

# EVOLVING BATTLE FORMATIONS IN MASSIVELY MULTIPLAYER ONLINE STRATEGY GAMES

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## Abstract

This paper presents a genetic algorithm for the development of battle formations for MMORTS games. We considered the context of the game *Call of Roma*, where the battles are turn based, where only two sides fight each other, which are the Attack and the Defense. The genetic algorithm takes as input a predetermined battle formation, presented by the defense, and returns a battle formation adapted for the Attack. The algorithm aims to maximize the balance of the Attack side. This balance is formed by the difference between the number of slaughtered soldiers in combat on both sides. The balance is used to calculate the fitness of individuals, which encode the various characteristics of the fighting heroes. The results demonstrate that the proposed algorithm is able to find a victorious solution for the Attack, even when it is under unfavorable conditions.

**Keywords::** Massively Multiplayer Online Real-time Strategy, Genetic Algorithms, *Call of Roma*.

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## 1 Introduction

MMORTS (Massively Multiplayer Online Real-Time Strategy) games have attracted the attention of millions of users in many countries around the world. MMORTS is a kind of game that involves real-time strategy (RTS) with a massive number of simultaneous players on the Internet. As indicated in a study available online [Yee 2005] these players spend 21 hours a week on average in online games. Such amount of time spent in virtual worlds can lead to different socializing experiences [Jewels 2002]. This possibility of interacting with such a high number of players is one of the main factors that might explain the success of these kind of games. For the companies that maintain MMORTS games, a massive number of active players is an important source of income. Just to give a perspective, the market of online games in 2002 represented something between \$15 and \$20 billions of dollars [Thurrott 2002].

In MMORTS, players can either fight each other in PvP (Player versus Player) battles or engage artificial players, known as NPC (Non-Player Character), in PvE (Player versus Environment) battles; they can also take different missions which are integrated to the story of game. Since such NPCs have predefined, static battle strategies, more experienced players find no challenge in engaging in PvEs. After some time, the game becomes tedious for these experienced players, who can easily defeat NPCs. As a consequence of this, the evasion of players in the server increases. With few active players remaining in the server, the possibility of interactions reduces, affecting the income of the company that hosts the game.

One idea to overcome this problem is to create intelligent, adaptive artificial players, presenting battle formations and strategies that are more efficient for PvE battles. In this paper we employ genetic algorithms to implement this idea. If NPCs present more dynamic, efficient and unanticipated battle formations in PvE, players will have to put more effort in the preparation for the battles, and more experienced players can still find stimulating battles to fight. Such characteristics are important to maintain their interest in the game and to reduce the evasion of players in the server. In [Fogel et al. 2004], the authors argue that artificial intelligence and machine learning techniques have the potential to increase the longevity of electronic games and also reduce its production costs. Heuristic techniques

such as evolutionary techniques have been recognized as a promising approach to generate strategies for many different games [Chelapilla and Fogel 1999], [Stanley et al. 2005]. The complexity of handcrafting strategies for artificial players make the evolutionary process very appealing, since useful strategies can be generated and discovered automatically. Strategies generated by evolutionary algorithms can be competitive to human strategies, see [Avery and Michalewicz 2008], [Miles et al. 2004]. In this way, high level NPCs can be generated by an evolutionary process as an additional tool to reduce the evasion of users from the server, giving them motivation to keep playing and investing in their accounts.

In the next section, we discuss the context of the game *Call of Roma*, used as a background and test bench to the proposed approach. We also define the problem of finding an efficient battle formation for this game. In section 3, we present an evolutionary approach for solve the defined problem and describe the genetic operators implemented for that. The section 4 shows the results of the proposed algorithm. We discuss the test cases and the best heroes found. Finally, the section 5 presents the conclusions of this paper and possible future works.

## 2 Context and Problem Definition

In this work we consider the context of the game *Call of Roma*, formerly known as *Caesary* [Caesary 2009]. *Call of Roma* is a MMORTS based in the history of the Roman Empire, the post republican phase of the ancient Roman civilization, which was characterized by an autocratic government and wide spread exploration in Europe and the Mediterranean. Players can build an empire, exploit resources, organize troops and fight enemies. The game was developed by Heroic Era and is similar to [Evony 2009], [Maegica 2010] and [Senatry 2011]. Although considering a specific context, the model proposed in this paper can be extended to several MMORTS games, since it shares common features of the battle system of these games, which are based on basic principles of role-playing games.

