Agent based Social Modeling and Simulation --- Understanding the Insurgent Emergent Behaviors Through Swarm Based Modeling

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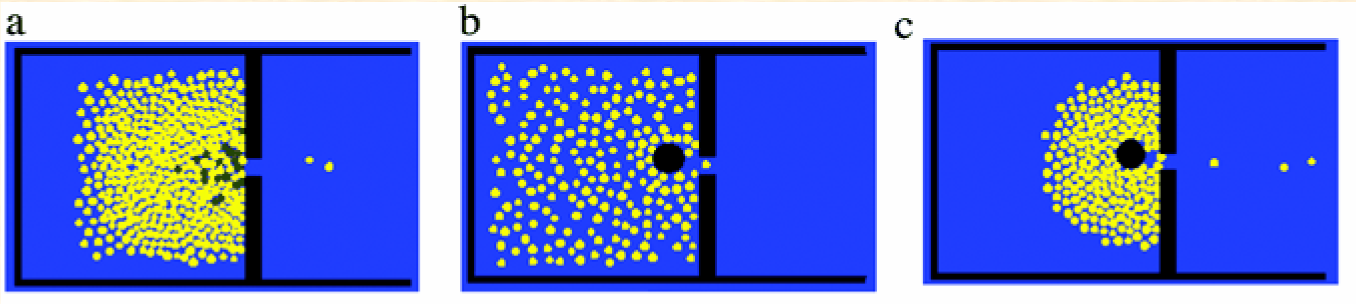
UT-BATTELLE

Agent Based Modeling (ABM)

- A multi-agent model consists of a number of software objects, the ‘agents.
- ‘Agents’ represent heterogeneous individuals who interact with each other and/or their environment based on set rules.
- From these interactions, macro-scale behaviors may emerge.

ABMS Examples

- Group control through indirect manipulation rather than explicit rules
- Evacuation: Fire escape situation in a confined space
  - How can one increase the outflow of people?
    - Put a column before exist
    - Exit without a column
  - Result: Counterintuitive emergent phenomena



Agent Based Social Simulation

- Social processes can be simulated by using ABM in the computer. Agents represent people or groups of people, and agent interaction represent processes of social interaction.
- In some circumstances, the ABM can be used to carry out experiments on artificial social systems that would be quite impossible or unethical to perform on human populations.
- The research of ABSS is on complex human social systems and how collective behavior rises from such systems

Idealized and Detailed Models

- **Idealized models**
  - **Boil down a collective phenomenon to its functional essence.**
  - **Describe domain-general mechanisms with a wide sphere of application.**
- **Detailed Models**
  - **Tied to a specific domain that include a considerable amount of detail derived from real world datasets for answering a specific real-world question.**

Strategy for choosing models

- **Start from a very simple model, which is easy to specify and implement.**
- **When one understands this simple model and its dynamics, extend the model to encompass more features and more complexity.**

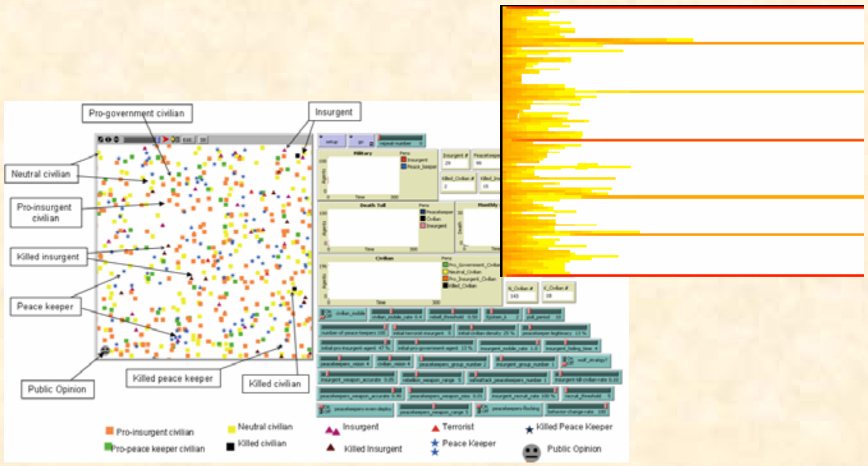
Scientific Understanding the Emergent Behaviors of Insurgency Warfare

- The insurgency warfare is the most widely used military tactic for against American forces around the world. Understanding how insurgent forces are formed, how they fight, and how to defeat them is a significant challenge for the U.S. military and the country.

