Machine Intelligence in Decision-making (*MInD*)
Automated Generation of *CB* Attack Engagement Scenario Variants

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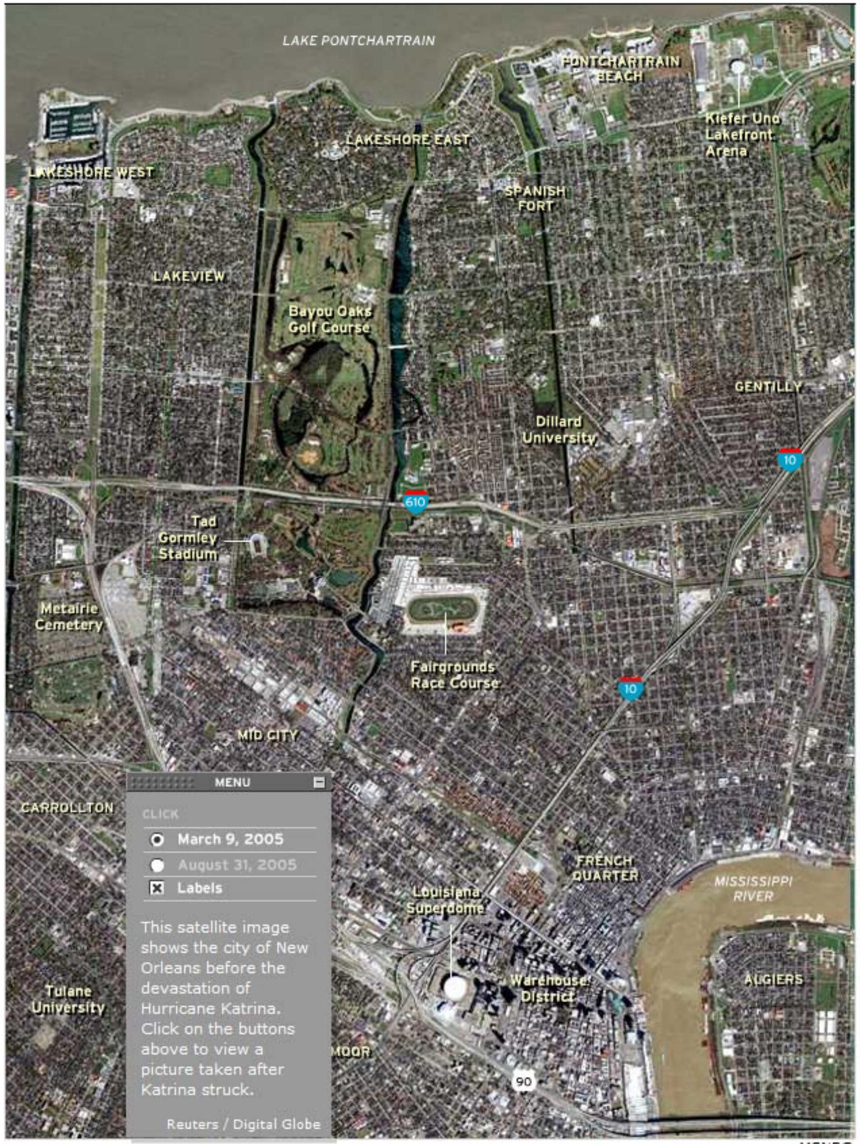
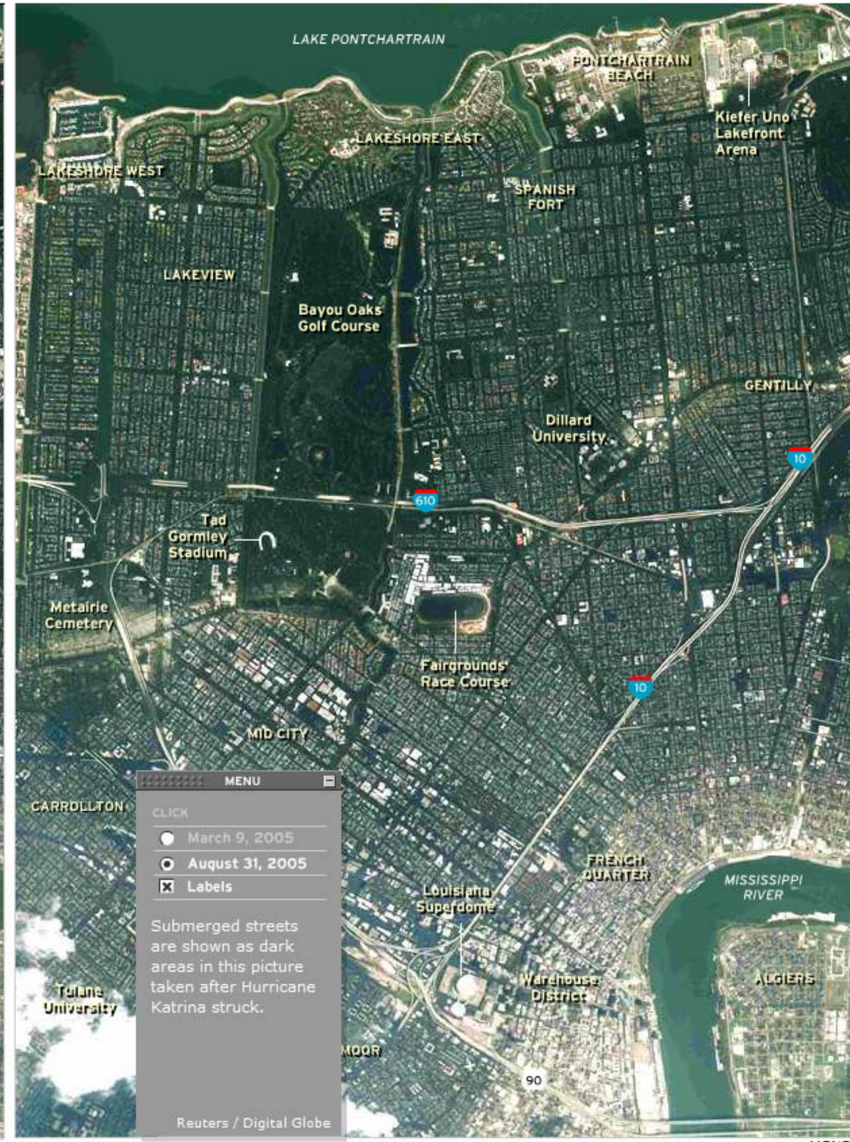
BO05MSB070: Multivariate Decision Support Tool for CB Defense
DTRA University Strategic Partnership
Gold Team

