國立交通大學

電信工程研究所碩士班

碩 士 論 文

利用賽局理論之多網路系統最佳化入侵防護策略

Optimal Intrusion Protection Strategy for Multiple Network Systems using Game Theory

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指導教授：李程輝　教授

中 華 民 國　一　佰 零 二 年 七 月

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摘　　要

隨著網際網路的發達，網路安全越來越受到重視。網路科技的來臨，為生活帶來了高度的便利性，我們可以因此輕鬆快速地獲得資訊、完成任務，讓生活變的更美好，但其背後的風險絕對不能忽視。因為在當今的社會中，很多資訊都能透過網路取得，有專業知識背景的人甚至可以透過這個管道來獲得不法利益，如果保護好這些資訊，避免它被非法取得，將會是個重要且必須面對的問題。

在這篇論文當中，我們使用賽局理論去分析在有多個系統要保護且資源有限的情況下，攻擊者跟系統管理者的最好策略。

關鍵字：賽局理論、網路安全

Optimal Intrusion Protection Strategy for Multiple Network Systems using Game Theory

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ABSTRACT

In this paper, we present a game-theory based strategy for protecting multiple network systems. We consider the interactions between the attacker and the defender as a two-player, and non-cooperative game in both sequential and simultaneous mode. Optimal strategies for both the attacker and the defender are derived.

Keywords: Game Theory, network security

誌　　謝

能夠完成這篇論文，我必須感謝我的指導教授－李程輝教授。他總是不辭辛勞地教導我作研究的態度，在這兩年的研究所生活中，我不只學習到專業知識還有獨立思考的能力，更重要的是我從老師身上學到了研究以及做事的正確態度。這些處理事情的態度對我將來工作上會有很大的幫助。

感謝我的朋友，在我最焦慮徬徨無助時，給我建議和鼓勵，陪我紓解壓力，讓我不致於被壓力吞沒。

最後謹將此論文獻給身邊所有愛我的人及我愛的人。

2012/07　李彥良

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Chapter 1. Introduction

1.1 Introduction

Today we live in a world that is highly dependent on the Internet. Smart phones, personal computers, traffic lights, etc., all rely on the network to provide their services. With these services, our lives become much more convenient than ever. However, network suffers from security problems. Network security has become a challenging issue because many new network attacks have appeared increasingly sophisticated and caused vast loss to network resources. How to protect multiple network systems with limited resources is one of the critical issues we must face.

In this paper, we assume that there is an intruder who wants to intrude a set of systems that are guarded by a defender. The defender can only protect one of the systems while the intruder launches his attack. We discuss how game theory can be applied to this problem. We have derived an optimal strategy for the intruder to maximize his benefits, and an optimal strategy for the defender to minimize the intruder's benefits.

1.2 Related works

Several papers concerning about network security using game theory have been proposed.

In[1], Kong-wei Lye and Jeannette Wing model the network security problem as a general-sum stochastic game between the intruder and the defender. They also compute the Nash equilibrium strategies for the players.

In[2], Sankardas Roy, Charles Ellis, Sajjan Shiva, Dipankar Dasgupta, Vivek Shandilya, and Qishi Wu categorize game theory into many different groups, discuss the relationship

between network security and game theory. Our system model in this paper belongs to one of the games mentioned in this paper.

In[4], Xiannuan Liang, and Yang Xiao provide a survey and classifications of existing game theoretic approaches to network security. They show the short comings of traditional solutions to network security, and that game theoretic approachs are powerful tools for solving network security problems.

Chapter 2. Background and Problem Formulation

2.1 An Overview of Game Theory

Game theory describes the multi-person decision scenario as games where each person chooses the actions that results in the best rewards for himself. Here we introduce some of the terminologies of game theory.

Game

The interaction among rational, mutually aware players, where the decisions of some players impacts the payoffs of others. A game is described by its players, each player's strategies, and the resulting payoffs from each outcome. Additionally, in sequential games, the game stipulates the timing of moves.

Action

An action constitutes a move within a game.

Player

Any participant in a game who has more than one set of strategies and selects among the strategies based on payoffs. If a player is non-strategic, selecting strategies randomly, the player is termed a nature player.

Payoff

In any game, payoffs are positive or negative numbers which represent the motivations

of each player. Payoffs may represent profit, quantity, or rank the desirability of outcomes. In all cases, the payoffs must reflect the motivations of the particular player.

Strategy

A strategy defines a set of moves or actions a player will follow in a game. A strategy must be complete, defining an action in every contingency, including those that may not be attainable in equilibrium. For example, a strategy for the game of checkers would define a player's move at every possible position attainable during a game.

Sequential Game

A sequential game is one in which players make decisions following a certain predefined order, and in which at least some players can observe the moves of players who preceded them.

Simultaneous Game

A simultaneous game is one in which all players make decisions without knowledge of the strategies that are being chosen by other players. Even though the decisions may be made at different points in time, the game is simultaneous because each player has no information about the decisions of others; thus, it is as if the decisions are made simultaneously.

Static Game

This is the type of game that we discuss through out this paper. Static game is a one-shot game where all players make decisions at the same time. Even though the decisions may be made at different points in time, the game is simultaneous because each player has no information about the decisions of others; thus, it is as if the decisions are made simultaneously.

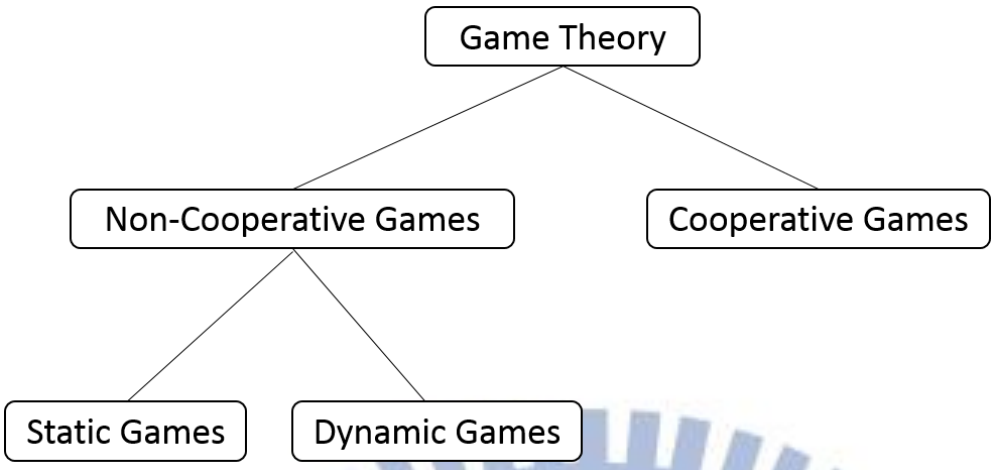

Figure 1. An overview of game theory

In game theory, usually we have the following basic elements and assumptions:

1. Every decision player has two or more well-specified actions or sequences of actions.
2. Each possible combination of actions leads to a well-defined end-state (win, loss, or draw) that terminates the game.
3. Each player's end-state has its corresponding payoff.
4. All players are rational, which means that given two choices, each player would choose the one that results in higher payoff.

2.2 Prisoner's Dilemma

We exemplify the above descriptions by introducing a well-known game: the Prisoner's Dilemma. The prisoner's dilemma describes the story of two criminals (player I, and player II) who have been arrested for a crime being interrogated separately. They are told that if both of them keep silence, the case against them is weak and they will be convicted and punished for lesser charges. If this happens, each will be sent to jail for two years. If both of them confess, each will be sent to jail for five years. If only one player confesses and testifies against the other, the one who does not cooperate with the police would get a ten-year sentence and the one who cooperate will go free. Table 1 illustrates the structure of payoffs.

Table 1. Payoffs of prisoner's dilemma

		Player II	
		Confess	Silence
Player I	Confess	2, 2	4, 0
	Silence	0, 4	3, 3

Meanings of the payoffs

0: sent to jail for 10 years

2: sent to jail for 5 years

3: sent to jail for 2 years

4: go free

In table 1, each cell of the matrix shows the payoffs for the two players. Player I's payoff is shown as the first number in each pair, Player II's as the second. As the upper-left cell shows, if both players confess, they get a payoff of 2 (sent to jail for 5 years). If both of them keep silence, they each gets a of 3 (sent to jail for 2 years), which is shown in the lower-right cell. If player I confesses and player II remains silent, then player I gets a payoff of 4 (going free) and player II gets a payoff of 0 (sent to jail for 10 years). This appears in the upper-right cell. The lower-left cell illustrates the reverse situation.