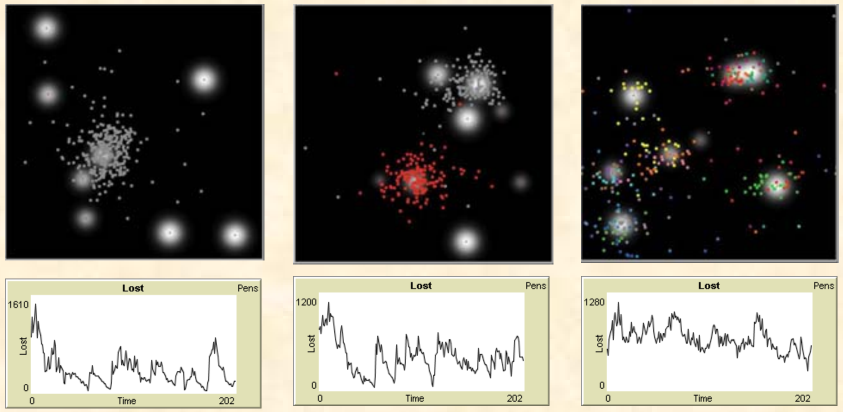
- Developing such a scientific understanding typically requires a great deal of time and effort in building detailed models of human behavior. An idealized Modeling Simulation is used in this research. The idealized modeling trade sophistication for speed and lower simulation costs.

- Using a high performance computer or computing grid to run a simulation thousands or millions of times across a large parameter and value space. The result is a "landscape" of output that can be analyzed for trends, anomalies, and insights in multiple parameter dimensions.

- The end results of this effort will enable military strategist to understand how the different kinds of social interactions and decisions at the individual level can eventually emerge as insurgency behaviors in macroscopic level. The simulation will help war fighters make a comparative examination of the current strategic approaches to COIN and develop alternate strategies for effectively neutralizing the insurgency threats.



