

CS 535 Term Project

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PAPER INTRODUCTION

The paper [1] tries to explore game theory to model the situation for wireless network with malicious nodes and solve the problem of secure wireless communications by using a game-based approach; several efficient game-based algorithms that support reliable and secure wireless communications against the attacks of malicious nodes in the wireless sensor networks. Additionally, the paper evaluates provided algorithm with a simulation experiment and analyzes the simulation results in detail (Mao, Zhu, & Wei, p.1, 2013).

ABSTRACT

For the term project of Wireless Network Security Course (coded as CS 535) at Sabanci University, this report tries to; understand the paper, replicate the provided method, replicate the provided simulation for the method and compare replicated and provided simulation results.

1.NETWORK MODEL

In the paper [1], WSN is assumed to be a simple-undirected-unweighted graph that consists of k nodes with static locations and having at least one edge.

In the WSN, there can be two different types of nodes: normal and malicious. Each node in the WSN has 4 different types of actions: Forward, Receive, Detect /Jam (depends on node type), and Sleep.

An assumption about WSN is that the number of normal nodes is much larger than the number of malicious nodes. Another assumption is that each node in WSN knows only the type of itself (Mao, Zhu, & Wei, p.2, 2013).

2.GAME THEORETIC FORMULATION

In the paper [1], to calculate payoffs for each node in WSN by game theory, pairwise simultaneous games are constructed between the node and its neighbors.

Pairwise simultaneous games' payoffs are calculated for each node. After that, according to the rules of spatial structured game, payoffs are recalculated (Mao, Zhu, & Wei, p.2, 2013).

2.2 Pairwise Simultaneous Game

The paper [1] states that between any two neighbors, there is a simultaneous game where each node has four action types represented with the first letter of the actions [F, R, D/J, S].

[Table 1] shows some of the defined variables for the game-theoretic formulation.

| Denotation | Meaning |
|-------------|---|
| Y | Direct income for a node to forward successfully. |
| A_F | Probability that a node forwards successfully. |
| A_J | Probability that a node jams successfully. |
| P | Punishment to a detected jamming |
| S | Stimulus to a successful jamming detection of the normal node |
| B1 | Cost to receive a packet or detect jamming |
| $\Delta B1$ | Additional cost to detect jamming |
| B2 | Cost to forward a packet or jam |
| $\Delta B2$ | Additional cost to jam |

[Table 1: Defined variables for the game theoretic formulation (Mao, Zhu, & Wei, p.2, 2013)]

The paper [1] specifies payoffs for three different scenarios for two-nodes games. Normal-Normal, Malicious-Normal (vice versa) and Malicious-Malicious. These payoffs can be seen in [Figure 1].

| Normal node (n) | | | | |
|--------------------------|--|---|---|-------------------------------------|
| | Forward | Detect | Receive | Sleep |
| Malicious node (m) | | | | |
| Forward | $\{-\beta_2, -\beta_2\}$ | $\{-\beta_2, -(\beta_1 + \Delta\beta_1)\}$ | $\{\alpha_F \gamma - \beta_2, -\beta_1\}$ | $\{-\beta_2, 0\}$ |
| Jam | $\{-(\beta_2 + \Delta\beta_2), -\beta_2\}$ | $\{-p - (\beta_2 + \Delta\beta_2), s - (\beta_1 + \Delta\beta_1)\}$ | $\{\alpha_J \gamma - (\beta_2 + \Delta\beta_2), -\beta_1\}$ | $\{-(\beta_2 + \Delta\beta_2), 0\}$ |
| Receive | $\{-\beta_1, \alpha_F \gamma - \beta_2\}$ | $\{-\beta_1, -\beta_1\}$ | $\{-\beta_1, -\beta_1\}$ | $\{-\beta_1, 0\}$ |
| Sleep | $\{0, -\beta_2\}$ | $\{0, -\beta_1\}$ | $\{0, -\beta_1\}$ | $\{0, 0\}$ |
| Malicious node (m_1) | | | | |
| | Forward | Jam | Receive | Sleep |
| Malicious node (m_2) | | | | |
| Forward | $\{-\beta_2, -\beta_2\}$ | $\{-\beta_2, -(\beta_2 + \Delta\beta_2)\}$ | $\{\alpha_F \gamma - \beta_2, -\beta_1\}$ | $\{-\beta_2, 0\}$ |
| Jam | $\{-(\beta_2 + \Delta\beta_2), -\beta_2\}$ | $\{-(\beta_2 + \Delta\beta_2), -(\beta_2 + \Delta\beta_2)\}$ | $\{\alpha_J \gamma - (\beta_2 + \Delta\beta_2), -\beta_1\}$ | $\{-(\beta_2 + \Delta\beta_2), 0\}$ |
| Receive | $\{-\beta_1, \alpha_F \gamma - \beta_2\}$ | $\{-\beta_1, \alpha_J \gamma - (\beta_2 + \Delta\beta_2)\}$ | $\{-\beta_1, -\beta_1\}$ | $\{-\beta_1, 0\}$ |
| Sleep | $\{0, -\beta_2\}$ | $\{0, -(\beta_2 + \Delta\beta_2)\}$ | $\{0, -\beta_1\}$ | $\{0, 0\}$ |
| Normal node (n_1) | | | | |
| | Forward | Detect | Receive | Sleep |
| Normal node (n_2) | | | | |
| Forward | $\{-\beta_2, -\beta_2\}$ | $\{-\beta_2, -(\beta_1 + \Delta\beta_1)\}$ | $\{\alpha_F \gamma - \beta_2, -\beta_1\}$ | $\{-\beta_2, 0\}$ |
| Detect | $\{-(\beta_1 + \Delta\beta_1), -\beta_2\}$ | $\{-\beta_1, -\beta_1\}$ | $\{-\beta_1, -\beta_1\}$ | $\{-\beta_1, 0\}$ |
| Receive | $\{-\beta_1, \alpha_F \gamma - \beta_2\}$ | $\{-\beta_1, -\beta_1\}$ | $\{-\beta_1, -\beta_1\}$ | $\{-\beta_1, 0\}$ |
| Sleep | $\{0, -\beta_2\}$ | $\{0, -\beta_1\}$ | $\{0, -\beta_1\}$ | $\{0, 0\}$ |