Nash equilibrium describes the steady state where no player, given all other players' choice, would prefer to change his strategy because that would decrease his payoff. In the case of prisoner's dilemma, the Nash equilibrium is reached when both players confess.

Chapter 3. System Model

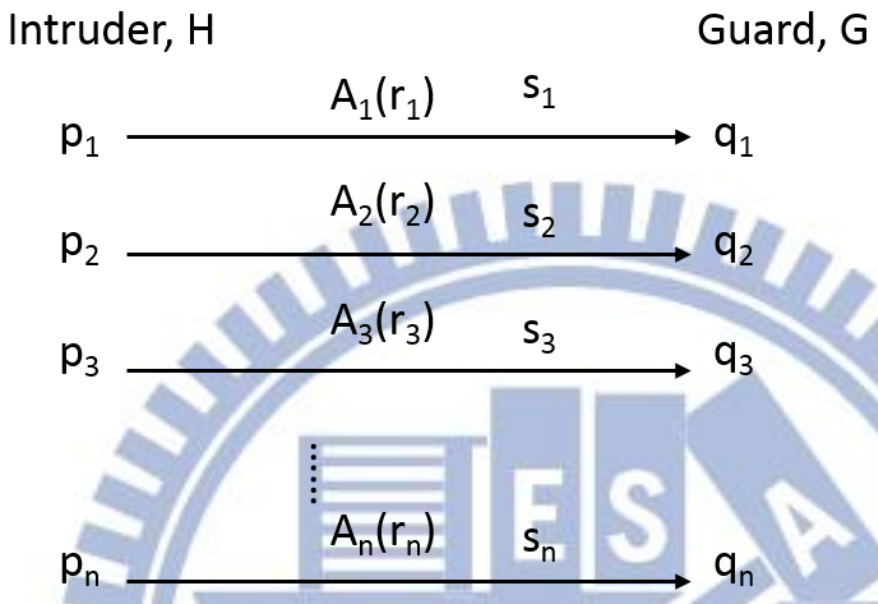

Figure 2. System model

Figure 2 illustrates the system model in this paper. The meanings of the characters are listed below.

p_i: the probability that the intruder attacks system i

q_i: the probability that the defender appears at system i

A_i: reward for intruder

r_i: the probability for intruding system i successfully

s_i: the i^{th} system

In this paper, we assume there is an intruder, H, who wants intrude n systems, $S = \{s_1, s_2, \ldots, s_n\}$, that are guarded by a defender, G, who can only protect one system while H is intruding. H can only intrude one system at a time. The probabilities for H to intrude systems $s_1, s_2, \ldots, s_n$ are $P = \{p_1, p_2, \ldots, p_n\}$, respectively. The probability that H successfully enters system i is r_i. The reward for intruding these systems are $A=\{A_1, A_2, \ldots, A_n\}$, respectively, which means that if H successfully intrude s_i, then he will get a reward of A_i, $1 \le i \le n$. G

chooses to protect s_1, s_2, s_3…, s_n with probabilities Q={q_1, q_2, …, q_n}, respectively. If H chooses to intrude s_j, and G chooses to protect s_j, then H would be caught and punished for $k*A_j$, where k is a constant $k > 0$, $1 \le j \le n$. Two questions then arise, "How does the intruder, H, decide his strategy, P, so that his expected reward can be maximized?" and "How does the defender, G, decide his strategy, Q, so that H's expected reward can be minimized?" We will discuss the above two questions under two scenarios throughout this paper. Whenever the attacker chooses a system, three situations will occur with corresponding probabilities.

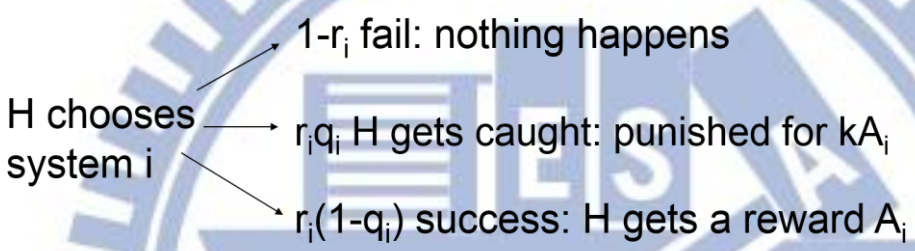

Figure 3. Results of the attacker

Chapter 4. Analysis

The two questions, “How does the intruder, H, decide his strategy, P, so that his expected reward can be maximized?” and “How does the defender, G, decide his strategy, Q, so that H’s expected reward can be minimized?” will be analyzed in the following analyses.

Analysis 1

First we consider the question about how G can minimize H’s expected reward by deciding the probabilitiy distribution of Q. In order to do this, we first list some important parameters.

E[X] = $\sum_{i=1}^{n} p_i A_i r_i$: Expected reward of H when G does not exist (4.1)

E[R] = $\sum_{i=1}^{n} p_i A_i r_i (1-q_i) - k\sum_{i=1}^{n} p_i A_i r_i q_i = \sum_{i=1}^{n} p_i A_i r_i - (k+1)\sum_{i=1}^{n} p_i A_i r_i q_i$: Expected reward of H when G appears (4.2)

Assume intruder’s strategy, P, is given, our goal is to minimize E[R] by setting defender’s strategy, Q. We can have the following derivation.

$$\min_{q_1,q_2,\ldots,q_n} \{E[R]\} = \min_{q_1,q_2,\ldots,q_n} \{E[X] - (k+1)\sum_{i=1}^{n} p_i A_i r_i q_i\} = E[X] - (k+1)\max_{1\le i\le n}\{p_i A_i r_i\} \quad (4.3)$$

Define $V_j = p_j A_j r_j$. From the above derivation, we know that G can minimize E[R] by picking up the maximum V_j, and set it to 1, no matter how H set P. This means that the defender will always defend the system that has the maximum reward for the attacker.

Next we consider how H can maximize his reward by selecting P if he knows G’s strategy.

$$\max_{p_1,p_2,\ldots,p_n} \{\min_{q_1,q_2,\ldots,q_n} \{E[R]\}\} = \max_{p_1,p_2,\ldots,p_n} \{\sum_{i=1}^{n} p_i A_i r_i - (k+1)\max_{1\le i\le n}\{p_i A_i r_i\}\} \quad (4.4)$$

Suppose $p_x A_x r_x$ is the maximum term, which means $p_x A_x r_x \ge p_y A_y r_y$ for $x \ne y, 1 \le x \le n, 1 \le y \le n$. We can increase $\min_{q_1,q_2,\ldots,q_n} \{E[R]\}$ by an amount of

$\sum_{1\le y\le n, y\ne x}^{n} (A_y r_y \Delta_y) + (1+k) A_x r_x \varepsilon$ if we decrease p_x by an amount of ε and increase p_y by ε. This can be represented as the following, $p'_x = p_x - \varepsilon, p'_y = p_y + \varepsilon$. We can keep doing this process until every $p_i A_i r_i$ becomes the same, which means $p_i A_i r_i = C$ for $1 \le i \le n$, where C is a constant. The optimal strategy for the attacker is then derived as

$$p_i = \frac{1}{\sum_{j=1}^{n} \frac{1}{A_j r_j}} \times \frac{1}{A_i r_i} \quad \text{for } 1 \le i \le n \tag{4.5}$$

P can be solved by using the fact that $\sum_{i=1}^{n} p_i = 1$ and $p_i A_i r_i = C$ for $1 \le i \le n$.

Analysis 2

We now consider the situation where H knows G's strategy, Q. The problem to be solved is how H can maximize his reward by selecting P? The process of the maximization, $\max_{p1, p2, ..., pn} \{E[R]\}$ can be derived as follows.

$$\max_{p1, p2, ..., pn} \{E[R]\} = \max_{p1, p2, ..., pn} \{\sum_{i=1}^{n} p_i A_i r_i - (k+1) \sum_{i=1}^{n} p_i A_i r_i q_i\} =$$

$$\max_{p1, p2, ..., pn} \{\sum_{i=1}^{n} p_i [A_i r_i - (k+1) A_i r_i q_i]\} = \max_{1 \le i \le n} \{A_i r_i (1 - (k+1) q_i)\} \tag{4.6}$$

According to the above equations, we know that H can maximize his reward by setting p_j =1 for $A_j r_j (1 - (k+1) q_j) \ge A_i r_i (1 - (k+1) q_i)$, $1 \le i \le n$, and $i \ne j$. This means that no matter what the defender's strategy is, the intruder would always intrude the system whose expected reward, $A_i r_i (1 - (k+1) q_i)$, is the maximal.