Simulation for Counter-insurgency Operation Analysis

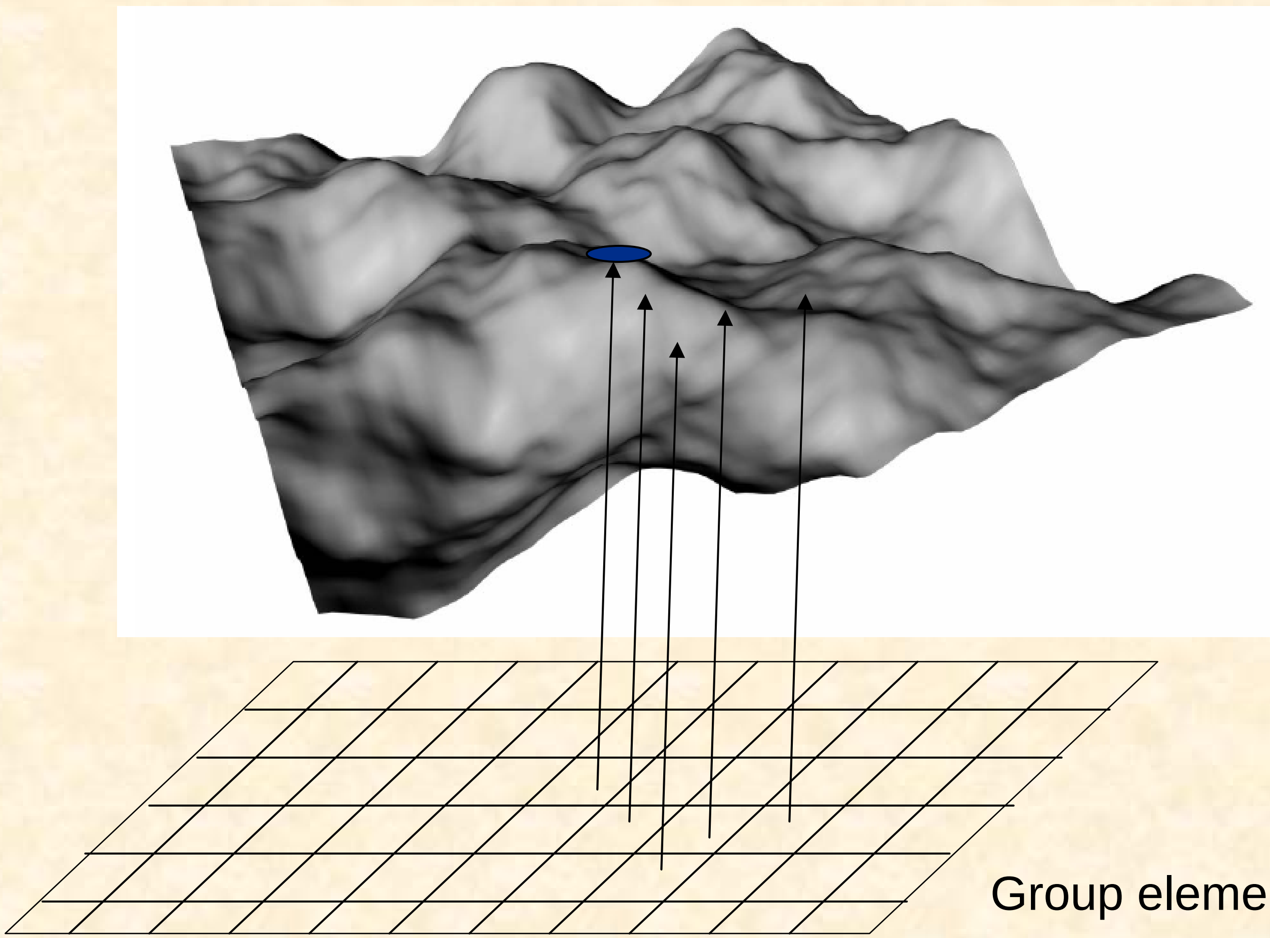


Trajectories and performance of insurgent agents for (a) one group, 300 insurgents, (b) two groups, 150 insurgents per group, (c) twenty groups, 15 insurgents per group

Research focus

- Social adaptive learning in insurgent groups' strategy evolution
  - Modeling the social adaptive and learning behavior of insurgent groups
  - Understanding of the impact of lacking unified leadership, planning, and effective communication among insurgent groups
- The emergence of extremism opinion
  - Simulate the Extremism Prevalence in Civilian Groups
  - Understanding of the micro-level motivations of extremism and local civilian behaviors for threat anticipation.
  - Developing a counter-extremism strategy for stopping the prevalence of radical opinion and eventually stopping the emergence of the insurgency.

Strategy Profit Landscape

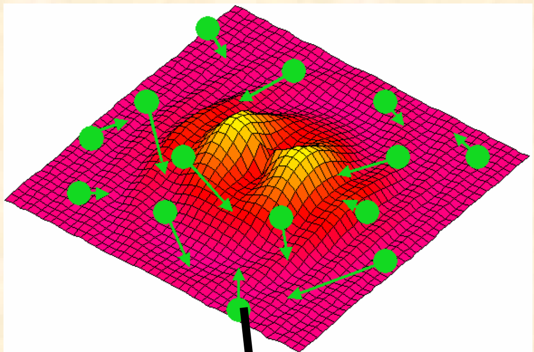


Group element strategy grid

PSO Based Human Group Strategy Searching Model

- **Particle swarm social adaptive**
  - **Every particle can be considered as a human group and particles interact with each other.**
  - **The group can learn skills and behaviors by observations. Particle are more likely to imitate models whose behavior is rewarded.**
  - **Each particle is constantly watching the particles around it to see how they are doing and adjust its behavior accordingly. (people can learn by observation)**
  - **Each particle also has a memory of its behavior history. (people can learn from their own experiences)**

