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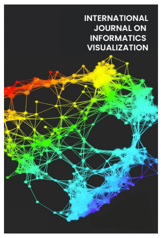

Genetic Algorithm for Artificial Neural Networks in Real-Time Strategy Games

Yudi Widhiyasana [a], Maisevli Harika [a,*], Fahmi Faturahman Nul Hakim [a], Fitri Diani [a], Kokoy Siti Komariah [b], Diena Rauda Ramdania [c]

[a] *Department of Computer and Informatics, Politeknik Negeri Bandung, West Java, Bandung, 40559, Indonesia*
[b] *Dept. of IT Convergence and Applications Engineering, Pukyong National University, 45 Yongso-ro, Nam-Gu, Busan, Republic of Korea*
[c] *Dept. of Informatics, UIN Sunan Gunung Djati, West Java, Bandung, 48513, Indonesia*

*Corresponding author: *widhiyasana@polban.ac.id*

Abstract— **Controlling each member of the soldiers to carry out battle with Non-Playable Characters (NPC) is one of the secrets to winning Real-Time Strategy games. The game could be more complicated and offer a more engaging experience if every NPC acts like humans rather than machines with patterned behavior. Like people during a war, each army member's command requires rapid reflexes and direction to strike or evade attacks. An intelligent opponent based on ANN as NPC can react quickly to their opponents. The accuracy of ANN could be enhanced by weight modifications using a Genetic Algorithm (GA). The crossover and mutation rates significantly impact GA's performance as an ANN setup. This research aims to find the best crossover and mutation rates in GA as a weight adjustment in ANN. Experiments were conducted using an RTS game simulator using 20 scenarios on a maximum of 4000 iterations. The initial setup of each troop is random, with a seven-unit type available. In this research, the troops won because their men were subjected to fewer attacks than the opposing forces. The GA optimal crossover and mutation rates are determined using troop victories as a baseline. According to the findings, the best crossover rate for GA as an ANN weight adjustment is 0.6, whereas the specific mutation rate is 0.09. The crossover rate of 0.6 has the highest average win value and tends to increase every generation. As for the mutation rate of 0.09, it has the highest average win value. Thus, this preliminary study can develop NPC more humanly.**

Keywords— **Artificial neural networks; game AI; human-like behavior; real-time strategy games.**

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I. Introduction

Many genres in video games include action-adventure, adventure, role-playing, strategy, and others [1], [2]. Each genre focuses on its playing style [1]. Like the strategy genre, it prioritizes careful planning from players to achieve victory. In strategy games, there are characters called Non-Playable Characters (NPC). NPCs can act as observers, allies, or enemies in the game. NPCs respond interactively to player interactions [1], [3].

Today, video games are becoming a popular subject, ranging from entertainment to improving understanding of learning[2], [4]. Much research has been done involving video games. One of the popular genres related to Artificial Intelligence (AI) is the Real-Time Strategies (RTS) genre [5]–[7]. Players of this RTS game need to collect resources, build infrastructure, train military units, upgrade technology, declare war, and defeat enemies [8]. So, in general, decision-making in RTS games is categorized into two. Macro-management (MaM) and micromanagement (MiM)[9].

Macro management is decision-making for long-term planning, such as: building military barracks, conducting technological research, training military units, and others. Micromanagement can plan small units in battle or small units to minimize unit losses and maximize damage to opponents [9], [10]. Small units are NPCs. NPCs with human-like decision-making habits could improve the gaming experience [11], [12]. Making NPCs with human-like decision-making abilities can use AI [13], [14]. One of them uses the Artificial Neural Network (ANN) method.

ANN is a mathematical method that tries to simulate the structure and function of biological neural networks in the human brain [15]. The basic form of ANN is an artificial network with simple mathematical operations. The ANN inputs and outputs are weighted[15]. Weight set is a significant problem in the use of ANN. Algorithms such as backpropagation, genetic algorithms, and others are a choice of solutions[16].

