HS301: Supporting Material
Understanding Terrorism Dynamics & Implementing Countermeasures

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Analysis of the Model:

The provided NetLogo simulation models the interactions between civilians, terrorists, and police agents within a social environment, focusing on radicalization, law enforcement actions, and de-radicalization. This analysis delves into the components, procedures, and simulation controls of the model, followed by an exploration of its dynamics and potential insights.

A. Components of the code

I. **Agent Breeds**
The simulation features three agent breeds: civilians, terrorists, and policemen represented by white, red and blue colors respectively, each representing distinct roles within the simulated environment.

II. **Global Variables**
Key global variables such as radicalization-threshold, radicalization-threshold_1, and learning-threshold influence agent behavior and interactions, setting thresholds for radicalization, de-radicalization, and police learning rates.

III. **Turtle Variables**
Each agent possesses an opinion_strength variable, determining their level of radicalization or commitment, influencing their interactions along with its characteristic color.

IV. **Procedures**
The model defines procedures for initializing the simulation, controlling agent movements, simulating police actions, checking for radicalization and de-radicalization, and adjusting police learning rates based on nearby terrorists.

V. Simulations Controls
The simulation runs for a specified number of ticks or until there are no terrorists left, with coefficients adjusting rates of radicalization, de-radicalization, and learning.
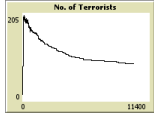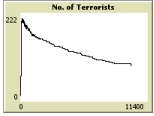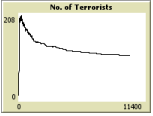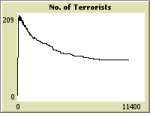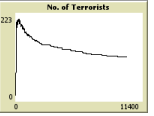
B. Analysis

The simulation mirrors real-world radicalization, law enforcement, and community dynamics. It shows how civilians can be influenced by extremists to become terrorists and how law enforcement adapts to counterterrorism efforts. By considering factors like opinion strength and learning thresholds, it offers insights into radicalization prevalence, law enforcement effectiveness, and community stability, aiding policymakers in devising strategies. So, in the following analysis we will study the effect of increasing the size of the police force along with tweaking other parameters like radicalization threshold, de-radicalization threshold and learning rate.
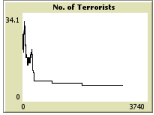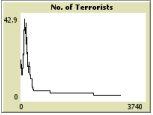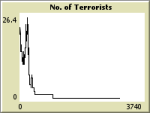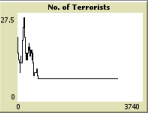
I. Effect of Police Force Size
The analysis underscores the significance of police force size in shaping counterterrorism effectiveness and resource allocation. Finding the optimal balance between police presence and resource expenditure is essential for mitigating terrorism activities while minimizing civilian casualties. Strategic deployment and complementary preventive measures play pivotal roles in enhancing the long-term efficacy of counterterrorism strategies. By fixating the following values, we tweak the number of policemen accordingly while examining each cases;

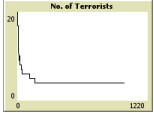| No. of civilians:	250
No. of terrorists:	20
rad_thres:	0.30
learn_rate:	0.30
rad_factor:	0.92
conv_factor:	0.95
rad_thres_1:	1.65
learn_rate_factor:	0.4
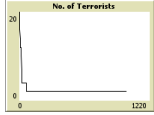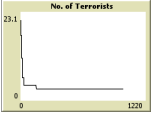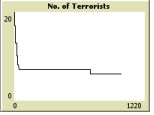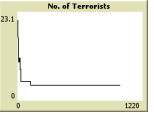
Case:1 No. of policemen = 5

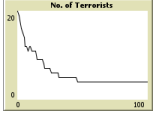| Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	3	7	5	9	2
Terrorists alive	87	94	109	98	113
Number of Ticks	9125	9329	10421	9784	9618
Plot					
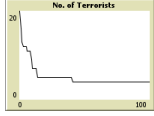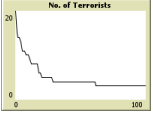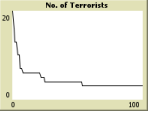
Case:2 No. of policemen = 20

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	257	230	209	215	232
Terrorists alive	7	6	3	1	7
Number of Ticks	1027	2875	3022	2751	2142
Plot					

Case:3 No. of policemen = 50

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	267	264	264	264	265
Terrorists alive	2	4	3	6	4
Number of Ticks	909	1012	928	1164	974
Plot					

