# HYBRIDIZATION OF MULTIOBJECTIVE EVOLUTIONARY ALGORITHM WITH COEVOLUTION FOR ENEMY TEAM IN MS. PAC-MAN GAME

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**Abstrak**

Kini, semakin ramai penyelidik telah menunjukkan minat mengkaji permainan Kecerdasan Buatan (KB). Permainan seumpama ini menyediakan tapak uji yang sangat berguna dan baik untuk mengkaji asas dan teknik-teknik KB. Teknik KB, seperti pembelajaran, pencarian dan perencanaan digunakan untuk menghasilkan agen maya yang mampu berfikir dan bertindak sewajarnya dalam persekitaran permainan yang kompleks dan dinamik. Dalam kajian ini, satu set pengawal permainan autonomi untuk pasukan hantu dalam permainan Ms. Pac-man yang dicipta dengan menggunakan penghibridan Evolusi Pengoptimuman Multiobjektif (EPM) dan ko-evolusi persaingan untuk menyelesaikan masalah pengoptimuman dua objektif iaitu meminimumkan mata dalam permainan dan bilangan neuron tersembunyi di dalam rangkaian neural buatan secara serentak. Arkib Pareto Evolusi Strategi (APES) digunakan, teknik pengoptimuman multiobjektif ini telah dibuktikan secara saintifik antara yang efektif di dalam pelbagai aplikasi. Secara keseluruhannya, keputusan eksperimen menunjukkan bahawa teknik pengoptimuman multiobjektif boleh mendapat manfaat daripada aplikasi ko-evolusi persaingan.

**Kata Kunci:** Rangkaian neural buatan, Ko-evolusi persaingan, Permainan kecerdasan buatan, Permainan Ms. Pac-man, Algoritma evolusi multiobjektif

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***Abstract***

*Recently, researchers have shown an increased interest in game Artificial Intelligence (AI). Games provide a very useful and excellent testbed for fundamental AI research. The AI techniques, such as learning, searching and planning are applied to generate the virtual creatures that are able to think and act appropriately in the complex and dynamic game environments. In this study, a set of autonomous game controllers for the ghost team in the Ms. Pac-man game are created by using the hybridization of Evolutionary Multiobjective Optimization (EMO) and competitive coevolution to solve the bi-objective optimization problem of minimizing the game's score by eating Ms. Pac-man agent and the number of hidden neurons in neural network simultaneously. The Pareto Archived Evolution Strategy (PAES) is used that has been proved to be an effective and efficient multiobjective optimization technique in various applications. Overall, the results show that multiobjective optimizer can benefit from the application of competitive coevolutionary.*

***Keywords:*** *Artificial neural network, Competitive coevolution, Game artificial intelligence, Ms. Pac-man game, Multiobjective evolutionary algorithm*

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## 1.0 Introduction

The hypothesis of this paper is that the competitive coevolution Multiobjective Evolutionary Algorithm (MOEA) (Deb, 2001) performs better than MOEA alone for evolving the enemy team of ghosts in the Ms. Pac-man game. Hence, the objective of this paper is to investigate the coevolutionary architectures (de Jong & Pollack, 2004) for designing the ghost team to demonstrate the generality of the developed artificial intelligence system, and then to assess its performance against MOEA. The overview of the paper is illustrated in Figure 1. There are two game controllers proposed: Pareto Archived Evolution Strategy Neural Network (PAESNet) and PAESNet with K Random Opponents (PAESNet_KRO). Additionally, two experiments are conducted to evaluate the performance of these two proposed controllers. In the first experiment, different numbers of random opponents, K are tested to find the best value of K for the PAESNet_KRO. On the other hand, in the second experiment, the best PAESNet_KRO model is benchmarked against the standard PAESNet.

The organization of this paper is as follows. Section 2 presents the methodology involved in the study. Next, in Section 3 gives the explanation on experimental results and discussions of the proposed controllers. Finally, the conclusions are shown in Section 4.

