Exploring Optimization Methodologies for Systematic Identification of Optimal Defense Measures for Mitigating CB Attacks

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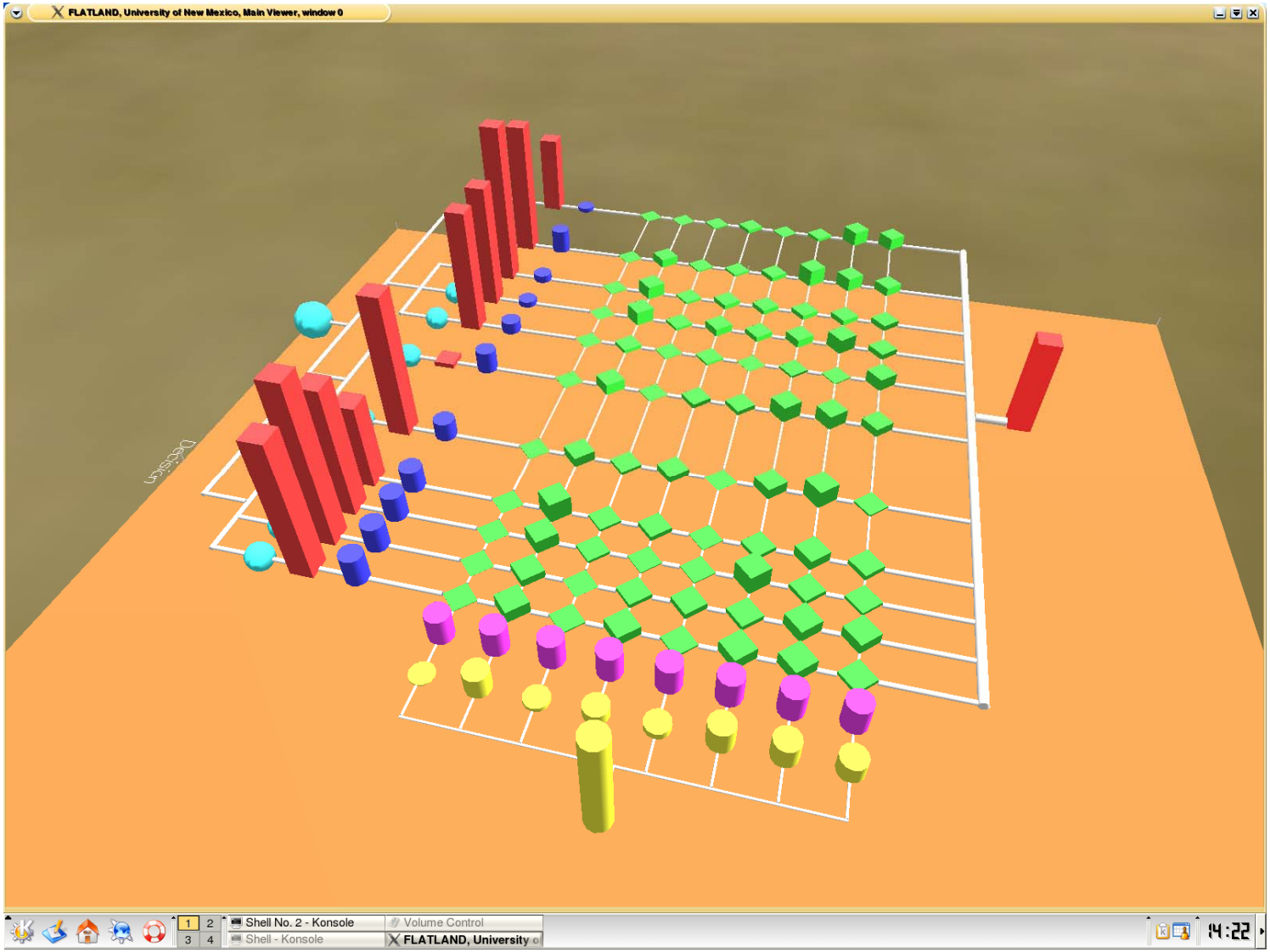
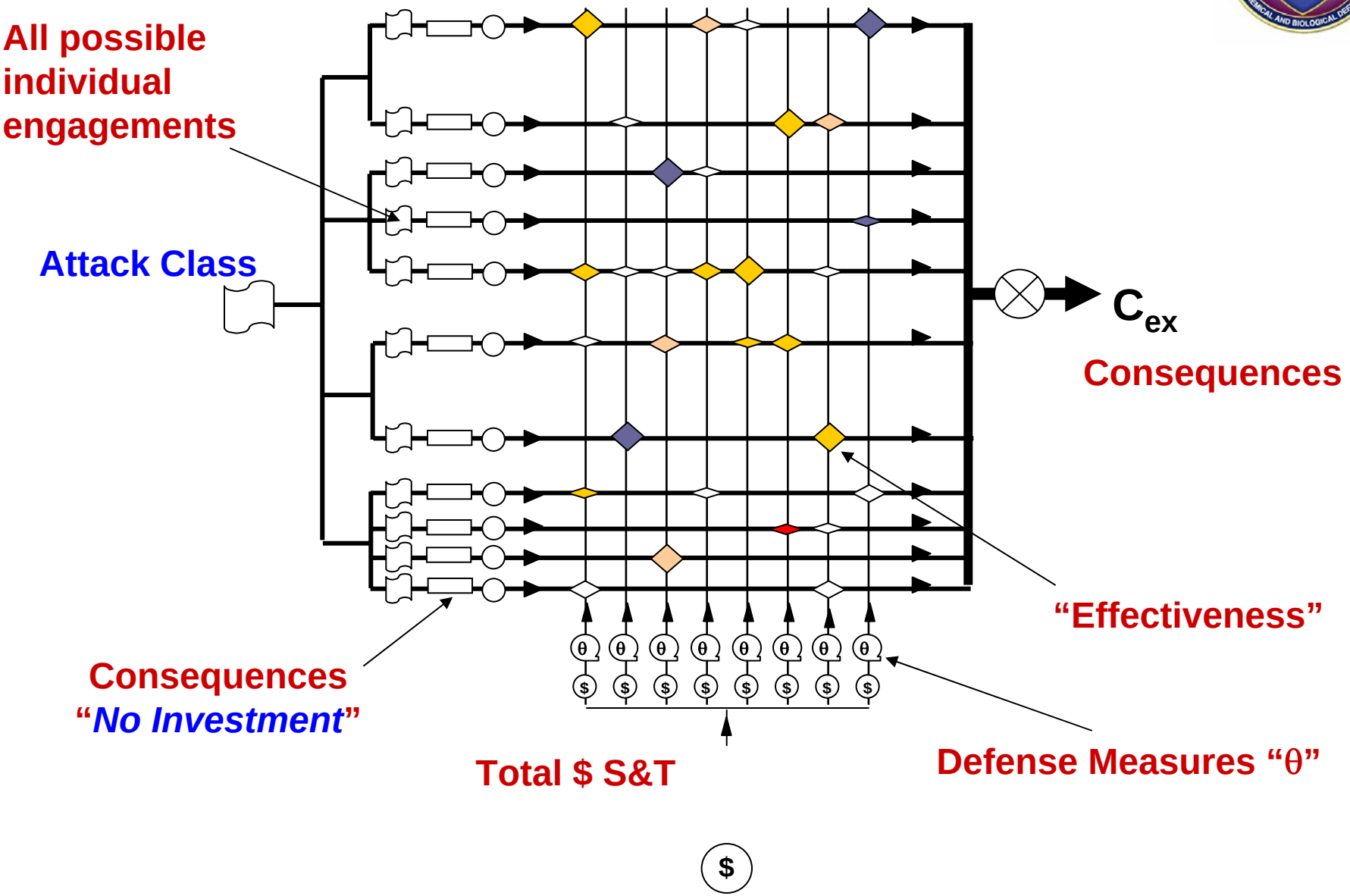
Outline