[Figure 1: Specified payoffs for each possible scenario between any two types of nodes (Mao, Zhu, & Wei, p.3-4, 2013).]

[Figure 1] can be simplified with the following [pseudo code 1].

```
def calculatePayOff(action):
    if action.type == F:
        if action.success == True:
            return  $A_F * Y - B_2$ 
        else:
            return  $-B_2$ 
    if action.type == D:
        if action.success == True:
            return  $S - (B_1 + \Delta B_1)$ 
        else:
            return  $-(B_1 + \Delta B_1)$ 
    if action.type == J:
        if action.success == True:
            return  $A_J * Y - (B_2 + \Delta B_2)$ 
        elif action.detected == True:
            return  $-P - (B_2 + \Delta B_2)$ 
        else:
            return  $-(B_2 + \Delta B_2)$ 
    if action.type == R:
        return  $-B_1$ 
    if action.type == S:
        return 0
```

[Pseudo Code 1: Simplified version of Figure 1]

2.3 Spatial Structured Game

For each node in WSN, a pairwise simultaneous game for each neighbor pair can be constructed. Since another neighbor may affect payoffs for a neighbor pair, additional rules are introduced. These rules are deducted by WSN network topology considering with 3 nodes (denoted as n_1, n_2, n_3 where n_2 and n_3 are neighbors of n_1). [Figure 2] shows network topology in detail which is used to generate the rules.

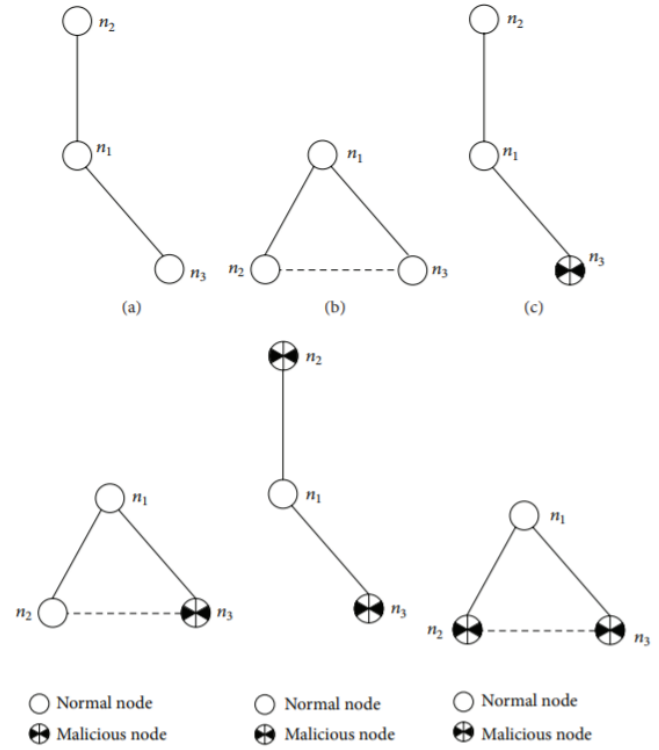
The following [Table 2] shows denotations for the spatial structured game.