A Genetic Algorithm is a widespread evolutionary algorithm. The ability to obtain the best generation due to crossover, mutation, and selection determines the performance of GA. Some previous studies have used this algorithm for several purposes. An example: academic scheduling [17], sentiment review analysis of fashion online companies [18], microgrid energy management [19], children activities model [20], operational planning of cement mills loading [21], corporal Portal Search Engines [22], the optimal combination of forest fire [23], heart sound segmentation [24], detection of urban areas [25], short-term solar power forecasting [26], breast cancer [27], mobile robot path [28], Bone Cancer Survivability Prognosis [29], Space-Based Telescopes [30], et cetera. This study aims to adjust the weight on the ANN using a genetic algorithm (GA) to determine the best crossover rate and mutation rate values for troops in RTS games. This study could show the best crossover rate and mutation rate for GA to weigh ANN against troop wins in RTS games.

II. Material and Method

The stages of research carried out in this study started from identifying the problem and research objectives, then conducting a literature study, collecting data used as input, conducting system design, system testing, analyzing results, and finally drawing conclusions. This section discusses related to research rather than the stages of research. The research steps are more or less the same as research in general. They started by identifying the problem and research objectives. Then do a literature study, develop a simulator to simulate an RTS game, test the simulator, conduct experiments, and conclude the investigation.

A. Research Analysis

The input layer of the ANN is information related to the environment and unit information, while the output layer controls the unit. This research uses one hidden layer with 18 neurons. We utilize the sigmoid function as an activation function to get a result between zero and one.

Gene is a weighted ANN with 56 chromosomes for one fitness function. The battle between two armies is a fitness function and has seven different units, or each type consists of four teams. The initial formation of the troops is randomly chosen. The battle could last as long as all units can move and start Returning to the initial appearance if all teams are not moving.

After getting the fitness value of each chromosome at the fitness function stage, a selection is made. The selection method used is Tournament selection (TOS). The principle of TOS is first to select several k in all individuals and then find the most significant fitness value. The crossover method in this study uses a one-point crossover.

B. Experiment Unit

In the RTS game, each unit has four parameters: health, attack damage, fire damage, and delay. Health is the unit's health value with a minimum value of one, and damage is the unit attack value that can reduce the health value of the enemy. This study has two categories: damage for melee attacks and fire or long-range attacks and delays. Delays is a unit's movement to move forward or attack the enemy. This parameter has a fairness of 10. Fairness data on each unit can be seen in Table I.

TABLE I
FAIRNESS DETAILS FOR EACH UNIT

Type	Unit	Attack	Fire	Delay	Health	Total
1	Swordman	2	1	5	2	10
2	Archer	2	4	3	1	10
3	Spearman	3	3	3	1	10
4	Axeman	3	1	4	2	10
5	Heavy	3	1	3	3	10
6	Very Heavy	4	1	1	4	10
7	Cavalry	2	1	6	1	10

The experimental unit is a simulation of the RTS game that GA has set as the ANN weight setting for the troop control unit. The simulation accepts input in crossover rate and mutation rate values, and the output is the ANN model after weight adjustment. This model could be the input to determine the best crossover and battle mutation rates. The battle output is the winning percentage for each crossover rate and mutation rate used in the learning stage.

C. Experimental Scenario

The experiment in this study has two scenarios, learning and measuring the win rate of learning—experiments on learning change the crossover rate and mutation rate values. This study's maximum number of generations is 4000 [31]. ANN model with each weight after learning is the result. The crossover rate uses 0.6 to 0.9 based on the research results of Soon et al. [32].

The second scenario measures the win rate from the first scenario. It aims to find out the win rate for each weight. Both designs have conducted a battle between two armies with unit weights according to the results of the learning scenario. The flow of the simulation game in this experiment is divided into several processes.

1) GA Process Flow: GA process flow is a process flow that describes the process of GA after it is implemented with ANN, ground manager, and units. Fig. 1 is an illustration of the GA process flow. In Fig. 1, the GA process flow. Initial weight is the initial weight initiation of the GA process. The ground manager sets respawn units, stores fitness values, and calculates the number of wins. Selection weight is the stage of choosing the weight to be the parent, selection repeatedly until getting a parent with half the population.

2) ANN Process Flow is the ANN process flow after implementing GA. The flow is shown in Fig. 2. The first step is to set the weight to assign weights from the comma-separated values (CSV) file to the ANN model. Weight is a single-line CSV file. Furthermore, ANN running receives input. Save output saves ANN output on a variable that can be used for further processing.