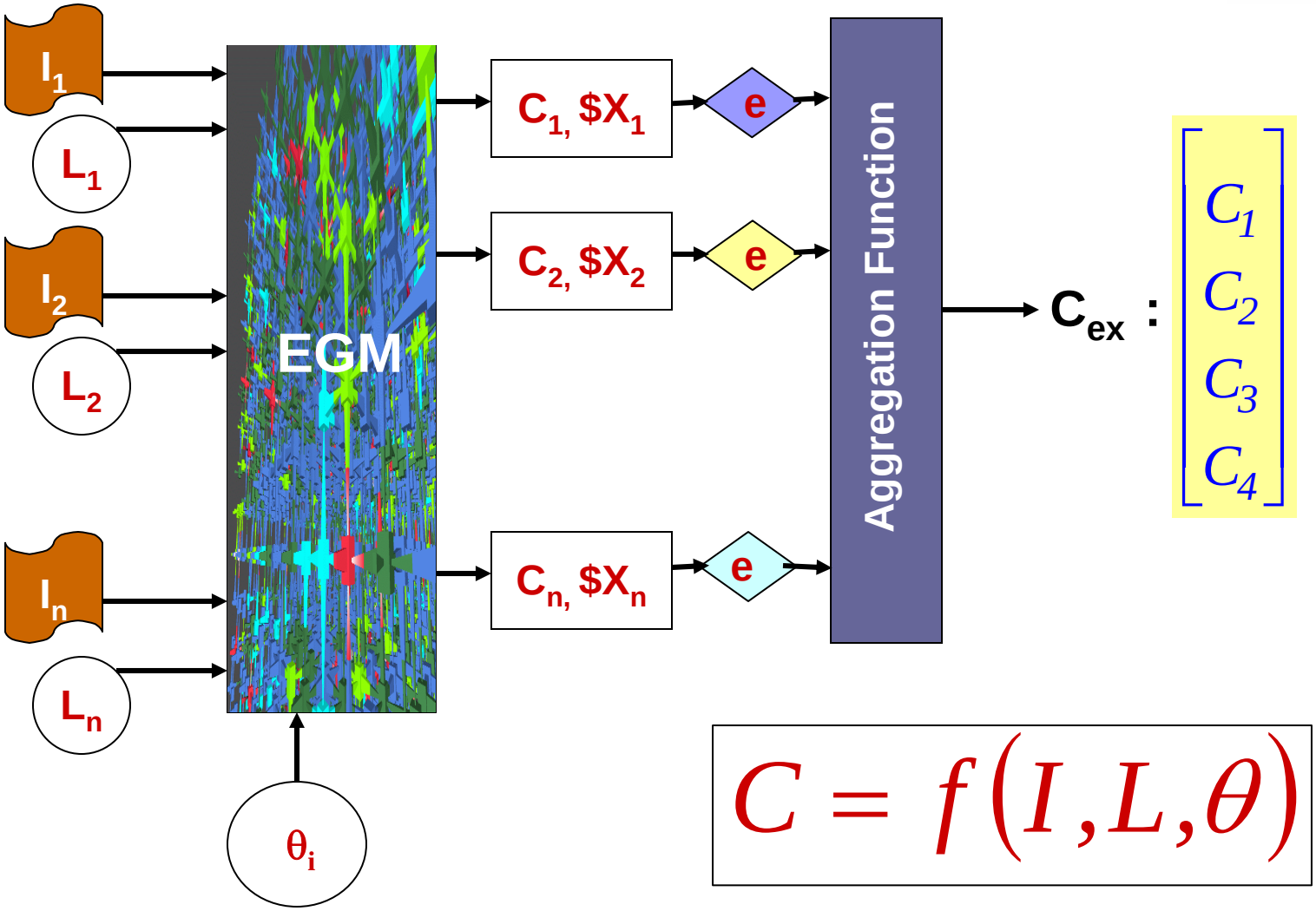
- The general architecture
- How the analytic tool relates to the architecture
- Optimization mode: the problem
- Optimization Techniques With Example Application
- Conclusions

The General architecture




All possible individual engagements
Attack Class
C_{ex}
Consequences
"Effectiveness"
Consequences
"No Investment"
Total $ S&T
Defense Measures "θ"
θ
$

The Analytic Tool "Exploration Mode"



$$C = f(I, L, \theta)$$

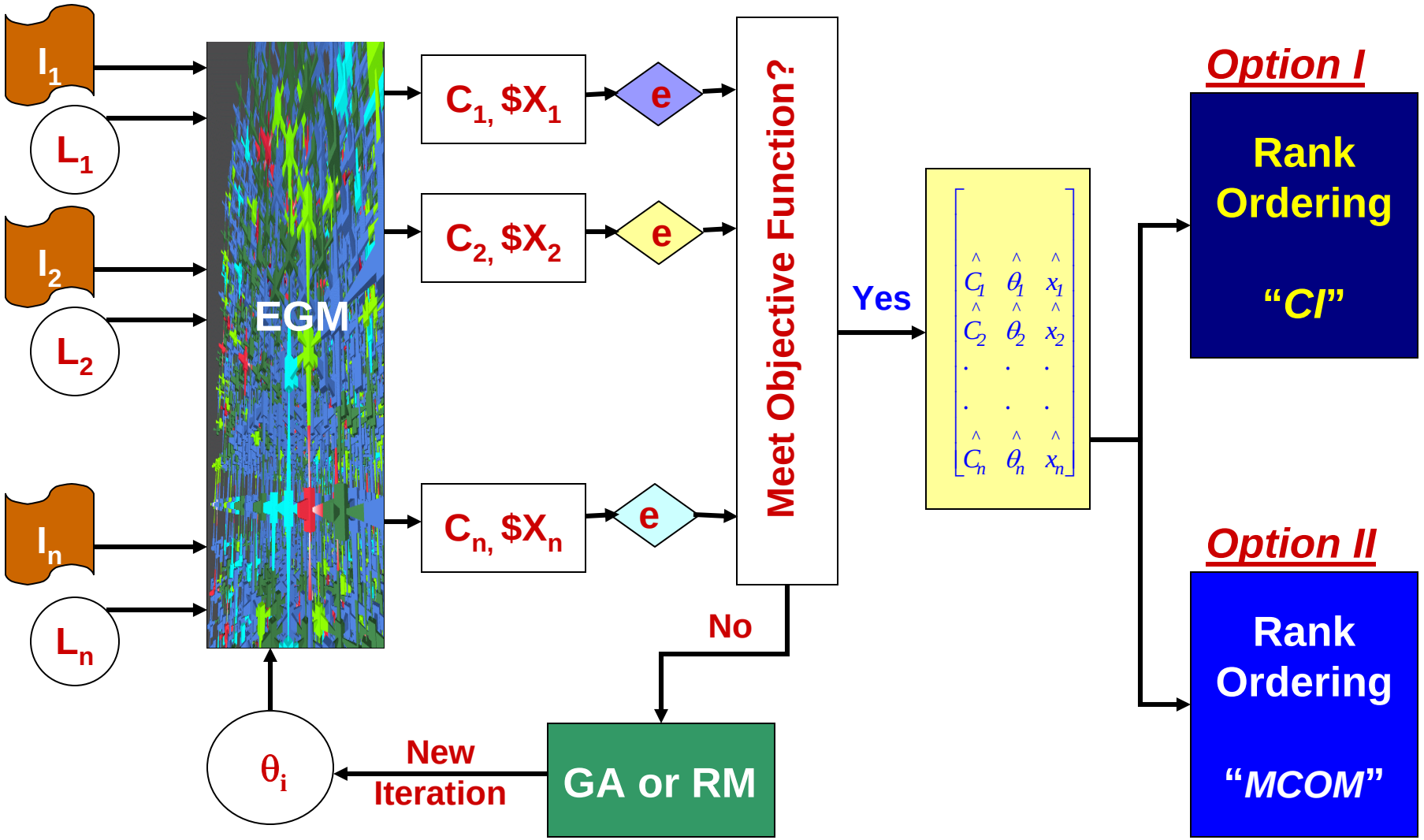
EGM: Engagement Generation Module

The Analytic Tool: "Optimization Mode"

❑ Problem Statement

What is the ***optimal way*** to distribute ***$X*** to ***N (mitigating variables) defense measures*** in order to reduce damage ***(consequences) of a CB attack***?

