefield. Churchill's work focuses on placing a variety of 8 vs 8 armies against each other. The MOEA analysis is based off of a 25 vs 25 single unit battle. While MOEA performance is much slower than the 5 ms restriction used in Churchill's paper, it is still capable of actively changing actions based on battlefield situations. His process is expanded to create a portfolio greedy search algorithm for analysis of larger scale combat [34]. This modified search was only tested against other alpha-beta searches in order to present a comparative level of improvement over his previous developments.

Additional research has been performed in the past analyzing the use of Monte Carlo Tree Search methods on the RTS tactical decision making problem [64]. In his research, Balla utilizes the UCT algorithm in order to train an agent to make combat decisions in the Wargus RTS environment. His research shows that while MCTS are trainable to achieve objective optimization, the UCT algorithm was unable to achieve online performance, even with small army sizes of 4 units. This outcome shows that the initial results of MOEAs for use in solving the RTS tactical decision making problem are promising, as they allow solutions to be generated online without any prior training.

5.6 Chapter Summary

This chapter reviewed and analyzed the data found during the experimentation into the use of a MOEA as a tactical decision making tool in RTS games. A custom problem representing the RTS tactical decision making problem is developed and in-

tegrated into the PyGMO code. This code is then added to the Spring RTS engine for use in online simulations. The three MOEAs under test are executed in the simulated first round of combat, with the NSPSO algorithm drastically outperforming the alternatives due to its more focused search methods. Finally, the NSPSO algorithm is placed into the MOEA tactic for use in online testing. This MOEA tactic outperforms all three of the scripted methods, and demonstrates that MOEAs can be used as tactical decision making tools in a real time environment.

VI. Conclusion

6.1 Evaluation of Results

The results of the series of experiments accomplishes the objectives stated in Chapter 1.4. The data acquired validates that MOEAs can perform correctly and efficiently as a tactical decision making tool in an RTS AI agent, and have potential for use in actual military simulation hardware. The final results of performance analysis show that the MOEA based agent is capable of matching the expected win rate of tactical decision making methods discussed in Chapter 2.7, achieving an 80% win rate against the default tactic with requiring any sort of prior training or intensive tree search analysis. While initial testing required offline comparison between different MOEAs, once an MOEA is selected there is no longer a requirement for offline standardization in order to allow that MOEA to perform in an online environment.

Each objective is satisfied, with objective one serving as a design requirement for the successful testing of objectives two and three. Objective two is thoroughly investigated and the results of the three tested MOEAs indicate that knowledge of the expected structure of the fitness function results in a better selection of an MOEA for use, as shown in Section 5.3. This difference of utility between MOEAs is explained by the "No Free Lunch" theorem (Section 2.9), which states that there is no such thing as a universally optimal algorithm that can efficiently solve all problems. Each problem has an optimal method of approach which outperforms other potential solutions, but this method of approach does not perform optimally in other search landscapes [47]. Therefore the user must have an understanding of the search landscape in order to choose the best MOEA option.

The aggregated fitness function of the RTS tactical decision making problem is found to have numerous peaks within a small range of each other due to the heavy

reliance of a "kill" during a round of combat. There are numerous ways to achieve a "kill" within combat and that typically a solution with a high amount of focused fire leads to a solution very close to one with a "kill". This analysis of the aggregated fitness function for a tactical decision making agent performed for this series of experiments is correct in stating that the NSPSO algorithm performs the "best" due to its ability to focus the search area of future generations around these semi-optimal solutions. This more focused search of the landscape allows the particle swarm based NSPSO algorithm to find results with nearly five times the hypervolume metric increase per second of the population of solutions found by the more uniform search structure used by SPEA or the random search method used by NSGA. Therefore the result of objective two is that out of the three MOEAs chosen for this research, NSPSO outperformed SPEA2 and NSGA-II by a large margin as shown in Section 5.3.

Objective three is performed by utilizing and analyzing the animations within the Spring RTS engine. Each battle performed is viewed and measured in order to gather the metrics used to measure the usefulness of the MOEAs and scripted tactics. By using a series of online battles the NSPSO MOEA controlled tactical agent is placed against a variety of scripted tactical methods. The MOEA outperformed the scripted methods in all metrics considered. The MOEA tactic is able to combine a high win rate and a fast battle completion time with a large amount of remaining units. The use of multiple objectives when determining courses of action helps to overcome some of the limitations created by the use of a single variable. For example, an agent relying on a kill/death ratio or some modification thereof as it's objective is limited in capability when given an army that cannot outright kill an opponent in a single round. The required foresight required to determine the course of future

actions requires more computational time which is not available to the AFIT tactical decision manager in its current form.

The current version of the AFIT tactical decision manager requires a large amount of processing power for the quarter second needed to generate a solution. This increase in processing power results in noticeable lag to a human opponent, which in turn slows down gameplay and human player interaction with the Spring Engine. The lag is more pronounced during the initial phases of combat between the time when armies come within visual range of each other and lasts until units move into position. Other tactical AI agents are not affected by this slowdown of the game, as their commands run within the game environment itself and are therefore not affected by the game user interface lockdown caused by prolonged processing.

The overall goal for this research, stated in Chapter 1, is accomplished. An MOEA has been successfully integrated within the existing AFIT agent, and supplies solutions that are capable of beating many different scripted agents. The AFIT agent is now able to defeat these scripted agents in battle without requiring previous experience against an opponent or off-line computation and training. Once engaged in combat the agent is able to quickly redetermine optimal firing solutions within a quarter of a second.

6.2 Future Work

There are various vectors future researchers can follow due to the scope of integrating AI into RTS games:

- Optimize building locations to optimize economy generation and maintain open pathways
- Integrate the capability to change strategies to counter opponents

- Integrate movement into the tactical decision making manager
- Reduce calculation time of the tactical manager to reduce lag impact to human players
- Develop a new scouting manager which would remove the AFIT AI agent's reliance of removing fog of war

Each of these areas are important upgrades to the current performance of the agent as well as another way to improve its ability to serve as a method to train military personnel on battlefield decision making methods.

6.3 Final Remarks

The research presented in this thesis shows a strong argument for the integration of MOEAs into tactical decision making agents in both RTS and other military combat simulations. The additional time required for the MOEA in comparison to other scripted methods is negligible, and the results of the MOEA far exceed the capabilities of the tested scripted agents, and performed as well as results achieved in previous research [13, 37]. With more effort the time requirements for MOEA can be further mitigated and additional command options can be included to create a more robust agent capable of decision making in many different environments. The integration of the MOEA controlled tactical decision manager significantly improves the performance of the AFIT agent and serves as a stepping stone for future RTS AI research.

Appendix A. Code for Offline Simulation

This Appendix provides the custom code created to integrate the PyGMO and Spring RTS engine. The integration is performed through creating the `moea.py` file and modifying the currently existing `group.py` manager in the AFIT agent.

1.1 moea.py

The `moea.py` file is a new manager placed in the `.config/spring/AI/Skirmish/Tactics/*version` folder. It is used to hold the custom MOEA problem class for the tactical decision making problem as well as a new distance function to determine if enemies are within range.

```
from PyGMO.problem import base
from math import *
from copy import deepcopy
import agent

def dist(p1,p2):
    return((p1[0]-p2[0])**2 + (p1[1]-p2[1])**2)**0.5

class ROUND(base):

    def __init__(self, allies=[[0,0,0,[0,0],0,0],[0,0,0,[0,0],0,0]],
        ↪ enemies=[[0,0,0,[0,0],0,0],[0,0,0,[0,0],0,0]]):
        # Solution is len(allies), with 4 objectives
        self.allies = allies
        self.enemies = enemies
        super(ROUND,self).__init__(len(self.allies),0,4)
        # Potential solutions are constrained to the number of enemies
```

```
        self.set_bounds(0,len(self.enemies)-1)


    def _objfun_impl(self,x):
        # Matrices are [ID, HP, ALIVE, [XPOS,ZPOS], DAM, RANGE]
        astart = self.allies
        estart = self.enemies
        anew = deepcopy(astart)
        enew = deepcopy(estart)

        # Simulate allied units firing
        for i in range(0,len(anew)):
            target = int(x[i])
            if dist(anew[i][3],enew[target][3]) <= anew[i][5]:
                enew[target][1] = enew[target][1] - anew[i][4]
               # PROXIMITY DAMAGE CHECK
                for k in range(0,len(enew)):
                    if k != int(x[i]):
                        if dist(enew[target][3],enew[k][3]) <= 48:
                            enew[k][1] = enew[k][1] - (anew[i][4]*(48 - dist(
                                ↪ enew[target][3],enew[k][3])) / 72)


        # Check for destroyed enemy units
        for i in range(0,len(enew)):
            if enew[i][1] <= 0:
                enew[i][1] = 0
                enew[i][2] = 0

        # Simulate enemies firing
```

```
for i in range (0,len(enew)):
    pot_target = []
    for j in range(0,len(anew)):
        apos = anew[j][3]
        epos = enew[i][3]
        distance = dist(apos, epos)
        pot_target.append(distance)
    sort = sorted(range(len(pot_target)), key=pot_target.__getitem__
        ↪ )
    target = sort[0]
    anew[target][1] = anew[target][1] - enew[i][4]
    if anew[target][1] < 0:
        anew[target][1] = 0
    if anew[target][1] == 0:
        anew[target][2] = 0


# Difference in number of units
f1 = 0
# Difference in HP totals
f2 = 0
# Difference in damage capability
f3 = 0
# Focus fire
f4 = 0


for i in range(0,len(enew)):
    f1 = f1 + enew[i][2]
    f2 = f2 + enew[i][1]
```

```
            if enew[i][2] == 1:
                f3 = f3 + enew[i][4]

        for i in range(0,len(anew)):
            f1 = f1 - anew[i][2]
            f2 = f2 - anew[i][1]
            if anew[i][2] == 1:
                f3 = f3 - anew[i][4]

        for i in range(0,len(enew)):
            count = 1
            for j in range(0,len(anew)):
                if int(x[j]) == i:
                    f4 = f4 - count
                    count = count + 1

        return (f1,f2,f3,f4,)
```