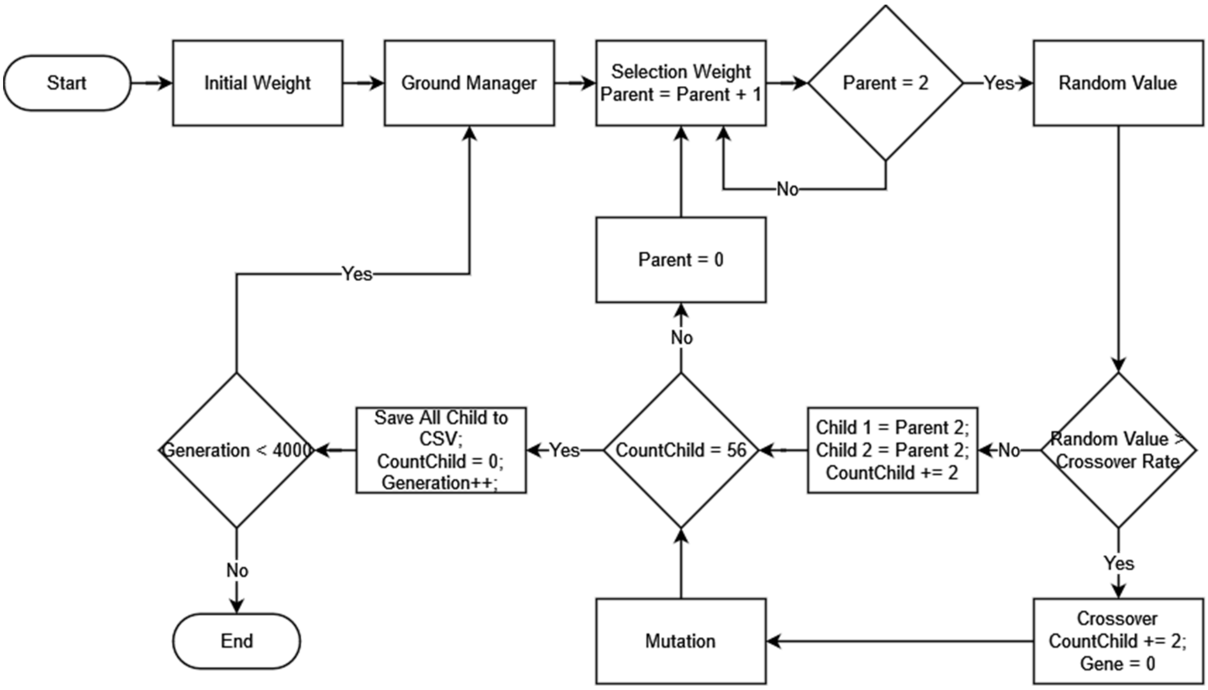

Fig. 1 GA Process flow in the experiment

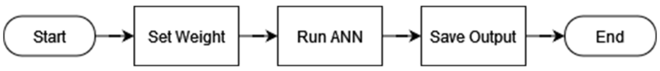

Fig. 2 ANN process flow in the experiment

ANN input in the form of neurons connected to the hidden layer. The two input neurons are information about the unit's environment and the unit itself. The large-scale environment of the unit is depicted as a four-region overall battle environment, as shown in Fig. 3a, while the small-scale environment of the unit is depicted in eight grids, as shown in Fig. 3b.

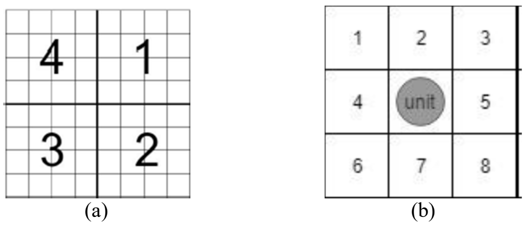

Fig. 3 Large-scale environment (a) and small-scale environment (b)

Each region in a large-scale environment could record information in the form of:

- The average distance of opponents in each region,
- The average friend distance in each region,
- Number of opponents in each region, and
- The number of friends in each region.

The small-scale environment could record information in the form of whether or not friends or foes are present on each grid, including unit information itself, such as:

- Current health,
- Delay value,
- Attack value,
- Fire value, and
- Previous outputs.