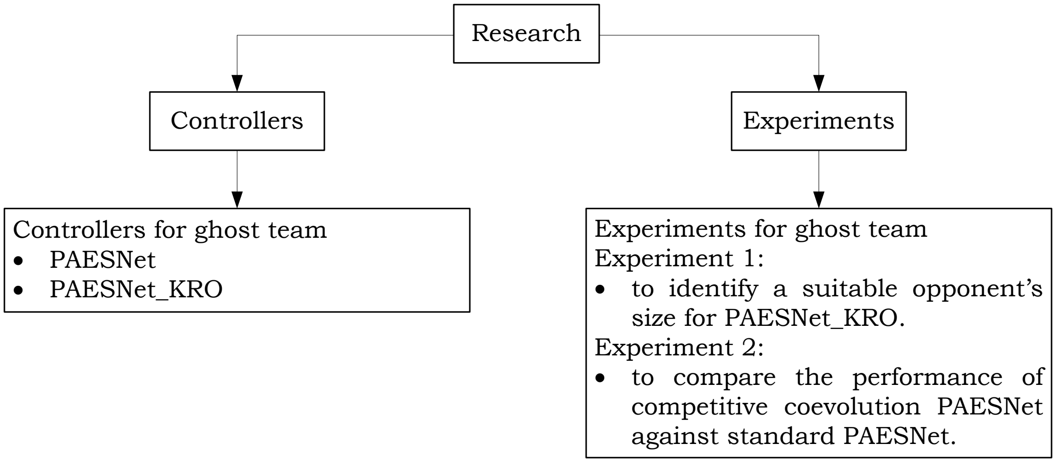


**Figure 1: The overview of the research**

## 2.0 Methods

This section is divided into three subsections to present and describe the PAES, the PAESNet and the PAESNet_KRO.

### 2.1 Pareto archived evolution strategy

Pareto Archived Evolution Strategy or PAES, first introduced by Knowles and Corne (1999), is one of the simplest yet effective MOEAs. The mutation operator plays a major role in this algorithm by altering the genes in each chromosome in the population, such as Cauchy mutation, Gaussian mutation and so on. Additionally, PAES implements the elitism approach by preserving the best individuals from every generation, and an archive stores all the nondominated solutions along the Pareto front. A crowding method which works by recursively breaking down the objective space into d-dimensional grids is also introduced for diversity maintenance of the nondominated solutions in the archive. There are three different basic forms of PAES: (1+1)-PAES, (1+λ)-PAES and (μ+λ)-PAES (Knowles & Corne, 2000). The (1+1)-PAES generates a single offspring from a single parent through a mutation mechanism, and the offspring will then compete with the parent for survival. In the (1+λ)-PAES, a set of λ offspring is created from a single parent and the fittest individual is chosen among the λ offspring and the parent. In the (μ+λ)-PAES, a set of λ offspring is generated from μ parents. The next generation consists of the μ best individuals selected from the union of μ parents and λ offspring. Overall, the (1+1)-PAES is becoming more popular as compared to other forms because of its simplicity, which has also been applied to serve as a baseline algorithm for handling multiobjective optimization problems.

### 2.2 Pareto archived evolution strategy neural network

Pareto Archived Evolution Strategy Neural Network or PAESNet is discussed. In this proposed system, two objectives are involved. The first objective, F1 is to minimize the game scores of Ms. Pac-man agent as shown in Equation 1 whereas the second objective F2 is to minimize the number of hidden neurons in the feed-forward Artificial Neural Network (ANN) as shown in Equation 2. The initial value of hidden neurons is set to 20. At the start of the initialization phase, the ANN weights, biases and active hidden neurons in hidden layer are encoded into a chromosome from uniform distribution with range [-1, 1] to act as parent and its fitness is evaluated. Subsequently, polynomial mutation operator is used with distribution index = 20.0 to create an offspring from the parent and its fitness is evaluated. After that, the fitness of the offspring and parent are compared. If the offspring performs better than the parent, then the parent is replaced by the offspring as a new parent for the next evaluation. Otherwise the offspring is eliminated and a new mutated offspring is generated. If the parent and the offspring are incomparable, the offspring is compared with set of previously nondominated individuals in the archive.

The proposed algorithms are run 10 times with 5000 evaluations in each. Figure 2 shows the flowchart of PAESNet.

$$(1)\quad F_1 = \sum_{n=1}^{N} (\text{Ms. Pac - man scores})$$

$$(2)\quad F_2 = \sum_{i=1}^{M} h_i$$

where n and N represent the number of lives in a full game, M and hi represent the number of hidden neurons in the feed-forward ANN.