1.2 group.py

The `group.py` manager has been modified to implement the new PyGMO code. Like the other python files it is also located in `.config/spring/AI/Skirmish/*version*/python`. The changes made to account for a tactical decision making search include importing `moea.py` at the beginning of the file and changing the attack function within the manager. The original version of the attack function is saved as "default" and is used as a comparison for test throughout Phase 3 of the experimentation.

```
import ctypes, math
import cdata
```

```
from PyGMO import *
from PyGMO.util import *
import moea

cdata.clb.move.argtypes = [ctypes.c_int, ctypes.c_int,
                           ctypes.c_float, ctypes.c_float]

class Group:
    groupId = 0

    def __init__(self, sid, gMap, unitManager, tactics):
        self.sid = sid
        self.gMap = gMap
        self.unitManager = unitManager
        self.units = []
        self.defense = True      # Am I the current defense group
        self.order = 'move'
        self.lastIdleEventFrame = 0
        self.pendingIdleEvent = False
        self.groupId = Group.groupId
        self.mode = 'ground'
        Group.groupId += 1
        self.tactics = tactics

    def remove(self, unit):
        self.units.remove(unit)
        if len(self.units) == 0:
```

```
            return False
        else:
            return True

    def add(self, unit):
        if len(self.units) == 0:
            if unit.defi.name in self.unitManager.aircraftNames:
                self.mode = 'air'
            else:
                self.mode = 'ground'
        self.units.append(unit)
        unit.group = self

    def setAttacking(self):
        self.defense = False
        self.units.sort(key=lambda unit: unit.defi.speed)

    # Attack command modified 0.4.1
    def attack(self):
        if self.tactics == 'default':
            # Update gMap unit pos and time stamp
            # clear old enemy values in gMap
            for cell in self.gMap.iterateCells():
                cell.enemyGroundUnits = []
            # Get position of each enemy ground unit; enemyGroundUnits is a
                ↪ dict
            enemyMap = self.unitManager.enemyGroundUnits
            size = len(enemyMap)
```

```
unitIds = enemyMap.keys()
enemyPositions = cdata.clb.getPositions(self.sid, unitIds, size)
for i in range(size):
    enemy = enemyMap[unitIds[i]]
    # attach pos to enemy unit
    pos = enemyPositions[i]
    enemy.pos = pos
    # get cell containing pos
    cell = self.gMap.getCellContainingPoint(pos)
    # attach enemy unit to cell.enemy*.append(unit)
    cell.enemyGroundUnits.append(enemy)
xavg, zavg = self._getCenterOfMass()
enemy = None
for cell in self.gMap.generateCells((xavg, 25.0, zavg)):
    enemyBuilding = cell.enemyBuilding
    enemies = cell.enemyGroundUnits
    if not enemyBuilding is None:
        # attack building
        enemy = enemyBuilding
        break
    elif len(enemies) > 0:
        # attack unit
        enemy = self._getClosestEnemy(xavg, zavg, enemies)
        break
if self.mode == 'air':
    enemy = self.unitManager.enemyCom
if enemy is None:
    return
```

```
            elif self.unitManager.LOS[enemy.unitId]:
                self.order = 'attack'
                self.attackEnemy(enemy)
            else:
                # Since enemy is outside of LOS, find a point to move to
                self.order = 'move'
                pos = enemy.pos
                self.movePos = pos
                if self.mode == 'air':
                    for unit in self.units:
                        cdata.clb.move(self.sid, unit.unitId, pos[0], pos[2])
                else:
                    target, guards = self.units[0], self.units[1:]
                    cdata.clb.move(self.sid, target.unitId, pos[0], pos[2])
                    self._guard(target, guards)
        elif self.tactics == 'proximity':
            # Update gMap unit pos and time stamp
            # clear old enemy values in gMap
            for cell in self.gMap.iterateCells():
                cell.enemyGroundUnits = []
            # Get position of each enemy ground unit; enemyGroundUnits is a
                ↪ dict
            enemyMap = self.unitManager.enemyGroundUnits
            size = len(enemyMap)
            unitIds = enemyMap.keys()
            enemyPositions = cdata.clb.getPositions(self.sid, unitIds, size)
            for i in range(size):
                enemy = enemyMap[unitIds[i]]
```

```
        # attach pos to enemy unit
        pos = enemyPositions[i]
        enemy.pos = pos
        # get cell containing pos
        cell = self.gMap.getCellContainingPoint(pos)
        # attach enemy unit to cell.enemy*.append(unit)
        cell.enemyGroundUnits.append(enemy)
    xavg, zavg = self._getCenterOfMass()
    enemy = None
    for cell in self.gMap.generateCells((xavg, 25.0, zavg)):
        enemyBuilding = cell.enemyBuilding
        enemies = cell.enemyGroundUnits
        if not enemyBuilding is None:
            # attack building
            enemy = enemyBuilding
            break
        elif len(enemies) > 0:
            # attack unit
            enemy = self._getClosestEnemy(xavg, zavg, enemies)
            break
    if self.mode == 'air':
        enemy = self.unitManager.enemyCom
    if enemy is None:
        return
    elif self.unitManager.LOS[enemy.unitId]:
        self.order = 'attack'
        for unit in self.units:
```

```
                selfPos = cdata.clb.getUnitPosition(self.sid, unit.unitId
                    ↪ )
                pot_target = []
                for enemy in self.unitManager.enemyGroundUnits:
                    enemyPos = cdata.clb.getUnitPosition(self.sid, enemy)
                    Pos1 = [selfPos[0],selfPos[2]]
                    Pos2 = [enemyPos[0],enemyPos[2]]
                    distance = moea.dist(Pos1,Pos2)
                    pot_target.append([distance,enemy])
                target = sorted(pot_target)
                cdata.clb.attack(self.sid, unit.unitId, target[0][1])
        else:
            # Since enemy is outside of LOS, find a point to move to
            self.order = 'move'
            pos = enemy.pos
            self.movePos = pos
            if self.mode == 'air':
                for unit in self.units:
                    cdata.clb.move(self.sid, unit.unitId, pos[0], pos[2])
            else:
                target, guards = self.units[0], self.units[1:]
                cdata.clb.move(self.sid, target.unitId, pos[0], pos[2])
                self._guard(target, guards)
    # ATTACK WEAKEST
     elif self.tactics == 'weak':
        # Update gMap unit pos and time stamp
        # clear old enemy values in gMap
        for cell in self.gMap.iterateCells():
```

```
    cell.enemyGroundUnits = []
# Get position of each enemy ground unit; enemyGroundUnits is a
    ↪ dict
enemyMap = self.unitManager.enemyGroundUnits
size = len(enemyMap)
unitIds = enemyMap.keys()
enemyPositions = cdata.clb.getPositions(self.sid, unitIds, size)
for i in range(size):
    enemy = enemyMap[unitIds[i]]
    # attach pos to enemy unit
    pos = enemyPositions[i]
    enemy.pos = pos
    # get cell containing pos
    cell = self.gMap.getCellContainingPoint(pos)
    # attach enemy unit to cell.enemy*.append(unit)
    cell.enemyGroundUnits.append(enemy)
xavg, zavg = self._getCenterOfMass()
enemy = None
for cell in self.gMap.generateCells((xavg, 25.0, zavg)):
    enemyBuilding = cell.enemyBuilding
    enemies = cell.enemyGroundUnits
    if not enemyBuilding is None:
        # attack building
        enemy = enemyBuilding
        break
    elif len(enemies) > 0:
        # attack unit
        enemy = self._getClosestEnemy(xavg, zavg, enemies)
```

```
                break
        if self.mode == 'air':
            enemy = self.unitManager.enemyCom
        if enemy is None:
            return
        elif self.unitManager.LOS[enemy.unitId]:
            self.order = 'attack'
            pot_target = []
            for enemy in self.unitManager.enemyGroundUnits:
                enemyHP = cdata.clb.getUnitHealth(self.sid, enemy)
                pot_target.append([enemyHP,enemy])
            target = sorted(pot_target)
            for unit in self.units:
                cdata.clb.attack(self.sid, unit.unitId, target[0][1])
        else:
            # Since enemy is outside of LOS, find a point to move to
            self.order = 'move'
            pos = enemy.pos
            self.movePos = pos
            if self.mode == 'air':
                for unit in self.units:
                    cdata.clb.move(self.sid, unit.unitId, pos[0], pos[2])
            else:
                target, guards = self.units[0], self.units[1:]
                cdata.clb.move(self.sid, target.unitId, pos[0], pos[2])
                self._guard(target, guards)
    # USE MOEA
     elif self.tactics == 'moea':
```

```
# Update gMap unit pos and time stamp
# clear old enemy values in gMap
for cell in self.gMap.iterateCells():
    cell.enemyGroundUnits = []
# Get position of each enemy ground unit; enemyGroundUnits is a
    ↪ dict
enemyMap = self.unitManager.enemyGroundUnits
size = len(enemyMap)
unitIds = enemyMap.keys()
enemyPositions = cdata.clb.getPositions(self.sid, unitIds, size)
for i in range(size):
    enemy = enemyMap[unitIds[i]]
    # attach pos to enemy unit
    pos = enemyPositions[i]
    enemy.pos = pos
    # get cell containing pos
    cell = self.gMap.getCellContainingPoint(pos)
    # attach enemy unit to cell.enemy*.append(unit)
    cell.enemyGroundUnits.append(enemy)
xavg, zavg = self._getCenterOfMass()
enemy = None
for cell in self.gMap.generateCells((xavg, 25.0, zavg)):
    enemyBuilding = cell.enemyBuilding
    enemies = cell.enemyGroundUnits
    if not enemyBuilding is None:
        # attack building
        enemy = enemyBuilding
        break
```

```
        elif len(enemies) > 0:
            # attack unit
            enemy = self._getClosestEnemy(xavg, zavg, enemies)
            break
    if self.mode == 'air':
        enemy = self.unitManager.enemyCom
    if enemy is None:
        return
    elif self.unitManager.LOS[enemy.unitId]:
        self.order = 'attack'
        self.allies = []
        self.enemies = []
        for unit in self.units:
            hp = cdata.clb.getUnitHealth(self.sid, unit.unitId)
            pos = cdata.clb.getUnitPosition(self.sid, unit.unitId)
            self.allies.append([unit.unitId, hp, 1, [pos[0],pos
                ↪ [2]],97, 350])
        for enemym in self.unitManager.enemyGroundUnits:
            hp = cdata.clb.getUnitHealth(self.sid, enemym)
            pos = cdata.clb.getUnitPosition(self.sid, enemym)
            self.enemies.append([enemym, hp, 1, [pos[0],pos[2]],97])
        #self.calculating = 0
        #print 'Number allies = {0}'.format(len(self.allies))
        prob = moea.ROUND(self.allies, self.enemies)
        algo = algorithm.nspso(gen=5)
        isl = island(algo,prob,20)
        popu = isl.population
        popu = algo.evolve(popu)
```

```
            #print 'Best Solution is {0}'.format(popu.champion.x)
            #print 'Optimization score is {0}'.format(popu.champion.f)
            #print 'Closest Calculating Complete'
            best = popu.champion.x
           # EVALUATE CHAMPION
            for i in range(0,len(best)):
                cdata.clb.attack(self.sid, self.allies[i][0], self.
                    ↪ enemies[int(best[i])][0])
            return
        else:
            # Since enemy is outside of LOS, find a point to move to
            self.order = 'move'
            pos = enemy.pos
            self.movePos = pos
            if self.mode == 'air':
                for unit in self.units:
                    cdata.clb.move(self.sid, unit.unitId, pos[0], pos[2])
            else:
                target, guards = self.units[0], self.units[1:]
                cdata.clb.move(self.sid, target.unitId, pos[0], pos[2])
                self._guard(target, guards)



def attackEnemy(self, enemy):
    for unit in self.units:
        cdata.clb.attack(self.sid, unit.unitId, enemy.unitId)
```

```
def guard(self, target):
    self._guard(target, self.units)

def _guard(self, target, guards):
    for guard in guards:
        cdata.clb.guardUnit(self.sid, guard.unitId, target.unitId)

def _updateUnitPositions(self):
    unitIds = [unit.unitId for unit in self.units]
    size = len(self.units)
    friendlyPositions = cdata.clb.getPositions(self.sid, unitIds, size)
    for unit, pos in zip(self.units, friendlyPositions):
        unit.pos = pos
    return friendlyPositions

def _getCenterOfMass(self):
    size = len(self.units)
    xsum = zsum = 0
    for pos in self._updateUnitPositions():
        xsum += pos[0]
        zsum += pos[2]
    xavg = xsum/size
    zavg = zsum/size
    return xavg, zavg

def _getClosestEnemy(self, x, z, enemies):
    minDist = 25600
    closest = None
```

```
        for enemy in enemies:
            dist = calcDist((x, 0.0, z), enemy.pos)
            if dist < minDist:
                minDist = dist
                closest = enemy
        return enemy


def calcDist(p1, p2):
    'Calculate distance from p1 to p2 in true euclidean coordinates'
    return math.sqrt((p2[0] - p1[0])**2 + (p2[2] - p1[2])**2)


class IdleEventFilter:
    'Ensures only one idleEvent per group per interval'

    def __init__(self):
        self.frame = 0

    def newEvent(self, group):
        if self.frame > group.lastIdleEventFrame:
            group.lastIdleEventFrame = self.frame
            group.pendingIdleEvent = False
            return True
        else:
            group.pendingIdleEvent = True
            return False
```