All input neurons can be seen in Table II.

TABLE II
INPUT NEURON

Id input	Information
1	*Region one Enemy Average Distance*
2	*Region two Enemy Average Distance*
3	*Region three Enemy Average Distance*
4	*Region four Enemy Average Distance*
5	*Region one Friend Average Distance*
6	*Region two Friend Average Distance*
7	*Region three Friend Average Distance*
8	*Region four Friend Average Distance*
9	*Region one Number of Enemy*
10	*Region two Number of Enemy*
11	*Region three Number of Enemy*
12	*Region four Number of Enemy*
13	*Region one Number of Friend*
14	*Region two Number of Friend*
15	*Region three Number of Friend*
16	*Region four Number of Friend*
17	*Self-Current Health*
18	*Self-Delay*
19	*Self-Attack*
20	*Self-Fire*
21	*Prev (Attack/Fire/Move)*
22	*Enemy at Grid one*
23	*Enemy at Grid two*
24	*Enemy at Grid three*
25	*Enemy at Grid four*
26	*Enemy at Grid five*
27	*Enemy at Grid six*
28	*Enemy at Grid seven*
29	*Enemy at Grid eight*
30	*Friend at Grid one*
31	*Friend at Grid two*
32	*Friend at Grid three*
33	*Friend at Grid four*
34	*Friend at Grid five*
35	*Friend at Grid six*
36	*Friend at Grid seven*
37	*Friend at Grid eight*

The results of the output neurons must be able to contain the values of output 1 (attack) and output 3 (fire). Output 2 has the value of the movement with the illustration of Fig. 4.

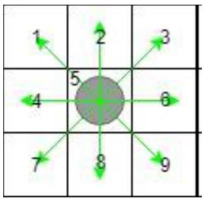

Fig. 4 Movement representation on output neurons

The condition of the unit that could attack, fire, or move can be seen in Table III.

TABLE III
REPRESENTATION OUTPUT NEURON

Output 1 (*Fire*)	**Output 3 (*Attack*)**	**Information**
Value 0 to 0.5	Value 0 to 0.5	Units move
Value 0 to 0.5	Value 0.5 to 1	Unit *attack*
Value 0.5 to 1	Value 0 to 0.5	Unit *fire*
Value 0.5 to 1	Value 0.5 to 1	Unit does not act

A unit could attack if output 1 is between 0.5 and one and output three is zero to 0.5. Likewise, the team could fire if output 1 is between zero and 0.5 and output three is between 0.5 and one. Meanwhile, the team could move if outputs 1 and 3 are between zero and 0.5. The unit may not act if output one and output 3 are between 0.5 and one. A unit could attack, fire, or move to the north or grid number two in Table IV if output 2 is between 0.11 to 0.22, as in Table IX, row two. So, a unit could fire to the east or grid number six in Table III if output 1 is between zero and 0.5, output 3 is between 0.5 to one, and output 2 is between 0.55 to 0.66.

TABLE IV
OUTPUT VALUE AS A GRID NUMBER

Output 2 (Coordinate)	**Grid Number**
Value 0 to 0,11	1
Value 0.11 to 0.22	2
Value 0.22 to 0.33	3
Value 0.33 to 0.44	4
Value 0.44 to 0.55	5
Value 0.55 to 0.66	6
Value 0.66 to 0.77	7

3) *Ground Manager Process Flow*: The ground manager is the function of controlling the entire existing unit, and f is the ground manager process flow.

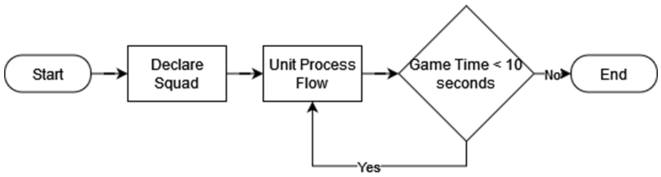

Fig. 5 Ground manager process flow in experiments

The declared squad stage is the process of respawning units on the ground. Unit positions are determined randomly according to each team and followed by unit process flow.

4) *Unit Process Flow*: Unit process flow helps manage units. Fig. 6 shows the process flow. Read environment process to see environmental conditions for ANN input. The Do output stage is a unit process running ANN output and finally calculating the fitness value.