Units are divided into frontal and rear units. Frontal units engage in close combat, while rear units fight at distance. Among the different unit attributes, in this paper we consider only those that affect the performance of the soldiers during the battle, since the effects of the other attributes are beyond the scope of this research. The attributes considered are: *Offense (OFF)*, the capacity of attacking opponents; *Defense (DEF)*, the capacity of defending from the enemies' attacks; *Damage (DMG)*, indicating the damage of an attack performed by the unit; *Vitality or Hit Points (HP)*, related to the capacity of absorbing the damage inflicted by enemies. The damage of the units is uniformly distributed within a given interval, introducing some degree of randomness to the battles.

In this paper, only 2 units are evaluated, one frontal unit and one rear unit. The frontal unit is named *Hastatus*, consisting in one soldier with light armor, low lethality, performing close range combat with a spear. The *Hastatus* has small production cost and short training time. The rear unit is named *Sagittarius*, consisting in an archer with light armor, a bow and arrows, small production cost and short training time. When the frontal units are killed, the *Sagittarii* become incapable of fighting at distance and they engage in close combat, with a penalized damage (50% reduction). Moreover, the *Sagittarius* has a special ability termed *Dispersion*. *Dispersion* means that the *Sagittarius* unit can attack all units of the opponent inflicting 25% of *DMG*. *Dispersion* is used only if the sum of the total damage inflicted to enemy units is greater than the total damage caused by a direct assault to a single unit. In other words, the *Sagittarius* applies *Dispersion* only when it is advantageous. Otherwise, a distal assault is used with 100% of damage. The table 1 shows the base attributes of the evaluated units in this work.

**Table 1:** *Units.*

Unit	Attributes			
	DMG	OFF	HP	DEF
Hastatus	3 - 6	8	60	8
Sagittarius	3 - 5	9	45	5

Units are sent to a battle under the leadership of a Hero. Heroes have 3 traits that influence their performance in a battle: Sway (SW), Bravery (BR), and Parry (PA). Sway is related to the leadership faculty of the hero. The higher this faculty the higher the number of soldiers that can be allocated to this hero. Bravery affects the offensive performance of the units, increasing their damage in combat. Parry affects the defensive performance of the units, reducing casualties in combat. Units have fixed values for their attributes but the values for the heroes' traits can be chosen by the user according to his/her strategies. Users can assign integer values to each attribute under the constraint that the highest value can not surpass the sum of the other two. Each hero has a total amount of points to be distributed among the attributes. In this work, we assume that each hero has a total of 969 Unassigned Trait Points (UTPs). The faculty of a hero can be assigned by

$$faculty = 30000 + 500 \times SW. \quad (1)$$

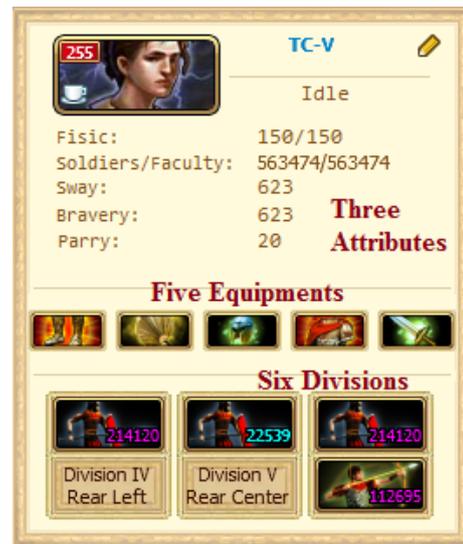
The value of 30000 faculty is a base value applied to all heroes and each SW point gives more 500 points do faculty. Each Hastatus or Sagittarius under the leadership of a given hero requires 1 faculty point of the same. Thus, a single hero can lead hundreds of thousands of soldiers.

Heroes can be equipped with 5 different types of equipments, which are boots, shield, helmet, armor, and weapon. Each equipment gives a special bonus to all soldiers led by the hero. In this paper, we consider the 3 most important sets of equipments in Call of Roma: Saturn, Fearlessness, and Hard Core, detailed in Table 2.