| Denotation | Meaning |
|----------------|--|
| * | Any action |
| -X | Any action except X |
| U_{n_i, n_j} | Payoff function for n_i in the subgame between n_i and n_j |

[Table 2: Denotations for the spatial structured game (Mao, Zhu, & Wei, p.3, 2013)]

As it can be observed from [Figure 2], there are subgames between n_1 - n_2 and n_1 - n_3 at the same time. Therefore, some of the costs shouldn't be calculated more than once.

[Figure 3.a-b-c] shows exception rules for network topologies



[Figure 2: WSN network topology (Mao, Zhu, & Wei, p.3, 2013)]

(a, b)-(c,d)-(e,f). For (a, b) both neighbors of n_1 are normal, for (c, d) one of neighbors of n_1 are malicious, for (e, f) both neighbors of n_1 are malicious.

If $u_{n_1, n_2}(F, R) = \alpha_F \gamma - \beta_2$, then $u_{n_1, n_3}(F, *) = 0$, and vice versa (Rule 1).

If $u_{n_1, n_2}(F, *) = -\beta_2$, then $u_{n_1, n_3}(F, -R) = 0$ and $u_{n_1, n_3}(F, R) = \alpha_F \gamma$, and vice versa (Rule 2).

If $u_{n_1, n_2}(D, *) = -(\beta_1 + \Delta \beta_1)$ or $u_{n_1, n_2}(D, *) = -\beta_1$, then $u_{n_1, n_3}(D, *) = 0$, and vice versa (Rule 3).

If $u_{n_1, n_2}(R, *) = -\beta_1$, then $u_{n_1, n_3}(R, -F) = 0$, and vice versa (Rule 4).

[Figure 3.a: Rules for network topology a and b (Mao, Zhu, & Wei, p.4, 2013)]

If $u_{n_1, n_2}(D, *) = -(\beta_1 + \Delta \beta_1)$ or $u_{n_1, n_2}(D, *) = -\beta_1$, then $u_{n_1, n_3}(D, *) = 0$, and vice versa (Rule 5).

If $u_{n_1, n_3}(R, *) = -\beta_1$, then $u_{n_1, n_3}(R, -F) = 0$, and vice versa (Rule 6).

If $u_{n_3, n_1}(J, R) = \alpha_J \gamma - (\beta_2 + \Delta \beta_2)$, then $u_{n_2, n_1}(F, R) = -\beta_2$ (Rule 7).

In pattern (d), we have one more exception rule.

If $u_{n_3, n_1}(J, R) = \alpha_J \gamma - (\beta_2 + \Delta \beta_2)$, then $u_{n_1, n_2}(F, R) = -\beta_2$ (Rule 8).

[Figure 3.b: Rules for network topology c and d (Mao, Zhu, & Wei, p.4, 2013)]

If $u_{n_1, n_2}(R, *) = -\beta_1$, then $u_{n_1, n_3}(R, R) = 0$ and $u_{n_1, n_3}(R, S) = 0$, and vice versa (Rule 9).

If $u_{n_2, n_1}(J, R) = \alpha_J \gamma - (\beta_2 + \Delta\beta_2)$, then $u_{n_3, n_1}(F, R) = -\beta_2$, and vice versa (Rule 10).

In pattern (f), we have one more exception rule.

If $u_{n_2, n_1}(J, R) = \alpha_J \gamma - (\beta_2 + \Delta\beta_2)$, then $u_{n_1, n_3}(F, R) = -\beta_2$, and vice versa (Rule 11).

[Figure 3.c: Rules for network topology e and f (Mao, Zhu, & Wei, p.4, 2013)]

The first two rules stated in [Figure 3.a] are also included in the other two network topologies stated in [Figure 3.a-b].

As it can be observed from [Figure 3.a-b-c], since all nodes take an action simultaneously in each turn, no node should pay more than once for an action. Payoff values for nodes and their corresponding neighbors are recalculated according to the defined rules.

3.IMPLEMENTATION

In this section, implementation details are explained. Additionally, there are several additional assumptions/differences in the implementation compared to the original work. These are also explained in this section.