Next, we consider how G can minimize H's reward by selecting Q if G knows H's strategy. Suppose there exists an optimal solution, Q*, for G, which can minimize H's reward. We will prove that that the following statements are satisfied if G applies Q*.

I. For any two of the systems, if G guards them with a probability > 0, then their expected rewards are equal and would be $\max_{1 \le i \le n} \{V_i\}$.

II. If G guards system h with probability 0, then the expected reward of h ≤ the expected

reward of the systems that are guarded with probability > 0.

For the convenience of analysis and reading, we define the following parameters.

$W_i = A_i r_i (1-(k+1)q_i)$: expected reward of system i (4.7)

F: the set of systems such that $j \in F$ if and only if $W_j = W_f, W_f = \max_{1 \le i \le n}\{W_i\}$.

|F|: number of elements in F

Proof of statement I:

We want to prove that if $q_h^* > 0$, and $q_i^* > 0$, then $W_h = W_j$. This can be proved by contradiction. Suppose that if $q_h^* > 0$, and $q_i^* > 0$, then $W_j > W_h$. Let $q_j' = q_j^* + \varepsilon$, and $q_h' = q_h^* + \varepsilon$ such that $W_j' = A_j r_j (1-(k+1)q_j') > A_h r_h (1-(k+1)q_h') = W_h'$. In this way, we find that $\max_{1 \le i \le n}\{W_i\}$ can be further reduced, meaning that the intruder's reward can be reduced, which implies that Q is not an optimal solution for G to minimize H's reward. Therefore a contradiction occurs. Statement I is proved.

Proof of statement II:

We want to prove that if $q_h^* = 0$, then $W_h = A_h r_h \le A_j r_j (1-(k+1)q_j^*) = W_j$, where $q_j^* > 0$. This can also be proved by contradiction. First we suppose that if $q_h^* = 0$, then $W_h > W_j$. Let $q_h' = q_h^* + \varepsilon$, and $q_j' = q_j^* - \varepsilon$ such that $A_h r_h (1-(k+1)q_h') > A_j r_j (1-(k+1)q_j'), \forall j \in F$. In this way we find that $\max_{1 \le i \le n}\{W_i\}$ can be further reduced, meaing the intruder's reward can be reduced, which implies that Q is not an optimal solution for G to minimize H's reward. Therefore a contradiction occurs. Statement II is proved.

After proving the above two facts, we can calculate Q* as follows.

Let $V_i = A_i r_i (1-(k+1)q_i) = C \quad \forall$ i, where C is a constant (4.8)

We can derive

$$q_i = \frac{1}{k+1}\left(1 - \frac{n-k-1}{A_i r_i \sum_{j=1}^{n} \frac{1}{A_j r_j}}\right) \tag{4.9}$$

by using the fact that $\sum_{i=1}^{n} q_i = 1$.

Note that in order to satisfy equation (), some of the q_i may be smaller than 0, which is undefined. This situation can be avoided by setting $k \geq n-1$. Thus we have proved that Q* is the optimal solution by proving statement I and II to be true.

Chapter 5. Simulation

From previous discussions, we know that when k=n-1, then the expected reward of the intruder would be

$$\sum_{i=1}^{n} p_i A_i r_i - (k+1)\sum_{i=1}^{n} p_i A_i r_i q_i = np_1 A_1 r_1 - n\sum_{i=1}^{n} p_i A_i r_i q_i = np_1 A_1 r_1 - np_1 A_1 r_1 \sum_{i=1}^{n} q_i = 0. \quad (5.1)$$

This is a fair scenario for both the attacker and the intruder. Because no one can get reward in this game. In this paper, we present our simulation results to verify that our strategies are optimal.

Table 2. Parameters of the simulations

Number of systems	4
Number of rounds	10000
Reward for each system	{23, 24, 3, 14}
Success probability of each system	{50%, 50%, 50%, 50%}

Table 2 shows the parameters used in our simulation. Assume there are a total of four systems. The rewards for each of them are 23, 24, 3, and 14 respectively. Every system has a intruding success probability of 50%. We simulate the attacker's reward in a 10000 round sequential game.

Firstly, we show the simulation results where k=n-1, and the defender chooses the intruding system first in each round of the game. In the first simulation, the defender chooses systems with randomly determined probabilities, and the attacker chooses the system that has the maximum expected reward.

For k=n-1, defender chooses systems with randomly determined probabilities

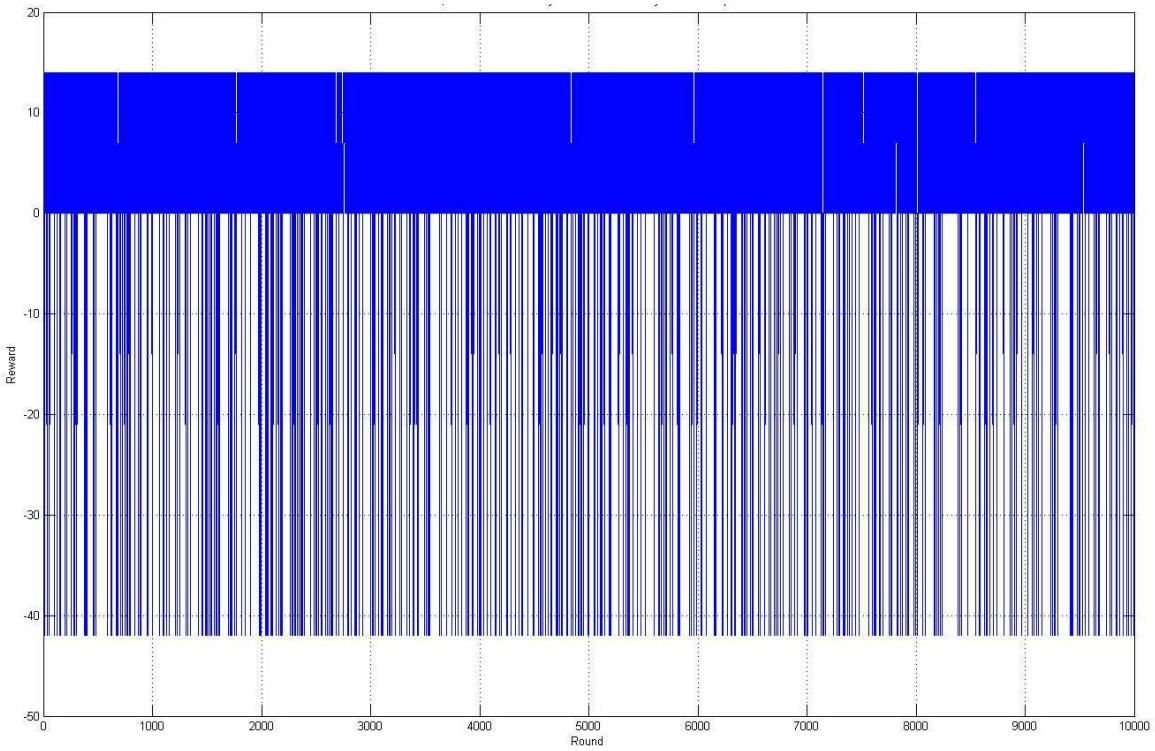

Figure 4. For k=n-1, defender chooses systems with randomly determined probabilities

In figure 4, the defender chooses systems 1, 2, 3, and 4 with probabilities 41.09%, 34.73%, 15.83%, and 8.35%. The average reward for the attacker during the 10,000 round game is 4.63. Apparently, the attacker's strategy works for him, meaning that he can get a positive reward by using this strategy. Next, let us see what happens if the defender applies our optimal strategy.