1.3 agent.py

The `agent.py` file, located in `.config/spring/AI/Skirmish/Tactics/*version*/python`, is changed in order to incorporate the PyGMO software as well as to allow the instant creation of units for the purpose of analyzing battlefield performance of the tactical agent. The instant generation of units is performed in the update portion of the `agent.py` file, as it is where a time-based command can be implemented. Only the first portion of the `agent.py` file is be displayed here as the remainder of the file is unchanged from the original version.

```
import ctypes, shelve
import cdata, gamemap, unitmanager, buildmanager, defensemanager,
    ↪ attackmanager
import group

from PyGMO import *
from PyGMO.util import *
import moea

# load callback library using ctypes
cdata.clb.saveAgentClb.argtypes = [ctypes.c_int, ctypes.py_object]



class Agent:

    def __init__(self, sid, cap):
        self.sid = sid                  # skirmishAI ID number
        print '<Agent {0}> saving callback'.format(sid)
        cdata.clb.saveAgentClb(sid, cap) # store callback in library
```

```
        self.frame = 0
        if not cdata.unitDefsLoaded:
            cdata.loadUnitDefs(sid)
            cdata.unitDefsLoaded = True
            gamemap.loadMapData(sid)
            print '<Agent {0}> map data loaded'.format(sid)
        config = cdata.playerConfigs[sid]
        self.collectData = config[1]
        strategy = cdata.strategies[config[0]]
       # tactics searches config in cdata.py
        self.tactics = config[2]
        print '<Agent {0}> has {1} tactic selected'.format(sid, self.tactics
            ↪ )
        gMap = gamemap.Map(sid)
        self.unitManager = unitmanager.UnitManager(sid, gMap)
        self.idleEventFlilter = group.IdleEventFilter()
        self.attackManager = attackmanager.AttackManager(
            sid, self.idleEventFlilter)
       # tactics passed to defense manager so it can be passed to group
        self.defenseManager = defensemanager.DefenseManager(
            sid, strategy, self.attackManager, self.unitManager,
            gMap, self.idleEventFlilter, self.tactics)
        self.buildManager = buildmanager.BuildManager(
            sid, strategy, gMap, self.defenseManager)
        cdata.clb.cheat(sid)
        self.data = []

    def update(self, frame):
```

```
self.frame = frame
# Quit after 37 minutes
# Number of minutes * 60 sec/min * 30 frame/sec
if frame > 5 * 60 * 30:
    self._endGame('timeup')
if frame % 5 == 0:
    self.idleEventFlilter.frame = frame
    self.defenseManager.update(frame)
    self.attackManager.update(frame)
if frame % 15 == 0:
    self.buildManager.update(frame)
# Write to file every 5 seconds
if self.collectData and frame % (5 * 30) == 0:
    self._captureState()
if frame == 30*1:
    if self.sid == 0: # tank 155 infantry 123
        for i in range(0,25):
            cdata.clb.giveUnit(0,(2048,0,900),ctypes.c_int(155))
    if self.sid == 1:
        for i in range(0,25):
            cdata.clb.giveUnit(1,(2048,0,3100),ctypes.c_int(155))
if frame == 30*30:
    self.defenseManager.group.setAttacking()
    self.attackManager.add(self.defenseManager.group)
    self.defenseManager.resetGroup()
```

1.4 config.txt

The `config.txt` is replaced with a variety of combat focused tactics which allow for the instantaneous use of the tactical changes in the `group.py` file to take effect. Each of the first three lines is focused entirely on producing a certain number of Stumpy tanks to battle. The final tactic "tac" places 100% effort on economic construction, which means that the commander unit does not construct any new units throughout the life of the game. This tactic is introduced to facilitate the instantaneous army generation used for the online simulation of combat.

```
#      | B   E   D   U|f p r j h w|j f s s p s j|f k t|M S|
5v5      0   0   0 100 0 0 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0 3 3
13v13    0   0   0 100 0 0 0 0 0 0 0 0 0 0 0 0 13 0 0 0 0 4 4
25v25    0   0   0 100 0 0 0 0 0 0 0 0 0 0 0 0 25 0 0 0 0 6 6
tac      0   100 0   0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0 3 3
```

Appendix B. Raw Data for Offline Simulation

This Appendix provides the raw data used for the creation of the tables discussed in Section 5.3. The appendix is split into three sections: one for each MOEA used. Each section is split into five subsections which refer to the different population settings used during the testing of each MOEA. Each subsection begins with a statement of the average hypervolume found for a single generation which is used for the remainder of that subsection as the variable $1G$. This variable is used in order to find the values of the average hypervolume increase per second.

2.1 Data for NSGA-II Algorithm

NSGA-II Algorithm Data for 20 Population.

Average Initial Hypervolume for 20 Population (1G) = 98903

Table 9. NSGA-II 20 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-441	-41	0.18	108450	9547	53041
2	1	-5	-421	-43	0.18	103175	4272	23735
3	1	-5	-470	-42	0.18	103310	4407	24485
4	1	-4	-387	-49	0.18	108214	9311	51729
5	1	-4	-375	-49	0.18	109460	10557	58652
6	1	-5	-441	-46	0.18	109635	10732	59624
7	1	-5	-475	-50	0.19	119455	20552	108170
8	1	-5	-398	-50	0.18	109925	11022	61235
9	1	-5	-424	-41	0.18	106196	7293	40518
10	1	-5	-447	-49	0.19	110085	11182	58854
avg	**1**	**-4.8**	**-428**	**-46**	**0.18**	**108791**	**9888**	**54004**

Table 10. NSGA-II 20 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-472	-47	0.26	110920	12017	46220
2	1	-5	-410	-50	0.26	113245	14342	55163
3	1	-5	-435	-49	0.24	112295	13392	55801
4	1	-5	-464	-50	0.25	116000	17097	68389
5	1	-5	-410	-50	0.26	114750	15847	60951
6	1	-5	-421	-47	0.26	106275	7372	28355
7	1	-5	-461	-48	0.26	131114	32211	123890
8	1	-4	-381	-49	0.25	109866	10963	43853
9	1	-5	-455	-51	0.26	118155	19252	74047
10	1	-5	-450	-51	0.26	115220	16317	62759
avg	**1**	**-4.9**	**-436**	**-49**	**0.26**	**114784**	**15881**	**61943**

Table 11. NSGA-II 20 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-458	-53	0.33	123830	24927	75537
2	1	-5	-447	-46	0.33	122025	23122	70068
3	1	-5	-467	-41	0.33	116660	17757	53810
4	1	-5	-432	-50	0.31	117880	18977	61217
5	1	-5	-481	-46	0.33	119880	20977	63568
6	1	-5	-452	-39	0.33	105455	6552	19855
7	1	-5	-458	-39	0.33	125575	26672	80825
8	1	-5	-458	-42	0.33	115658	16755	50774
9	1	-5	-467	-41	0.33	117705	18802	56977
10	1	-5	-404	-50	0.33	113415	14512	43977
avg	**1**	**-5.0**	**-452**	**-45**	**0.33**	**117808**	**18906**	**57661**

Table 12. NSGA-II 20 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-441	-50	0.41	119450	20547	50115
2	1	-5	-450	-50	0.40	115145	56242	140606
3	1	-5	-472	-47	0.41	113070	14167	34554
4	1	-5	-458	-44	0.40	114811	15908	39771
5	1	-5	-410	-55	0.42	125980	27077	64470
6	1	-6	-490	-42	0.41	161620	62717	152968
7	1	-5	-475	-44	0.41	122385	23482	57274
8	1	-5	-464	-55	0.41	130130	31227	76164
9	1	-5	-447	-48	0.39	108330	9427	24173
10	1	-5	-461	-43	0.40	114040	15137	37843
avg	**1**	**-5.1**	**-457**	**-48**	**0.41**	**126496**	**27593**	**67794**

NSGA-II Algorithm Data for 40 Population.

Average Initial Hypervolume for 40 Population (1G) = 109554

Table 13. NSGA-II 40 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-438	-44	0.38	111008	1454	3827
2	1	-4	-358	-47	0.38	104492	-5062	-13320
3	1	-5	-464	-48	0.38	115290	5736	15096
4	1	-5	-435	-45	0.39	106870	-2684	-6881
5	1	-5	-461	-46	0.37	124110	14556	39342
6	1	-5	-478	-45	0.38	109855	301	493
7	1	-5	-432	-48	0.38	109808	254	669
8	1	-5	-390	-52	0.38	120365	10811	28451
9	1	-5	-470	-50	0.37	117500	7946	21477
10	1	-5	-470	-38	0.38	114230	4676	12306
avg	**1**	**-4.9**	**-440**	**-46**	**0.38**	**113352**	**3799**	**10176**

Table 14. NSGA-II 40 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-418	-65	0.51	150150	40596	79601
2	1	-5	-410	-50	0.52	118170	8616	16570
3	1	-5	-472	-47	0.51	113027	3473	6811
4	1	-5	-464	-50	0.52	117440	7886	15166
5	1	-5	-418	-53	0.51	122660	13106	25699
6	1	-5	-484	-48	0.52	132550	22996	44224
7	1	-5	-458	-52	0.51	120880	11326	22209
8	1	-5	-470	-42	0.52	113685	4131	7945
9	1	-5	-390	-51	0.52	118830	9276	17839
10	1	-6	-498	-51	0.52	170433	60879	117076
avg	**1**	**-5.1**	**-448**	**-51**	**0.52**	**127782**	**18229**	**35314**

Table 15. NSGA-II 40 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-415	-54	0.65	132720	23166	35641
2	1	-5	-458	-51	0.67	121490	11936	17816
3	1	-6	-501	-53	0.65	159318	49764	76561
4	1	-5	-472	-48	0.65	131360	21806	33548
5	1	-6	-501	-47	0.67	157602	48048	71714
6	1	-5	-478	-50	0.67	148740	39186	58487
7	1	-5	-484	-52	0.66	152120	42566	64495
8	1	-5	-467	-49	0.66	128115	18561	28123
9	1	-5	-472	-49	0.67	125010	15456	23069
10	1	-5	-455	-42	0.67	120340	10786	16099
avg	**1**	**-5.2**	**-470**	**-50**	**0.66**	**137682**	**28128**	**42555**

Table 16. NSGA-II 40 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-470	-55	0.82	158635	49081	59855
2	1	-5	-432	-60	0.80	141320	31766	39708
3	1	-5	-461	-49	0.81	114205	4651	5742
4	1	-5	-467	-52	0.80	174941	65387	81734
5	1	-6	-487	-45	0.81	151890	42336	52267
6	1	-6	-501	-49	0.81	159174	49620	61260
7	1	-6	-495	-60	0.79	178200	68646	86894
8	1	-6	-490	-53	0.81	171064	61510	75939
9	1	-5	-410	-57	0.81	130440	20886	25786
10	1	-5	-467	-45	0.79	118425	8871	11230
avg	**1**	**-5.4**	**-468**	**-53**	**0.81**	**149829**	**40276**	**50042**

NSGA-II Algorithm Data for 60 Population.

Average Initial Hypervolume for 60 Population (1G) = 110904

Table 17. NSGA-II 60 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-401	-54	0.55	132790	21886	39792
2	1	-5	-461	-42	0.56	111650	746	39708
3	1	-5	-464	-45	0.55	120923	10019	18216
4	1	-5	-430	-47	0.56	108870	-2034	-3633
5	1	-5	-455	-47	0.55	127850	16946	30810
6	1	-4	-384	-49	0.56	115536	4632	8271
7	1	-5	-438	-53	0.55	125680	14776	26865
8	1	-4	-380	-51	0.56	114671	3767	6726
9	1	-5	-470	-44	0.56	128185	17281	30858
10	1	-6	-492	-43	0.55	138611	27707	50376
avg	**1**	**-4.9**	**-438**	**-48**	**0.56**	**122477**	**11572**	**20961**

Table 18. NSGA-II 60 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-472	-51	0.77	122510	11606	15072
2	1	-5	-435	-47	0.77	128870	17966	23332
3	1	-5	-484	-43	0.78	122620	11716	15020
4	1	-5	-441	-49	0.77	114865	3961	5144
5	1	-5	-424	-49	0.78	120100	9196	11789
6	1	-5	-461	-36	0.76	114135	3231	4251
7	1	-6	-487	-46	0.77	134412	23508	30529
8	1	-5	-464	-38	0.77	121760	10856	14098
9	1	-6	-492	-47	0.75	164429	53525	71366
10	1	-5	-470	-49	0.78	119460	8556	10968
avg	**1**	**-5.2**	**-463**	**-46**	**0.77**	**126316**	**15412**	**20157**

Table 19. NSGA-II 60 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-484	-48	1.00	153322	42418	42418
2	1	-5	-472	-44	0.98	127820	16916	17261
3	1	-5	-455	-46	0.99	130095	19191	19384
4	1	-6	-487	-47	0.98	153517	42613	43482
5	1	-4	-381	-53	0.97	124114	13210	13618
6	1	-6	-487	-62	0.97	181164	70260	72433
7	1	-5	-481	-52	0.99	125060	14156	14299
8	1	-6	-501	-50	0.98	162750	51846	52904
9	1	-6	-498	-46	0.98	156712	45808	46742
10	1	-5	-478	-44	1.00	125300	14396	14396
avg	**1**	**-5.3**	**-472**	**-49**	**0.98**	**143985**	**33081**	**33694**

Table 20. NSGA-II 60 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-475	-56	1.25	144675	33771	27016
2	1	-5	-464	-69	1.23	193544	82640	67187
3	1	-5	-475	-58	1.21	139400	28496	23550
4	1	-5	-481	-59	1.20	141895	30991	25826
5	1	-5	-444	-54	1.20	159100	48196	40163
6	1	-5	-452	-61	1.21	174584	63680	52628
7	1	-4	-338	-63	1.21	182212	71308	58932
8	1	-5	-452	-54	1.20	133405	22501	18751
9	1	-5	-478	-42	1.12	126065	15161	13536
10	1	-6	-504	-53	1.22	160272	49368	40465
avg	**1**	**-5.0**	**-456**	**-57**	**1.21**	**155515**	**44611**	**36805**

NSGA-II Algorithm Data for 80 Population.