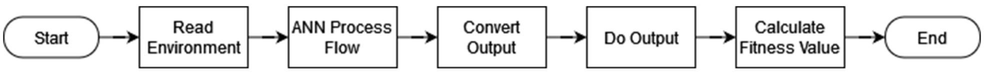

Fig. 6 Unit process flow in the experiment

D. Battle Analysis

The battle between two teams lasts for 10 seconds, and each unit uses its attributes. For example, unit type 1 could run ANN every 0.2 seconds. Unit type 2 could run ANN every 0.4 seconds, and so on. The unit ability is shown in Table V according to the points of each unit in Table I.

TABLE V
ABILITY THE UNIT AND ANN PROCESSING TIME

Unit Type	**Unit Name**	**Damage Attack**		**Damage Fire**		**Delay**		**Health**	
		Point	**Real**	**Point**	**Real**	**Point**	**Real (s)**	**Point**	**Real**
1	*Swordman*	2	20	1	10	5	0,2	2	100
2	*Archer*	2	20	4	40	3	0,4	1	50
3	*Spearman*	3	30	3	30	3	0,4	1	50
4	*Axe man*	3	30	1	10	4	0,3	2	100
5	*Heavy*	3	30	1	10	3	0,4	3	150
6	*Very Heavy*	4	40	1	10	1	0,6	4	200
7	*Cavalry*	2	20	1	10	6	0,1	1	50

Issues could have a real value using the equation, multiplied by ten for each case for the damage parameter and 50 for each point for the health parameter. Meanwhile, the delay parameter uses the formula $(5-point)/10$. The unit could not perform ANN or die until health is zero. Unit health can be reduced if the unit receives an attack from the enemy unit.

The battle is a fitness function from GA to get a fitness score, where the higher the fitness score, the better the unit. The fitness function is recorded for every unit's movement, as shown in Table VI. Each fitness score could be totaled after the battle takes place. The lowest possible value for each unit is -2050. The lowest value could occur if unit type 7 attacks on space until the end of the battle and is hit by attacks from enemy units until health is zero. In comparison, the highest possible value is 2000. The highest value could occur if unit type 7 attacks the enemy unit during the battle.

TABLE VI
REWARDS AND PUNISHMENT FOR EACH UNIT

Fitness Function	**Fitness Score**	**Reward Code**
Move Success	0,1/move	RC1
Damage Taken	-1/damage	RC2

Fitness Function	Fitness Score	Reward Code
Damage Given Enemy	1/damage	RC3
Attack	1/damage	RC3.1
Fire	1/damage	RC3.2
Crash with Wall	-0,1/crash	RC4
Damage Given Friend	-1/damage	RC5
Attack	-1/damage	RC5.1
Fire	-1/damage	RC5.2
Crash with Friend or Enemy	-0,1/crash	RC6
Damage to Nothing or Self	-1/damage	RC7
Nothing	-1/damage	RC7.1
Self	-1/damage	RC7.2
Attack and Fire (both)	-1	RC8

E. GA Analysis as ANN Weight Setting

The ANN structure consists of the input layer, hidden layer, and output layer. The input layer consists of 37 neurons, where each neuron is represented in Table II. The hidden layer consists of 18 neurons, and the output layer consists of 3 neurons. The number of weights on the ANN is 720, consisting of 666 weights connecting id input 1 to input id 37 to hidden neurons 1 18, and 54 weights connecting hidden neurons 1 to hidden neurons 18 to output 1 to output 3. Each weight has an id starting from 1 connecting id input 1 to hidden neuron 1 to 720 connecting hidden neuron 18 to output 3. Visualization explanation Fig. 7.