For k=n-1, defender applies optimal strategy

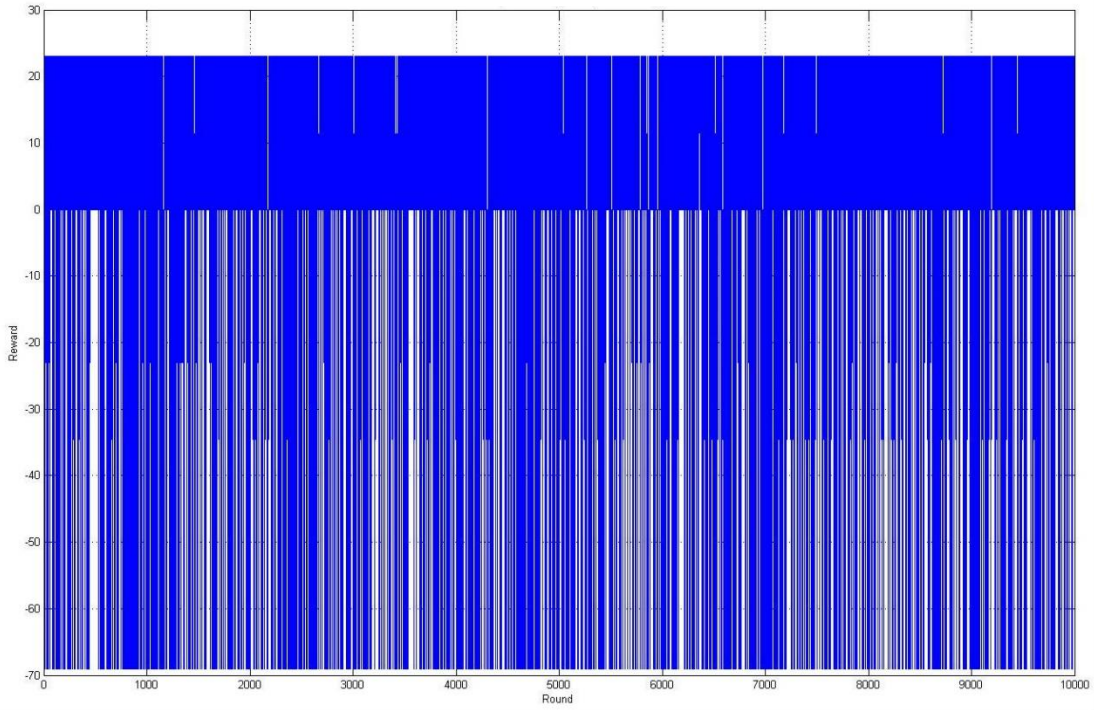

Figure 5. For k=n-1, defender applies optimal strategy

The average reward in figure 5 is 0.17. Because the defender applies the optimal strategy, the expected rewards of all systems become the same, making the atttacker impossible to pick up the system that has the maximum expeced reward. As a result, the attacker will always get an average reward that is less than that of figure 4. This shows that our strategy for the defender is effective for the defender for reducing the attacker's reward.

Next, we consider the scenario where the attacker makes his decision first in each round of the game. In this simulation, the attacker chooses systems with randomly determined probabilities, the defender will always choose the system that has the maximum $p_jA_jr_j$ term, where $1 \le j \le n$.

For k=n-1, attacker chooses systems with randomly determined probabilities

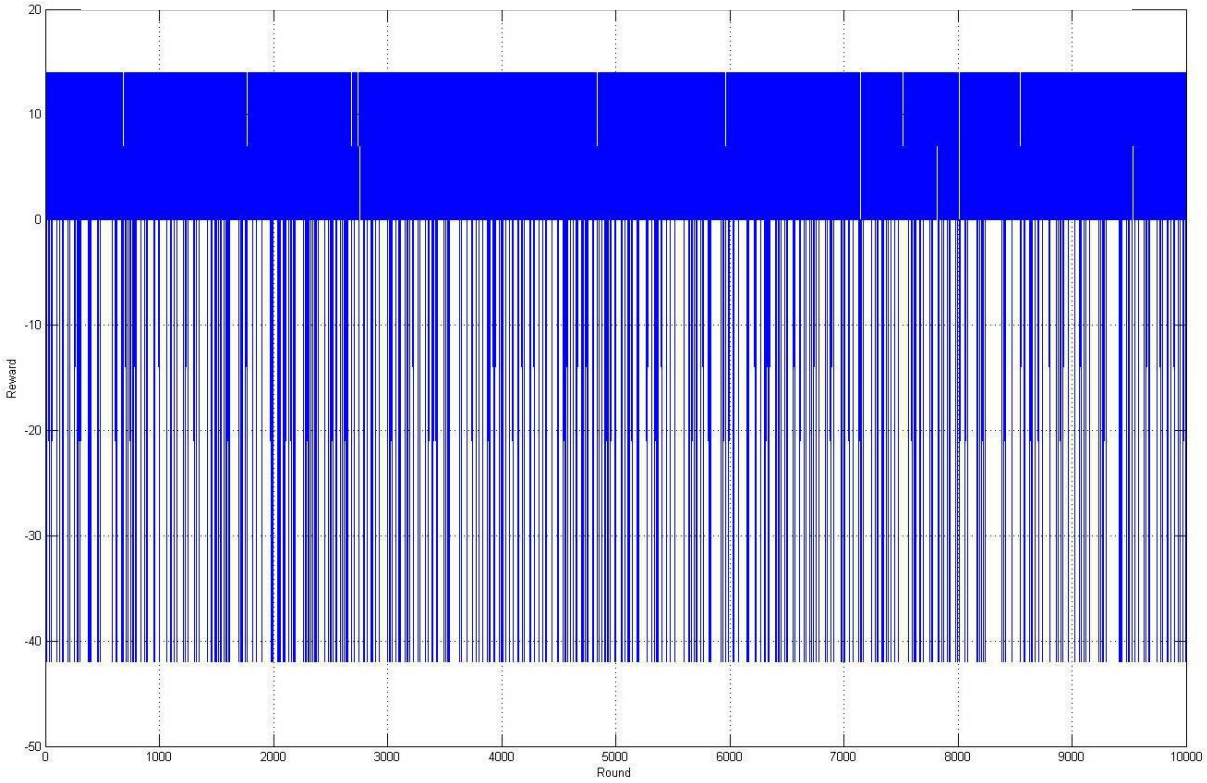

Figure 6. For k=n-1, attacker chooses systems with randomly determined probabilities

In figure 6, the attacker chooses systems 1, 2, 3, and 4 with probabilities of 13.48%, 2.90%, 41.80%, and 41.82% respectively. The average reward in figure 6 is -2.84. Next, we see how the results change if the attacker applies the optimal strategy we derived in this paper.

For k=n-1, attacker chooses systems with randomly determined probabilities

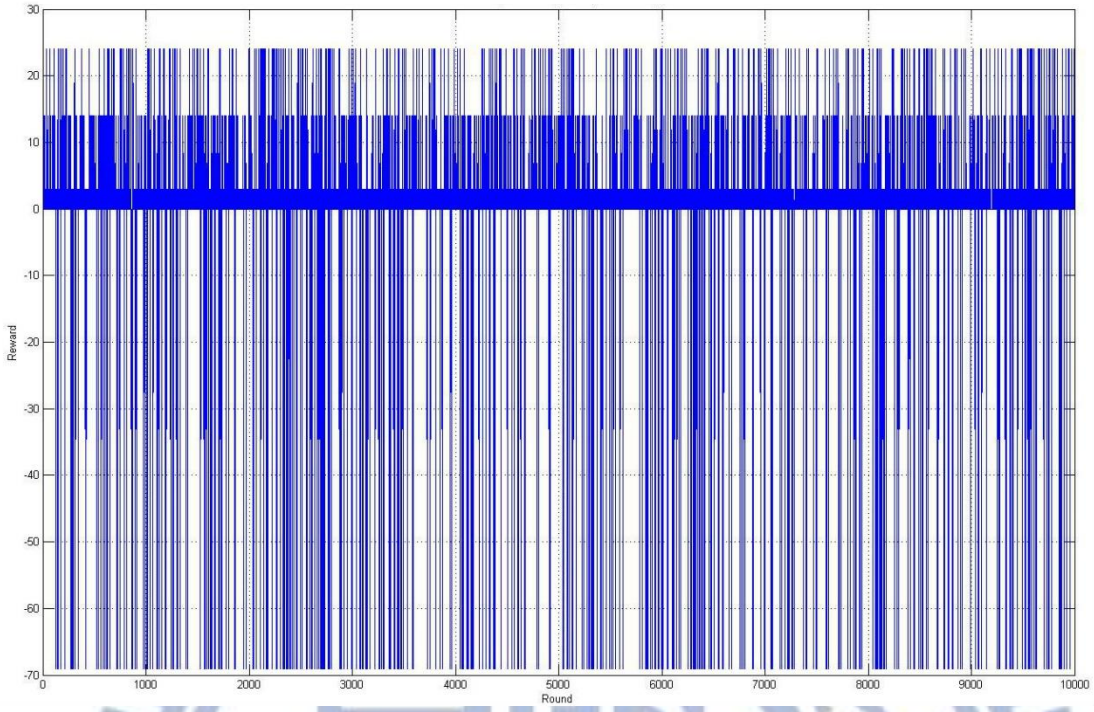

Figure 7. For k=n-1, attacker applies optimal strategy

In the above figure, the average reward for the attacker is 0.01. Compare figure 7 with figure 6, we can see clearly that the average reward has increased. This is because when the attacker applies the optimal strategy, the defender has no informatin about which system the attacker may intrude.