A Particle in a Swarm



$X = <x_{t0}, x_{t1}, \ldots, x_{tn-1}>$

$P = <p_{t0}, p_{t1}, \ldots, p_{tn-1}>$

$G = <g_{t0}, g_{t1}, \ldots, g_{tn-1}>$

$V = <v_{t0}, v_{t1}, \ldots, v_{tn-1}>$

x-fitness = ?

p-fitness = ?

g-fitness = ?

A particle (individual) is composed of:

- **Four vectors:**
  - x-vector: **particle current position**
  - v-vector: **current velocities of the particle**
  - p-vector: **location of the best solution found by the individual particle**
  - g-vector: **location of the best solution found by the whole swarm.**
- **Three fitness values:**
  - x-fitness **the fitness of the x-vector**
  - p-fitness **the fitness of the p-vector**
  - g-fitness **the fitness of the g-vector.**

Update of Personal Best Value and Global Best Value

•Once the particle moves to the new location and computes the new X_i, it then evaluates its new location $f(x_i)$.

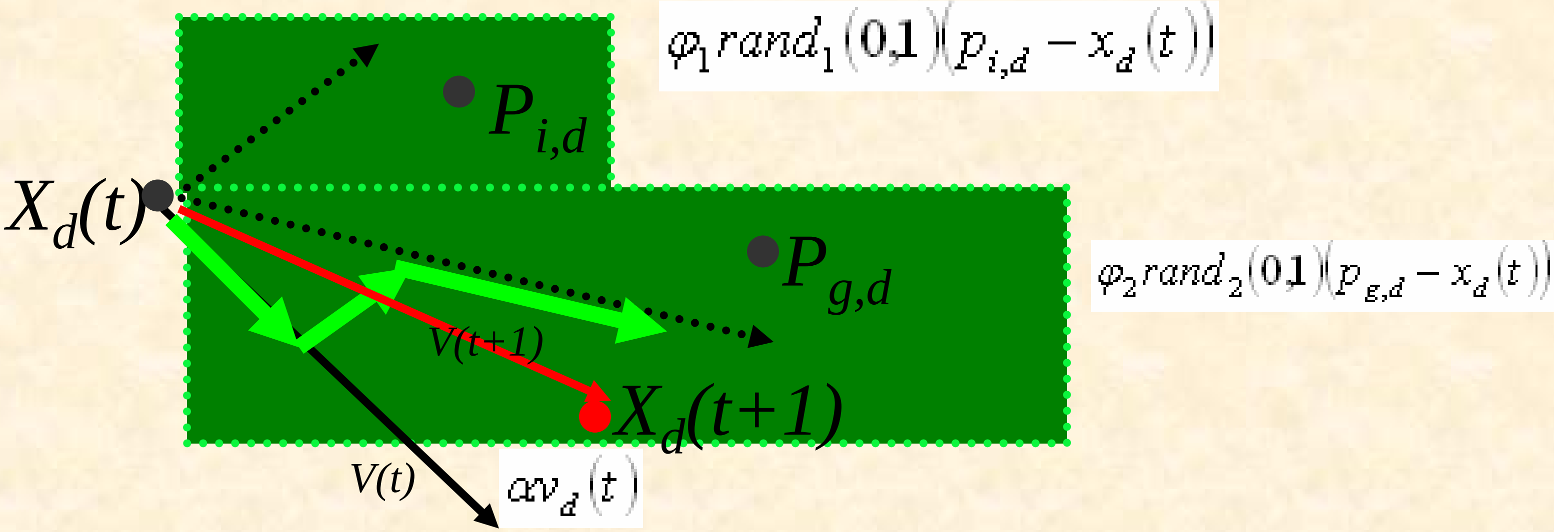
•If f(xi) is better than the value in particle's memory, then Pi = Xi and personal best value = current fitness value.