Average Initial Hypervolume for 80 Population (1G) = 112483

Table 21. NSGA-II 80 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-498	-63	0.75	188244	75761	101015
2	1	-4	-387	-63	0.76	139768	27285	35902
3	1	-5	-418	-53	0.76	121850	9367	12326
4	1	-5	-432	-47	0.75	121350	8867	11823
5	1	-4	-381	-54	0.75	122106	9623	12831
6	1	-5	-407	-51	0.75	117285	4802	6403
7	1	-5	-475	-53	0.74	128947	16464	22249
8	1	-5	-441	-47	0.76	123615	11132	14648
9	1	-5	-432	-49	0.73	114488	2005	2747
10	1	-5	-455	-49	0.75	111475	-1008	-1343
avg	**1**	**-4.9**	**-433**	**-53**	**0.75**	**128913**	**16430**	**21860**

Table 22. NSGA-II 80 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-427	-52	1.05	122770	10287	9798
2	1	-5	-338	-52	1.06	149310	36827	34743
3	1	-5	-407	-58	1.06	131470	18987	17913
4	1	-5	-435	-53	1.05	126480	13997	13331
5	1	-5	-472	-48	1.04	139775	27292	26243
6	1	-4	-344	-50	1.04	113996	1513	1455
7	1	-5	-461	-52	1.08	126085	13602	12595
8	1	-5	-407	-50	1.07	121110	8627	8063
9	1	-5	-447	-55	1.05	129690	17207	16388
10	1	-5	-455	-54	1.05	132905	20422	19450
avg	**1**	**-4.9**	**-419**	**-52**	**1.06**	**129359**	**16877**	**15998**

Table 23. NSGA-II 80 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-492	-58	1.35	171216	58733	43506
2	1	-5	-484	-46	1.35	130000	17517	12976
3	1	-5	-455	-54	1.34	129830	17347	12946
4	1	-5	-432	-56	1.39	157520	45037	32401
5	1	-5	-481	-44	1.44	129370	16887	11727
6	1	-6	-492	-45	1.40	173947	61464	43903
7	1	-5	-475	-54	1.37	154835	42352	30914
8	1	-5	-470	-46	1.40	137265	24782	17702
9	1	-5	-441	-58	1.40	138410	25927	18520
10	1	-5	-427	-56	1.42	134165	21682	15269
avg	**1**	**-5.2**	**-465**	**-52**	**1.39**	**145656**	**33173**	**23986**

Table 24. NSGA-II 80 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-484	-43	1.61	137730	25247	15682
2	1	-6	-487	-48	1.64	166411	53928	32883
3	1	-5	-401	-57	1.63	160609	48126	29525
4	1	-6	-490	-51	1.64	170695	58212	35495
5	1	-6	-495	-47	1.63	153840	41357	25373
6	1	-4	-375	-63	1.64	171165	58682	35782
7	1	-4	-364	-60	1.61	137777	25294	15711
8	1	-6	-501	-55	1.64	197850	85367	34980
9	1	-6	-495	-61	1.65	181170	68687	41629
10	1	-6	-501	-47	1.62	175512	63029	38907
avg	**1**	**-5.4**	**-459**	**-53**	**1.63**	**162476**	**49993**	**30597**

NSGA-II Algorithm Data for 80 Population.

Average Initial Hypervolume for 80 Population (1G) = 119007

Table 25. NSGA-II 100 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-438	-46	0.93	117205	-1802	-1938
2	1	-5	-427	-47	0.93	108965	-10042	-10798
3	1	-5	-450	-52	0.93	121575	2568	2761
4	1	-5	-470	-47	0.92	121455	2448	2661
5	1	-5	-450	-46	0.94	134885	15878	16891
6	1	-4	-384	-49	0.94	112337	-6670	-7096
7	1	-5	-410	-52	0.93	118755	-252	-271
8	1	-5	-472	-45	0.94	124344	5337	5677
9	1	-5	-470	-53	0.93	148420	29413	31627
10	1	-6	-501	-50	0.94	165060	46053	48992
avg	**1**	**-5**	**-447**	**-49**	**0.93**	**127300**	**8293**	**8851**

Table 26. NSGA-II 100 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-481	-48	1.30	137790	18783	14448
2	1	-5	-467	-49	1.33	127795	8788	6607
3	1	-5	-435	-53	1.32	125205	6198	4695
4	1	-5	-441	-49	1.30	128050	9043	6956
5	1	-4	-364	-59	1.30	132164	13157	10121
6	1	-5	-438	-55	1.32	131545	12538	9498
7	1	-5	-475	-41	1.30	132935	13928	10714
8	1	-5	-410	-54	1.31	130020	11013	8407
9	1	-5	-450	-56	1.32	163974	44967	34066
10	1	-5	-404	-55	1.32	128735	9728	7370
avg	**1**	**-4.9**	**-437**	**-52**	**1.31**	**133821**	**14814**	**11288**

Table 27. NSGA-II 100 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-452	-52	1.73	124515	5508	3184
2	1	-5	-464	-58	1.68	167226	48219	28702
3	1	-5	-464	-49	1.72	151700	32693	19007
4	1	-5	-415	-59	1.71	171650	52643	30785
5	1	-5	-472	-52	1.70	161056	42049	24735
6	1	-5	-424	-60	1.73	175808	56801	32833
7	1	-5	-461	-56	1.70	158801	39794	23408
8	1	-5	-432	-64	1.67	149125	30118	18035
9	1	-6	-490	-49	1.67	184055	65048	38951
10	1	-6	-495	-59	1.69	175230	56223	33268
avg	**1**	**-5.2**	**-457**	**-56**	**1.70**	**161917**	**42909**	**25291**

Table 28. NSGA-II 100 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-515	-63	2.06	194670	75663	36730
2	1	-6	-504	-51	2.09	181410	62403	29858
3	1	-6	-490	-52	2.06	167886	48879	23728
4	1	-5	-481	-59	2.05	175228	56221	27425
5	1	-6	-510	-50	2.10	211495	92488	44042
6	1	-6	-495	-57	2.05	169290	50283	24528
7	1	-5	-452	-58	2.07	164400	45393	21929
8	1	-6	-498	-51	2.07	157550	38543	18620
9	1	-6	-507	-60	2.05	191286	72279	35258
10	1	-6	-512	-48	2.03	183744	64737	31890
avg	**1**	**-5.8**	**-496**	**-55**	**2.06**	**179696**	**60689**	**29401**

2.2 Data for SPEA2 Algorithm

SPEA2 Algorithm Data for 20 Population.

Average Initial Hypervolume for 20 Population (1G) = 105714

Table 29. SPEA2 20 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-464	-36	0.15	104995	-719	-4795
2	1	-5	-435	-45	0.15	100170	-5544	-36962
3	1	-5	-458	-37	0.14	114160	8446	60326
4	1	-5	-450	-38	0.15	97830	-7884	-52562
5	1	-4	-361	-54	0.15	115834	10120	67465
6	1	-5	-464	-41	0.15	130520	24806	165371
7	1	-5	-450	-40	0.15	106770	1056	7038
8	1	-5	-450	-40	0.15	111580	5866	39105
9	1	-5	-461	-34	0.15	114115	8401	56005
10	1	-4	-378	-48	0.14	108489	2775	19819
avg	**1**	**-4.8**	**-437**	**-41**	**0.15**	**110446**	**4732**	**32081**

Table 30. SPEA2 20 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-464	-39	0.18	106510	796	4421
2	1	-5	-452	-42	0.18	101670	-4044	-22468
3	1	-5	-418	-54	0.19	120375	14661	77162
4	1	-5	-481	-43	0.19	119165	13451	70794
5	1	-5	-470	-41	0.18	114910	9196	51087
6	1	-5	-461	-39	0.18	112475	6761	37559
7	1	-5	-458	-39	0.18	102885	-2829	-15718
8	1	-5	-458	-41	0.19	100605	-5109	-26891
9	1	-5	-472	-41	0.18	121575	15861	88115
10	1	-5	-461	-35	0.19	116430	10716	56398
avg	**1**	**-5.0**	**-460**	**-41**	**0.18**	**111660**	**5946**	**32046**

Table 31. SPEA2 20 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-467	-42	0.22	116340	10626	48299
2	1	-5	-467	-39	0.22	111195	5481	24912
3	1	-5	-432	-53	0.22	119255	13541	61549
4	1	-5	-441	-60	0.23	137320	31606	137416
5	1	-5	-458	-41	0.22	117340	11626	52844
6	1	-5	-470	-43	0.22	121190	15476	70344
7	1	-4	-350	-49	0.23	108384	2670	11607
8	1	-5	-478	-44	0.22	113635	7921	36003
9	1	-5	-413	-58	0.22	133900	28186	128117
10	1	-4	-330	-57	0.23	125700	19986	86894
avg	**1**	**-4.8**	**-431**	**-49**	**0.22**	**120426**	**14712**	**65799**

Table 32. SPEA2 20 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-404	-52	0.26	117005	11291	43426
2	1	-5	-470	-49	0.26	117895	12181	46849
3	1	-6	-487	-43	0.25	141836	36122	144487
4	1	-5	-484	-46	0.26	122345	16631	63964
5	1	-5	-481	-55	0.25	144660	38946	155783
6	1	-5	-472	-42	0.26	135975	30261	116387
7	1	-5	-464	-43	0.26	121335	15621	60080
8	1	-5	-478	-50	0.25	128685	22971	91883
9	1	-5	-404	-58	0.26	134565	28851	110964
10	1	-6	-487	-43	0.26	149576	43862	168699
avg	**1**	**-5.2**	**-463**	**-48**	**0.26**	**131388**	**25673**	**100252**

SPEA2 Algorithm Data for 40 Population.