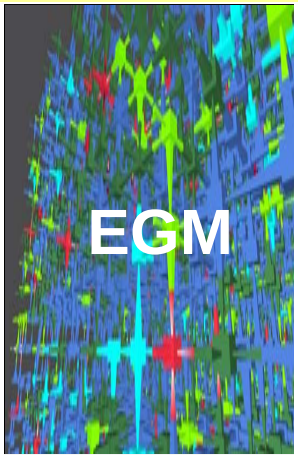
The Analytic Tool: "Optimization Mode"



Analytic Toolbox

- Three main components

Component I:



Component II:

Optimization Module

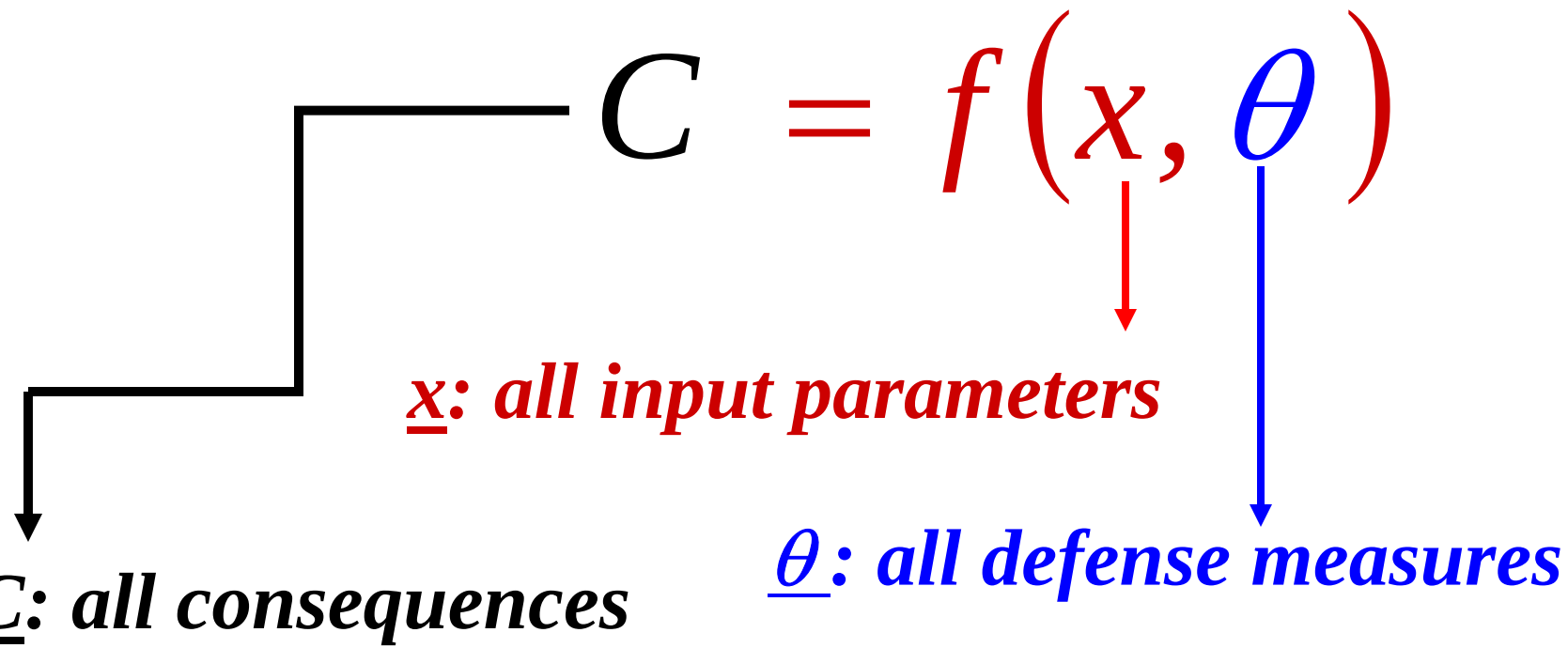
Component III:

Rank Ordering Module

Focus of this talk

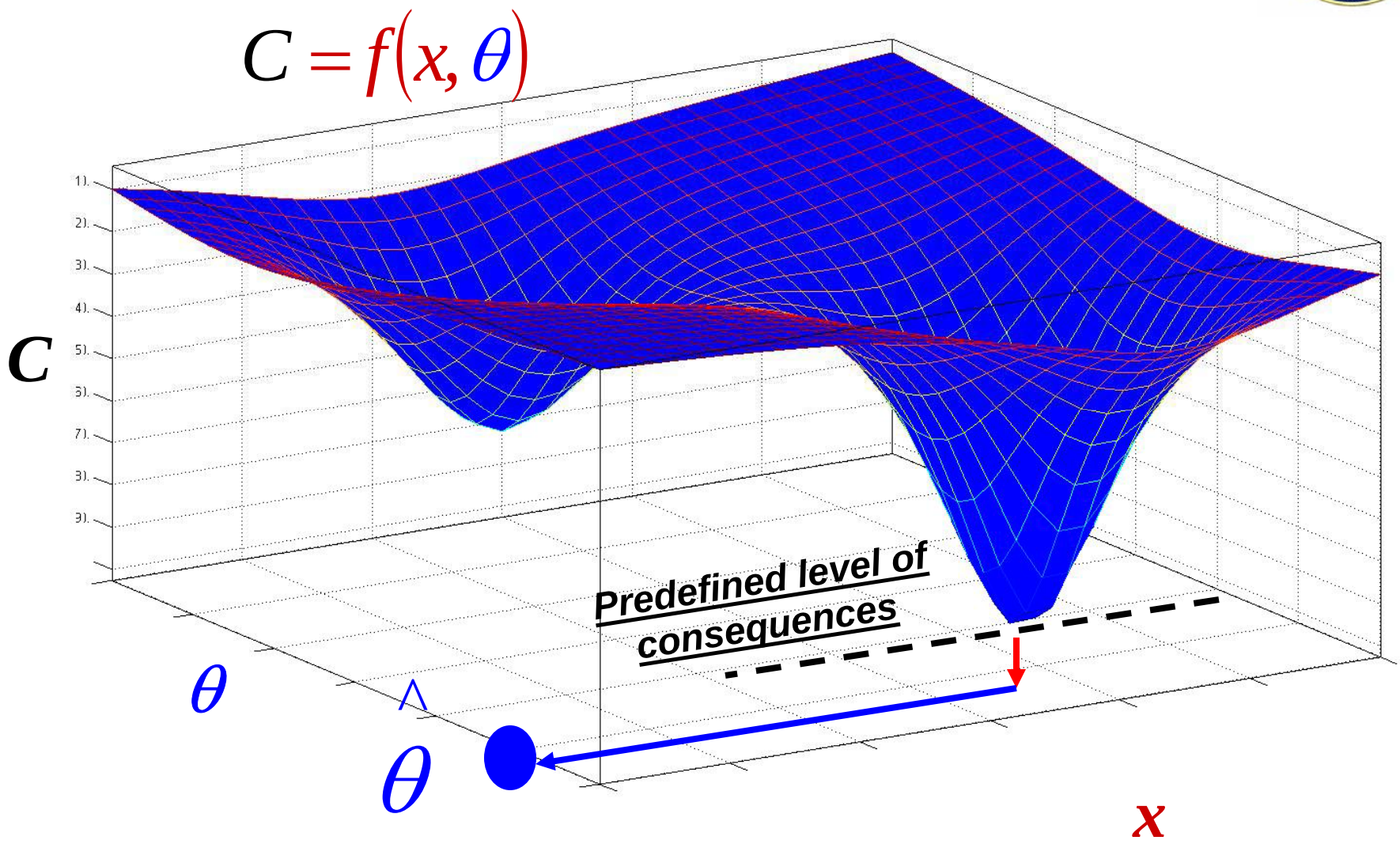
Component II: Optimization Module

Mathematically, we can describe ***the relation*** as



The ***optimization module*** targets finding the optimal ***defense measures*** ($\hat{\theta}$) and their associated ***cost*** ($\$\hat{X}$) that achieves a predefined set of consequences ($\boldsymbol{C_{ex}}$) considering all possible attacking engagementss.

If we have a bimodal surface



The challenge is that the ***function*** that can describe the ***relationship*** between ***CB attack parameters*** (attack target, attacker, etc), the defense measures and the ***attack consequences*** is ***unknown***

When ***the function is unknown***, a well known technique ***is to minimize the error*** (squared error) between the ***desired output*** and the ***model's output***.

predefined consequences

EGM output

$$E(\theta) = \sum_{k=1}^{n} \left(C_{desired} - f(x, \theta) \right)^2$$

Objective function

Two optimization approaches can be used here

Stochastic approximation

-Robbins Munro Optimization (RM)

Search Methods (Derivative free optimization)

- Genetic Algorithms (GA)

- Simulated Annealing (SA)

- The first technique is ***Robbins Munro (RM)*** as a technique to perform ***stochastic optimization***.

-This method is designed to find the roots of ***an unknown function f (θ)*** when the value of ***f(θ)*** can be provided for any specified θ

- ***By replacing f(θ) by its derivative f(θ)'***, the optimal defense measures $\hat{\theta}$ to achieve ***pre-specified consequences (C_0)***can be found.

Capabilities of RM

-Due to the use of a numerical gradient in determining the rate of convergence, this method has ***high ability to adapt to local rates*** of change of the function along its many parameters.