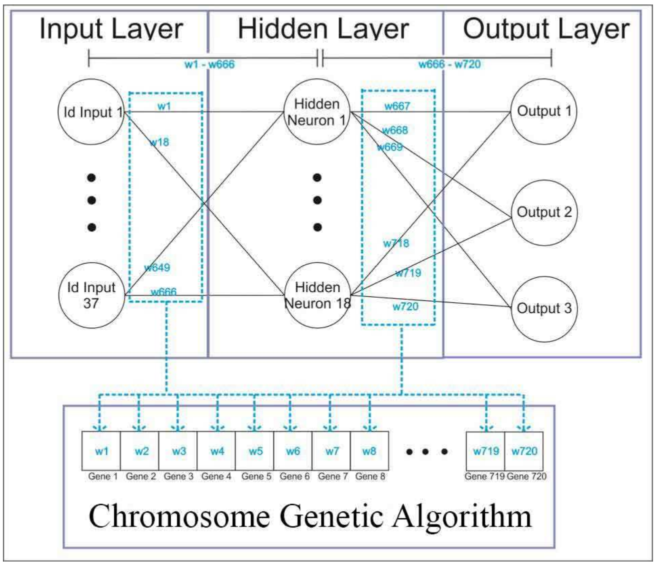

Fig. 7 ANN structure and its mapping to GA

The GA chromosome is a set of 720 ANN weights. The GA chromosome consists of 720 genes which represent 720 ANN weights. Gene 1 on the GA chromosome is 1 in ANN, gene 2 is w2 on ANN, and so on until gene 720 is 720 in ANN. The number of chromosomes used in this study is 56 chromosomes. Chromosome 1 could use ANN belonging to id unit 1, chromosome 2 use ANN belonging to id unit 2, and so on until chromosome 56 for id unit 56 representation can be seen in Fig. 8.

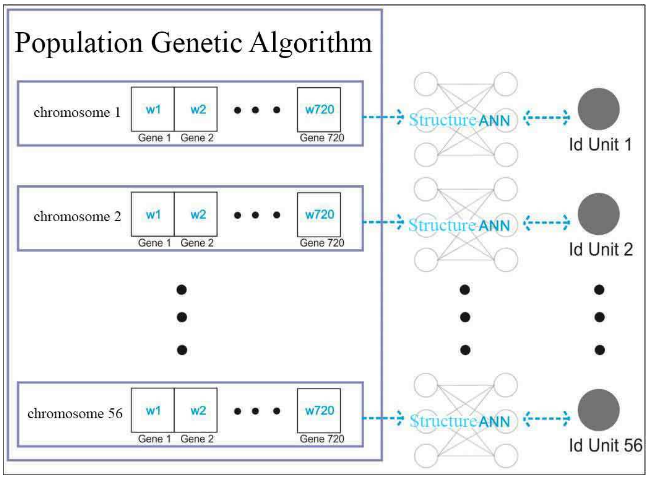

Fig. 8 Representation of chromosomes to units

Each unit could be divided into two teams, as shown in Fig. 9, team A and team B. Unit id 1 to unit id 28 is team A, and unit id 29 to unit id 56 is team B.

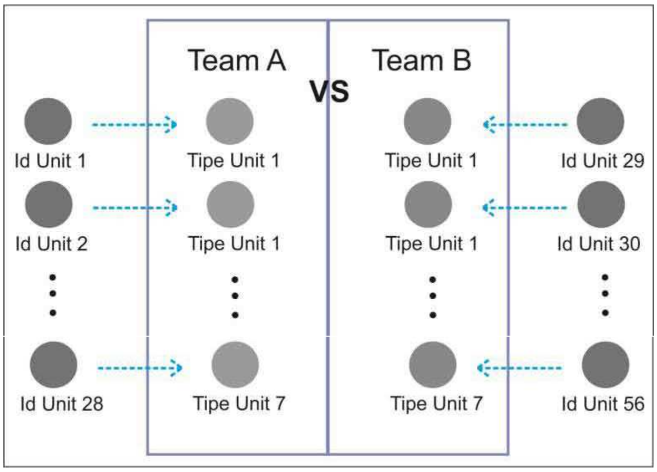

Fig. 9 Representation of unit id to unit type

III. Result and Discussion

Before the experiment is carried out, developing a simulator using the C# programming language with the Unity Game Engine library is necessary. The simulator has been tested with test cases, as shown in Table VII.