**Figure 1:** *The battle system in Call of Roma*

The battle system in Call of Roma tries to simulate the way battles were fought in the time of Roman civilization. In the battles, only two sides face each other, the Attack and Defense. Each side take turns to attack the opponent. The units killed in battle are removed from the hero's divisions at the end of each turn. For the allocation of soldiers, there are 6 different divisions placed side by side, 3 frontal divisions (left  $d_1$ , center  $d_2$  and right  $d_3$ ) and 3 rear divisions (left  $d_4$ , center  $d_5$  and right  $d_6$ ). Players are free to organize their divisions into formations. Figure 1 illustrates the battle formation and frontal and rear divisions. Figure 2 illustrates a sample hero data used in this work.

There are other factors that influence the performance of soldiers in combat. For instance the level of research in the academy of the city where the heroes originated from. Research bonus is given to the sum of values of the unit attributes plus the bonus given by

**Figure 2:** *A sample hero*

the equipments. We considered 4 lines of research at their maximum levels, adding 65% to OFF and DEF, 75% to HP, and 65% to the faculty of the hero. Other factors are medals and special items. Medals give bonuses of 25% to the attributes of heroes, respecting the UTP's restrictions. Special items adds more 10% to both OFF and DEF. The effect of these factors were implicitly taken into account in this work, however they are not included as variables of the solution. Therefore, in the conception of a battle formation, one must consider which equipments are more suitable for the units, how the UTPs are going to be distributed among the attributes of the hero, and the disposition of the units in frontal and rear divisions.

The goal of this paper is to propose a computational intelligence algorithm able to generate a winning and efficient battle formation, considering all the relevant factors. This is a complex combinatorial problem, which would require a heuristic approach. Among heuristic methods, we have selected Genetic Algorithms (GAs) [Holland 1975], [Goldberg 1989], which are methods inspired by the adaptation principle of the Darwinian Natural Selection Theory [Darwin and Huxley 2003] to evolve candidate solutions to the problem.

### 3 Proposed Approach

GAs belong to a family of methods inspired by nature, based on the principles of evolution by natural selection. They are very general and high level heuristics, applicable to a wide range of real-world problems. Individuals in the population of the GA represent candidate solutions that compete for reproduction and survival. In the problem considered in this paper, an individual codes for a particular battle formation in the game Call of Roma. Given the factors that influence the battle, the codification proposed employs three "chromosomes": (i) chromosome  $E$  codes for the 5 types of equipments used by the hero, consisting in an array of 5 integer "genes", where each gene indexes an respective equipment set, (ii) chromosome  $A$  codes for the distribution of the UTPs among the attributes of the hero, consisting in an array of 3 integer genes, where each gene represent the points given to a respective trait, (iii) chromosome  $D$  codes for the organization of soldiers in the 6 divisions, consisting in an array of 3 integer genes, where each gene represent the number of soldiers, as a percentage of the hero's faculty, allocated in a respective division.

The algorithm receives as input a battle formation for the defense side. Individuals of the GA represent formations for the attack side. The evaluation of an individual is done by using a deterministic battle simulator, implemented by the first author based on information available at [QuestUnlocked 2011]. The battle simulator can be found at [Armageddon 2012] for future research. In the simulation, the number of soldiers killed by each side is counted and the net

**Table 2:** Sets of equipments considered in the work.

Type	Saturn				Fearlessness				Hard Core			
	DMG	OFF	HP	DEF	DMG	OFF	HP	DEF	DMG	OFF	HP	DEF
Boots	-	-	+25	-	+8	+8	-	+8	+10	+18	-	-
Shield	+10	-	+100	-	-	-	+90	+30	-	-	+25	+40
Helmet	-	+5	+80	+1	+5	+10	+60	-	-	+26	-	+24
Armor	-	-	+100	+10	-	-	+60	+20	-	-	+125	+10
Sword	+15	+40	+20	-	+30	+60	-	-	+50	-	-	-
Total	+25	+45	+325	+11	+43	+78	+210	+58	+60	+69	+165	+34

balance (killed enemies minus killed friends) of deaths is used as a fitness value for the individual. Thus, the capacity of the individual to adapt to the environment is directly related to its performance in the battle simulation against the test case.