$$P_i(t+1) = \begin{cases} P_i(t) & f(X_i(t+1)) \le f(X_i(t)) \\ X_i(t+1) & f(X_i(t+1)) \rangle f(X_i(t)) \end{cases}$$

$$P_g(t+1) = \begin{cases} P_g(t) & MAX(P_i(t+1)) \le P_g(t) \\ P_i(t+1) & MAX(P_i(t+1)) \succ P_g(t) \end{cases}$$

Particle Swarm Optimization:
Searching for high benefit strategy

- Each particle's movement is partly influenced by its own previous experience, "p_i", *a*lso partly influenced by the best solution in the whole group, "p_g".



$$v_d(t+1) = wv_d(t) + c_1 rand_1(0,1)(p_{i,d} - x_d(t)) + c_2 rand_2(0,1)(p_{g,d} - x_d(t))$$

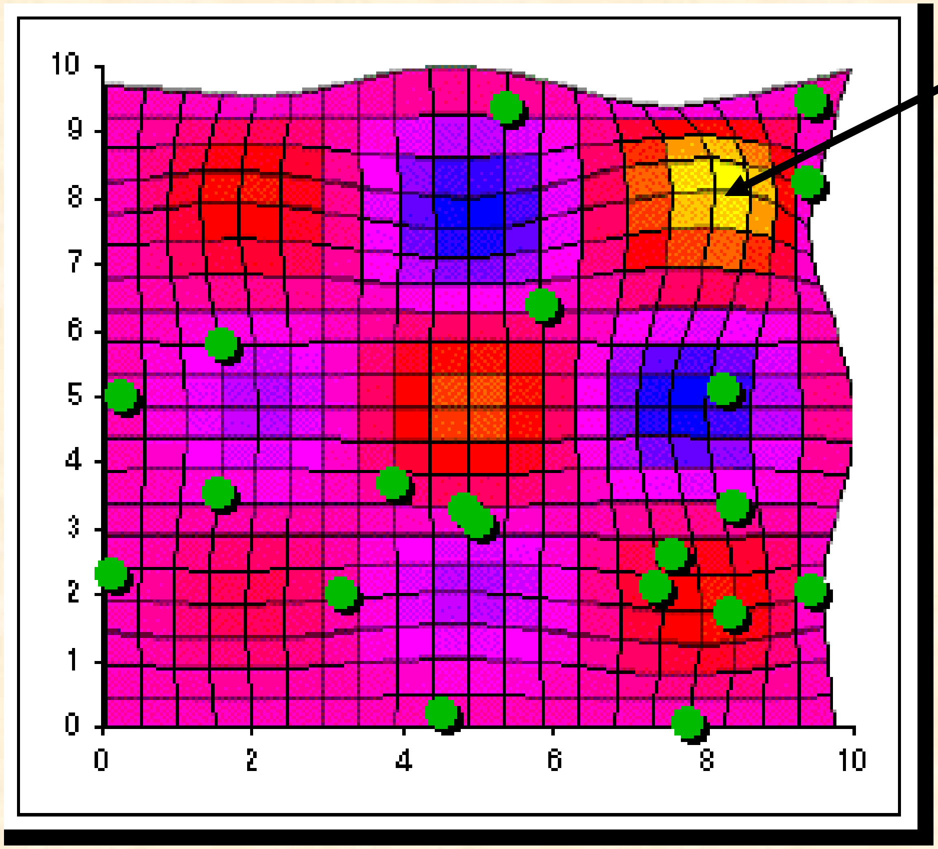
Personal Cognition　　Social Adaptive Learning