We next show the simulation scenario where k>n-1 (here we set k=n+1). This is the case that is beneficial for the defender. Again, in the first simulation, the defender chooses systems with randomly determined probability, while the attacker chooses the system that has the maximum expected reward.

For k=n+1, defender chooses systems with randomly determined probabilities

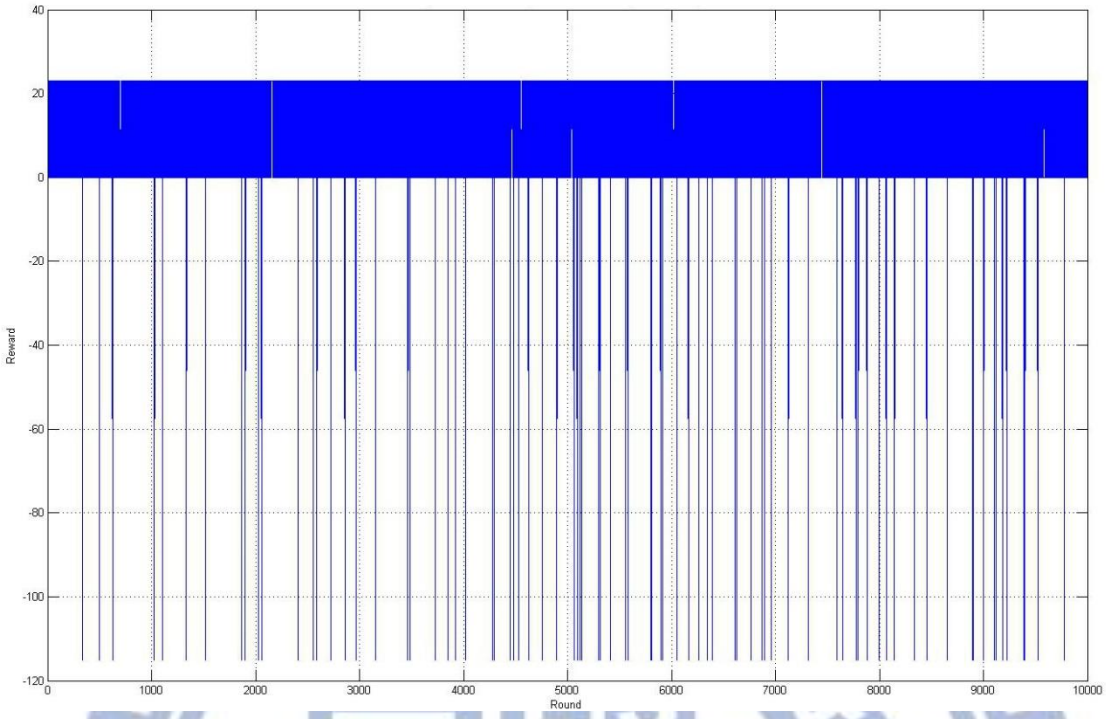

Figure 8. For k=n+1, defender chooses systems with randomly determined probabilities

In figure 8, the defender protects systems 1, 2, 3, and 4 with probabilities 1.65%, 40.03%, 19.29%, 39.03%. The average reward in the 10,000 round game in figure 8 is 10.42. Compare figure 8 with figure 4, we can clearly see that the average score is decreased. This is because the penalty multiplier is set to a value that is beneficial for the defender. Next we see how the average score changes when the defender applies the optimal strategy we derived previously.

For k=n+1, defender applies optimal strategy

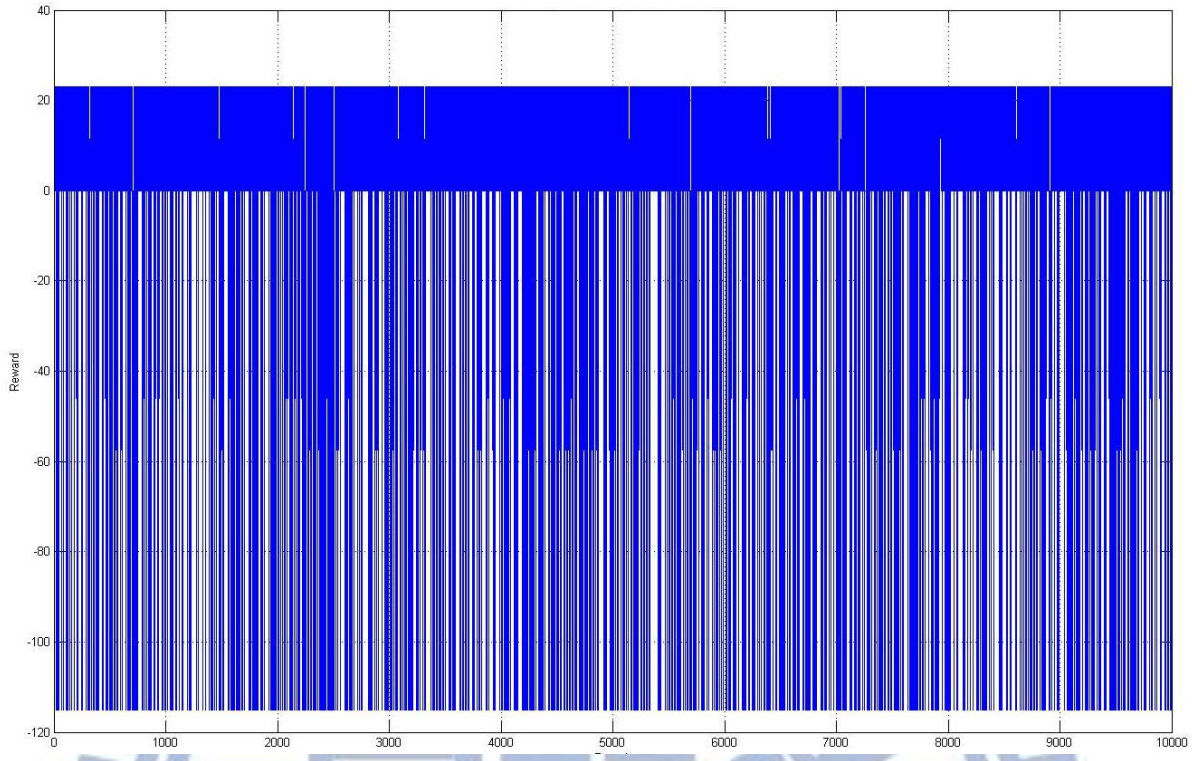

Figure 9. Defender applies optimal strategy

The average score in figure 9 is -2.54. Compare figure 9 with figure 5, we see that the average score is decreased. We next show the simulation results where k=n+1 and attacker makes decision first in each round of the game. Attacker chooses systems with randomly determined probabilites in this scenario.