This approach resembles other work in the literature such as the work of Louis and colleagues, who employ an injection model of test cases and a GA (CIGAR - *Case-Injected Genetic Algorithm*) to generate artificial agents in games [Miles et al. 2004], [Louis and McDonnell 2004], [Louis and Miles 2005], [Louis 2005]. Despite the similarities, our work does not employ CIGAR for a number of reasons. First, test cases selected for fitness evaluation are taken from human experts, and cases generated by the GA are not injected into the database. Additionally, the main goal is not to find a solution capable of beating all test cases, but just the current opponent with maximum efficiency. There are other differences regarding the way solutions are represented in our work.

The initial population contains  $\mu = 100$  individuals, generated randomly according to a uniform distribution. Each chromosome is randomly initialized by suitable methods, considering the range of possible values for each chromosome. Individuals are selected for reproduction by means of a binary tournament. In a binary tournament, two individuals are randomly selected and their fitness values are compared, and that individual with the best fitness is selected for mating.

Each pair of selected individuals undergo crossover with recombination rate  $\rho_r = 0.9$ . Each chromosome is recombined separately using a random cutting point and uniform distribution. The cutting point divides the chromosomes in two parts. Recombination produces two offspring, formed by the permutation of the divided chromosomes of their parents. Special attention should be given to methods of recombination. It is possible that they generate invalid individuals in their process. This is due to the characteristics and constraints of the second and third chromosome. In the event of generating an invalid solution by crossover, a repair operator fix the individual.

After recombination, the offspring is subject to the mutation operators. We employ different mutation operators, suitable for each chromosome. The chromosome  $E$  suffers mutation with rate  $\rho_m^E = 0.005$ . Mutation operator ME randomly replaces one element in the chromosome by another equipment. Chromosome  $A$  has mutation rate  $\rho_m^A = 0.01$  and a mutation operator is applied randomly. Mutation MA1 performs a simple swap and Mutation MA2 adds a random perturbation to the value of one of the genes subtracting the same value from another gene in  $A$  such that the limit of 969 is not violated. The chromosome  $D$  has mutation rate  $\rho_m^D = 0.02$  with three mutation operators chosen randomly. Mutation MD1 is a simple swap; Mutation MD2 selects two divisions  $d_i \neq d_j$  and randomly allocate some points from  $d_i$  to  $d_j$  keeping the sum equal to 100; Mutation MD3 removes all points from a randomly chosen division and add it to the biggest division, concentrating soldiers into one division. The goal of this operator is to reduce the losses caused by the Dispersion from opponent Sagittarii.

There is also a refinement operator, called refinement by minimization of losses (RML), which through a local search on  $D$ , tries to reallocate the soldiers that are scattered into smaller divisions to the largest division. The idea of this operator is to maintain a minimum and enough amount of soldiers in a weak division. The strategy is to benefit the stronger division, removing it from the action focus of the opponent hero, since it is forced to take more actions on the

weaker divisions, which have fewer soldiers. The RML operator can not be confused with the operator MD3. MD3 makes a drastic change in  $D$ , accepting a merging of two divisions, without any fitness assessment in this merging, but RML performs, step by step, a basic change in  $D$ , accepting it only if it provides a better fitness. In other words, MD3 aims to generate diversity, while RML searches for a local optimum.

The combination of GAs with operators refinement of the solution through a local search, has often been referred in the literature [Hao 2011]. Among the advantages in using these techniques, stands out of the exploitation and exploration capacities of the algorithm, which gives good results [Moscatto 1989]. The RML operator acts on a portion of  $\psi = 0.01$  individuals in the population.

The offspring replace the current population, characterizing a generational GA. The algorithm stops after 500 generations or when there is no improvement in 100 generations.

## 4 Results

In order to test the proposed GA, a test case (TC) data base has been modeled, containing 5 different TCs. Each case consists in a static battle formation, against which each individual is evaluated using the battle simulator. Some TCs model disadvantageous scenarios, where the opponent was given extra bonus points. A disadvantageous TC is marked with an asterisk and tests the ability of the GA to find victorious solutions, even when they seem impossible. A TC\* receives extra 50% of UTP and a 30% bonus in the faculty of the hero. These bonus do not exist in the original game and were proposed just to test the algorithm.