$$x_d(t+1) = x_d(t) + v_d(t+1)$$

$$w = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}}$$

$$\varphi = c_1 + c_2, \varphi > 4$$

Animated Illustration

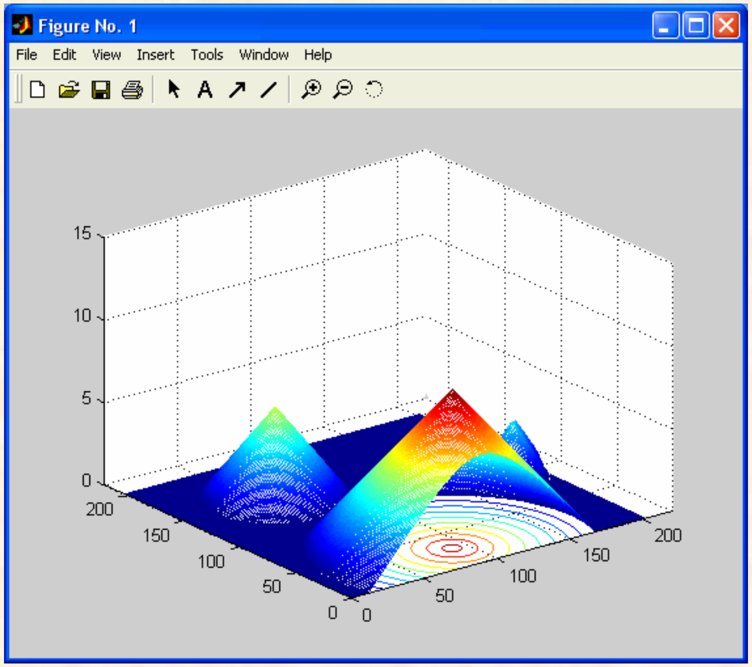


Global optimum

Slide source: M. Clerc's presentation.

Dynamic Strategy Adaptive Landscape

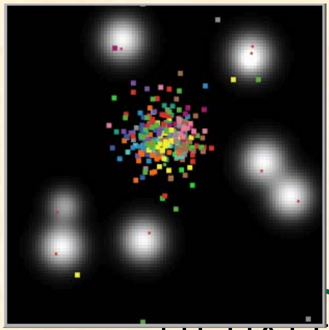
When the environment is dynamic, the task of the optimization is not only to acquire the extreme but also to track the extreme's trajectory as closely as possible.



There is no fix best strategy profit since the outcome profit from a strategy depends on the other insurgents.

Limitation of traditional PSO

- The dynamic change of the strategy profit value location requires the particle to renew its memory whenever the environmental status does not match its memorized knowledge.
- The traditional PSO lacks an update mechanism to renew the particles' memory when the environment changes. The particle will continue use the obsolete knowledge to direct its search, and the particle can be easily trapped in the region of the former optimal solution.



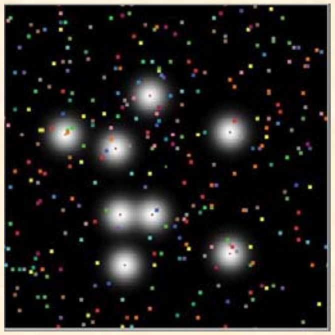
Tracking Dynamic PSO (TDPSO)

- A new parameter, the evaporation rate T, is introduced into PSO. The personal best fitness value and global best fitness value will evaporate (decrease) at the rate of the evaporation rate T over time.
- The evaporation rate T is a constant between 0 and 1.

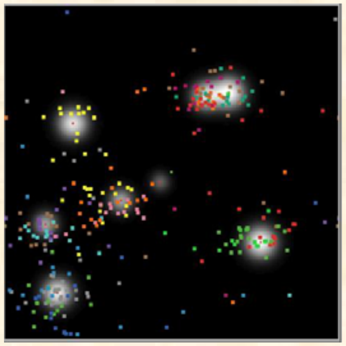
$$P_i(t+1) = \begin{cases} P_i(t) * T & f(X_i(t+1)) \le P_i(t) * T \\ X_i(t+1) & f(X_i(t+1)) \rangle P_i(t) * T \end{cases} \qquad T \in (0,1)$$

$$P_g(t+1) = \begin{cases} P_g(t) * T & MAX(P_i(t+1)) \le P_g(t) * T \\ P_i(t+1) & MAX(P_i(t+1)) \succ P_g(t) * T \end{cases} \qquad T \in (0,1)$$