New Orleans Scenario



MSNBC



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Fundamental Principles

1. Human decision-making is analogous to finding Order within Chaos
2. Order requires Structure
3. Structure requires Rules for preservation
4. Rules must be learned and applied
5. New Rules are discovered as Information (Data) evolves

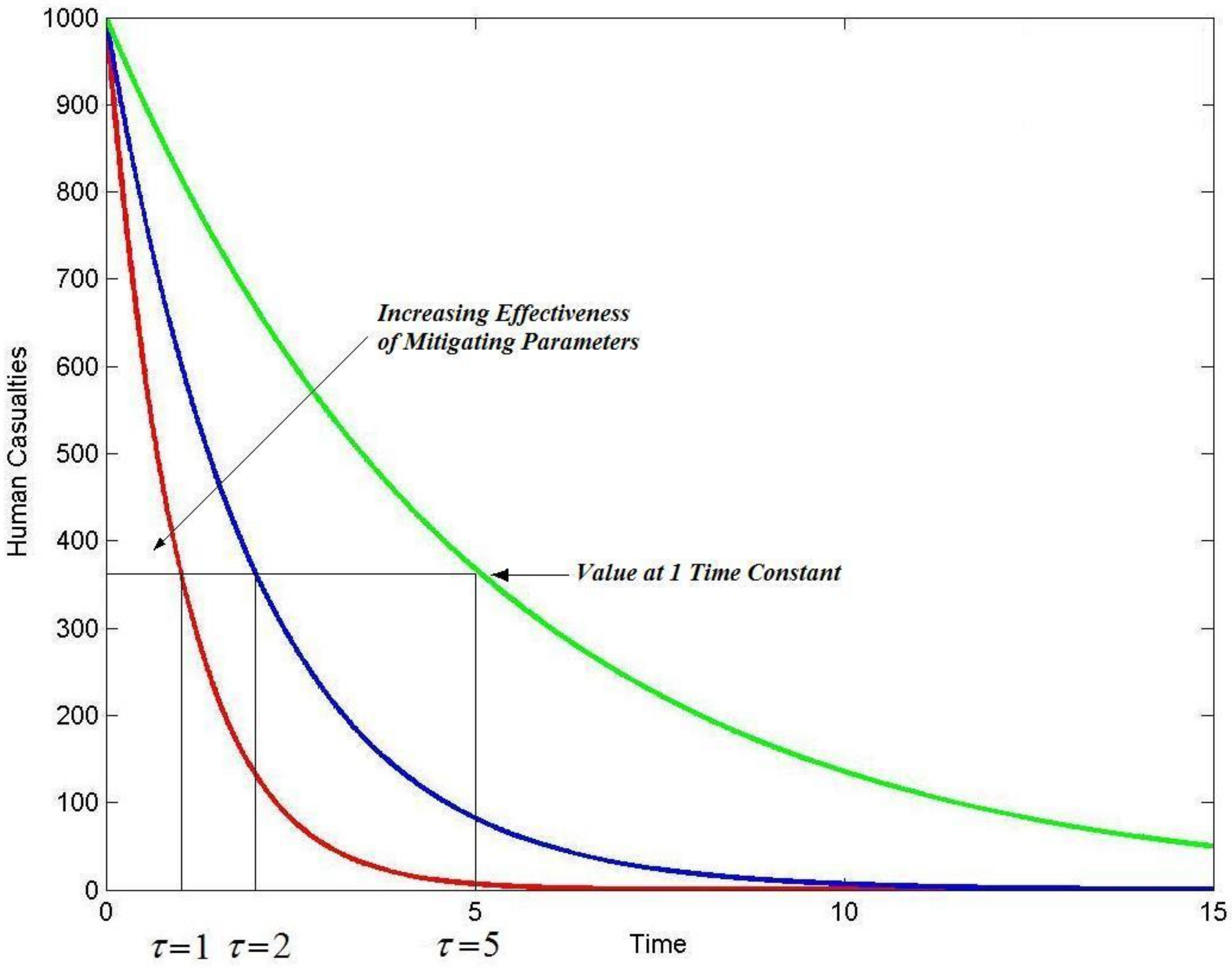
Order in Scenario Generation

- **Experts match the characteristics of the attacker with postulated attack characteristics to generate engagement scenarios that provide a basis to evaluate the consequences of the attack**
- **Base-Case Variants show the effectiveness of mitigating factors on the consequences including the cost of mitigation**
- **The set of Base-Case and Variant exemplars provide the means to develop appropriate cost models that can aid in evaluating S&T funding required to mitigate the consequences**
- **To preserve "order" in scenario variant generation, a set of Rules governing the relationships between the *CB* attack Base-Case and Variant exemplars must be "extracted" and "learned" so that many Variants can be generated for further analysis**