Table 3 presents the 8 modeled TCs. The first column, Hastatus, presents the final values assigned to the unit Hastatus, considering the set of equipments used and applying the research and special items bonus. The column Sagittarius presents the final values assigned to the unit Sagittarius. The column Traits presents the values for the heros' traits considering the medals. Finally, the column Divisions presents the number of soldiers allocated to each division.

TC-I, TC-II, and TC\*-II maintain a balance between OFF and DEF, with the complete use of the set BR. TC-I, which is the most common formation among users of Call of Roma, maximizes SW in order to lead the highest number of units, more the 560 thousand soldiers, while keeping a balanced division between BR and PA. The majority of units are frontal units, concentrated in the right flank. The Hastati with high HP protect the Sagittarii. TC-II presents an equal distribution of UTP, leading less soldiers, about 397 thousand units, but with higher defensive and offensive performance. Units are more scattered, occupying all divisions, with higher concentration in the center. This is a common tactic in current NPC. TC\*-II is a bonus version of TC-II. The increase in SW and the bonus in the faculty allows a formation composed with about 730 thousand soldiers.

TC-III and TC\*-III aim at keeping units alive for more time, the combination of the helmet Hard Core and the set Fearlessness maximizes DEF and PA. TC\*-III has strong offensive and defensive, since BR is maximized. The resistance of the frontal units allows a high number of Sagittarii, exploiting the favorable effects of Dispersion.

TC-IV, TC-V and TC\*-V consist in highly offensive formations. TC-IV combines the set Hard Core and Saturn to maximize DMG.

**Table 3:** Test case data base.

TC	Hastatus			Sagittarius			Traits			Frontal Divisions			Rear Divisions		
	DMG	OFF	HP DEF	DMG	OFF	HP DEF	SW	BR	PA	$d_1$	$d_2$	$d_3$	$d_4$	$d_5$	$d_6$
TC-I	46 - 49	150	472 115	46 - 48	152	446 110	623	322	321	5634	5634	450780	5634	5634	90156
TC-II	46 - 49	150	472 115	46 - 48	152	446 110	422	422	422	39765	119295	39765	39765	119295	39765
TC*-II	46 - 49	150	472 115	46 - 48	152	446 110	623	623	623	84521	169042	84521	84521	225390	84521
TC-III	41 - 44	178	367 157	41 - 43	180	341 152	623	20	623	56347	84521	28173	225390	0	169042
TC*-III	41 - 44	178	367 157	41 - 43	180	341 152	623	623	623	56347	112695	56347	281737	0	225390
TC-IV	73 - 76	91	498 73	73 - 75	92	472 68	623	623	20	185946	191581	185946	0	0	0
TC-V	58 - 61	168	603 31	58 - 60	169	577 26	623	623	20	214120	22539	214120	0	0	112695
TC*-V	58 - 61	168	603 31	58 - 60	169	577 26	623	623	623	242294	50712	242294	0	0	197216

TC-IV maintains a solid frontal line, concentrating soldiers in frontal divisions. On the other hand, TC-V, which is considered by experienced players one of the best known formations, focuses on DMG and OFF. However, since this formation is weak in defense, selected equipments aim at increasing the HP of the units, to make them last longer in the battle. Frontal units are placed on the flanks, while rear units are concentrated into a single division. The strategic quality of TC-V is maintained in TC\*-V with bonus.

For each test case, the genetic algorithm was executed 30 times. The results are summarized in Table 4. The results show that the GA is able to find winning solutions, even when facing unfavorable conditions. All columns present the results obtained by the GA when fighting the corresponding TC. Table 5 presents the best hero found by the GA for each TC.