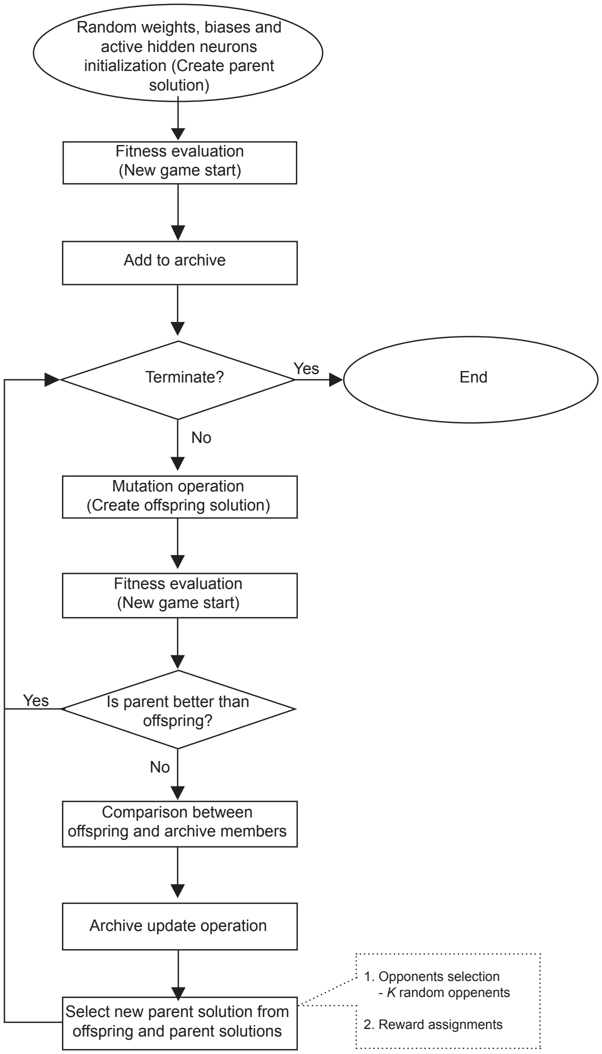


**Figure 2. The flowchart of PAESNet/PAESNet_KRO**

## 2.3 Pareto archived evolution strategy neural network with K random opponents

In this subsection, one proposed competitive coevolution PAESNet: Pareto Archived Evolution Strategy Neural Network with K Random Opponents (PAESNet_KRO) is presented for creating the Ms. Pac-man ghost team to solve two objective optimization problems. Basically, the framework of the PAESNet_KRO model is similar to the PAESNet as shown in Figure 2. The main differences of PAESNet_KRO in comparison to PAESNet are the two additional methods for parent selection process, opponent selection and reward assignment. The opponent selection method will select individuals as the opponents based on the K Random Opponents strategy (KRO) (Panait & Luke, 2002). The fitness of each individual is measured against K number of random opponents without self-play as shown in Figure 3. With this strategy, this method will randomly select opponents from the archive. The K is tested with the values of 2, 4, 6, 8 and 10 in this study. After the opponent selection process, each individual will compete against the entire set of opponents. During the tournament, the reward value will be calculated for each competition by the reward function as shown in Equation 3. Each reward value will be summed up as the fitness score for the individual using the reward assignment method. The individual with highest fitness score is selected as the next parent and the iteration continues. The predefined maximum number of evaluations serves as the termination criterion of the loop. In this study, the number of runs is set to 10 and each run is tested 5000 evaluations consecutively.

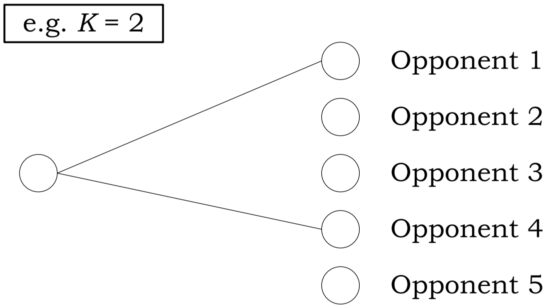


**Figure 3. KRO strategy**

The description of the reward function is as Equation 3. I represents the participating individual, while O represents the opponent. R is the raw fitness value, max(R) is the maximum raw fitness value and the min(R) is the minimum raw fitness value. The range for values in this function is within [-1, 1]. If Reward(I, O) = 0, it corresponds to the competition being a draw.

$$\text{(3)} \qquad Reward\ (I,O) = \frac{R(0) - R(I)}{\max\ (R) - \min\ (R)}$$

## 3.0 Experimental results and discussions

This study built the competitive coevolution-based PAESNet for the ghost team's chasing behavior in the Ms. Pac-man game. The objectives for these proposed controllers were to minimize game scores and the number of hidden neurons required in the hidden layer. Hence, for the first objective, the lower the score, the better the performance of the controller is. Two experiments were carried out to create the ghost team. First, Experiment 1 was conducted to select a suitable number K of random opponents for the PAESNet_KRO in Subsection 3.1. Then, Experiment 2 was used to analyze and compare the performance of the best PAESNet_KRO and standard PAESNet in Subsection 3.2.