Average Initial Hypervolume for 40 Population (1G) = 112646

Table 33. SPEA2 40 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-467	-40	0.30	111240	-14065	-4685
2	1	-5	-481	-50	0.30	120250	7604	25348
3	1	-5	-461	-42	0.30	105600	-7044	-23485
4	1	-4	-338	-48	0.30	105791	-6855	-22848
5	1	-5	-475	-35	0.30	114035	1389	4632
6	1	-5	-444	-39	0.30	111138	-1508	-5025
7	1	-5	-435	-54	0.30	121155	8509	28365
8	1	-5	-447	-41	0.30	110810	-1836	-6118
9	1	-4	-393	-47	0.30	104707	-7939	-26462
10	1	-5	-398	-56	0.30	125880	13234	44115
avg	**1**	**-4.8**	**-434**	**-45**	**0.30**	**113061**	**415**	**1384**

Table 34. SPEA2 40 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-472	-44	0.37	112715	69	188
2	1	-5	-481	-46	0.37	119585	6939	18755
3	1	-5	-478	-46	0.38	130670	18024	47433
4	1	-5	-467	-38	0.38	111780	-866	-2278
5	1	-5	-467	-41	0.37	113260	614	1661
6	1	-6	-487	-38	0.38	135936	23290	61291
7	1	-5	-472	-44	0.38	115230	2584	6801
8	1	-5	-461	-35	0.37	123905	11259	30431
9	1	-5	-395	-51	0.37	119560	6914	18688
10	1	-5	-481	-46	0.37	126617	13971.5	37761
avg	**1**	**-5.1**	**-466**	**-43**	**0.37**	**120926**	**8280**	**22073**

Table 35. SPEA2 40 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-4	-324	-61	0.46	129675	17029	37021
2	1	-5	-472	-39	0.46	114805	2159	4695
3	1	-5	-478	-43	0.46	125530	12884	28010
4	1	-6	-498	-55	0.45	180475	67829	150732
5	1	-5	-478	-42	0.45	121210	8564	19032
6	1	-5	-438	-53	0.46	124190	11544	25097
7	1	-6	-512	-68	0.45	208896	96250	213890
8	1	-5	-472	-42	0.45	115070	2424	5388
9	1	-5	-455	-52	0.45	126040	13394	29766
10	1	-6	-498	-55	0.45	164340	51694	114877
avg	**1**	**-5.2**	**-463**	**-51**	**0.45**	**141023**	**28378**	**62851**

Table 36. SPEA2 40 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-495	-66	0.53	196020	83374	157310
2	1	-6	-487	-50	0.54	154920	42274	78286
3	1	-6	-495	-51	0.55	167865	55219	100399
4	1	-5	-464	-39	0.54	121820	9174	16990
5	1	-6	-490	-53	0.54	155820	43174	79953
6	1	-5	-475	-55	0.53	132845	20199	38112
7	1	-6	-492	-56	0.53	165312	52666	99371
8	1	-6	-492	-47	0.54	161135	48489	89795
9	1	-6	-487	-44	0.54	155858	43212	80023
10	1	-5	-484	-45	0.53	134490	21844	41216
avg	**1**	**-5.7**	**-486**	**-51**	**0.54**	**154609**	**41963**	**78146**

SPEA2 Algorithm Data for 60 Population.

Average Initial Hypervolume for 60 Population (1G) = 109359

Table 37. SPEA2 60 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-481	-47	0.47	123715	14356	30546
2	1	-5	-461	-38	0.46	109985	626	1362
3	1	-5	-458	-43	0.47	118655	9296	19780
4	1	-6	-492	-55	0.46	162360	53001	115221
5	1	-5	-447	-47	0.46	110075	716	1558
6	1	-5	-467	-44	0.47	127818	18459	39276
7	1	-5	-478	-45	0.46	129530	20171	43851
8	1	-5	-464	-40	0.47	117120	7761	16514
9	1	-5	-470	-41	0.46	109490	131	286
10	1	-5	-467	-40	0.45	127665	18306	40681
avg	**1**	**-5.1**	**-469**	**-44**	**0.46**	**123641**	**14283**	**30907**

Table 38. SPEA2 60 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-4	-353	-52	0.58	116203	6844	11801
2	1	-5	-484	-43	0.59	115860	6501	11019
3	1	-5	-475	-46	0.58	141217	31858	54928
4	1	-5	-472	-41	0.59	121170	11811	20019
5	1	-5	-475	-52	0.58	124160	14801	25520
6	1	-5	-472	-39	0.59	126745	17386	29469
7	1	-5	-470	-43	0.58	121270	11911	20537
8	1	-5	-484	-48	0.58	132085	22726	39184
9	1	-5	-464	-46	0.58	120080	10721	18485
10	1	-5	-418	-57	0.59	132220	22861	38748
avg	**1**	**-4.9**	**-457**	**-47**	**0.58**	**125101**	**15742**	**26971**

Table 39. SPEA2 60 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-478	-37	0.68	132990	23631	34752
2	1	-6	-495	-53	0.69	166010	56651	82104
3	1	-6	-495	-47	0.68	165782	56423	82976
4	1	-5	-478	-38	0.69	137950	28591	41437
5	1	-6	-504	-51	0.69	162990	53631	77727
6	1	-5	-461	-62	0.69	143495	34136	49473
7	1	-5	-484	-52	0.69	125840	16481	23886
8	1	-6	-492	-43	0.69	151670	42311	61321
9	1	-5	-481	-42	0.68	121905	12546	18451
10	1	-6	-487	-51	0.68	155257	45898	67498
avg	**1**	**-5.5**	**-486**	**-48**	**0.69**	**146389**	**37030**	**53962**

Table 40. SPEA2 60 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-484	-44	0.81	144150	34791	42952
2	1	-6	-487	-45	0.81	148764	39405	48649
3	1	-6	-487	-48	0.81	166726	57367	70824
4	1	-6	-492	-54	0.81	175560	66201	81730
5	1	-6	-498	-58	0.81	182070	72711	89767
6	1	-5	-441	-75	0.81	204515	95156	117477
7	1	-5	-432	-66	0.81	191160	81801	100990
8	1	-6	-490	-53	0.81	155820	46461	57360
9	1	-6	-507	-52	0.81	195144	85785	105908
10	1	-6	-490	-50	0.81	156500	47141	58199
avg	**1**	**-5.7**	**-481**	**-55**	**0.81**	**172041**	**62862**	**77386**

SPEA2 Algorithm Data for 80 Population.

Average Initial Hypervolume for 80 Population (1G) = 114778

Table 41. SPEA2 80 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-484	-54	0.62	130680	15902	25648
2	1	-5	-461	-45	0.63	122915	8137	12916
3	1	-4	-347	-54	0.63	120054	5276	8374
4	1	-5	-467	-42	0.62	120570	5792	9342
5	1	-5	-455	-50	0.63	118455	3677	5836
6	1	-5	-467	-45	0.62	122240	7462	12035
7	1	-4	-378	-58	0.62	128757	13979	22547
8	1	-5	-461	-44	0.62	111985	-2793	-4505
9	1	-5	-404	-53	0.62	118370	3592	5793
10	1	-5	-464	-37	0.63	113820	-958	-1521
avg	**1**	**-4.8**	**-439**	**-48**	**0.62**	**120785**	**6007**	**9647**

Table 42. SPEA2 80 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-484	-40	0.80	141690	26912	33640
2	1	-6	-490	-50	0.80	153705	38927	48659
3	1	-5	-478	-48	0.79	124805	10027	12692
4	1	-5	-470	-44	0.80	125025	10247	12809
5	1	-5	-478	-44	0.80	130575	15797	19746
6	1	-5	-472	-38	0.79	127370	12592	15939
7	1	-5	-481	-44	0.78	119670	4892	6272
8	1	-5	-470	-45	0.79	121440	6662	8433
9	1	-5	-467	-45	0.79	123300	8522	10787
10	1	-6	-487	-54	0.79	157788	43010	54443
avg	**1**	**-5.2**	**-478**	**-45**	**0.79**	**132537**	**17759**	**22342**

Table 43. SPEA2 80 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-447	-62	0.94	148330	33552	35694
2	1	-6	-487	-52	0.95	160204	45426	47817
3	1	-5	-455	-56	0.94	132455	17677	18805
4	1	-5	-484	-61	0.97	147620	32842	33858
5	1	-5	-475	-38	0.95	123215	8437	8881
6	1	-6	-498	-49	0.93	165767	50989	54827
7	1	-5	-478	-43	0.94	125085	10307	10965
8	1	-6	-492	-42	0.93	168449	53671	57711
9	1	-5	-450	-67	0.94	157095	42317	145018
10	1	-6	-498	-58	0.93	193304	78526	84436
avg	**1**	**-5.4**	**-476**	**-53**	**0.94**	**152152**	**37374**	**39801**

Table 44. SPEA2 80 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-498	-54	1.09	179532	64754	59407
2	1	-6	-507	-52	1.09	176814	62036	56914
3	1	-4	-358	-53	1.07	126104	11326	10585
4	1	-5	-363	-67	1.08	187890	73112	67696
5	1	-6	-492	-49	1.08	160068	45290	41935
6	1	-6	-492	-47	1.08	148144	33366	30894
7	1	-6	-490	-58	1.07	170520	55742	52095
8	1	-6	-487	-48	1.09	152006	37228	34154
9	1	-6	-507	-62	1.08	188604	73826	168357
10	1	-5	-484	-55	1.08	135065	20287	18784
avg	**1**	**-5.6**	**-468**	**-55**	**1.08**	**162475**	**47697**	**44082**

SPEA2 Algorithm Data for 80 Population.

Average Initial Hypervolume for 80 Population (1G) = 118819

Table 45. SPEA2 100 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-432	-53	0.77	121820	3001	3897
2	1	-5	-484	-44	0.77	124145	5326	6917
3	1	-5	-478	-42	0.77	117345	-1474	-1915
4	1	-5	-467	-47	0.76	114385	-4434	-5834
5	1	-5	-484	-46	0.77	124310	5491	7131
6	1	-5	-481	-46	0.77	119010	191	248
7	1	-5	-467	-43	0.77	127885	9066	11774
8	1	-5	-464	-39	0.78	123135	4316	5533
9	1	-5	-467	-44	0.77	117398	-1421	-1846
10	1	-5	-472	-44	0.77	119090	271	352
avg	**1**	**-5.0**	**-470**	**-45**	**0.77**	**120852**	**2033**	**2626**

Table 46. SPEA2 100 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-490	-48	0.95	153285	34466	36280
2	1	-5	-401	-51	0.97	120576	1757	1811
3	1	-5	-464	-45	0.98	125830	7011	7154
4	1	-5	-481	-46	0.95	121374	2555	2689
5	1	-4	-324	-56	0.97	124223	5404	5571
6	1	-6	-490	-57	0.96	467580	48761	50793
7	1	-5	-472	-52	0.95	122720	3901	4106
8	1	-6	-495	-59	0.97	175230	56411	58155
9	1	-6	-487	-52	0.97	151944	33125	34149
10	1	-5	-472	-52	0.96	129425	10606	11048
avg	**1**	**-5.3**	**-458**	**-52**	**0.96**	**139219**	**20400**	**21176**

Table 47. SPEA2 100 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-481	-44	1.18	143270	24451	20721
2	1	-6	-495	-47	1.18	168035	49216	41708
3	1	-6	-498	-49	1.19	164232	45413	38162
4	1	-6	-490	-43	1.18	168550	49731	42145
5	1	-6	-501	-52	1.18	169542	50723	42985
6	1	-6	-490	-46	1.19	168970	50151	42144
7	1	-6	-492	-48	1.19	161143	42324	35566
8	1	-5	-475	-49	1.18	131630	12811	10857
9	1	-6	-492	-50	1.19	159225	40406	33954
10	1	-5	-481	-49	1.21	134085	15266	12616
avg	**1**	**-5.7**	**-490**	**-48**	**1.19**	**156868**	**38049**	**32086**

Table 48. SPEA2 100 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-498	-55	1.39	185805	66986	48191
2	1	-6	-492	-65	1.40	193680	74861	53472
3	1	-6	-501	-50	1.40	167118	48299	34499
4	1	-6	-507	-50	1.40	184770	65951	47108
5	1	-6	-524	-57	1.38	183358	64539	46767
6	1	-6	-495	-45	1.38	178089	59270	42949
7	1	-6	-501	-58	1.41	177300	58481	41476
8	1	-6	-504	-54	1.38	163296	44477	32230
9	1	-6	-504	-49	1.41	172656	53837	38182
10	1	-6	-504	-66	1.41	199584	80765	57280
avg	**1**	**-6.0**	**-503**	**-55**	**1.40**	**180566**	**61746**	**44215**

2.3 Data for NSPSO Algorithm

NSPSO Algorithm Data for 20 Population.