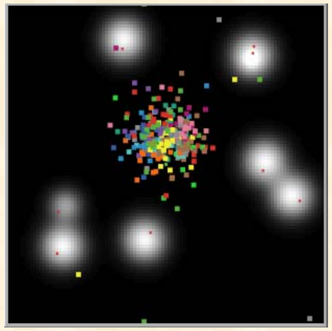
In TDPSO, each particle uses the same velocity function as PSO to calculate its next location



The initial environment

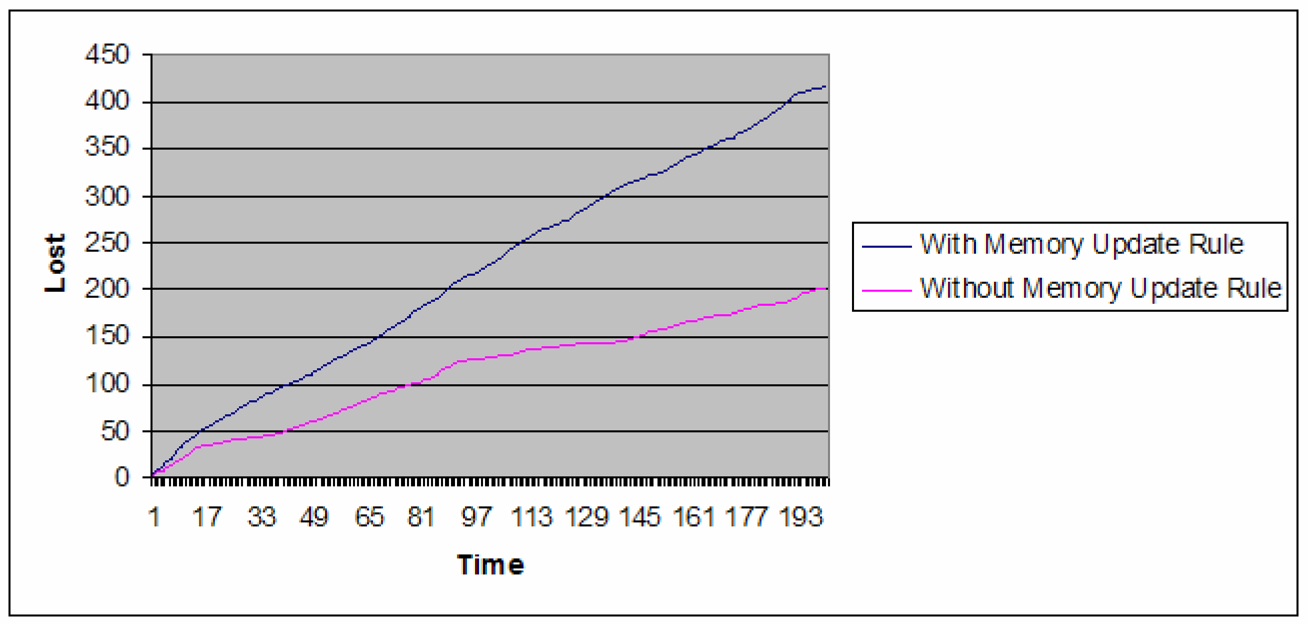


The strategy chose by insurgent particles with memory update capability



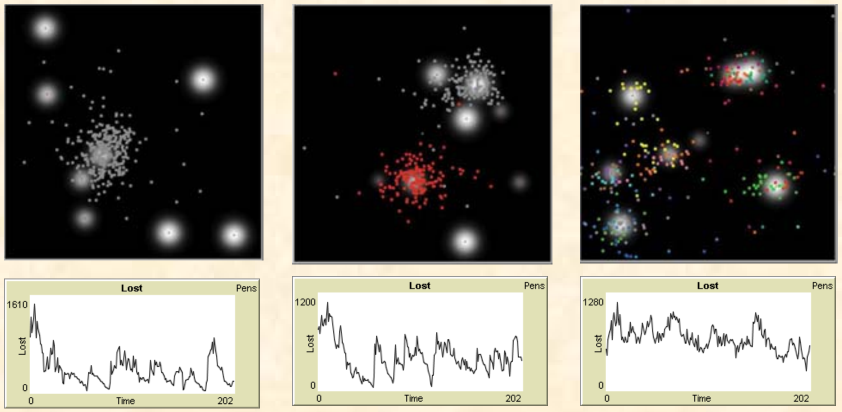
The strategy chose by insurgent particles without memory update capability