### 3.1 Experiment 1: determination of K (random opponents)

The main objective of this experiment was to select the best number of opponents, K was to create the PAESNet_KRO for ghost team with the values of 2, 4, 6, 8 and 10. Table 1 shows the experimental data of best game scores over 5000 evaluations in 10 runs. According to mean values, the PAESNet_KRO with 6 random opponents (632) is lower than other K random opponents such as 2, 4, 8 and 10 with the values of 635, 777, 637 and 816 respectively.

**Table 1. The best game scores over 5000 evaluations in 10 runs**

| Run | 2 RO | 4 RO | 6 RO | 8 RO | 10 RO |
|---|---|---|---|---|---|
| 1 | 630.00 | 640.00 | 630.00 | 630.00 | 640.00 |
| 2 | 650.00 | 630.00 | 630.00 | 630.00 | 630.00 |
| 3 | 630.00 | 730.00 | 630.00 | 630.00 | 1540.00 |
| 4 | 630.00 | 630.00 | 630.00 | 640.00 | 630.00 |
| 5 | 650.00 | 630.00 | 630.00 | 630.00 | 630.00 |
| 6 | 630.00 | 630.00 | 640.00 | 630.00 | 1550.00 |
| 7 | 630.00 | 630.00 | 630.00 | 650.00 | 630.00 |
| 8 | 630.00 | 1080.00 | 640.00 | 640.00 | 630.00 |
| 9 | 630.00 | 630.00 | 630.00 | 660.00 | 640.00 |
| 10 | 640.00 | 1540.00 | 630.00 | 630.00 | 640.00 |
| **Mean** | **635.00** | **777.00** | **632.00** | **637.00** | **816.00** |
| SD | 8.50 | 302.69 | 4.22 | 10.59 | 384.25 |
| Min | 630.00 | 630.00 | 630.00 | 630.00 | 630.00 |
| Max | 650.00 | 1540.00 | 640.00 | 640.00 | 1550.00 |

Note: RO = Random Opponents

In addition, the Pareto fronts generated by K random opponents strategy were compared to each other in terms of contribution, entropy and coverage metrics. Table 2 to Table 4 contain results of contribution, entropy and coverage metrics mean values for the 10 runs respectively. Based on the data of each comparison, the 6 random opponents structure has been shown to have dramatic effects on the PAESNet_KRO in all three metrics. Thus, it is selected as the benchmark to measure the performances of the PAESNet_KRO with different K random opponents such as K = 2, 4, 8 and 10.

Contribution metric: Table 2 presents the resulting values for the contribution metric of the Pareto fronts obtained by the 6 random opponents versus various types of K random opponents. As can be seen from the table, the PAESNet_KRO with 6 random opponents is the best model and also outperforms other K random opponents in terms of convergence ability. In all the pairwise comparisons, the contribution values of 6 random opponents are larger than 0.5, which indicates an improvement of the Pareto front. It is also noted that this model is able to find more Pareto optimal solutions. Generally, these results suggest that the 6 random opponents outperform other K random opponents.

**Table 2. Average contribution values of the different K random opponents**

| Contribution | Obtained value | Better performance |
|---|---|---|
| Cont(6 RO, 2 RO)<br>Cont(2 RO, 6 RO) | **0.5419**<br>0.4581 | 6 RO |
| Cont(6 RO, 4 RO)<br>Cont(4 RO, 6 RO) | **0.5370**<br>0.4630 | 6 RO |
| Cont(8 RO, 6 RO)<br>Cont(6 RO, 8 RO) | 0.4632<br>**0.5368** | 6 RO |
| Cont(10 RO, 6 RO)<br>Cont(6 RO, 10 RO) | 0.3651<br>**0.6349** | 6 RO |

Note: If Cont*(A, B)* > Cont*(B, A)*, then *A* is better than *B*

RO represents random opponents

Entropy metric: As Table 3 shows there are significant differences between pairs of sets of the PAESNet_KRO with 6 random opponents and various K random opponent models in diversity of the Pareto optimal solutions. From the data in table 2, it is apparent that the Pareto front obtained with 6 random opponents is the most diversified front. Hence, this model allows for obtaining of diversified Pareto fronts, which is one of the main goals in a multiobjective optimization. In short, the PAESNet_KRO with 6 random opponents has better outcomes than other K models.