Case:4 No. of policemen = 100

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	265	265	267	265	265
Terrorists alive	4	4	3	4	4
Number of Ticks	74	68	82	79	974
Plot					

These four cases provides an insight into the impact of police size in the process of counterterrorism;

a. *Increased Police Force:* More policemen lead to early mitigation of terrorism activities and fewer civilian casualties. This indicates higher effectiveness in neutralizing threats and maintaining community safety but it demands a huge investment in terms of resources which is not always feasible given a budget constraint.

b. *Decreased Police Force:* Fewer policemen result in prolonged response times and increased civilian casualties. While resource-efficient, this approach compromises counterterrorism effectiveness and community security.
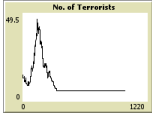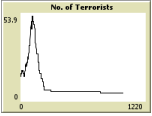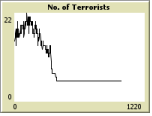
NOTE: For the analysis of the next three factors, the size of the police is fixated at 20.
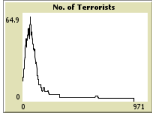
II.   Radicalization Threshold
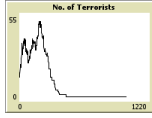
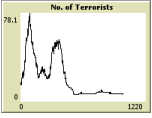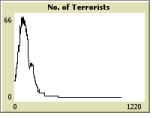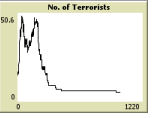By fixating the following values, we tweak the radicalization threshold accordingly while examining each cases;

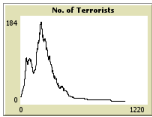|	
No. of civilians:	250
No. of terrorists:	20
learn_rate:	0.30
rad_factor:	0.92
conv_factor:	0.95
rad_thres_1:	1.65
learn_rate_factor:	0.4
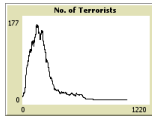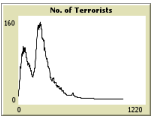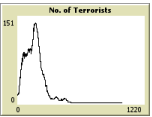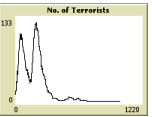
Case:1 rad_thres = 0.35

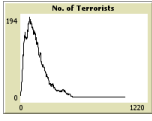| Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	148	213	203	222	190
Terrorists alive	2	6	5	5	2
Plot					
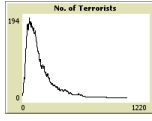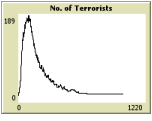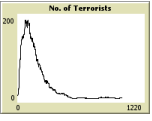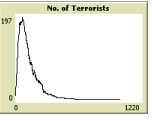
Case:2 rad_thres = 0.5

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	163	214	10	188	157
Terrorists alive	3	0	6	3	5
Plot					

Case:3 rad_thres = 0.75

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	17	29	24	22	11
Terrorists alive	9	7	10	2	4
Plot					

Case:4 rad_thres = 0.95

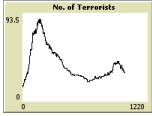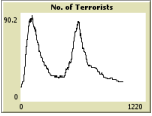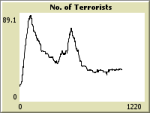| Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	23	24	15	18	28
Terrorists alive	10	12	7	10	7
Plot					

As we can infer from the above four cases, as the radicalization threshold increases (from 0.35 to 0.95), the number of civilians being radicalized increases. This indicates that a higher threshold makes civilians more susceptible to terrorist influence, leading to higher recruitment rates and vice-versa. The pattern indicates that the radicalization threshold plays a crucial role in determining the success rate of terrorist recruitment efforts. Higher thresholds facilitate easier radicalization, while lower thresholds act as barriers to recruitment.
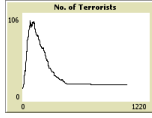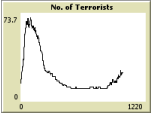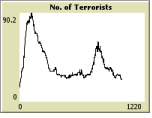
III.   De-radicalization Threshold

By fixating the following values, we tweak the deradicalization threshold accordingly while examining each cases;

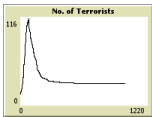|	
No. of civilians:	250
No. of terrorists:	20
learn_rate:	0.30
rad_factor:	0.92
conv_factor:	0.95
rad_thres:	0.45
learn_rate_factor:	0.4
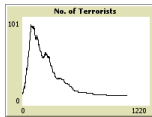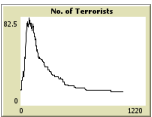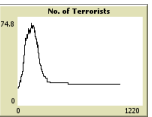
Case:1 rad_thres_1 = 0.65