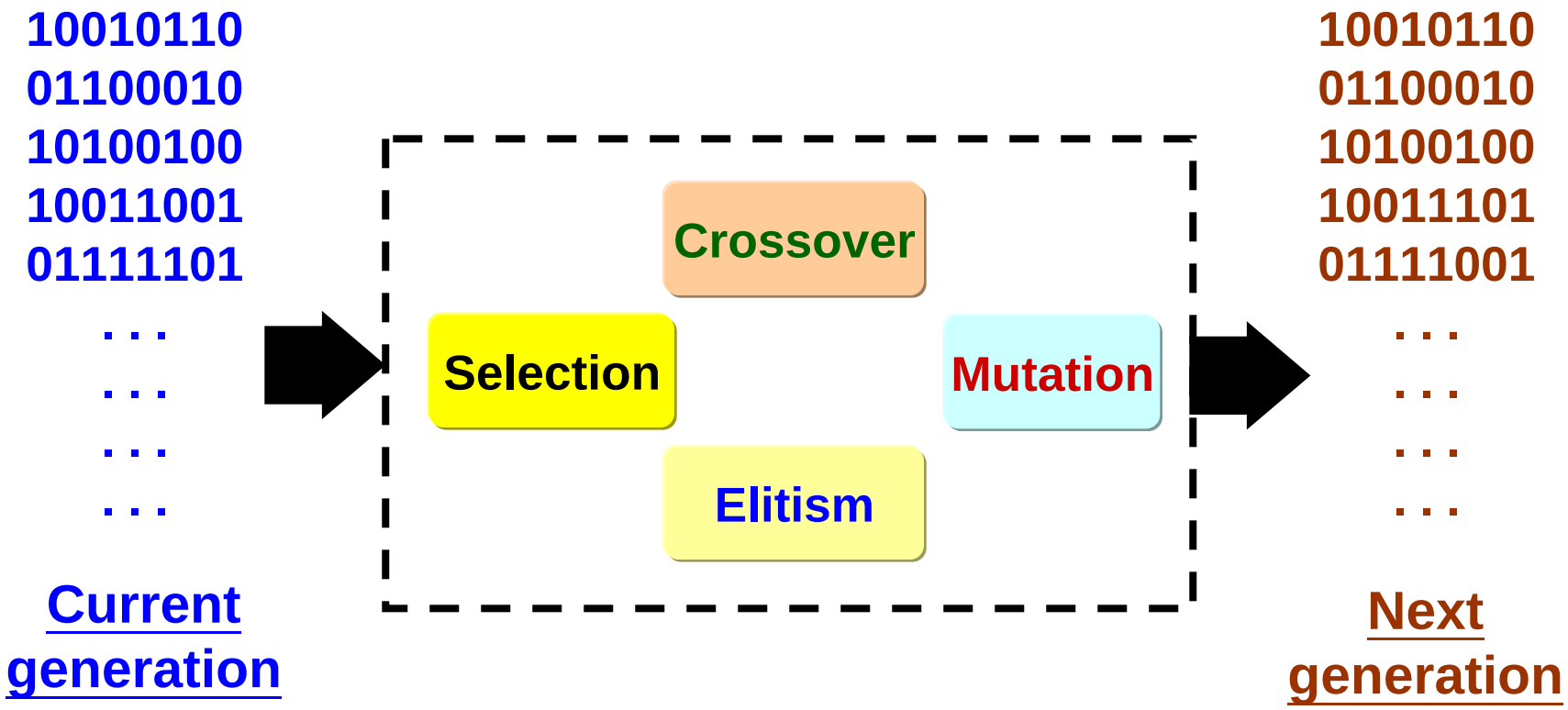
Limitations of RM

- There is an implicit assumption ***about the function being unimodal***.

Genetic Algorithms (GA) mimics laws of ***Natural Evolution*** which emphasizes "***survival of the fittest***".

In GA a "***population***" that contains different possible solutions to the problem is created.

Genetic Algorithms (GA)



The process is repeated until ***evolution happens***

"***a solution is found!***"

Capabilities of GA

- In contrast to traditional techniques, ***GA is the most likely technique to find global peaks*** than traditional techniques.

Limitations of GA

-Unlike traditional optimization methods, ***GA is not the best module for handling continuous variables***

- ***Relative fitness*** depends on probabilistic criteria of the variables that ***might be unknown***.

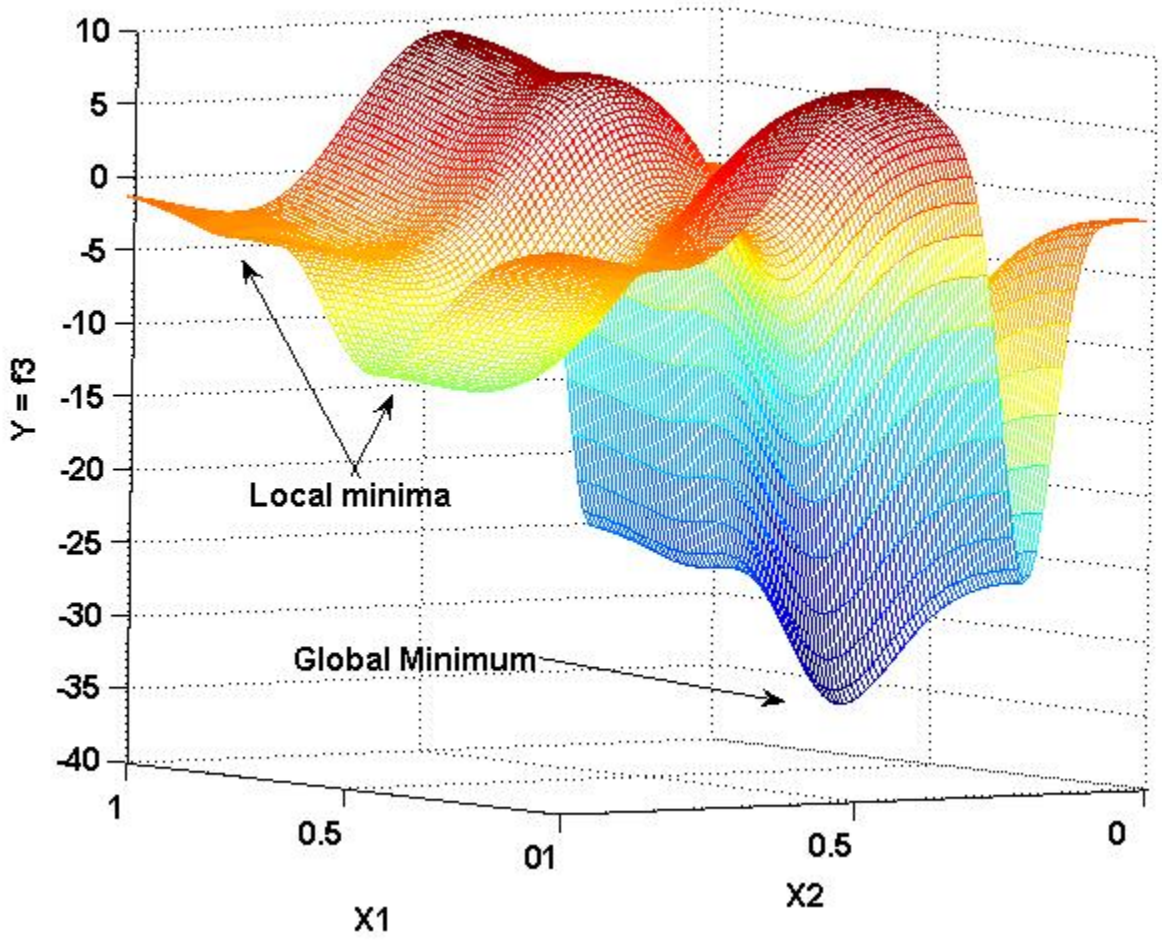
Comparison between GA and RM

-We have conducted a series of ***research experiments*** to compare efficiency of the RM and GA for ***functions*** with ***different levels of complexity.***

- We examined the methods on two, three, four dimensional multivariates.

- We present here example results for optimizing ***a two dimensional multivariate Gaussian functions.***

Comparison between GA and RM



Two dimensional multivariate Gaussian functions

Comparison between GA and RM

Method	Iteration #	x_1	x_2	y	
RM	1st Iteration **1000 iterations**	0.816	0.422	**-12.89**	**LM**
	2nd Iteration **1000 iterations**	0.815	0.753	**-4.71**	**LM**
	3rd Iteration **1000 iterations**	0.198	0.422	**-35.27**	**GM**
GA	1st Iteration **50 generations**	0.198	0.423	**-35.27**	**GM**
	2nd Iteration **50 generations**	0.191	0.440	**-34.84**	**GM**

Comparison between GA and RM

-It became obvious that **RM *is very sensitive to the starting point*** of the search. This is why RM algorithm ***fell in almost all local minima***

- On the contrary, **GA** is ***not sensitive to initial start*** and its temporal performance is better than RM.