//WSN is a simple-undirected-unweighted graph

// Node is any vertex on WSN

// PayOffs is a dictionary that keeps track of pay-offs for each neighbor pair on WSN. This is the same thing denoted as $U_{ni,nj}$ at [Table 2].

```
def pairwiseGamesForSingleNode(WSN, node, payOffs):
    for neighbor in node.neighbors:
        pairwiseGameForTwoNodes(node, neighbor, payOffs)
        // Update payOffs dictionary according to [Figure 1]
    for neighbor1, neighbor2 in node.neighbors:
        if neighbour1 != neighbor2:
            applyRules(node, neighbour1, neighbor2, payOffs)
            // Update payOffs dictionary according to [Figure 3]
    return payOffForNode(node, payOffs)

// Calculate total pay-off for node equals to  $\sum_{n_2}^R u_{n,n_2}$  where R
are neighbors of n.
```

[Pseudo Code 2:Game theoretical algorithm for a single node (Mao, Zhu, & Wei, p.5, 2013)]

[Pseudo Code 2] provides a game-theoretical algorithm to combine pairwise simultaneous games in [Figure 1] and exception rules in [Figure 3].

[Pseudo Code 2] only calculates the payoff for a single node. Therefore, to calculate all payoffs [Pseudo Code 3] is used. To

calculate payoffs for all nodes in WSN, it is preferred to traverse WSN with Breadth-First Search (BFS) and call the function in [Pseudo Code 2] for each traversed node.

// Output is dictionary of total payoffs for each node, defined as P

def getAllPayOffs(WSN, node, payOffs):

assignInitialActions(WSN)

// Randomly assigns an initial action to each node in WSN

for each n in BFS over WSN:

P[node] = pairwiseGamesForSingleNode(WSN, n, payOffs)

return P

[Pseudo Code 3:Game theoretical algorithm for WSN (Mao, Zhu, & Wei, p.6, 2013)]

[Pseudo Code 3] only iterates once for a WSN. It is impossible to get equilibrium by examining only one iteration. Therefore, multiple iterations are needed. [Pseudo Code 4] iterates the algorithm in [Pseudo Code 3] k times, and averages payoffs for each action-node pair. After averaging these actions for each node, calculate the equilibrium action for each node.

In [Figure 1] each node's payoff is -B1 when the action is Receive, on the other hand, each node's payoff is 0 when the action is Sleep. For this reason, an intelligent node would choose Sleep over Receive since it always gets a higher payoff. This is not specified in the paper, however, in this report, it is assumed that with %25 probability each node selects Sleep action to save battery. Equilibrium is calculated only considering the actions; Receive, Forward, Detect/Jam by looking at which action has a higher average payoff after k iterations. Therefore, the equilibrium state for a node is calculated with %75 probability.

// Output is dictionary of total payoffs for each node, defined as P

// Current payoff dictionary for WSN for the ith iteration, defined as payoff

// Average payoff dictionary for each node including ith iteration, defined as averagePayOffs

// A dictionary that keeps calculated equilibrium actions for each node, defined as equilibriumActions

def getEquilibriumActions(WSN, k):

for i in [1,...,k]:

payoff = pairwiseGamesForSingleNode(WSN, n, payOffs)

updateAveragePayOffs(averagePayOffs, payoff)

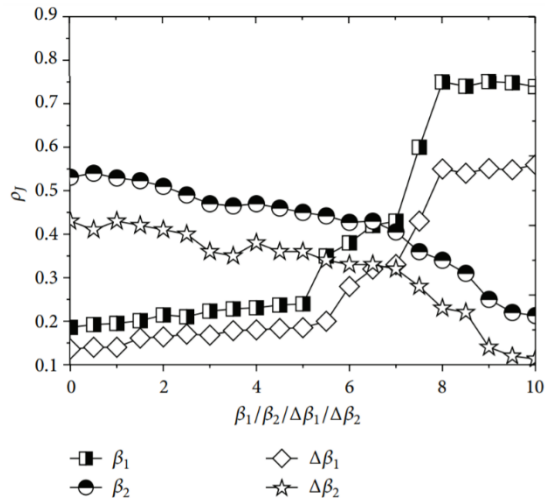
equilibriumActions = getEquilibriumActions(averagePayOffs)

return equilibriumActions

[Pseudo Code 4:Iterative Algorithm over Pseudo Code 3]

4.SIMULATION

There are significant differences in the simulation of [Pseudo Code 4] compared to provided simulation in the paper due to computational/time constraints. It results in some differences between replicated-provided simulations' results which are explained in [section 5].