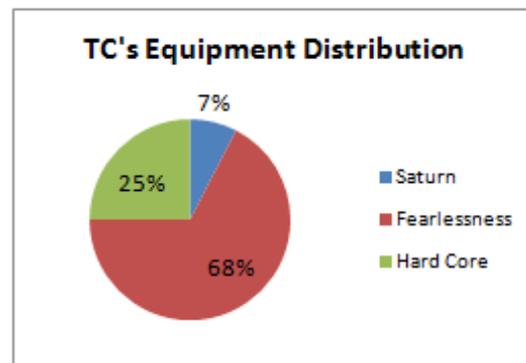
The results indicate that for normal TCs the proposed approach is indeed able to find triumphant solutions without much effort. For normal test cases, the hero found by the algorithm wins in all executions. The best and worst balances are close to the average showing a small variation for the results. This small deviation shows the robustness of the method. In most of the executions, the opponent TC was completely eliminated, and the casualties for the hero was about 2% of the total number of soldiers led. The only exception occurs for TC-V, since this case presents better strategic quality, making more difficult to the GA to find a winning solution. Nonetheless, the GA was still able to find a winning solution, through a good distribution of soldiers in each division. The best hero that beats TC-II presents a low balance but this is due to the low Sway of TC-II, which reduces the total number of soldiers led.

The results of the algorithm are so good that there is no need to test it against real players. It was necessary to add bonuses that don't exist in the game for the algorithm to lose a battle. Thus, testing against real players, which take into account only the factors available in the game, would not contribute significantly to this research. It is clear that the algorithm can find a winning solution, knowing the enemy hero. Despite the small number of test cases presented in this work, they were modeled to cover different kinds of strategies, as offensive and defensive formations, with concentrated and dispersed allocation of soldiers. It's valid to remember that the modeled test cases consist in the most common strategies used by the players of the game. Presumably, this means that the experiment with real players will not differ significantly from what presented here.

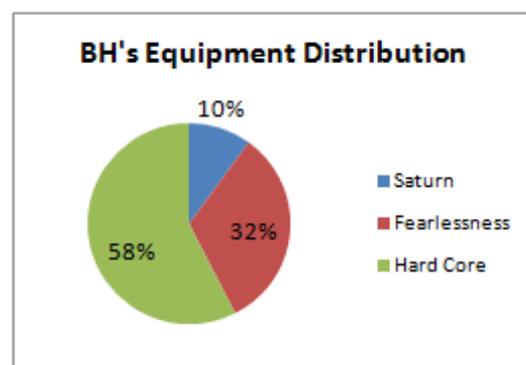
For the disadvantageous TCs, the GA obviously faces more challenges. TC\*-II and TC\*-III were defeated by the GA, however with considerable casualties. In 2 executions out of 30, the GA was not able to defeat TC\*-II but found a solution with positive balance. That means that, even losing all its 560 thousand soldiers, the hero found in such executions (worst case) was still able to kill more enemies, making the balance greater than zero. For TC\*-V, the algorithm was not able to find a victorious solution. Nevertheless, the performance of the solution against TC\*-V shows that the GA was still able to find a favorable solution in terms of balance, even though it loses the battle.

The figure 3(a) shows the equipment set distribution through all TC heroes, considering the five types of equipment that can be used by a single hero, as described in section 2. The Fearlessness equipments have 68% of participation in the equipment build, for the

modeled test cases. That occurs, because the TCs were modeled based in the players most common formations and the Fearlessness is the most accessible equipment set. Saturn set was available only for a short period of time, during the Saturn Festival Promotion and only a small minority of players acquired parts of this set. That is why the Saturn equipments are rare in Call of Roma and the best formation, modeled in TC-V, is not so common. The Hard Core set is the newest among the considered sets. Furthermore, it is a little more difficult to achieve. So, despite the high quality, the Hard Core set is not so common as Fearlessness set is. The figure 3(b) shows the equipment set distribution through all BHs found. While the Saturn set still having a low participation, now the Hard Core set is the most used, with 58% of participation. This does not mean the Hard Core set is better than Fearlessness set, but for the modeled TCs the Hard Core equipments were the best choice in 58% of times. A test base with different builds may result in a different set distribution through the best heroes found.



(a) TC's Equipment Distribution



(b) BH's Equipment Distribution

**Figure 3:** Distribution of equipment set through the modeled test cases and best heroes found.

BH-I and BH-II are offensive and defensive formations, that uses Hard Core Helmet and exploit PA and DEF as a way to reduce the opponent's damage. The disadvantages of those formations are the lower HP and DMG, but the perfect combination of the equipments and the hero traits can compensate that. BH-I presents a solid concentration of Hastati, avoiding losses caused by Dispersion. Rear divisions are wisely divided: central division employs Dispersion