- ***However***, it is well known that ***there is no optimal choice for optimization methods***, they are ***problem-dependent*** and thus ***further research is needed***.

Example Application of GA

GA for Optimal Defense Measures Identification

- Here we used the **EGM using ANFIS** ***as the relation model*** and ***examined*** using ***GA*** to ***identify the optimal defense measures*** ($\hat{\theta}$) for a given attack engagements.

- We operated the DS tool in
  - ***Exploration mode to validate EGM***
  - ***Optimization model to examine GA***

Exploration Mode

Engagement Description

CB attack on a U.S. Air force in the Persian Gulf

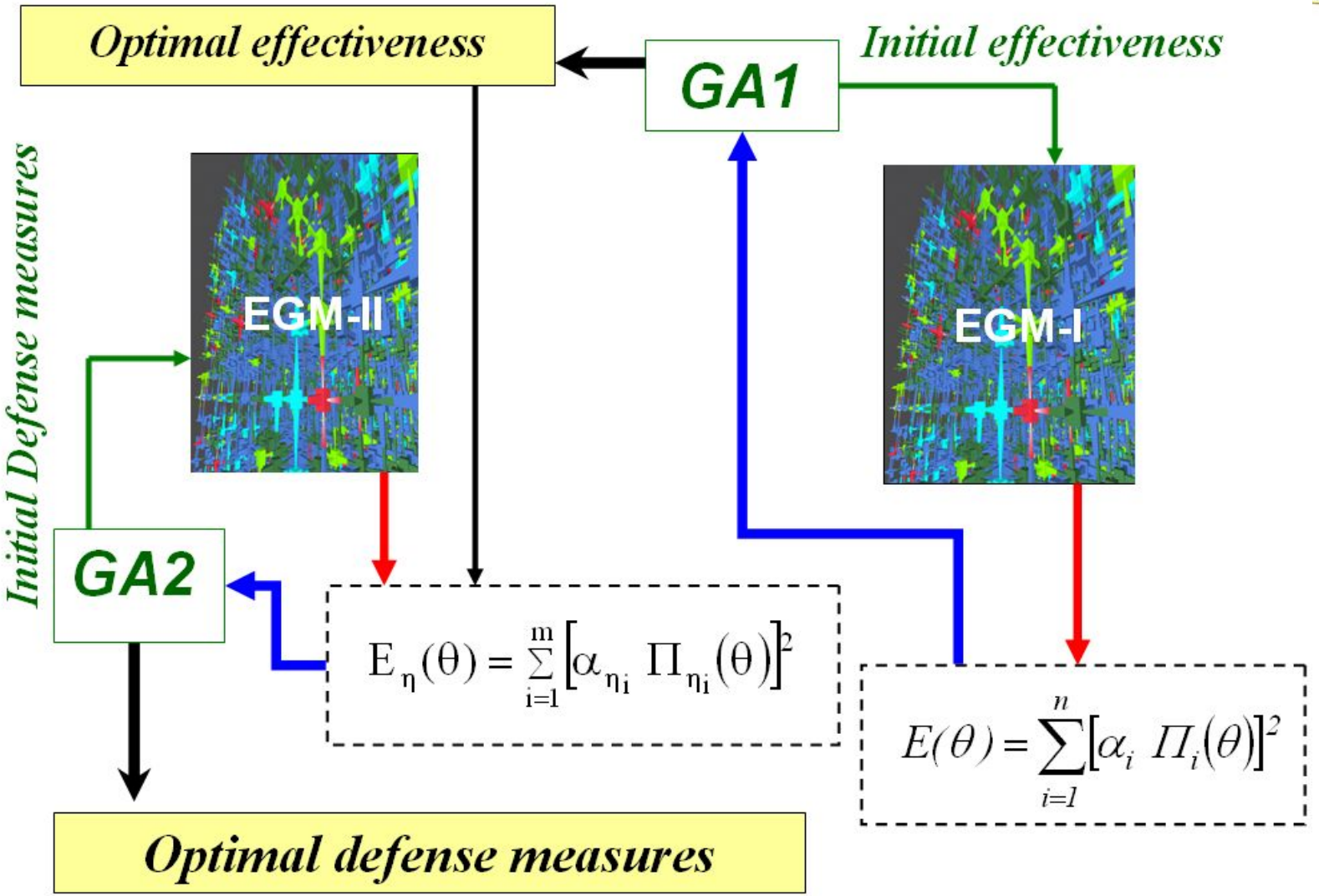
- ***Preparator***: Hostile foreign state
- ***Motivation***: Interrupt Strategic functions
- ***Military facilities***: Flight operation and support
- ***Chemical/Biological agent***: Vx
- ***Dispersal mechanism***: Missile warhead: Cluster
- ***Point of Release***: 2km SE of personnel area
- ***Other characteristics…..***

Exploration Mode

Consequences		Var 1	Var 2	Var 3
Casualties	Expected	150-350	150-250	150-250
	Model	**377**	**263**	**346**
Cost (US $ M)	Expected	70	65	60
	Model	**72**	**57**	**65**
Days of Int.	Expected	7	5	5
	Model	**7**	**5**	**5**

- EGM sensitivity to defense measures was examined.

Two stage GA


Optimal effectiveness
GA1
Initial effectiveness
Initial Defense measures
EGM-II
EGM-I
GA2
$E_\eta(\theta) = \sum_{i=1}^{m} [\alpha_{\eta_i} \Pi_{\eta_i}(\theta)]^2$
$E(\theta) = \sum_{i=1}^{n} [\alpha_i \Pi_i(\theta)]^2$
Optimal defense measures

Optimization Mode

- Predefined consequences include

Predefined level of Consequences	
Casualties	**430**
Remediation Cost $M	**70**
Days of Int.	**7**
Cost of Add. S&T $M	**170**

Optimization Results

The output of the ***optimization module*** was 250 ***possible combinations of defense measures*** that will

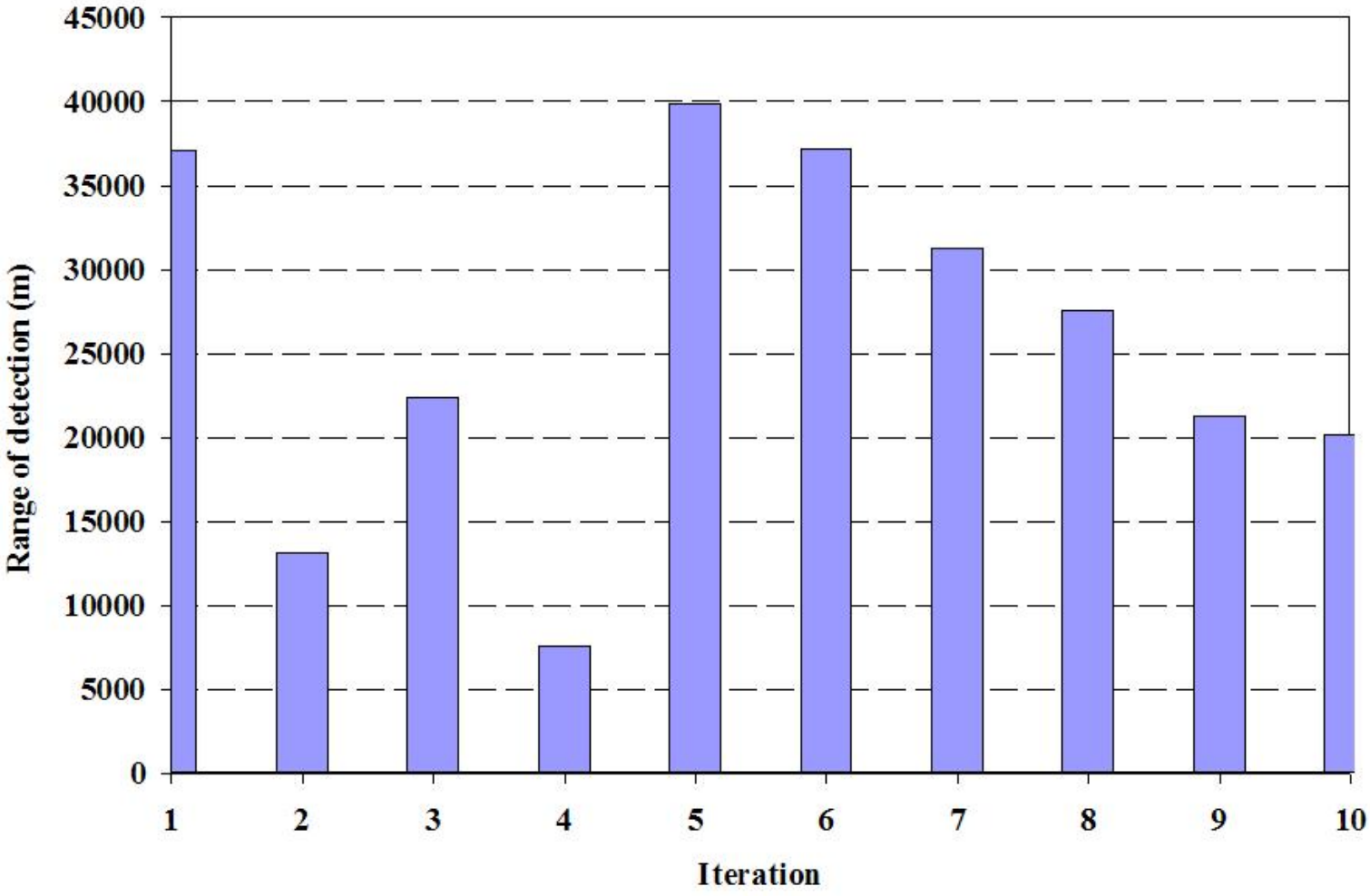
- Achieve a level of minimum ***consequences***