For k=n+1, attacker chooses systems with randomly determined probabilities

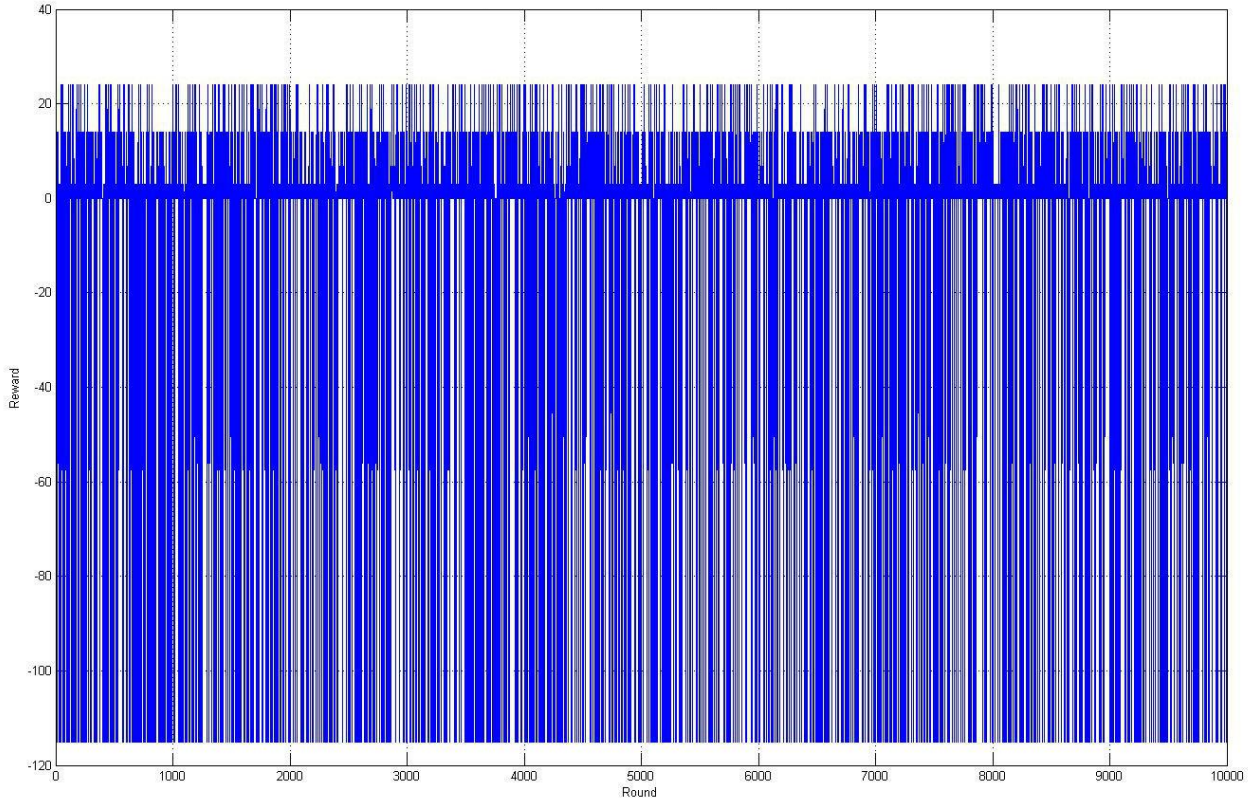

Figure 10. Attacker chooses systems with randomly determined probabilities

The average reward in figure 10 is -9.85. Compare this result with that of figure 6, we find that the average reward is decreased. This is due to the change of value in penalty multiplier, k. Next we see what happens if the attacker uses the optimal strategy.

For k=n+1, attacker applies optimal strategy

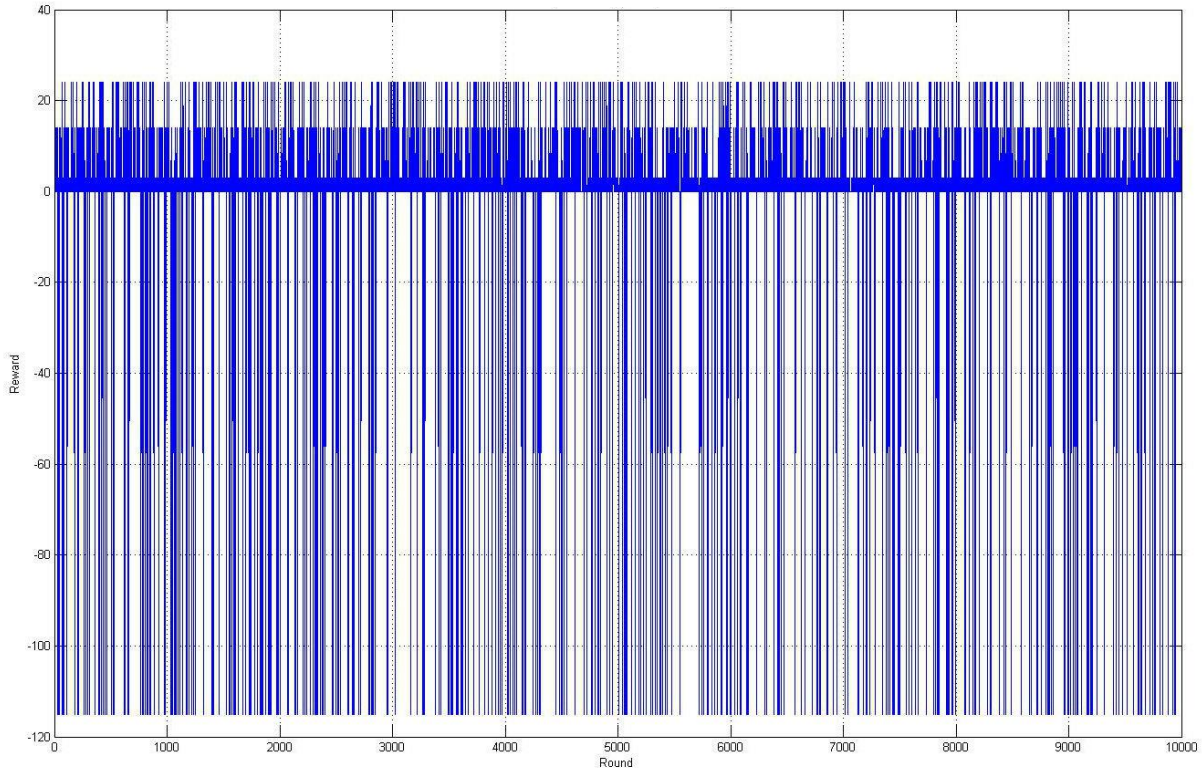

Figure 11. Attacker spplies optimal strategy

The average score in the 1000 round game in figure Figure 11. Attacker spplies optimal strategy is -1.62. Compare this result with figure 10, we find that the average score is increased. This shows that the optimal strategy is effective for increasing the attacker's average reward.

Next, we analyze the scenario where k=n-3. This is the scenario that is beneficial for the attacker. We first show the simulation results where the defender chooses systems with randomly determined probability and the attacker always chooses the system that has the maximum reward.