**Table 4:** *Simulation Results*

Test Case	Victories	Defeats	Best balance	Average balance	Worst balance
TC-I	30	0	557522	556419 ± 588	555564
TC-II	30	0	393773	392271 ± 3209	376105
TC*-II	28	2	474941	347166 ± 111605	35157
TC-III	30	0	559578	556453 ± 2997	550411
TC*-III	30	0	555825	518787 ± 66169	276384
TC-IV	30	0	561722	560487 ± 1942	556138
TC-V	30	0	394428	225386 ± 100137	326032
TC*-V	0	30	38856	-32958 ± -904	-33123

**Table 5:** *Best hero found.*

Best Hero	Hastatus				Sagittarius				Traits			Frontal Divisions				Rear Divisions			
	DMG	OFF	HP	DEF	DMG	OFF	HP	DEF	SW	BR	PA	$d_1$	$d_2$	$d_3$	$d_4$	$d_5$	$d_6$		
BH-I	43	46	196	481	126	43	45	197	455	120	623	141	502	0	0	281737	0	61982	219755
BH-II	41	44	178	481	140	41	43	180	455	134	420	275	572	0	106920	0	0	289080	0
BH*-II	58	61	168	603	31	58	60	169	577	26	623	623	20	0	112695	11269	0	11269	428241
BH-III	43	46	196	481	126	43	45	197	455	120	326	588	352	0	28660	0	0	289789	0
BH*-III	53	56	196	498	73	53	55	197	472	68	618	623	25	44748	0	78309	0	408325	27967
BH-IV	63	66	91	481	126	63	65	92	455	120	623	138	505	185946	191581	185946	0	0	0
BH-V	78	81	63	603	31	78	80	64	577	26	623	133	510	11269	354989	11269	0	16904	169042
BH*-V	78	81	63	603	31	78	80	64	577	26	623	623	20	22539	0	518397	0	0	22539

to clean the battlefield, while  $d_6$  uses Distal Assault with 100% damage. Figure 4 illustrates the first round of the battle. Figure 4(a) presents the initial position of the heroes. Blue arrows in Figure 4(b) indicate Dispersion applied by division  $d_5$  to BH-I. The red crosses in Figure 4(c) indicate the divisions struck. In this moment, it is better for  $d_6$  to use a distal assault, eliminating division  $d_6$  of the opponent. Finally, 4(d) shows division  $d_3$  of BH-I hitting  $d_3$  of opponent in a frontal assault. This sequence of actions, found by the GA, represents a big advantage for BH-I in this round and subsequent rounds. For BH-II, the Hastati and Sagittarii are concentrated in the central division to avoid losses caused by Dispersion. They both can eliminate the enemy with casualties below 10 thousand soldiers.

BH\*-II and BH\*-III are purely offensive formations, which maximize OFF and BR to inflict the highest damage possible. BH\*-II also have high HP, making units to survive longer. Given that the troops of TC\*-II are scattered, BH\*-II finds the strategy of using a very high number of Sagittarii, exploiting Dispersion assaults. BH-III keeps very offensive, but gives up a high DMG, high HP and high SW to strengthen its defense. Thus, BH-III explores the overly defensive formation of CT-III and can inflict a high damage, while avoiding the enemy. BH-IV and BH-V exploit the low defense formations of the opponents by using the Hard Core sword, which increases DMG without a high OFF, cause it's not necessary. BH-V presents a very sophisticated strategy, probably obtained by the RML operator, trying to avoid the attacks from TC-V. It places small quantities of soldiers, that are capable to survive to opponent's Sagittarii, in front of the main divisions of TC-V. By this way, the main divisions of TC-V strikes the remaining soldiers of those weak divisions, killing that small quantities, but wasting the opportunity to kill a large number of soldiers.

BH\*-V, is not able to beat TC\*-V, although it achieves a positive balance of deaths. The quantity of soldiers in TC\*-V allied to its strategy quality make it a very strong opponent, apparently invincible. BH\*-V then maximizes its BR and exploits the low defense of TC\*-V. Due to the challenge imposed by TC\*-V, the algorithm is not able to find a winning formation. Nonetheless, the 560 thousand soldiers of BH\*-V eliminate about 598 thousand soldiers of TC\*-V. In some sense, such achievement can be considered a very satisfactory result. Let us reiterate that TC\*-V is a experimental hero that uses extra bonuses that don't exist in game. Those bonuses were given just to test the capacities of the GA.