- Limit the ***S&T*** dollars to the total available fund

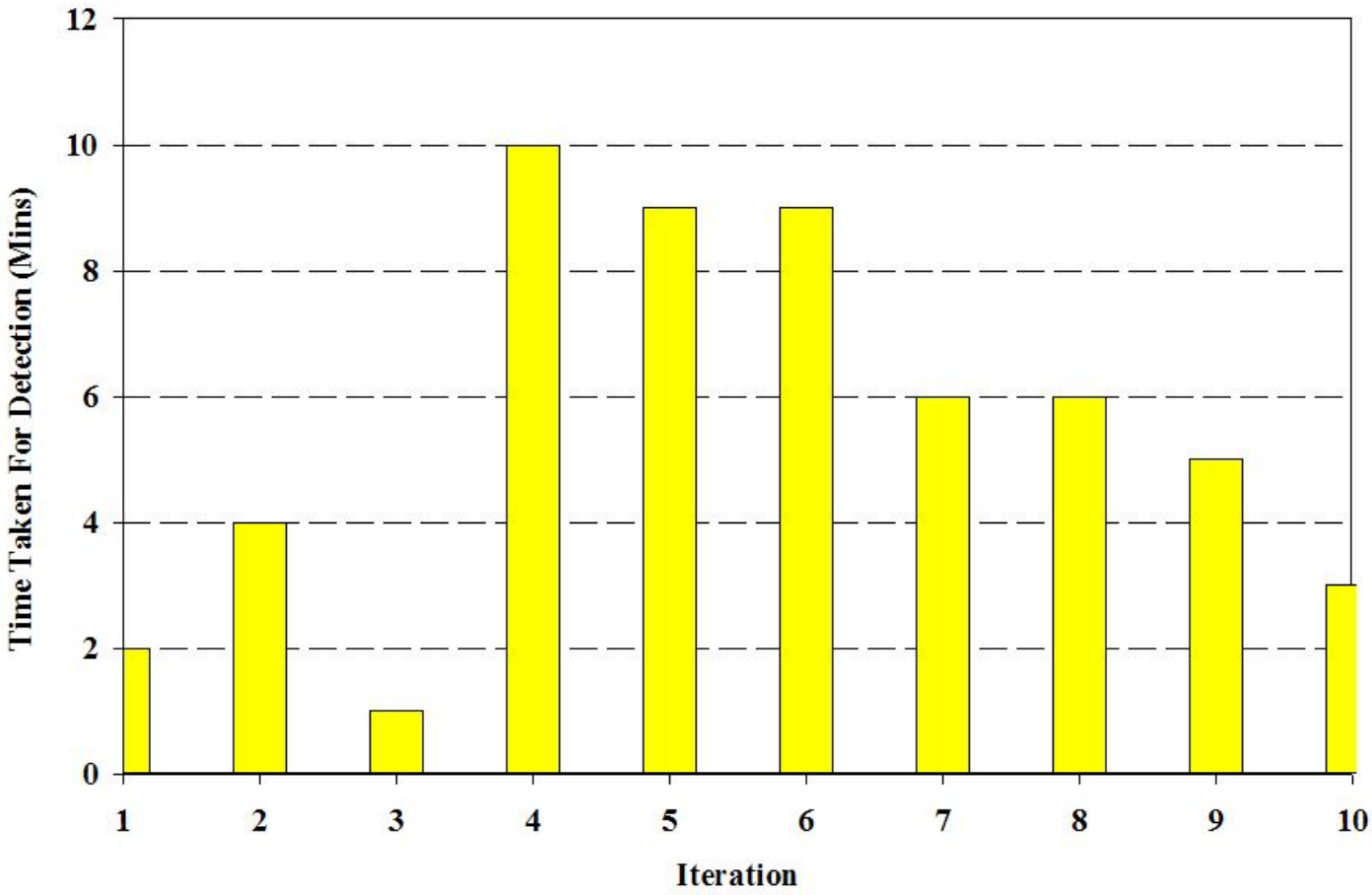
The question becomes

Which solution to choose?