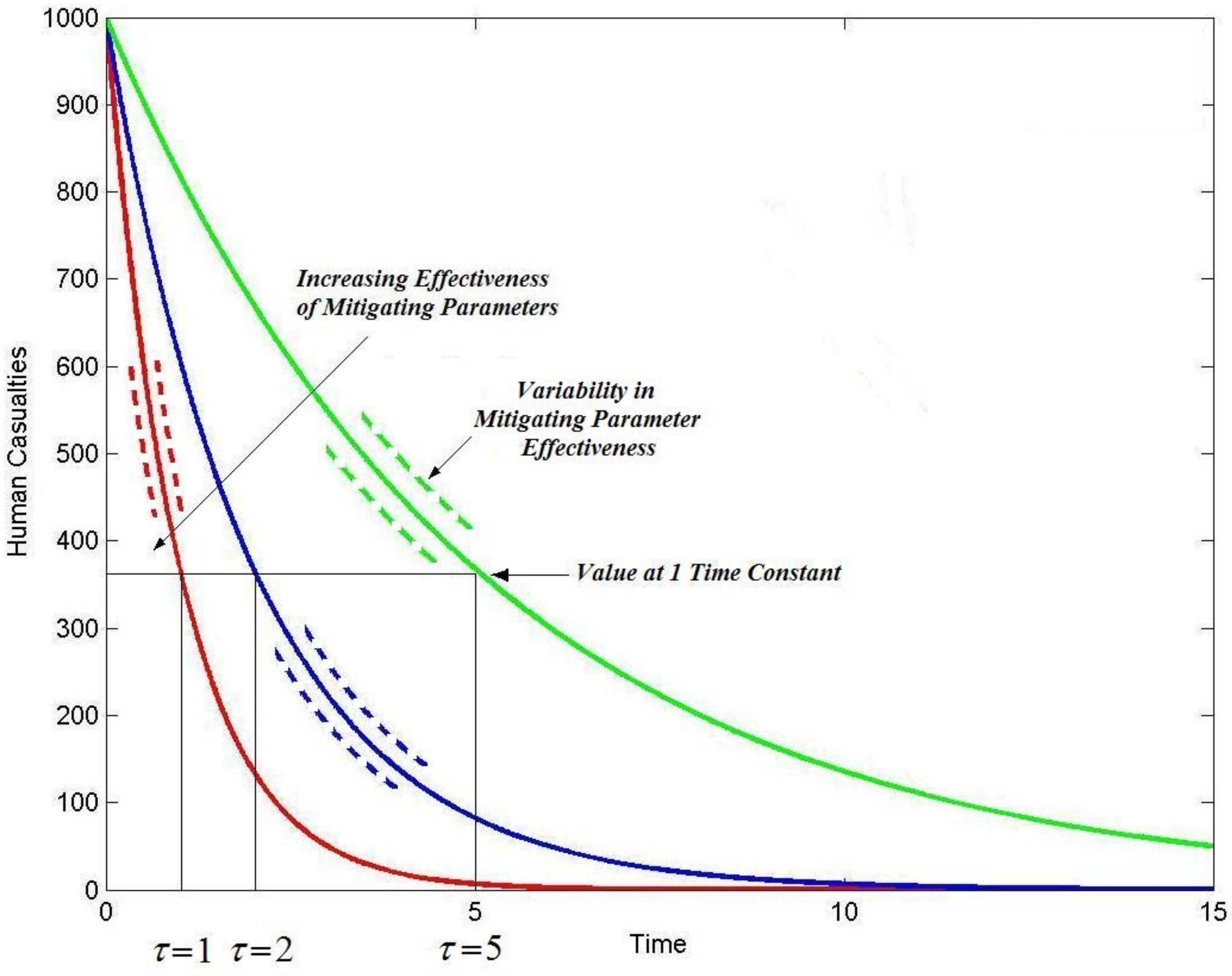
Basis For Automatic Scenario Generation

- Automatic scenario generation is based upon Bose-Einstein’s Large Deviation Theory (LDT)
- The fundamental principle of LDT is founded in: “Exponential Asymptotics for Good Sets”
  - What this means is that all sets of new scenario variants must exhibit exponential asymptotic behavior, and satisfy all properties of compact sets