To illustrate the method convergence, we take the evolution of BH-III and BH-V as example, as shown in figures 5(a) and 5(b). The evolutionary process of the other best heroes was similar to those ones. The figures shows the fitness of the best hero, the worst hero

and the average fitness of all population per generation. In both figures can be observed a fast evolution at the first generations and a large period of stable evolution and small improvements. The average fitness in the evolution of BH-III is closer to the best individual than BH-V's evolution, cause, as mentioned above, TC-V is considered by experienced players as the better battle formation of the game, so it imposes major difficulties to the method. The differences of balance between the cases TC-III and TC-V are shown in table 4. In some generations, the worst individual fitness in figure 5(a) is also close to the best individual, which may mean the occurrence of a takeover of the best individuals, but the method is able to generate diversity, escaping to this bad behavior and continue the evolution.

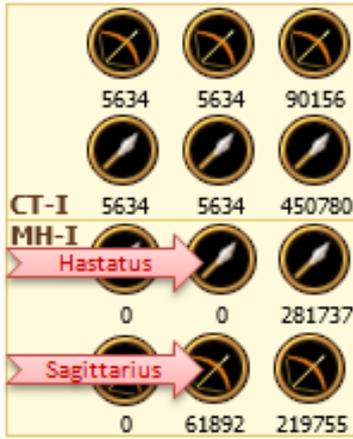
## 5 Conclusion and Future work

This paper presented an evolutionary approach for the automatic discovery of battle strategies for a MMORTS game. Currently, the NPC developed for these games present predefined and static strategies. This work follows the assumption that the development of computationally intelligent NPCs, that are able to adapt to human strategies, can contribute to making these games more attractive and challenging to human players. To illustrate the proposed approach, we considered the game Call of Roma, for which we developed a specific representation for the candidate solutions and suitable genetic operators. The GA is able to find a victorious and efficient solution for the most common formations in Call of Roma. In most cases, the algorithm finds a winning solution that minimizes casualties for the hero. Moreover, the GA was tested against unfavorable scenarios. Despite the disadvantages, the GA was able to keep a positive balance of deaths, finding at least a honorable defeat.

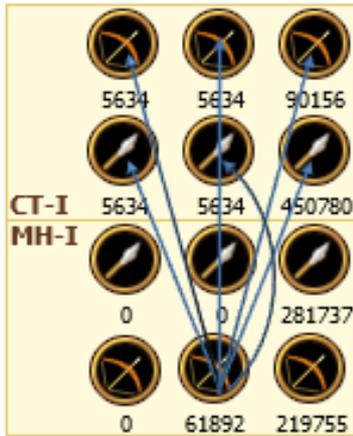
In this work the battles were simulated with only one hero against another hero. In the real MMORTS, teams of heroes can fight each other. Therefore, a cooperative coevolutionary approach would be an interesting topic for future work. Coevolution would allow the simultaneous evolution of multiple heroes in combat. Additionally, the population of the GA is evaluated using only one test case, which results in a very specific battle strategy. The application of multiple test cases, such as the approach adopted in CIGAR, would allow the generation of more general and robust strategies, able to beat not only one but a set of test cases.

## Acknowledgements

To Armageddon League, from server 9 of 337 César, for more than one year of server bloody domination!



(a) Start



(b) Dispersion

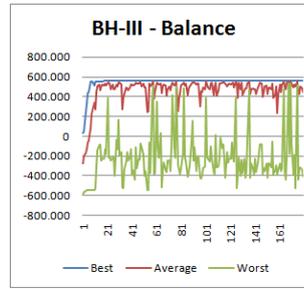


(c) Distal Assault

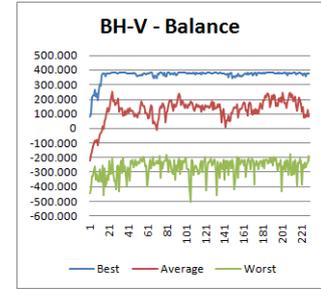


(d) Frontal Assault

Figure 4: BH-I vs. TC-I: Round 1 illustration.



(a) BH-III



(b) BH-V

Figure 5: BH-III and BH-V: the balance of deaths over generations.

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