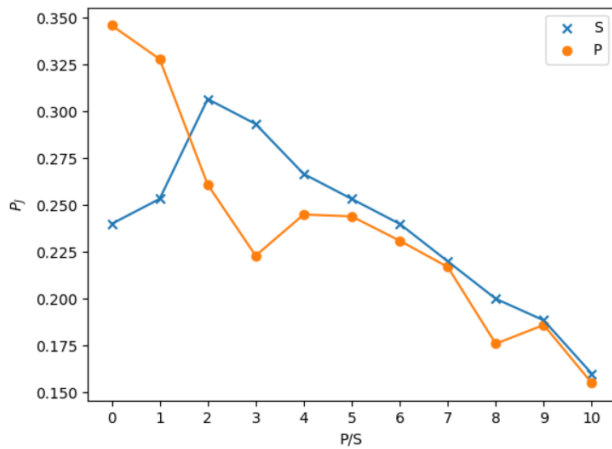


[Figure 4.a: Simulation results from the paper (Mao, Zhu, & Wei, p.6, 2013)]

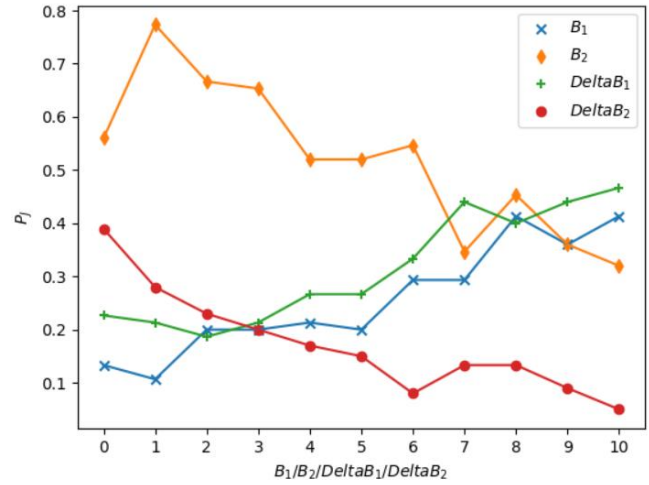
In the simulation, the effect of B_1 , B_2 , ΔB_1 , ΔB_2 , P , S on P_j (Fraction of malicious nodes that select jamming action) are examined by changing the value of one variable while keeping others' values the same.

Detailed variables' value-related information is explained in [Table 3].

| |
|--|
| Dynamic variables can take values of $[0,1,\dots,10]$. Their default value is 1. |
| Static Variables; $Y=1$, $A_F=0.75$ and $A_J=1$ |
| Average Number of Neighbors: 8 |
| Number of Nodes in a WSN: 1000 |
| Initial Probability for 4 Actions: %25 |
| Number of Different WSNs used: 1000 |
| Number of Malicious Nodes in a WSN: 100 |
| $P_j = \text{Average } ((\# \text{ of nodes decide to jam}) / (\# \text{ of malicious nodes}))$ for each WSN in the simulation) |



[Figure 5.b: Simulation results for replicated algorithm]



[Figure 4.b: Simulation results for replicated algorithm]

*Number of Iterations (k): 250 (In this report)

* Originally 3000 generations after 10.000 transient generations

*Due to time/computation power constraints simulation results obtained only after 250 iterations for each dynamic variable.

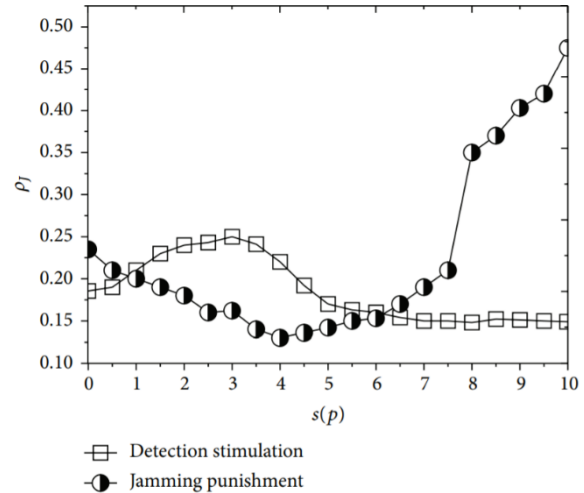
*Designed algorithm for this project is open further running-time improvements.

* This report does not include any joint affect analysis of dynamic variables due to the reasons specified above.