**Table 3. Average entropy values of the different K random opponents**

| Entropy | Obtained value | Better performance |
|---|---|---|
| Ent(6 RO, 2 RO)<br>Ent(2 RO, 6 RO) | **0.4672**<br>0.4547 | 6 RO |
| Ent(6 RO, 4 RO)<br>Ent(4 RO, 6 RO) | 0.4719<br>0.4572 | 6 RO |
| Ent(8 RO, 6 RO)<br>Ent(6 RO, 8 RO) | 0.4669<br>**0.4792** | 6 RO |
| Ent(10 RO, 6 RO)<br>Ent(6 RO, 10 RO) | 0.4473<br>**0.4877** | 6 RO |

Note: If Ent*(A, B)* > Ent*(B, A)*, then *A* is better than *B*

RO represents random opponents

Coverage metric: The coverage values in Table 4 indicates that the 6 random opponents offer better coverage results than the other K random opponents algorithms. This fact points out that PAESNet_KRO with 6 random opponents can find the Pareto optimal solutions that dominate more Pareto optimal solutions of others. Overall, it is interesting to note that this experiment has tended to suggest that K = 6 is the best value in creating the PAESNet_KRO for ghost team.

**Table 4. Average coverage values of the different K random opponents**

| Coverage | Obtained value | Better performance |
|---|---|---|
| C(6 RO, 2 RO)<br>C(2 RO, 6 RO) | **0.5149**<br>0.4186 | 6 RO |
| C(6 RO, 4 RO)<br>C(4 RO, 6 RO) | **0.4333**<br>0.4052 | 6 RO |
| C(8 RO, 6 RO)<br>C(6 RO, 8 RO) | 0.4186<br>**0.5108** | 6 RO |
| C(10 RO, 6 RO)<br>C(6 RO, 10 RO) | 0.3762<br>**0.6105** | 6 RO |

Note: If C*(A, B)* > *C(B, A)*, then *A* is better than *B*

RO represents random opponents

Overall, the PAESNet_KRO with 6 random opponents has performed well over a variety of K values in terms of contribution, entropy and coverage quality assessments front for the ghost team. This finding corroborates the ideas of Luke (2010), who suggests that the K random opponents competitive fitness strategy performs well with K set to somewhere in a range from 6 to 8 (integer value). The strong team of ghosts will greatly influence performance of the Ms. Pac-man agent. Generally, therefore, it seems that the ghost team is able to minimize the scores obtained by the Ms. Pac-man agent.

### 3.2 Experiment 2: performance evaluation for the best PAESNet_KRO and standard PAESNet

An empirical comparison of the best coevolution-based PAESNet and standard PAESNet was conducted. According to the previous experiment, the PAESNet_KRO with 6 random opponents is identified as the best controller. The evaluations were based on the three performance metrics: contribution, entropy and coverage. As can be seen from the Table 5, the PAESNet_KRO reported a notably less mean score than the standard PAESNet (632 and 1059 respectively), the PAESNet_KRO is better than the PAESNet.

**Table 5. The best game scores over 5000 evaluations in 10 runs**

| Run | PAESNet | PAESNet_KRO |
|---|---|---|
| 1 | 1480.00 | 630.00 |
| 2 | 630.00 | 630.00 |
| 3 | 650.00 | 630.00 |
| 4 | 1640.00 | 630.00 |
| 5 | 640.00 | 630.00 |
| 6 | 650.00 | 640.00 |
| 7 | 1500.00 | 630.00 |
| 8 | 1030.00 | 640.00 |
| 9 | 1730.00 | 630.00 |
| 10 | 640.00 | 630.00 |
| **Mean** | **1059.00** | **777.00** |
| SD | 474.94 | 4.22 |
| Min | 630.00 | 630.00 |
| Max | 1730.00 | 640.00 |

Furthermore, an analysis of the Pareto optimal solutions in multiobjective optimization is provided. Table 6 to Table 8 compare the performances of both algorithms in the sense of the mean contribution, entropy and coverage metrics for 10 runs respectively. The discussions of each performance metric are presented below.