Average Initial Hypervolume for 20 Population (1G) = 109554

Table 49. NSPSO 20 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-458	-44	0.15	141220	31666	211109
2	1	-5	-415	-54	0.15	126426	16872	112483
3	1	-5	-452	-40	0.15	147034	37480	249869
4	1	-5	-458	-38	0.15	117980	8426	56776
5	1	-5	-447	-40	0.15	108015	-1539	-10257
6	1	-5	-447	-40	0.15	110178	624	4163
7	1	-5	-432	-45	0.15	119989	10435	69569
8	1	-5	-450	-38	0.15	147005	374514	249676
9	1	-5	-430	-67	0.15	148890	39336	262243
10	1	-5	-423	-43	0.15	163658	54104	360696
avg	**1**	**-5.0**	**-401**	**-45**	**0.15**	**133039**	**23486**	**156573**

Table 50. NSPSO 20 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-4	-313	-71	0.19	135544	25990	136792
2	1	-5	-452	-38	0.19	166430	56876	299349
3	1	-5	-438	-66	0.18	189800	80246	445813
4	1	-5	-427	-65	0.19	147810	83256	201349
5	1	-5	-435	-42	0.19	181838	72284	380444
6	1	-5	-435	-36	0.19	147575	38021	200113
7	1	-5	-447	-35	0.19	141876	32322	170118
8	1	-6	-490	-48	0.19	160065	50511	265849
9	1	-5	-438	-34	0.19	162587	53033	279123
10	1	-5	-458	-45	0.19	183665	74111	390060
avg	**1**	**-5.0**	**-433**	**-48**	**0.19**	**161719**	**52165**	**276901**

Table 51. NSPSO 20 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-4	-381	-55	0.22	204674	94713	430515
2	1	-5	-464	-39	0.22	245750	138021	627370
3	1	-5	-441	-39	0.23	207520	97966	425941
4	1	-5	-475	-39	0.22	205854	96300	437729
5	1	-5	-467	-43	0.22	205682	96128	436947
6	1	-5	-452	-43	0.23	225029	115475	502067
7	1	-5	-438	-40	0.23	194428	84874	369019
8	1	-5	-455	-49	0.23	138552	28998	126080
9	1	-5	-455	-42	0.23	244395	134841	586267
10	1	-5	-421	-44	0.22	203797	94243	428379
avg	**1**	**-4.9**	**-445**	**-43**	**0.23**	**207710**	**98156**	**437031**

Table 52. NSPSO 20 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-413	-97	0.26	218155	108601	417698
2	1	-5	-452	-38	0.26	578660	469106	1804255
3	1	-5	-447	-40	0.26	259870	150316	578140
4	1	-5	-450	-40	0.26	204249	94695	364213
5	1	-5	-421	-52	0.26	159920	50366	193717
6	1	-5	-438	-44	0.26	242656	133102	511932
7	1	-5	-438	-37	0.26	191349	81795	314598
8	1	-4	-310	-107	0.26	282680	173126	665871
9	1	-5	-447	-93	0.26	210825	101271	389505
10	1	-5	-438	-39	0.26	223432	113878	437994
avg	**1**	**-4.9**	**-425**	**-59**	**0.26**	**257180**	**147626**	**567792**

NSPSO Algorithm Data for 40 Population.

Average Initial Hypervolume for 40 Population (1G) = 116479

Table 53. NSPSO 40 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-464	-49	0.30	119364	2885	9618
2	1	-5	-432	-58	0.30	194984	78505	261684
3	1	-5	-467	-53	0.30	126619	10140	33801
4	1	-5	-447	-38	0.30	124780	8301	27671
5	1	-5	-464	-38	0.30	146947	30468	101561
6	1	-5	-432	-46	0.30	142792	26313	87711
7	1	-5	-441	-46	0.30	169960	53481	178271
8	1	-5	-435	-48	0.30	149255	327766	109254
9	1	-5	-395	-61	0.30	137850	21371	71238
10	1	-5	-430	-46	0.30	151911	35432	118108
avg	**1**	**-5.0**	**-441**	**-48**	**0.30**	**146446**	**29968**	**99892**

Table 54. NSPSO 40 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-452	-44	0.38	164566	48087	126546
2	1	-5	-450	-39	0.37	204384	87905	237582
3	1	-5	-447	-42	0.38	190670	74191	195240
4	1	-5	-452	-131	0.38	336888	220409	280024
5	1	-5	-461	-41	0.38	177262	60783	159956
6	1	-5	-438	-45	0.38	140363	23884	62853
7	1	-5	-447	-37	0.38	190328	73849	194340
8	1	-5	-421	-46	0.38	169623	531446	139853
9	1	-5	-455	-79	0.38	210770	94291	248135
10	1	-5	-447	-39	0.38	151250	34771	91503
avg	**1**	**-5.0**	**-447**	**-54**	**0.38**	**193610**	**77132**	**203603**

Table 55. NSPSO 40 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-407	-50	0.45	203373	86894	193098
2	1	-5	-444	-39	0.45	222603	106124	235832
3	1	-5	-447	-76	0.46	210055	93576	203427
4	1	-5	-461	-41	0.46	163890	474119	103068
5	1	-5	-467	-46	0.45	644080	527601	1172447
6	1	-5	-455	-47	0.45	234464	117985	262190
7	1	-5	-464	-41	0.45	418131	301652	670338
8	1	-5	-438	-47	0.45	235789	119310	265134
9	1	-5	-438	-68	0.45	218039	101560	225690
10	1	-5	-458	-37	0.45	162000	45521	101158
avg	**1**	**-5.0**	**-448**	**-49**	**0.45**	**271242**	**154764**	**343238**

Table 56. NSPSO 40 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-455	-39	0.52	286633	170154	327220
2	1	-4	-378	-80	0.52	193030	76551	147214
3	1	-5	-464	-47	0.52	250393	133914	257528
4	1	-5	-484	-45	0.52	670360	553881	1065156
5	1	-5	-455	-94	0.52	490235	373756	718762
6	1	-5	-447	-48	0.52	207438	90959	174922
7	1	-5	-470	-40	0.53	629545	513066	968050
8	1	-5	-455	-46	0.52	262071	145592	279985
9	1	-5	-418	-85	0.52	221457	104978	201881
10	1	-5	-464	-45	0.52	769010	652531	1254868
avg	**1**	**-4.9**	**-449**	**-57**	**0.52**	**398017**	**281539**	**539559**

NSPSO Algorithm Data for 60 Population.

Average Initial Hypervolume for 60 Population (1G) = 124322

Table 57. NSPSO 60 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-452	-40	0.46	167485	43163	77077
2	1	-5	-455	-35	0.46	143869	19547	42493
3	1	-5	-484	-46	0.46	141364	17042	37048
4	1	-5	-413	-56	0.47	164590	40268	85677
5	1	-5	-410	-46	0.46	145710	21388	46496
6	1	-4	-358	-57	0.46	154444	30122	65483
7	1	-5	-452	-40	0.46	152802	28480	61913
8	1	-5	-450	-37	0.46	160783	36461	79263
9	1	-5	-455	-45	0.46	143232	18910	41109
10	1	-5	-452	-47	0.46	132448	8126	17665
avg	**1**	**-4.9**	**-438**	**-45**	**0.46**	**150673**	**26351**	**57098**

Table 58. NSPSO 60 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-470	-43	0.57	559745	435423	763900
2	1	-5	-447	-82	0.56	191520	67198	119996
3	1	-5	-452	-41	0.57	197630	73308	128611
4	1	-4	-370	-93	0.57	238696	114374	200656
5	1	-5	-455	-83	0.57	198893	74571	130826
6	1	-5	-450	-44	0.57	350500	226178	396803
7	1	-5	-447	-50	0.57	199974	75652	132723
8	1	-5	-467	-43	0.57	167244	42922	75302
9	1	-5	-458	-41	0.57	164423	40101	70353
10	1	-5	-438	-84	0.57	249870	125548	220260
avg	**1**	**-4.9**	**-445**	**-60**	**0.57**	**251850**	**127528**	**223943**

Table 59. NSPSO 60 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-455	-46	0.69	421409	297087	430561
2	1	-4	-301	-120	0.70	303138	178816	255451
3	1	-5	-455	-62	0.69	216815	92493	134048
4	0	-5	-403	-128	0.69	535180	410858	595446
5	1	-5	-455	-36	0.69	245782	121460	176029
6	1	-5	-464	-47	0.68	190204	65882	96885
7	1	-5	-452	-43	0.68	206048	81726	120185
8	0	-5	-429	-120	0.68	530590	406268	597453
9	1	-5	-444	-55	0.68	260449	136127	200187
10	1	-5	-461	-49	0.68	230018	105696	155435
avg	**0.8**	**-4.9**	**-432**	**-71**	**0.69**	**313963**	**189641**	**276168**

Table 60. NSPSO 60 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	0	-5	-443	-137	0.80	890280	765958	957448
2	0	-5	-430	-197	0.81	893950	769628	950158
3	1	-5	-464	-42	0.81	584933	460611	568656
4	1	-4	-353	-84	0.80	249726	125404	156755
5	1	-5	-461	-43	0.80	314880	190558	238198
6	1	-5	-481	-98	0.80	286014	161692	202115
7	1	-5	-464	-38	0.80	245582	121260	151575
8	1	-5	-470	-71	0.80	552325	428003	535004
9	1	-4	-318	-136	0.81	592323	468001	577779
10	0	-5	-428	-146	0.80	644025	519703	649629
avg	**0.7**	**-4.8**	**-431**	**-99**	**0.80**	**525404**	**401082**	**498732**

NSPSO Algorithm Data for 80 Population.

Average Initial Hypervolume for 80 Population (1G) = 123996

Table 61. NSPSO 80 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-398	-52	0.62	146366	22370	36080
2	1	-5	-432	-46	0.62	156570	32574	52538
3	1	-5	-447	-42	0.62	173935	49939	80546
4	1	-5	-418	-63	0.62	144915	20919	33740
5	1	-5	-478	-43	0.63	149293	25297	40153
6	1	-5	-447	-42	0.62	133192	9196	14832
7	1	-5	-481	-50	0.62	213064	89068	143657
8	1	-5	-472	-61	0.62	143960	19964	32199
9	1	-5	-427	-44	0.62	149530	25534	41183
10	1	-5	-415	-54	0.62	141801	17805	28717
avg	**1**	**-5.0**	**-442**	**-50**	**0.62**	**155263**	**31266**	**50365**

Table 62. NSPSO 80 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-478	-47	0.77	192955	68959	89557
2	1	-5	-455	-50	0.76	213847	89851	118224
3	1	-5	-455	-43	0.76	209205	85209	112117
4	1	-5	-470	-44	0.77	245793	121797	158177
5	1	-5	-455	-52	0.77	188499	64503	83770
6	1	-4	-344	-91	0.77	203476	79480	103220
7	1	-5	-472	-43	0.77	435517	311521	404572
8	1	-5	-455	-95	0.76	222221	98225	129243
9	1	-5	-464	-40	0.76	160354	36358	478389
10	1	-5	-461	-78	0.76	180855	56859	74814
avg	**1**	**-4.9**	**-451**	**-58**	**0.77**	**225272**	**101276**	**132153**

Table 63. NSPSO 80 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-450	-43	0.92	249986	125990	136945
2	1	-5	-415	-64	0.93	182795	58799	63224
3	1	-5	-484	-69	0.92	244035	120039	130477
4	1	-4	-321	-136	0.93	311386	187390	201494
5	1	-5	-455	-43	0.93	478237	354241	380904
6	1	-5	-452	-51	0.93	469961	345945	372005
7	1	-4	-335	-92	0.92	397459	273463	297242
8	1	-5	-458	-46	0.92	253239	129243	140481
9	0	-4	-317	-135	0.93	555592	431596	464081
10	1	-5	-458	-47	0.92	310789	186793	203035
avg	**0.9**	**-4.7**	**-415**	**-73**	**0.93**	**345348**	**221352**	**238989**

Table 64. NSPSO 80 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-6	-498	-47	1.09	751468	627472	575662
2	1	-5	-438	-100	1.10	284532	160536	145941
3	1	-5	-461	-49	1.09	261902	137906	126519
4	1	-5	-484	-73	1.10	276066	152070	138245
5	1	-5	-470	-40	1.09	397780	273784	251178
6	1	-5	-461	-85	1.10	209020	85024	77294
7	0	-5	-422	-178	1.10	866485	742489	674990
8	1	-5	-455	-84	1.09	642340	518344	475545
9	1	-4	-341	-112	1.09	503312	379316	347996
10	1	-5	-390	-92	1.10	286631	162635	147850
avg	**0.9**	**-5.0**	**-442**	**-86**	**1.10**	**447954**	**323957**	**296122**

NSPSO Algorithm Data for 100 Population.