TABLE VII
FUNCTIONAL REQUIREMENTS OF THE SIMULATOR

Req.ID	Requirements	Status
REQ.1	The simulator can accept input crossover rate, mutation rate, and total generation during the learning stage	Success
REQ.2	The simulator records the weight value of each population and generation into a .csv file inside a folder chosen at the learning stage	Success
REQ.3	The simulator displays information on the most significant fitness value in that generation and the total of the generations that have been carried out in the learning stage	Success
REQ.4	The simulator is capable of receiving input folder locations of each battle scenario and the total battles of each scenario at the measurement stage	Success
REQ.5	Simulator capable of measuring win rate, displaying and saving to .csv file	Success

The simulator display during the learning scenario can be seen in Fig. 10 and the win rate in Fig. 11.

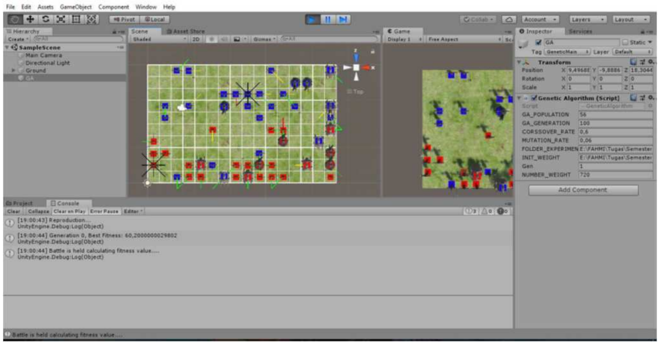

Fig. 10 Experiment simulator view when doing learning scenario

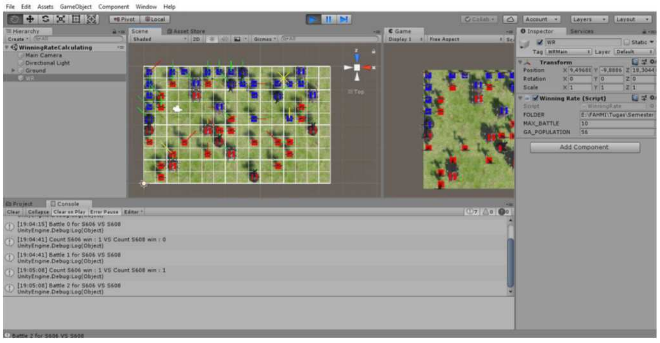

Fig. 11 The simulator display when carrying out the number of wins scenarios

After getting the number of wins in each scenario. The team's win percentage is added to each scenario code, and the winning generation is divided into the total battle. Table VIII shows the experimental results measuring the win rate for each scenario code.

TABLE VIII
WIN RATE EXPERIMENT RESULTS

Scenario Code	Generation			
	1000	2000	3000	4000
S606	45%	65%	42%	72%
S607	35%	63%	48%	39%
S608	47%	55%	41%	63%
S609	47%	45%	54%	57%
S610	47%	49%	46%	46%
S706	63%	29%	42%	41%
S707	53%	39%	45%	43%
S708	54%	35%	47%	47%
S709	45%	69%	58%	53%
S710	39%	57%	64%	51%
S806	42%	45%	41%	44%
S807	45%	51%	39%	43%
S808	56%	42%	61%	50%
S809	63%	59%	59%	47%
S810	48%	43%	44%	47%
S906	42%	27%	42%	37%
S907	37%	40%	54%	42%
S908	43%	60%	39%	36%
S909	57%	46%	48%	33%
S910	38%	34%	42%	57%

F. Experiment with Each Crossover rate

The average wins for the crossover rates generation are 1000, 2000, 3000, and 4000 (Table IX). The initial assumption of a crossover rate is 0.8, and 0.9 cannot give a better average win than 0.6 and 0.7. A crossover rate of 0.6 showed the best performance in Generation 2000 and 4000, while 0.7 in Generation 1000 and 3000. A crossover rate of 0.8 showed the best performance in Generation 1000, but the value was slightly different from 0.7. The best performance is 0.9 on the Generation 3000 Force, but the overall percentage is still under 47.5%.