For k=n-3, defender chooses systems with randomly determined probabilities

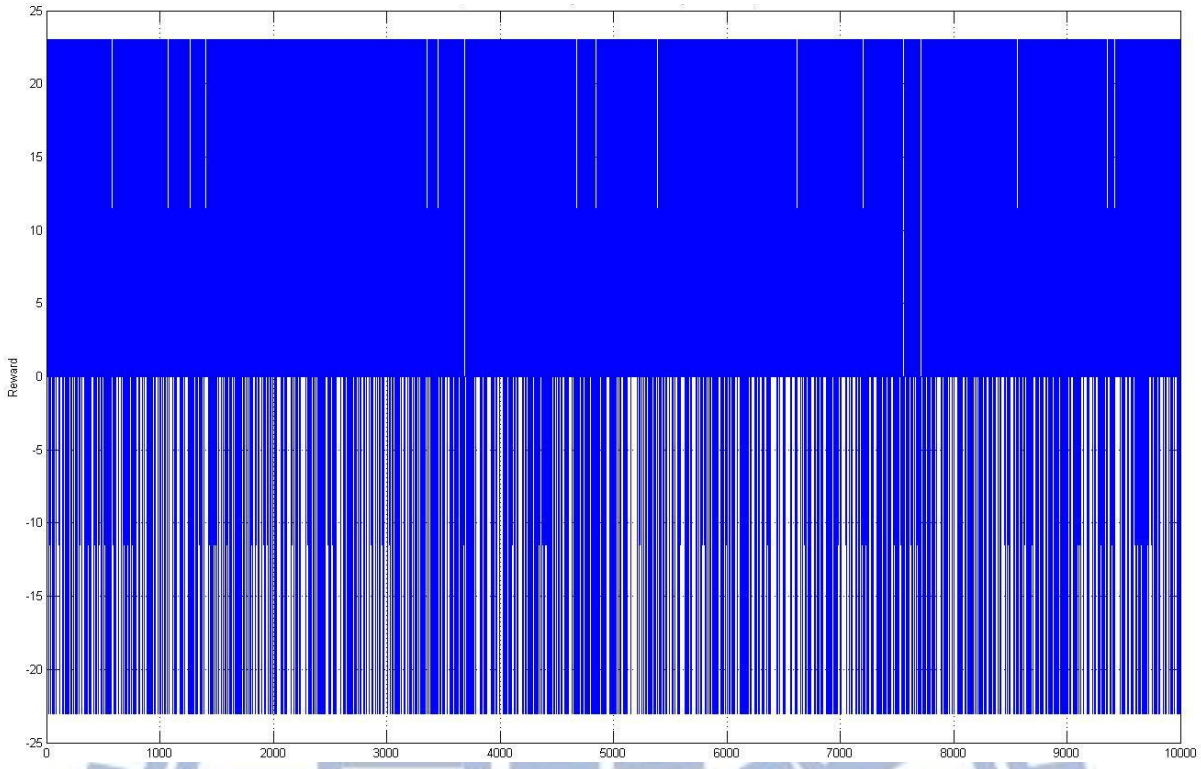

Figure 12. Defender chooses systems with randomly determined probabilities

In figure 12, the defender guards systems 1, 2, 3, and 4 with probabilities 24.45%, 39.53%, 5.78%, and 30.24% respectively. The average score of this 1000 round game is 6.39. Compare figure 11 with figure 4, we find that the average reward is increased. This is because the penalty multiplier has decreased, making the scenario beneficial to the attacker. Next, we see what happens if the defender applies the optimal strategy.

For k=n-3, defender applies optimal strategy

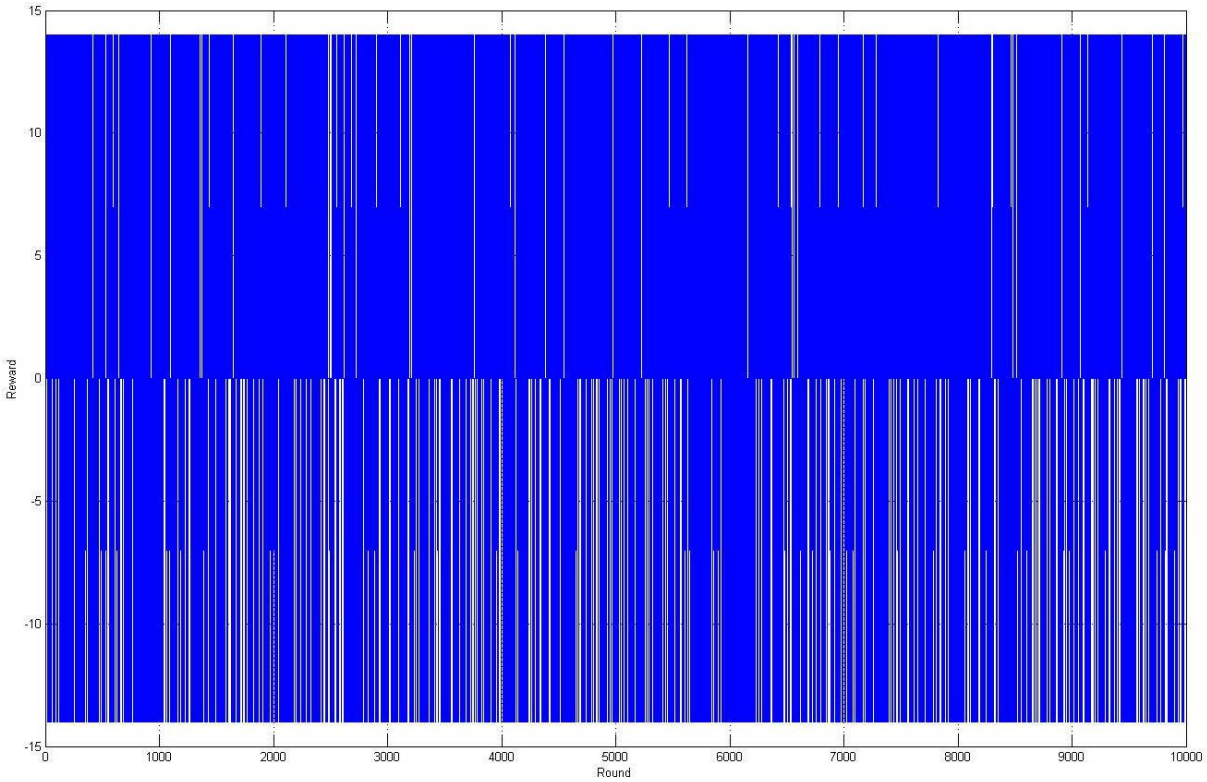

Figure 13. Defender applies optimal strategies

The average reward in figure 12 is 2.16. Obviously, the average reward is decreased when comparing figure 13 with figure 12. This means that the optimal strategy is effective for the defender to protect himself.

For k=n-3, attacker chooses systems with randomly determined probabilities

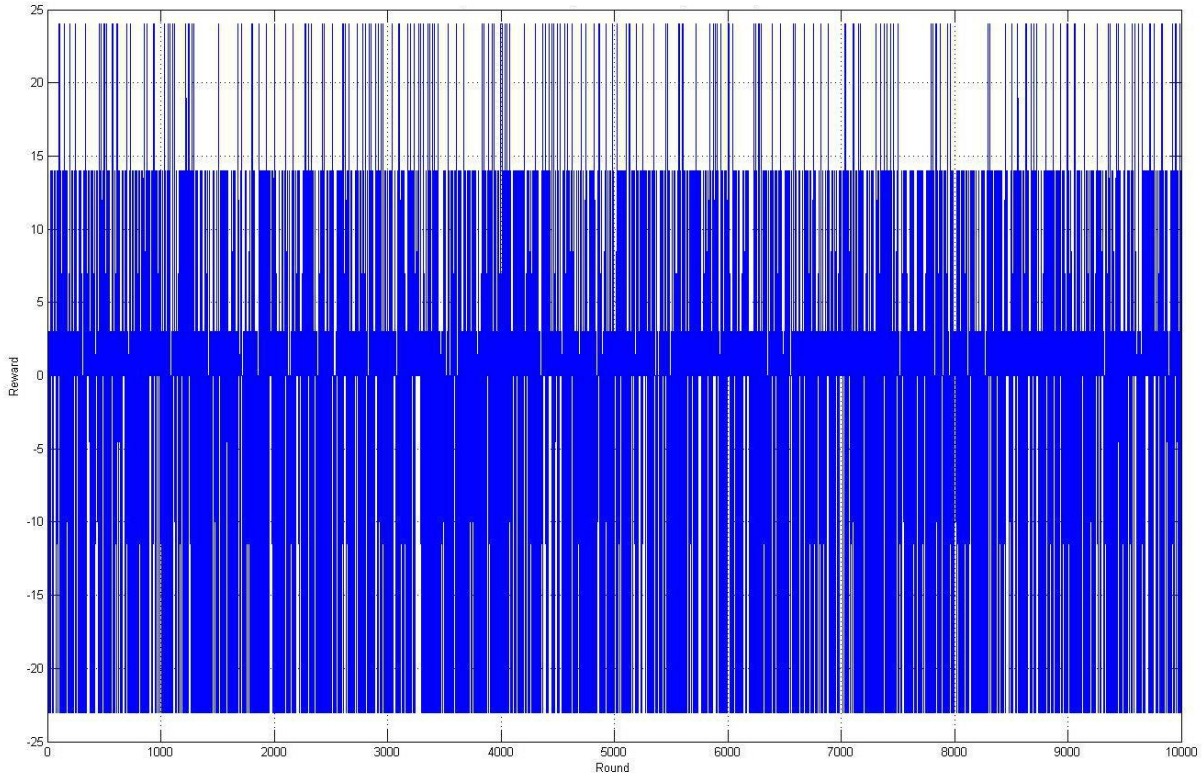

Figure 14. Attacker chooses system with randomly determined probabilities

In figure 14, the attacker intrudes systems with probabilities 5.73%, 37.37%, 46.17%, and 10.74% respectively. The average reward of figure 14 is -1.67. Compare the above figure with figure 6, we find that the average reward is increased from -8.48 to -4.40. This is caused by the decrease in the penalty multiplier, k.