Average Initial Hypervolume for 100 Population (1G) = 123724

Table 65. NSPSO 100 Population, 2 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-438	-55	0.78	135498	11774	15095
2	1	-5	-458	-43	0.78	205598	81874	104967
3	1	-4	-333	-67	0.79	141490	17766	22489
4	1	-5	-415	-49	0.79	159528	35804	45322
5	1	-5	-421	-50	0.80	195104	71380	89226
6	1	-5	-458	-48	0.79	158427	34703	43928
7	1	-5	-407	-53	0.78	154015	30291	38835
8	1	-5	-435	-49	0.78	200157	76433	97992
9	1	-5	-467	-40	0.79	160961	37237	47136
10	1	-5	-464	-43	0.78	149820	26096	33457
avg	**1**	**-4.9**	**-430**	**-50**	**0.79**	**166060**	**42336**	**53845**

Table 66. NSPSO 100 Population, 3 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-481	-45	0.97	602470	478746	493553
2	1	-5	-470	-50	0.97	268878	145154	149644
3	1	-5	-452	-51	0.98	216072	92348	94233
4	0	-5	-445	-147	0.98	711510	587786	599782
5	1	-5	-452	-56	0.98	204359	80635	82281
6	1	-5	-461	-42	0.97	192852	69128	71266
7	1	-4	-358	-100	0.97	266894	143170	147598
8	1	-4	-307	-92	0.97	263127	139403	143715
9	1	-5	-430	-51	0.97	166535	42811	44135
10	1	-4	-318	-112	0.97	241541	117817	121461
avg	**0.9**	**-4.7**	**-417**	**-75**	**0.97**	**313424**	**189700**	**194767**

Table 67. NSPSO 100 Population, 4 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-413	-118	1.17	574872	451148	385597
2	1	-5	-475	-78	1.17	671630	547906	468296
3	1	-5	-450	-107	1.17	274876	151152	129190
4	0	-5	-466	-134	1.17	646220	522496	446578
5	1	-5	-464	-40	1.17	660895	537171	459121
6	1	-5	-461	-48	1.17	565975	442251	377993
7	1	-4	-293	-123	1.17	251849	128125	109509
8	1	-5	-432	-72	1.16	247128	123404	106383
9	1	-5	-472	-43	1.17	545855	422131	360796
10	0	-5	-454	-149	1.17	682760	559036	477809
avg	**0.8**	**-4.9**	**-438**	**-91**	**1.17**	**512206**	**388482**	**332127**

Table 68. NSPSO 100 Population, 5 Generations

Run #	obj1	obj2	obj3	obj4	time(s)	HV	HV-1G	(HV-1G)/T
1	1	-5	-464	-54	1.37	230114	106390	77657
2	0	-5	-445	-145	1.37	748880	625156	456319
3	0	-5	-466	-137	1.38	687340	563616	408418
4	1	-5	-455	-108	1.37	619980	496256	362231
5	0	-5	-457	-150	1.37	985370	861646	628939
6	1	-5	-481	-42	1.38	645501	521777	378100
7	0	-5	-429	-131	1.37	662890	539166	393552
8	1	-5	-458	-45	1.37	250085	126361	92235
9	1	-5	-452	-44	1.38	284273	160549	116340
10	0	-4	-295	-151	1.38	657199	533475	386576
avg	**0.5**	**-4.9**	**-440**	**-101**	**1.37**	**577163**	**453440**	**330036**

Appendix C. Raw Data for Online Simulation

This appendix provides the raw win/loss rate and other statistical data acquired during simulations between various tactical decision making methods on the Spring RTS engine. For each series of battles the title is in the format "Online Simulation Results for X Tactic vs Y Tactic". The "X" tactic begins the battle at the start of the map, and the "Y" tactic begins on the bottom. There are be 10 battles between each type of tactic for each method from each direction.

3.1 Data for MOEA Tactic Starting From Top of Map

Table 69. Online Simulation Results for MOEA Tactic vs Default Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Win	0:32	12	758.17
Win	0:40	5	952.8
Win	0:35	7	793.29
Lose	0:28	15	720.67
Win	0:33	5	339.8
Lose	0:37	9	842.78
Win	0:29	12	1384.08
Win	0:32	10	1150
Win	0:37	8	1275.38
Lose	0:34	12	842.58

Table 70. Online Simulation Results for MOEA Tactic vs Proximity Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Win	0:36	5	664.4
Win	0:28	17	1166.65
Win	0:33	12	920.42
Lose	0:33	13	912.77
Lose	0:46	3	672.33
Win	0:40	4	827.25
Win	0:26	15	1118.13
Lose	0:44	3	669
Lose	0:42	13	783.69
Win	0:45	7	918

Table 71. Online Simulation Results for MOEA Tactic vs Weak Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Win	0:43	6	1332.5
Win	0:33	8	1105.88
Win	0:33	10	1299.7
Win	0:38	11	1465
Win	0:34	8	1329.63
Win	0:42	5	1150
Win	0:26	15	1141.6
Win	0:37	5	1247.8
Win	0:30	11	1391.73
Win	0:38	7	1396.43

3.2 Data for Default Tactic Starting From Top of Map

Table 72. Online Simulation Results for Default Tactic vs MOEA Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Lose	0:28	8	923.63
Win	0:42	4	903.5
Lose	0:45	4	1008
Lose	0:33	7	778.43
Lose	0:33	8	1144.13
Lose	0:40	5	811.2
Lose	0:35	8	1123.75
Lose	0:29	12	1609.08
Lose	0:26	12	1329.92
Lose	0:25	19	1440.26

Table 73. Online Simulation Results for Default Tactic vs Proximity Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Lose	0:30	10	1096.3
Win	0:37	5	982.6
Win	1:03	2	1007
Lose	0:49	3	418.33
Lose	0:40	5	1251.4
Win	0:56	2	210
Win	0:52	4	894.75
Lose	0:36	8	1010.25
Win	0:41	7	1229.43
Lose	0:42	5	1281

Table 74. Online Simulation Results for Default Tactic vs Weak Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Win	0:37	7	1268.57
Lose	0:45	7	1215.71
Win	0:37	7	1474.14
Win	0:31	9	1354.89
Win	0:43	4	1401.25
Win	0:45	3	1039
Win	0:41	5	1314.6
Win	0:36	7	1164
Win	0:35	7	1465
Win	0:48	4	1391.25

3.3 Data for Proximity Tactic Starting from Top of Map

Table 75. Online Simulation Results for Proximity Tactic vs Default Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Lose	0:38	11	978.36
Lose	0:46	7	768.86
Lose	0:44	4	653.25
Lose	0:41	5	1112.4
Win	0:42	5	822.2
Lose	0:36	8	1118.38
Lose	0:34	12	1262.42
Lose	0:38	10	1073.2
Win	0:34	7	1184.71
Win	0:45	4	1077

Table 76. Online Simulation Results for Proximity Tactic vs MOEA Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Lose	0:49	7	1213.14
Lose	0:25	14	1066.93
Lose	0:31	11	652.55
Lose	0:34	11	840.82
Lose	1:15	1	49
Win	0:39	4	565
Lose	0:50	5	1448.2
Lose	0:41	8	937.13
Win	0:52	5	815.8
Lose	0:42	7	1210.29

Table 77. Online Simulation Results for Proximity Tactic vs Weak Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Win	0:46	6	1408.67
Win	0:38	9	1162.11
Win	0.34	10	1522.6
Win	0:49	3	790.33
Win	0:47	3	898.33
Win	0:44	7	1428.71
Win	0:45	8	1090.25
Win	0:44	9	1356.56
Win	0:31	15	1391.13
Win	0:43	8	978.38

3.4 Data for Weak Tactic Starting from Top of Map

Table 78. Online Simulation Results for Weak Tactic vs Default Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Lose	0:37	9	1257.78
Lose	0:39	10	1419.4
Lose	0:35	6	1042.5
Lose	0:36	6	936.67
Lose	0:30	9	1244.22
Lose	0:36	9	1296.67
Lose	0:38	7	1373.14
Lose	0:35	5	1338.2
Win	0:39	7	996.86
Lose	0:34	7	999.57

Table 79. Online Simulation Results for Weak Tactic vs Proximity Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Lose	0:26	15	993.733
Lose	0:34	12	1486.83
Lose	0:44	9	1380.89
Lose	0:34	11	1501.09
Lose	0:55	3	1168.67
Lose	0:43	11	1386
Lose	0:38	12	1353.67
Lose	0:41	11	1200.45
Lose	0:42	6	1152.5
Lose	1:07	1	940

Table 80. Online Simulation Results for Weak Tactic vs MOEA Tactic

Win/Lose	Battle Duration	# Units Remaining	Average Remaining HP
Lose	0:31	14	1098.21
Lose	0:34	11	1346.27
Lose	0:36	8	1124.25
Lose	0:31	11	1549.64
Lose	0:31	12	1500.83
Lose	0:27	15	1455.53
Lose	0:30	10	1269.9
Lose	0:34	11	1380.09
Lose	0:28	12	1299
Lose	0:41	2	776.5

Appendix D. Online Simulation Data Sorted by Winner

This appendix takes the data from Appendix C and reorganizes it based on the simulation's winner. This helps to compile a quick-look at the statistics attained when a specific tactic is victorious. Because of this organizational structure, tactics that lose often do not have as many data points for analysis.

4.1 MOEA Tactic Victory Statistics

Table 81. Statistics for MOEA Tactic Victory against Default Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:32	12	758.17
0:40	5	952.8
0:35	7	793.29
0:33	5	339.8
0:29	12	1384.08
0:32	10	1150
0:37	8	1275.38
0:28	8	923.63
0:45	4	1008
0:33	7	778.43
0:33	8	1144.13
0:40	5	811.2
0:35	8	1123.75
0:29	12	1609.08
0:26	12	1329.92
0:25	19	1440.26

Table 82. Statistics for MOEA Tactic Victory against Proximity Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:36	5	664.4
0:28	17	1166.65
0:33	12	920.42
0:40	4	827.25
0:26	15	1118.13
0:45	7	918
0:49	7	1213.14
0:25	14	1066.93
0:31	11	652.55
0:34	11	840.82
1:15	1	49
0:50	5	1448.2
0:41	8	937.13
0:42	7	1210.29

Table 83. Statistics for MOEA Tactic Victory against Weak Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:43	6	1332.5
0:33	8	1105.88
0:33	10	1299.7
0:38	11	1465
0:34	8	1329.63
0:42	5	1150
0:26	15	1141.6
0:37	5	1247.8
0:30	11	1391.73
0:38	7	1396.43
0:31	14	1098.21
0:34	11	1346.27
0:36	8	1124.25
0:31	11	1549.64
0:31	12	1501.83
0:27	15	1455.53
0:30	10	1269.9
0:34	11	1380.1
0:28	12	1299
0:41	2	776.5

4.2 Default Tactic Victory Statistics

Table 84. Statistics for Default Tactic Victory against MOEA Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:28	15	720.67
0:37	9	842.78
0:34	12	841.58
0:42	4	903.5

Table 85. Statistics for Default Tactic Victory against Proximity Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:37	5	982.6
1:03	2	1007
0:56	2	210
0:52	4	894.75
0:41	7	1229.43
0:38	11	978.36
0:46	7	768.86
0:44	4	653.25
0:41	5	1112.4
0:36	8	1118.38
0:34	12	1262.42
0:38	10	1073

Table 86. Statistics for Default Tactic Victory against Weak Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:37	7	1268.57
0:37	7	1474.14
0:31	9	1354.89
0:43	4	1401.25
0:45	3	1039
0:41	5	1314.6
0:36	7	1164
0:35	7	1465
0:48	4	1391.25
0:37	9	1257.78
0:39	10	1419.4
0:35	6	1042.5
0:36	6	936.67
0:30	9	1244.22
0:36	9	1296.67
0:38	7	1373.14
0:35	5	1338.2
0:34	7	999.57

4.3 Proximity Tactic Victory Statistics

Table 87. Statistics for Proximity Tactic Victory against MOEA Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:33	13	912.77
0:46	3	672.33
0:44	3	669
0:42	13	783.69
0:39	4	565
0:52	5	815.8

Table 88. Statistics for Proximity Tactic Victory against Default Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:30	10	1096.3
0:49	3	418.33
0:40	5	1251.4
0:36	8	1010.25
0:42	5	1281
0:42	5	822.2
0:34	7	1184.71
0:45	4	1077

Table 89. Statistics for Proximity Tactic Victory against Weak Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:46	6	1408.67
0:38	9	1162.11
0:34	10	1522.6
0:49	3	790.33
0:47	3	898.33
0:44	7	1428.71
0:45	8	1090.25
0:44	9	1356.56
0:31	15	1391.13
0:43	8	978.38
0:26	15	993.73
0:34	12	1486.83
0:44	9	1380.89
0:34	11	1501.09
0:55	3	1168.67
0:43	11	1386
0:38	12	1353.67
0:41	11	1200.45
0:42	6	1152.5
1:07	1	940

4.4 Weak Tactic Victory Statistics

Table 90. Statistics for Weak Tactic Victory against MOEA Tactic

Battle Duration	# Units Remaining	Average Remaining HP
N/A	N/A	N/A

Table 91. Statistics for Weak Tactic Victory against Default Tactic

Battle Duration	# Units Remaining	Average Remaining HP
0:45	7	1215.71
0:39	7	996.86

Table 92. Statistics for Weak Tactic Victory against Proximity Tactic

Battle Duration	# Units Remaining	Average Remaining HP
N/A	N/A	N/A

Bibliography

1. John R. Boyd, "The essence of winning and losing," http://www.danford.net/boyd.essence.htm, Accessed: March 10, 2015.

2. Alan Sartori-Angus, "Cosmic conquest," *BYTE Magazine*, p. 124, December 1982.

3. "Nostalgia series: Dune II," http://www.rtsguru.com/game/101/article/123/Nostalgia-Series-Dune-2.html, Accessed: March 10, 2015.