[Table 3: Detailed information about simulation]

5.SIMULATION RESULTS

In [Figure 4], both replicated and provided simulation results for dynamic variables B_1 , B_2 , ΔB_1 and ΔB_2 by the paper [1] are provided. Also, in [Figure 5], simulation results are provided similarly for dynamic variables P and S .



[Figure 5.a: Simulation results from the paper (Mao, Zhu, & Wei, p.7, 2013)]

5.1 [Figure 4] Comparisons

In the following table, similarities and differences in the simulation results in [Figure 4] are compared. Examined variables in this section are B1, B2, $\Delta B1$ and $\Delta B2$.

| [Figure 4.a] | [Figure 4.b] |
|---|---|
| All the scatter plots nearly are *bitonic sequences | Too many fluctuations in the scatter plots |
| When B1 increases, P_j tends to increase. (especially from 5 to 8) | Similarly, When B1 increases, P_j tends to increase. (There are also some decreases, not the case in figure-a) |
| When B2 increases, P_j tends to decrease. (After 7, decrease is fastened) | Similarly, when B2 increases, P_j tends to decrease. (There are also some increases, not the case in figure-a) |
| When $\Delta B1$ increases, P_j tends to increase. (especially from 6 to 8) | Similarly, when $\Delta B1$ increases, P_j tends to increase. |
| When $\Delta B2$ increases, P_j tends to decrease. (After 7, decrease is fastened) | Similarly, when B2 increases, P_j tends to decrease. |

*sequence of numbers which is first strictly increasing then after a point strictly decreasing vice versa.

[Table 4: Simulation interpretations for [Figure 4]]

Although replicated algorithm produces fluctuating simulation results (probably due to the small number of iterations (k)), both results suggest that when B1(Cost to receive a packet/detect jamming) and $\Delta B1$ (Additional cost to detect jamming) increases P_j (Fraction of malicious nodes that select jamming action) tends to increase and vice versa.

On the other hand, both results suggest that when B2 (Cost to forward a packet/jam) and $\Delta B2$ (Additional cost to jam) increases P_j (Fraction of malicious nodes that select jamming action) tends to decrease and vice versa.

5.2 [Figure 5] Comparisons

In the following four tables, similarities and differences in the simulation results in [Figure 5] are compared. Examined variables in this section are P and S.

| [Figure 5.a] | [Figure 5.b] |
|--|--|
| All the scatter plots nearly are bitonic sequences | Only the scatter plot for S is nearly a bitonic sequence, whereas the scatter plot for S is fluctuating |
| When S increases from 0 to 3, P_j tends to increase. After 3, P_j tends to decrease. | When S increases from 0 to 2, P_j tends to increase. After 2, P_j tends to decrease. |
| When P increases from 0 to 4, P_j tends to decrease. After 4, P_j tends to increase. | Differently, when P increases, P_j always tends to decrease. (Although there are some fluctuations, the pattern is to decrease) |

[Table 5: Simulation interpretations for [Figure 5]]

Similarly, both results suggest that when S (Stimulus to a successful jamming detection of the normal node) increases, P_j tends to increase, and after some point, P_j tends to decrease.

Differently, the paper [1] suggests that when P (Punishment to detected jamming) increases, P_j tends to decrease and after some point, P_j tends to increase. On the other hand, the simulation result of replicated algorithm suggests that when P increases, P_j always tends to decrease (probably due to the small number of iterations (k)).

- ◆ S increases $\rightarrow P_j$ firstly increases to local maxima, then decreases to a stable value.
- ◆ P increases $\rightarrow P_j$ firstly decreases to local minima, then increases.
- ◆ Before threshold for S \rightarrow Not enough to encourage to detect jamming \rightarrow Increase in P_j
- ◆ After threshold for S \rightarrow # of jamming nodes are limited \rightarrow Limited income for detectors \rightarrow Decrease in P_j to a stable value
- ◆ For small P $\rightarrow P_j$ is constrained
- ◆ After threshold for P \rightarrow Income for malicious nodes exceeds income for detectors.

[Table 6: Further simulation interpretations for [Figure 5.a]]

6.SUMMARY

Although there are differences between the two simulation results (especially in S and some fluctuations in scatter plots), replicated algorithm mostly captures what the paper [1] suggests in its simulation results.

REFERENCES

- [1] Mao, Y., Zhu, P., & Wei, G. (2013). A Game Theoretic Model for Wireless Sensor Networks with Hidden-Action Attacks. International Journal of Distributed Sensor Networks, 9(8), 836056. doi:10.1155/2013/836056