For k=n-3, attacker applies optimal strategy

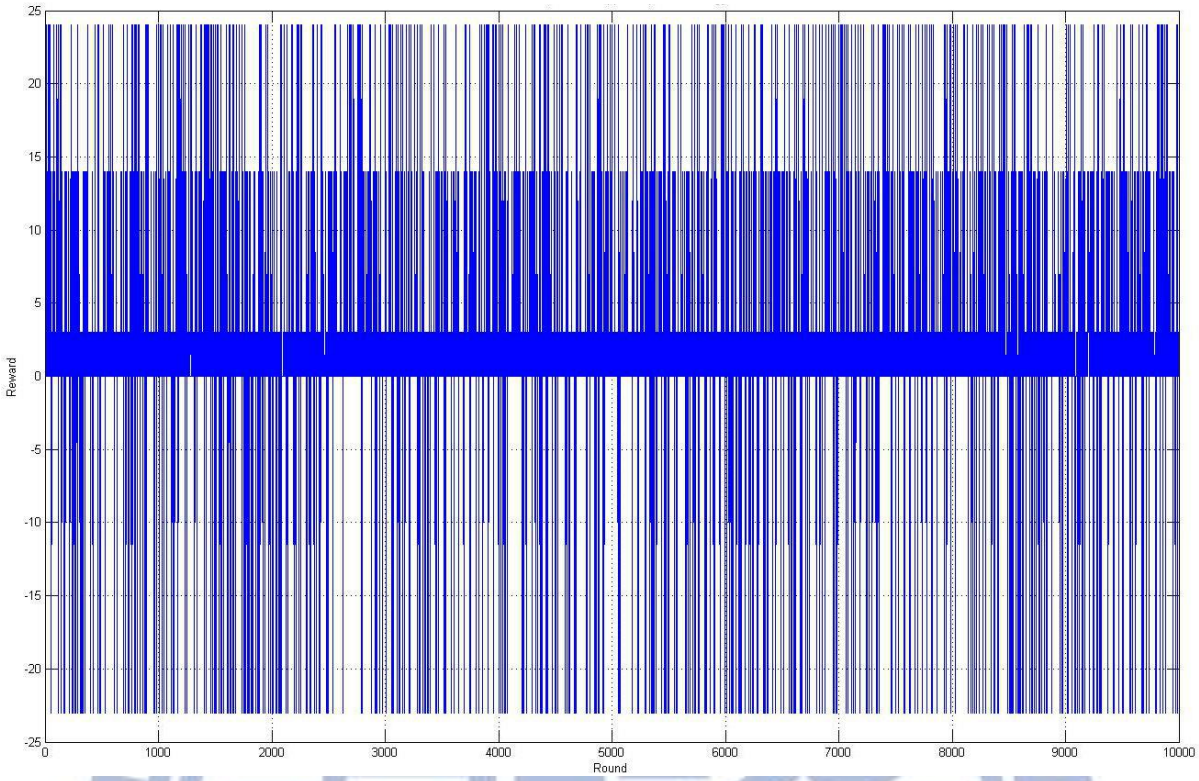

Figure 15. Attacker applies optimal strategy

The average reward of figure 15 is 1.93. Compare this figure with figure 14, we can clearly see that the average reward is increased, which is beneficial for the attacker. This means that the optimal strategy is effective for the attacker.

For the convenience of reading, we list the above average rewards in the following tables.

Table 3. Average scores when of k=n-1

k=n-1				
	defender chooses systems with randomly determined probability	defender applies optimal strategy	attacker chooses systems with randomly determined probability	attacker applies optimal strategy
Average Score	4.63	0.17	-2.84	0.01
Theoretical Score	4.66	0	-2.91	0

Table 4. Average scores when of k=n+1

k=n+1				
	defender chooses systems with randomly determined probability	defender applies optimal strategy	attacker chooses systems with randomly determined probability	attacker applies optimal strategy
Average Score	10.42	-2.54	-9.85	-1.62
Theoretical Score	10.36	-2.04	-9.61	-2.04

Table 5. Average scores when of k=n-3

k=n-3				
	defender chooses systems with randomly determined probability	defender applies optimal strategy	attacker chooses systems with randomly determined probability	attacker applies optimal strategy
Average Score	6.39	2.16	-1.67	1.93
Theoretical Score	6.13	2.04	-1.67	2.04

Chapter 6. Conclusion

In this paper, we derived the optimal strategies for the attacker and the defender in both simultaneous game and sequential game. From our previous analysis, we conclude that the best strategy for the attacker is

$$p_i = \frac{1}{\sum_{j=1}^{n} \frac{1}{A_j r_j}} \times \frac{1}{A_i r_i} \quad \text{for } 1 \le i \le n \tag{6.1}$$

and the best strategy for the defender is

$$q_i = \frac{1}{k+1}\left(1 - \frac{n-k-1}{A_i r_i \sum_{j=1}^{n} \frac{1}{A_j r_j}}\right) \quad \text{for } 1 \le i \le n \tag{6.2}$$

The above results applies in both simultaneous game and sequential game.

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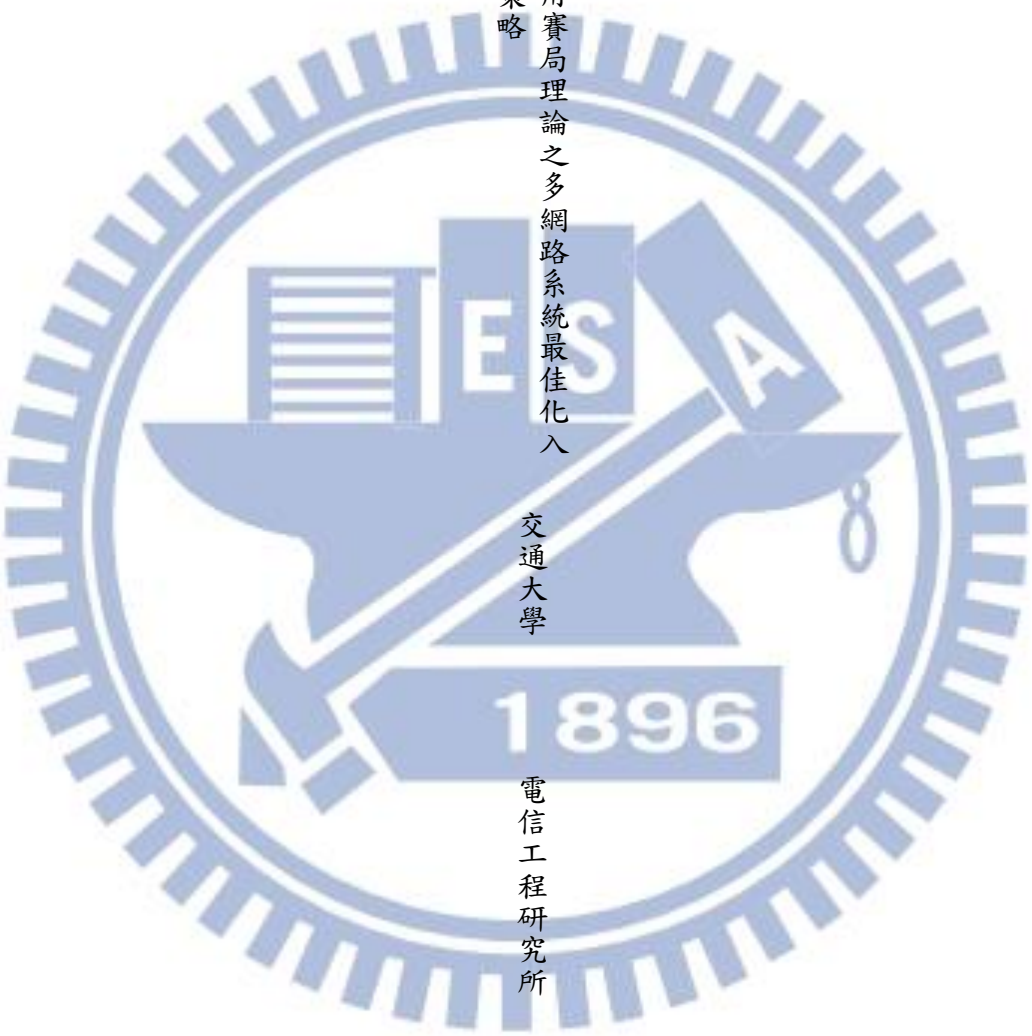

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