Contribution metric: Table 6 shows the mean contribution values of the PAESNet_KRO versus standard PAESNet. From the data in table, it is apparent that the coevolution-based PAESNet (76%) has superior convergence than the standard PAESNet (24%). In general, the results indicate that the coevolution-based PAESNet generate the Pareto front of substantially higher quality than the standard PAESNet. The competitive coevolutionary approach has an effect on the capability to converge towards the Pareto optimal front.

**Table 6. Average contribution values of PAESNet_KRO versus standard PAESNet**

| Contribution | Obtained value | Better performance |
|---|---|---|
| Cont(PAESNet_KRO, PAESNet)<br>Cont(PAESNet, PAESNet_KRO) | **0.7606**<br>0.2394 | KRO |

Note: If Cont*(A, B)* > Cont*(B, A),* then *A* is better than *B*

Entropy metric: According to this Table 7, the front produced by the PAESNet_KRO is much more uniform than the standard PAESNet (50% versus 44%). It means that the competitive fitness strategy have the ability to maintain the diversity of the population in the archive. In short, what is interesting in this data is that the PAESNet_KRO has better distribution of the generated nondominated solutions than the standard PAESNet in terms of solution diversity. This proposed system is also able to maintain uniform distribution along the Pareto front.

**Table 7. Average entropy values of PAESNet_KRO versus standard PAESNet**

| Entropy | Obtained value | Better performance |
|---|---|---|
| Ent(PAESNet_KRO, PAESNet)<br>Ent(PAESNet, PAESNet_KRO) | **0.5028**<br>0.4404 | KRO |

Note: If Ent*(A, B)* > Ent*(B, A)*, then *A* is better than *B*

Coverage metric: The coevolution-based PAESNet and standard PAESNet are compared by the coverage distributions in Table 8, which clearly shows that the set of nondominated solutions obtained from the coevolution-based PAESNet covers the solution set generated from the PAESNet very well in this game domain. The solutions of PAESNet_KRO dominate 76% of the solutions of standard PAESNet. Overall, the results indicate that performance of the standard PAESNet is worse than the competitive coevolution PAESNet as the improved PAESNet can find more valuable solution set.

**Table 8. Average coverage values of PAESNet_KRO versus standard PAESNet**

| Coverage | Obtained value | Better performance |
|---|---|---|
| C(PAESNet_KRO, PAESNet)<br>C(PAESNet, PAESNet_KRO) | **0.7563**<br>0.1943 | KRO |

Note: If C*(A, B)* > C*(B, A)*, then *A* is better than *B*

Overall, the PAESNet with competitive coevolution is better suited than the standard PAESNet for designing the ghost team controller. Through its competitive mechanism such as K random opponents, the optimal solutions of the improved PAESNet system is not only assures better convergence to the Pareto optimal front but also well distributed in the archive. Besides, the experimental results show that the solutions in the standard PAESNet are significantly dominated by the PAESNet with competitive fitness strategy. These findings support the idea of competitive coevolution used in the MOEA.

## 4.0 Conclusion

The main purpose of this paper is to study the effects of the hybridization of MOEA and competitive coevolution for enemy team in Ms. Pac-man game domain aiming at creating machines capable of general intelligent actions. The results show that the Pareto multiobjective competitive coevolutionary algorithm can be used successfully to improve the performance of the ghost team for minimizing the score obtained by the Ms. Pac-man agent and the complexity of the neural network. Two experiments were conducted to analyze the performances of the proposed algorithms.

Experiment 1 was executed to determine the best number of random opponents (the best K) for the PAESNet_KRO. Thus, the PAESNet_KRO with K values of 2, 4, 6, 8 and 10 are compared to each other. The empirical results identified the K = 6 as the best according to its performance in terms of contribution, entropy and coverage metrics.

Experiment 2 was conducted to compare the performance between the best PAESNet_KRO and standard PAESNet. The experimental results reveal that the competitive coevolution-based PAESNet can effectively reduce the game scores and computational complexity of the neural network. Thus, this experiment supported the hypothesis that the coevolution MOEA performed better than the MOEA alone for evolving the enemy team of ghosts.

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