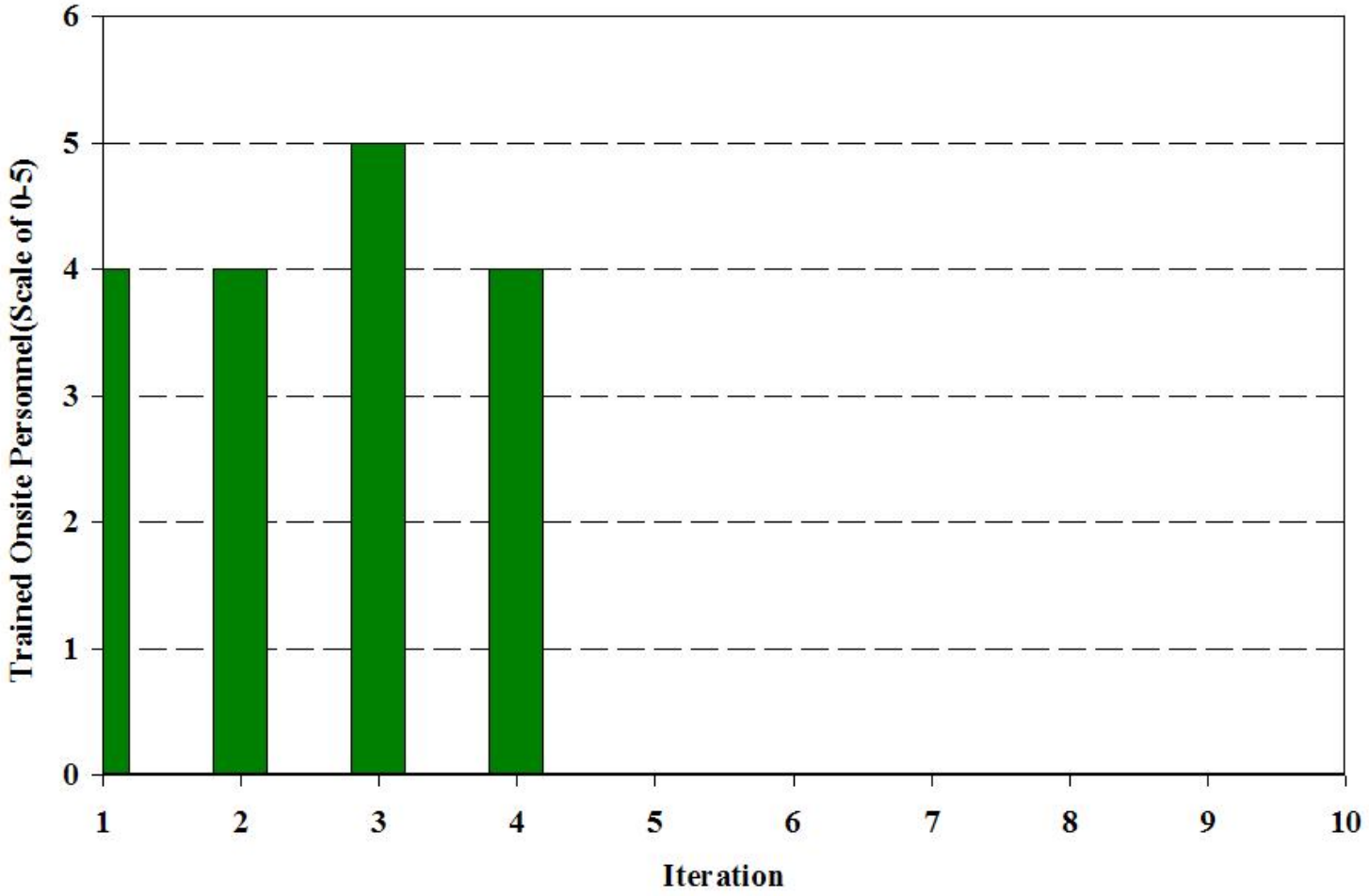
Possible solutions



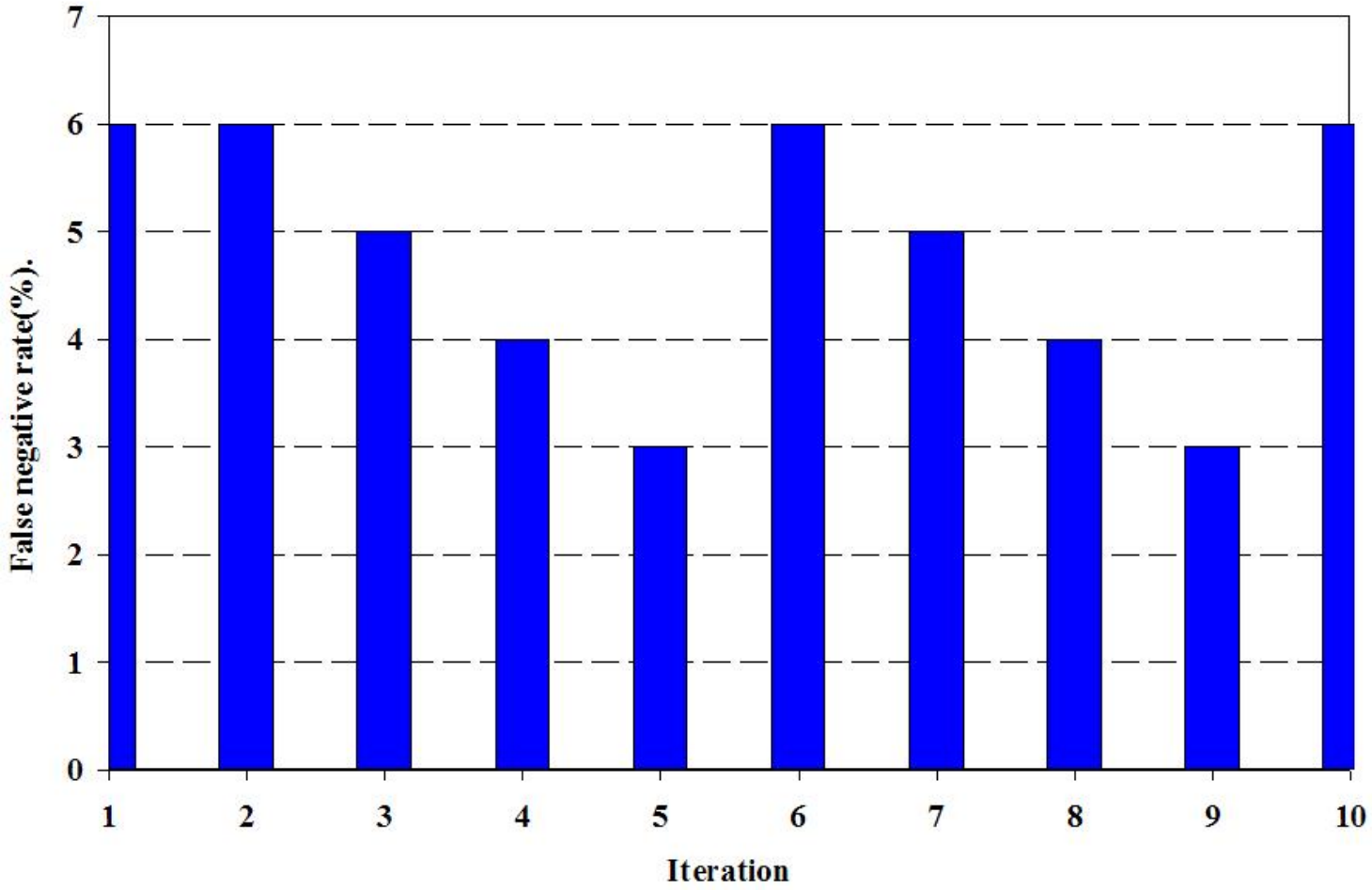
Possible solutions



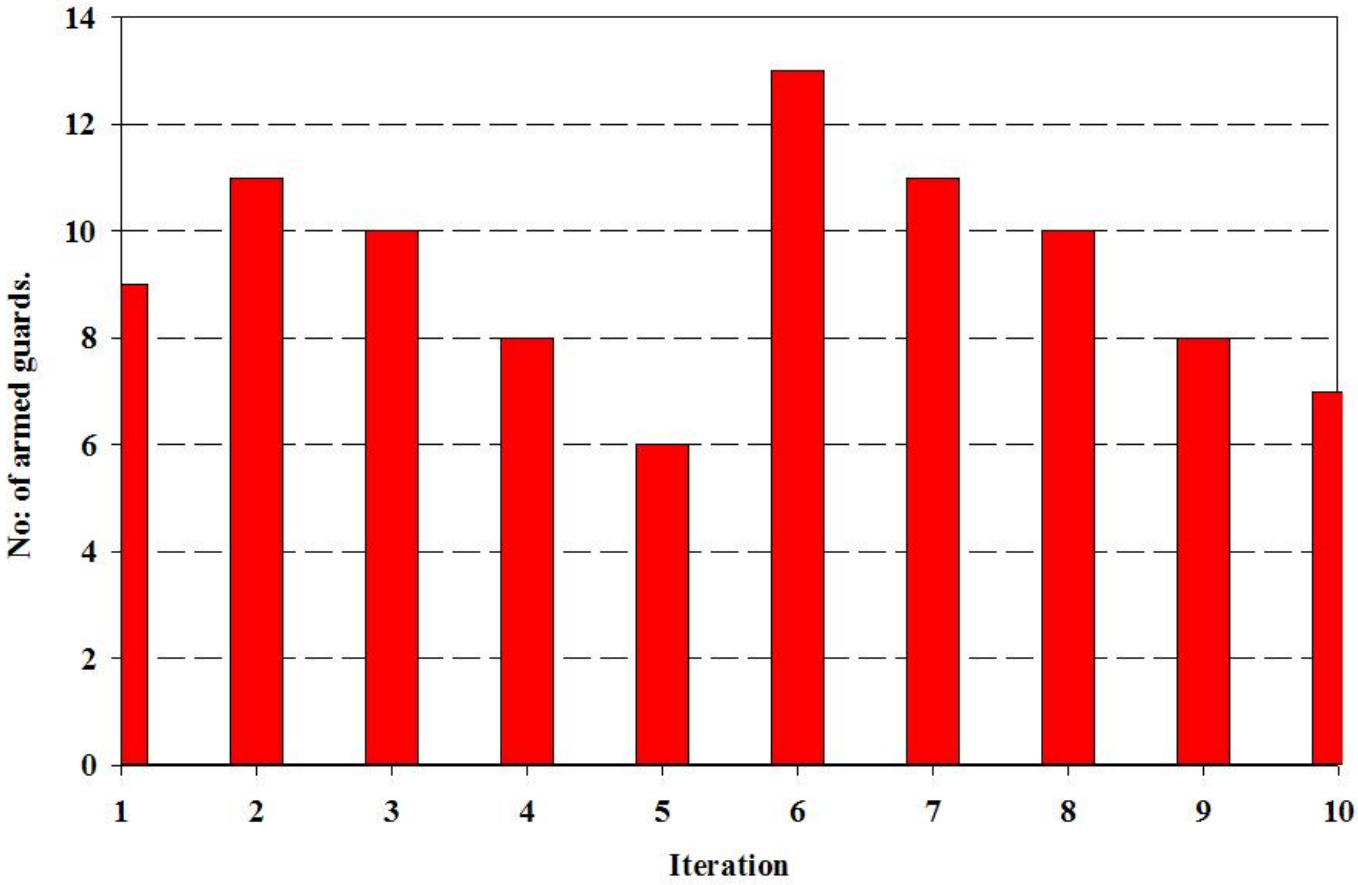
Possible solutions



Possible solutions



Possible solutions



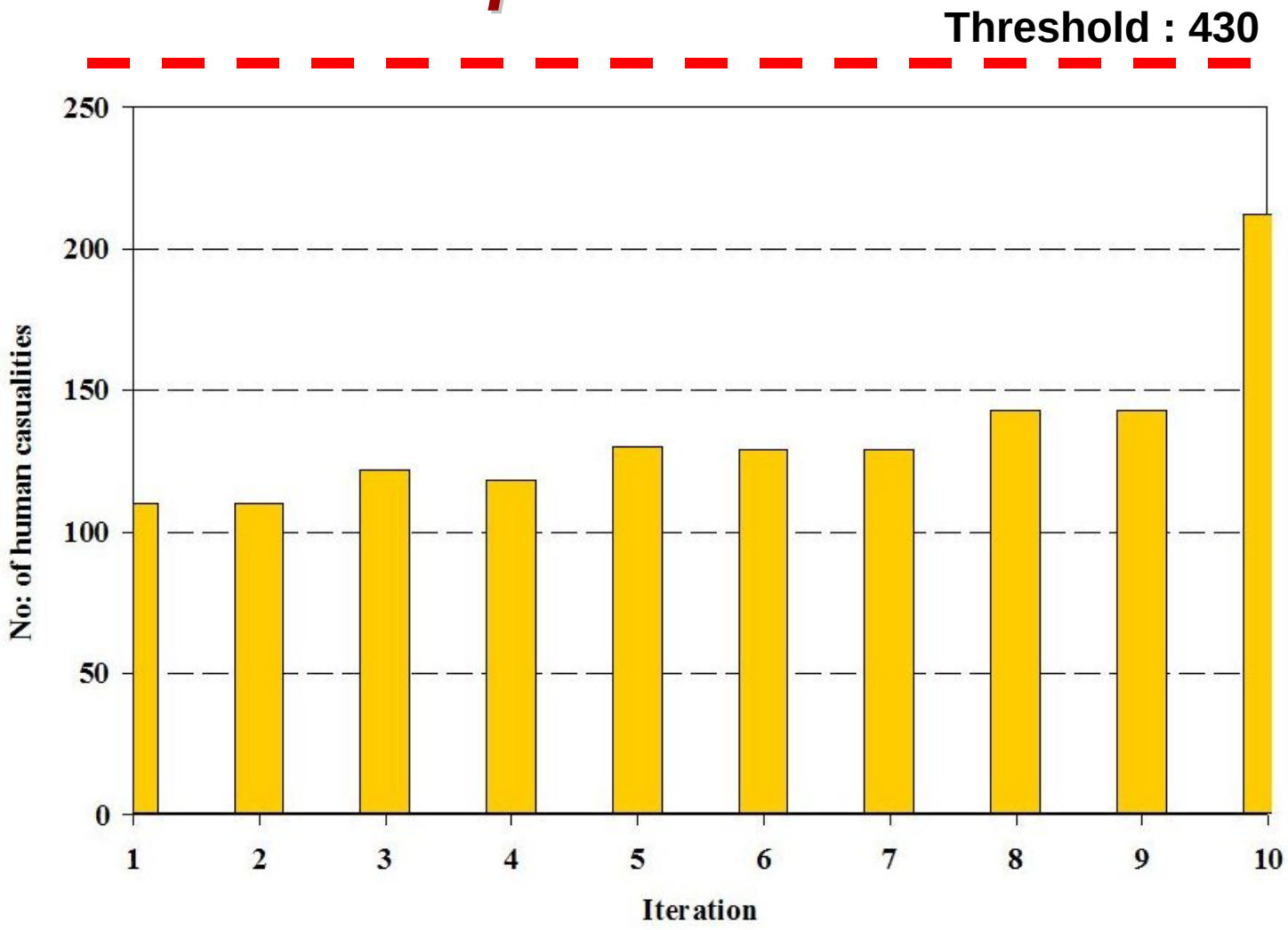
Rank ordering

In our problem, ***ranking criteria are interactive***. In such a situation, ***it is proved in decision theory that nonlinear aggregation operators are more efficient***.

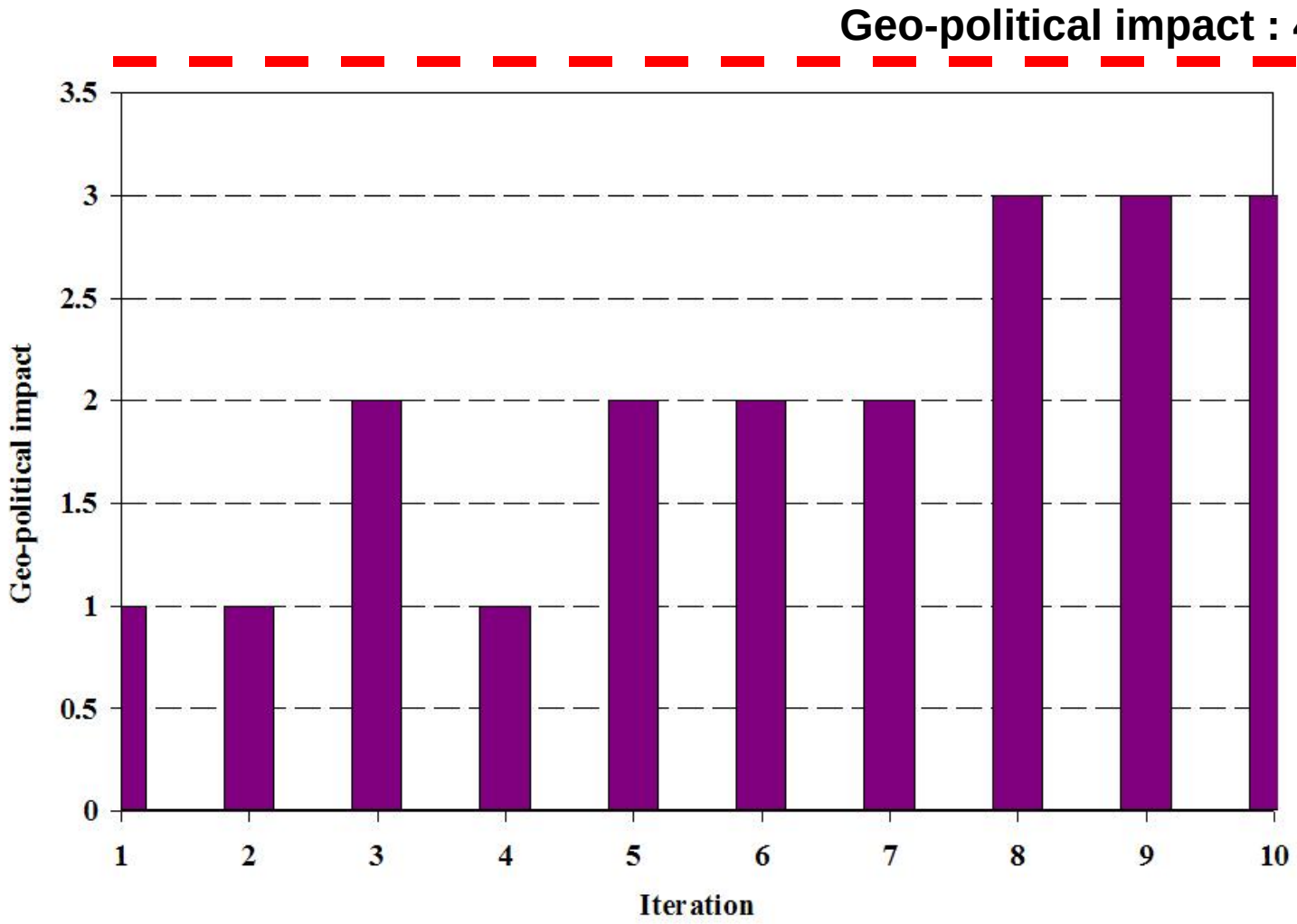
A few possible techniques

- ***Choquet Integral (CI)***
- ***Multi criteria decision making (MCDM)***

Consequences If optimal defense measures are implemented



Consequences If optimal defense measures are implemented



Conclusions

-We demonstrated the possible use of derivative-free optimization as an efficient system for optimization for finding the optimal S&T investments to minimize the consequences of CB attacks

-A two step optimization using GA proved more efficient than a one-stage optimization methods in performing the analysis

- The optimization tool showed good accuracy in finding the optimal defense measures to minimize consequences due to CB attacks

- Research is currently on-going to integrate this method with rank ordering module.

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Questions