TABLE IX
THE AVERAGE WINS FOR THE CROSSOVER RATES

Crossover Rate	Generation				Average
	1000	2000	3000	4000	
0.6	44.4%	55.3%	46.1%	55.4%	50.3%
0.7	50.8%	45.9%	51.2%	46.8%	48.7%
0.8	50.6%	48.1%	48.9%	46.4%	48.5%
0.9	43.5%	41.2%	45.1%	41.1%	42.7%

G. Experiment for Each Mutation Rate

Table X shows the average win rate for each mutation rate in the generation 1000, 2000, 3000, and 4000. In Table X, the mutation rate of 0.09 shows the best performance in the generation 1000, 2000, and 3000, while the generation 4000 mutation rate of 0.1 is better. Mutation rates of 0.06 and 0.07 gave the best performance of 48%, which is the average value of the overall mutation rate. The mutation rate of 0.1 shows an increase in each generation of generations, from 1000, worth 43%, to the generation of 4000, worth 50%. The 0.09 mutation rate shows its best performance in each generation, except for 4000 (shown in Table X, line four with a value of 47,7%). However, it is still, on average, the overall mutation rate.

TABLE X
THE AVERAGE WINS FOR THE MUTATION RATES

Mutation Rate	Generation				Average
	1000	2000	3000	4000	
0.06	48.0%	41.4%	41.8%	48.2%	44.9%
0.07	42.6%	48.2%	46.4%	41.7%	44.7%
0.08	49.9%	48.0%	47.2%	49.2%	48.6%
0.09	53.1%	54.7%	54.7%	47.7%	52.5%
0.1	43.2%	45.8%	48.9%	50.3%	47.0%

H. Experiment for Each Crossover Rate and Mutation Rate

Table XI shows the win rate for each scenario code carried out. The highest victory rate for generation 1000 is scenario code S706 or crossover rate 0.7 and mutation 0.06 with a value of 62.9 %, which is 0.3 % more than scenario code S809 with a value of 62.6 %. The "generation 2000" scenario code S709 has the highest win rate with a win percentage of 69.5 %. Next, with 63.9 %, "generation 3000" scenario code S710 has the highest victory rate, and "generation 4000" scenario code S606 has the best win rate with 71.6 %. Overall, with a value of 56.9%, the S809 scenario code delivers the best average for each generation, a difference of 0.5 % from the second place, namely the S709 scenario.

TABLE XI
THE AVERAGE WINS FOR THE CROSSOVER RATES AND MUTATION RATE

Scenario Code	Generation				Average
	1000	2000	3000	4000	
S606	45.0%	65.3%	41.8%	71.6%	55.9%
S607	35.3%	62.6%	47.9%	38.9%	46.2%
S608	47.4%	55.0%	41.3%	63.4%	51.8%
S609	47.4%	45.0%	53.9%	56.8%	50.8%

Scenario Code	Generation				Average
	1000	2000	3000	4000	
S610	47.1%	48.7%	45.5%	46.1%	46.8%
S706	62.9%	28.9%	42.4%	40.8%	43.8%
S707	52.6%	39.2%	44.7%	42.6%	44.8%
S708	54.2%	34.7%	47.1%	46.8%	45.7%
S709	45.3%	69.5%	57.6%	53.4%	56.4%
S710	39.2%	57.1%	63.9%	50.5%	52.7%
S806	41.8%	44.7%	40.5%	43.7%	42.7%
S807	45.0%	51.3%	39.2%	43.2%	44.7%
S808	55.5%	42.1%	61.3%	50.3%	52.3%
S809	62.6%	58.7%	58.9%	47.4%	56.9%
S810	48.2%	43.4%	44.5%	47.4%	45.9%
S906	42.1%	26.8%	42.4%	36.8%	37.0%
S907	37.4%	39.7%	53.9%	42.1%	43.3%
S908	42.6%	60.0%	38.9%	36.3%	44.5%
S909	57.1%	45.5%	48.4%	33.2%	46.1%
S910	38.4%	33.9%	41.6%	57.1%	42.8%

IV. Conclusion

Micromanagement in RTS games significantly affects the victory of the game. Reasonable reaction control on NPCs could make the RTS experience more challenging. Using GA as ANN weight adjustment proves that NPCs can learn well. The correct crossover rate for this study is 0.6 because it has the highest average win value and tends to increase every generation. Meanwhile, the exact mutation rate in this study is 0.09 because it has the highest average win value. After the correct crossover rate and mutation rate, this research can be continued to other cases or add more input to ANN, such as dangerousness and attack range parameter for long-range attack type units.

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