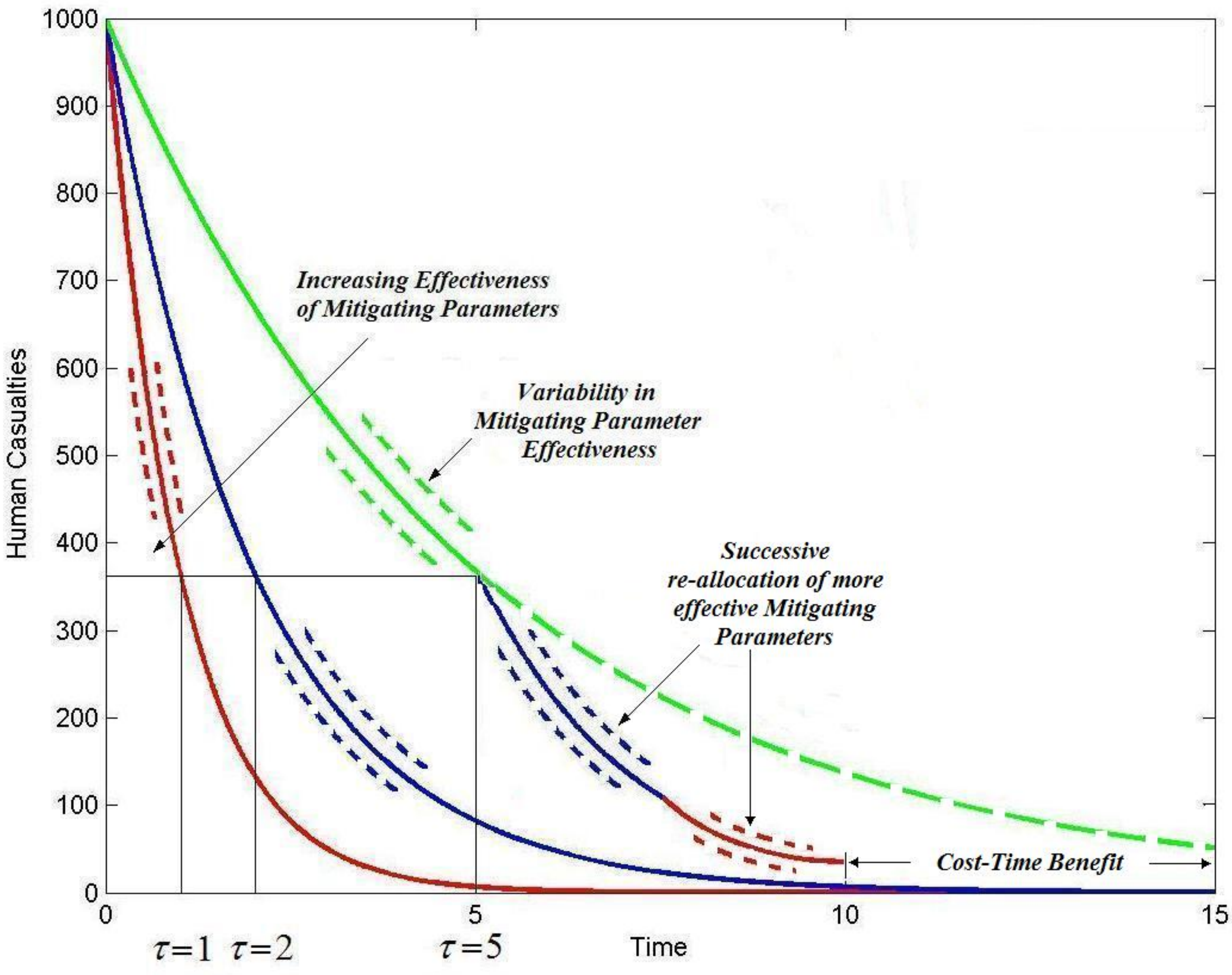
Exponential Asymptotics



Exponential Asymptotics



Exponential Asymptotics



Exemplar Set of Base-Case Engagement Scenario and Variants

PERPETRATORS (X)		Islamist Terrorist Group
MOTIVATIONS (M)		Tactical: Casualties
MILLITARY FACILITIES (T)		Education and Training
CHEMICAL/BIOLOGICAL AGENTS (A)		Sarin (GB) (moderate/high purity)
DISPERSAL MECHANISM (D)		Improvised: Truck
INHERENT CHARACTERISTICS (B)	*Proximity to Civilian Infrastructure*	High
	Air flows	South-Southeast
	Time of Attack	9:00 AM
	Access to Offsite Medical Service(Scale of 0-5)	3
	Access to Civilian Hazmat response(Scale of 0-5)	3