4. "Warcraft: From 1994 to WoW wrath of the lich king," http://www.pcgameshardware.com/aid,669750/Warcraft-From-1994-to-WoW-Wrath-of-the-Lich-King-game-classics-in-series/News/, Accessed: March 10, 2015.

5. Jason M Blackford, "Online build-order optimization for real-time strategy agents using multi-objective evolutionary algorithms," M.S. thesis, Air Force Institute of Technology, 2014.

6. Lyall J Di Trapani, "A real-time strategy agent framework and strategy classifier for computer generated forces," M.S. thesis, Air Force Institution of Technology, 2012.

7. "Multi-objective optimization - wikipedia, the free encyclopedia," http://en.wikipedia.org/wiki/Multi-objective_optimization, Accessed: March 10, 2015.

8. "Real-time strategy - wikipedia, the free encyclopedia," http://en.wikipedia.org/wiki/Real-time_strategy, Accessed: March 10, 2015.

9. "Air education and training command," http://www.aetc.af.mil/, Accessed: March 10, 2015.

10. Strategy World, *Air Force Wargaming is Different*, March 10, 2015.

11. Glen Robertson and Ian Watson, "A review of real-time strategy game AI," *AI Magazine*, vol. 35, no. 4, pp. 75–104, 2014.

12. "Ai script - starcraft and starcraft II wiki," http://starcraft.wikia.com/wiki/AI_script, Accessed: March 10, 2015.

13. David Churchill, Abdallah Saffidine, and Michael Buro, "Fast heuristic search for rts game combat scenarios.," in *Artificial Intelligence and Interactive Digital Entertainment*, 2012.

14. "Starcraft AIb competition," http://webdocs.cs.ualberta.ca/~cdavid/starcraftaicomp/, Accessed: March 10, 2015.

15. Malcolm Gladwell, *Blink: The power of thinking without thinking*, Hachette Digital, Inc., 2007.

16. "Welcome to the officer training school homepage," http://www.au.af.mil/au/holmcenter/OTS/index.asp, Accessed: March 10, 2015.

17. "Welcome to the air university," http://www.au.af.mil/au/soc/sos.asp, Accessed: March 10, 2015.

18. David G. Ullman, "OO-OO-OO! the sound of a broken OODA loop," *Crosstalk - The Journal of Defense Software Engineering*, pp. 22–25, 2007.

19. "Dune II - wikipedia, the free encyclopedia," http://en.wikipedia.org/wiki/Dune_II, Accessed: March 10, 2015.

20. Bob Bates, *Game Developer's Market Guide (Game Development)*, Muska & Lipman/Premier-Trade, 2003.

21. Blizzard Entertainment, "Blizzard entertainment: Classic games," `http://us.blizzard.com/en-us/games/legacy`, Accessed: March 10, 2015.

22. "Wargus — home," `www.wargus.sourceforge.net`, Accessed: March 10, 2015.

23. "Stratagus — a real time strategy engine," `www.stratagus.com`, Accessed: March 10, 2015.

24. "Sparcraft - starcraft combat simulation," `https://code.google.com/p/sparcraft/`, Accessed: March 10, 2015.

25. "Spring rts engine," `http://springrts.com`, Accessed: March 10, 2015.

26. Carl Von Clausewitz, *On war*, Digireads.com Publishing, 2004.

27. Ljubica Erickson and Mark Erickson, *Russia: war, peace and diplomacy-essays in honour of John Erickson*, Weidenfeld & Nicolson, 2005.

28. "[interviews] bisu, coach park, and jaedong," `http://www.teamliquid.net/forum/news-archive/339200-interviews-bisu-coach-park-and-jaedong`, Accessed: March 10, 2015.

29. Kurt Weissgerber, "Developing an effective and efficient real time strategy agent for use as a computer generated force," M.S. thesis, Air Force Institute of Technology, 2010.

30. Raúl Lara-Cabrera, Carlos Cotta, and Antonio J Fernández-Leiva, "A review of computational intelligence in RTS games," in *Foundations of Computational Intelligence (FOCI), 2013 IEEE Symposium on*. IEEE, 2013, pp. 114–121.

31. Stuart Russel, Peter Norvig, et al., "Artificial intelligence: A modern approach, 1995," *Cited on*, p. 20, 1994.

32. David W Aha, Matthew Molineaux, and Marc Ponsen, "Learning to win: Case-based plan selection in a real-time strategy game," in *Case-based reasoning research and development*, pp. 5–20. Springer, 2005.

33. Santiago Ontanón, Gabriel Synnaeve, Alberto Uriarte, Florian Richoux, David Churchill, and Mike Preuss, "A survey of real-time strategy game AI research and competition in starcraft," *Computational Intelligence and AI in Games, IEEE Transactions on*, vol. 5, no. 4, pp. 293–311, 2013.

34. David Churchill and Michael Buro, "Portfolio greedy search and simulation for large-scale combat in starcraft," in *Computational Intelligence in Games (CIG), 2013 IEEE Conference on*. IEEE, 2013, pp. 1–8.

35. Guillaume Chaslot, *Monte-carlo tree search*, Ph.D. thesis, Maastricht University, 2010.

36. A Fernández-Ares, P Garcıa-Sánchez, AM Mora, PA Castillo, and JJ Merelo, "Designing competitive bots for a real time strategy game using genetic programming," `http://ceur-ws.org/Vol-1196/cosecivi14_submission_24.pdf`, Accessed: March 10, 2015.

37. Ben George Weber, Michael Mateas, and Arnav Jhala, "Building human-level AI for real-time strategy games.," in *AAAI Fall Symposium: Advances in Cognitive Systems*, 2011.

38. Marius Stanescu, Nicolas A Barriga, and Michael Buro, "Hierarchical adversarial search applied to real-time strategy games," in *Tenth Annual AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE)*, 2014.

39. Carlos Coello Coello, Gary B Lamont, and David A Van Veldhuizen, *Evolutionary algorithms for solving multi-objective problems, 2nd edition*, Springer Science & Business Media, 2007.

40. Swiss Federal Institute of Technology Zurich, "Dtlz2 test problems," `http://www.tik.ee.ethz.ch/sop/download/supplementary/testproblems/dtlz2/`, note=Accessed: March 10, 2015.

41. Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *Evolutionary Computation, IEEE Transactions on*, vol. 6, no. 2, pp. 182–197, 2002.

42. Eckart Zitzler and Lothar Thiele, "Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach," *Evolutionary Computation, IEEE Transactions on*, vol. 3, no. 4, pp. 257–271, 1999.

43. Eckart Zitzler, Marco Laumanns, Lothar Thiele, Eckart Zitzler, Eckart Zitzler, Lothar Thiele, and Lothar Thiele, "SPEA2: Improving the strength pareto evolutionary algorithm," 2001.

44. Yang Liu, "A fast and elitist multi-objective particle swarm algorithm: NSPSO," in *Granular Computing, 2008. GrC 2008. IEEE International Conference on*. IEEE, 2008, pp. 470–475.

45. N Chase, M Rademacher, E Goodman, R Averill, and R Sidhu, "A benchmark study of multi-objective optimization methods," Tech. Rep., Red Cedar Technology.

46. R Timothy Marler and Jasbir S Arora, "Survey of multi-objective optimization methods for engineering," *Structural and multidisciplinary optimization*, vol. 26, no. 6, pp. 369–395, 2004.

47. David H Wolpert and William G Macready, "No free lunch theorems for optimization," *Evolutionary Computation, IEEE Transactions on*, vol. 1, no. 1, pp. 67–82, 1997.

48. El-Ghazali Talbi, *Metaheuristics: from design to implementation*, vol. 74, John Wiley & Sons, 2009.

49. "jMetal web site," `http://jmetal.sourceforge.net/`, Accessed: March 10, 2015.

50. "MOEA framework, a java library for multi-objective evolutionary algorithms," `http://www.moeaframework.org/`, Accessed: March 10, 2-15.

51. "Welcome to PyGMO," `http://esa.github.io/pygmo/`, Accessed: March 10, 2015.

52. "ParadisEO, paradiseo home page," `http://paradiseo.gforge.inria.fr/`, Accessed: March 10, 2015.

53. Arnaud Liefooghe, Laetitia Jourdan, and El-Ghazali Talbi, "A software framework based on a conceptual unified model for evolutionary multiobjective optimization: Paradiseo-moeo," *European Journal of Operational Research*, vol. 209, no. 2, pp. 104–112, 2011.

54. "Borg MOEA, a high-performance, robust, adaptive multi-objective evolutionary algorithm," `www.borgmoea.org`, Accessed: March 10, 2015.

55. "MOEA software availability," `http://www.cs.cinvestav.mx/~emoobook/apendices/appendix-h.pdf`, Accessed: March 10, 2015.

56. Carlos A Coello Coello, "Software," `http://delta.cs.cinvestav.mx/~ccoello/EMOO/EMOOsoftware.html`, Accessed March 10, 2015.

57. "Balanced annihilation - spring," https://springrts.com/wiki/Balanced_Annihilation, Accessed: March 10, 2015.

58. "Multi-objective optimization - wikipedia, the free encyclopedia," http://en.wikipedia.org/wiki/Multi-objective_optimization, Accessed: March 10, 2015.

59. "Quick start - PyGMO 1.1.5 documentation," http://esa.github.io/pygmo/quickstart.html, Accessed: March 10, 2015.

60. "Fog of war - wikipedia, the free encyclopedia," http://en.wikipedia.org/wiki/Fog_of_war, Accessed: March 10, 2015.

61. Alexander Kovarsky and Michael Buro, "Heuristic search applied to abstract combat games," in *Advances in Artificial Intelligence*, pp. 66–78. Springer, 2005.

62. "Balanced annihilation v7.60 - armstump," http://imolarpg.dyndns.org/modinfo/ba760/armstump.html, Accessed: March 10, 2015.

63. Peter Sarkozy, "Balanced annihilation mod info," http://balancedannihilation.org/modinfo/, Accessed: March 10, 2015.

64. Radha-Krishna Balla and Alan Fern, "UCT for tactical assault planning in real-time strategy games.," in *International Joint Conferences on Artificial Intelligence*, 2009, pp. 40–45.

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14. ABSTRACT

The real time strategy (RTS) tactical decision making problem is a difficult problem. It is generally more complex due to its high degree of time sensitivity. This research effort presents a novel approach to this problem within an educational, teaching objective. Particular decision focus is target selection for a artificial intelligence (AI) RTS game model. The use of multi-objective evolutionary algorithms (MOEAs) in this tactical decision making problem allows an AI agent to make fast, effective solutions that do not require modification to fit the current environment. This approach allows for the creation of a generic solution building tool that is capable of performing well against scripted opponents without requiring expert training or deep tree searches. The experimental results validate that MOEAs can control an on-line agent capable of out performing a variety AI RTS opponent test scripts.

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