The average profit gained by insurgents with memory update and without memory update



The impact of lacking unified leadership, planning, and effective communication among insurgent groups

- **the performance of the insurgent particles for one insurgent group with 300 insurgents, two insurgent groups with 150 insurgents in each group , and twenty insurgent groups with 15 insurgent in each group are compared.**



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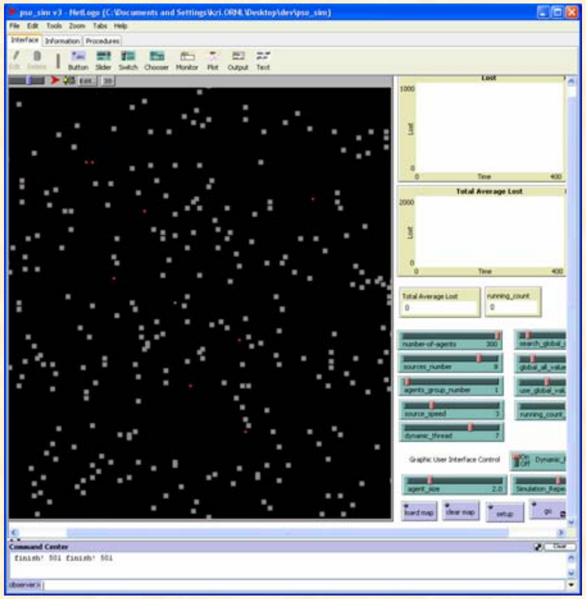
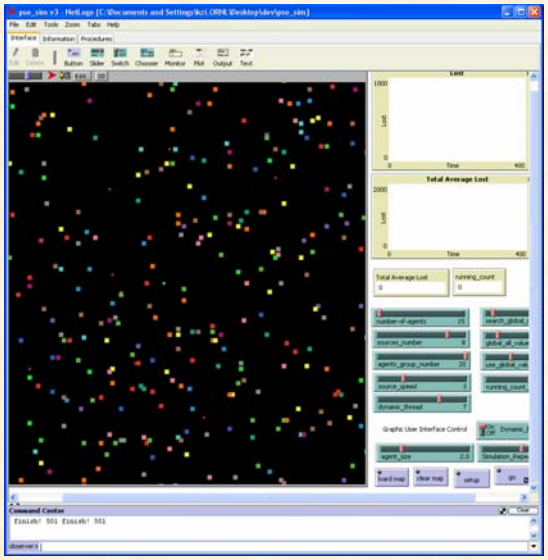
The results show that unified leadership, strategic planning, and effective communication between insurgent groups are not the necessary requirements for insurgents to efficiently attain their objective.





Without combining the insurgent strategy choosing with the dynamic change of the strategy profit, it is hard to understand the emergent behavior of the insurgent groups.

Summary

- **Modeling complex situations is very costly and labor intensive**
- **Swarm models use simple individual behavior to quickly model complex dynamic interactions.**

Conclusion

- Rerunning the simulation with a new random starting configuration will yield a different pattern of behaviors (Clusters in Schelling model).
- The important point about most ABSS models is not that they generate a particular pattern of behaviors, but that in every case, for a specific set of parameters, some behavior trends always emerges.

Verification Challenge

- **There are many different models may yield the same emergent patterns. In the insurgent simulation, the trend and pattern output of PSO model doesn’t means this model is the correct model that represents the real world situation.**

Thanks!

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