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	13	6	2	21	0
Terrorists alive	14	30	20	32	16
Plot					
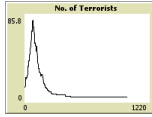
Case:2 rad_thres_1 = 1.05

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	104	23	83	17	98
Terrorists alive	20	16	24	22	22
Plot					

Case:3 rad_thres_1 = 1.35

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	138	150	162	168	177
Terrorists alive	11	29	13	25	18
Plot					

Case:4 rad_thres_1 = 1.65

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	195	140	156	179	210
Terrorists alive	5	5	3	5	0
Plot					
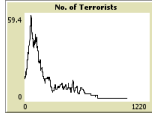
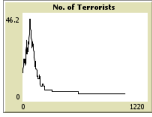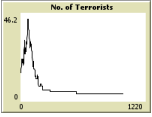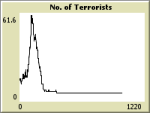We can infer from the above plots that a lower de-radicalization threshold (e.g., 0.65 and 1.05) results in fewer terrorists being converted back to civilians, indicating that lower thresholds make it harder for law enforcement to de-radicalize terrorists and vice-versa. The pattern suggests that the de-radicalization threshold influences the success of law enforcement efforts in reducing the number of active terrorists within the simulated environment.
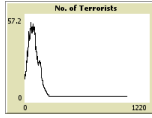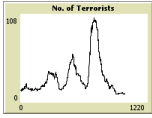
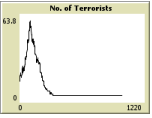## IV. Learning rate
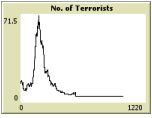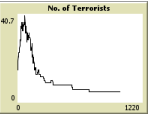
By fixating the following values, we tweak the learning rate accordingly while examining each cases;

No. of civilians:	250
No. of terrorists:	20
rad_thres:	0.45
rad_factor:	0.92
conv_factor:	0.95
rad_thres_1:	1.65
learn_rate_factor:	0.4
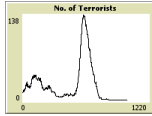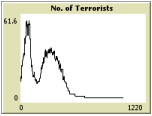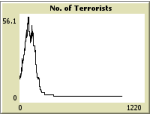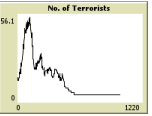
Case:1 learn_rate = 0.35

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	157	212	176	190	189
Terrorists alive	2	4	6	6	5
Plot					
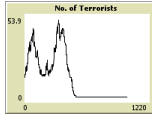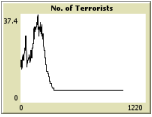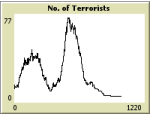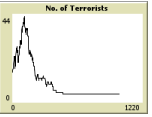
Case:2 learn_rate = 0.5

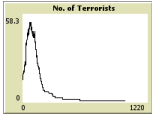| Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	182	16	175	186	231
Terrorists alive	4	10	5	5	5
Plot					

Case:3 learn_rate = 0.75

Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	15	220	115	194	159
Terrorists alive	4	1	3	4	5
Plot					

Case:4 learn_rate = 0.95

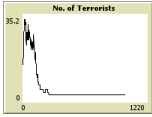| Index no.	Iteration-1	Iteration-2	Iteration-3	Iteration-4	Iteration-5
Civilians alive	149	226	199	12	181
Terrorists alive	3	3	5	5	4
Plot					

A higher learning rate (e.g., 0.75 and 0.95) for law enforcement leads to more effective counterterrorism actions, as evidenced by the lower number of terrorists remaining active over iterations. Conversely, a lower learning rate (e.g., 0.35 and 0.5) results in less effective law enforcement actions, with a higher number of terrorists remaining active. The pattern indicates that a higher learning rate enables law enforcement agents to adapt more quickly to the tactics and strategies employed by terrorists, resulting in better outcomes in terms of neutralizing terrorist threats.

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Ryan, Alex, and Anne-Marie Grisogono. "Hybrid Complex Adaptive Engineered Systems: A Case Study in Defence." (2004).

Zahedzadeh, Giti. "Containing Terrorism: A Dynamic Model." *Journal of Strategic Security*, vol. 10, no. 2, 2016, pp. 48-59.