			Iteration 0	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7	Iteration 8	Iteration 9	Iteration 10
CB DEFENSE VARIABLES and SUB-VARIABLES (M)	*Chemical Agent Detectors*	Type of detector.	N/A	C03	C03	C03	C4	C5	C5	C5	C6	C7	C8
		Range of detection (m)	N/A	5000	5000	5000	5500	5500	5500	5500	10000	25000	40000
		Time Taken For Detection (Mins)	N/A	10	10	10	8	8	5	5	5	5	0
		False positive rate(%).	N/A	5	5	5	7	5	5	5	5	0	0
		False negative rate(%).	N/A	3	3	3	7	5	5	5	5	5	5
		No: of sensors.	N/A	3	3	3	3	3	3	3	3	3	3
	Perimeter Protection	Presence of wall/fence.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
		Presence of barricaded gates.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
		No: of armed guards.	5	5	15	15	15	15	15	15	15	15	15
	Personal Protection Equipment	Positive Pressure Systems	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO	YES
		Avbl of Masks (%)	0	0	50	50	80	100	100	100	100	100	100
		Avbl of NBC Suits (%)	0	0	50	50	80	100	100	100	100	100	100
		Wearability (Scale of 0-5)	0	0	3	3	3	4	4	4	4	4	5
		% of personnel indoors	80	80	80	80	80	80	80	80	80	80	80
	Trained Onsite Personnel(Scale of 0-5)		1	1	2	4	4	4	4	4	5	5	5
	Chemical Prophylaxis	Type of prophylaxis.	N/A	N/A	N/A	N/A	N/A	PC4	PC5	PC6	PC6	PC6	PC7
		Risk level of side effects.	N/A	N/A	N/A	N/A	N/A	High	Med	Low	Low	Low	Low
		Effectiveness.	N/A	N/A	N/A	N/A	N/A	Med	Med	High	High	High	High
		Max. no: of days safe to take continually.	N/A	N/A	N/A	N/A	N/A	14	60	90	90	90	180
		No: of days before it becomes effective.	N/A	N/A	N/A	N/A	N/A	1	1	1	1	1	1
		Min. no: of days between pre-treatment cycle.	N/A	N/A	N/A	N/A	N/A	30	14	7	7	7	7
		No: of base personnel receiving it under normal conditions(%).	N/A	N/A	N/A	N/A	N/A	10	80	92	92	92	96
	Medical Treatment	Type of medicine.	MT3	MT3	MT3	MT3	MT2	MT4	MT4	MT4	MT4	MT4	MT4
		Effectiveness(Scale of 0-5).	3	3	3	3	5	5	5	5	5	5	5
		Personnel covered by Antidote (%).	0	0	0	100	95	100	100	100	100	100	100
		Capacity to treat (Scale of 0-5)	1	1	2	2	2	3	3	3	4	4	4
IMPACT and COST VARIABLES (C, Cost)	*No: of human casualties*		400-550	400-550	200-250	0-25	100-200	50-75	25-75	0-50	0-25	0-25	0-10
	Remediation costs(in millions of US $)		4	4	2.5	1	2	1	1	1	1	1	1
	No: of days of mission disruption		30	30	30	30	30	30	30	30	30	30	30
	Geo-political impact		High	High	High	Low	Med	Low	Low	Low	Low	Low	Low
	Cost of S&T into CB defensive measures		0	0	0	0	600	750	1750	3000	3400	4000	7500
	Cost of deployment (in millions US $)		0	45	57	907	182	275	525	785	985	1335	1785
	S & T Time (months)		0	0	0	0	60	60	72	96	60	96	120
	Deployment Time (months)		0	12	12	48	24	60	36	36	24	24	36

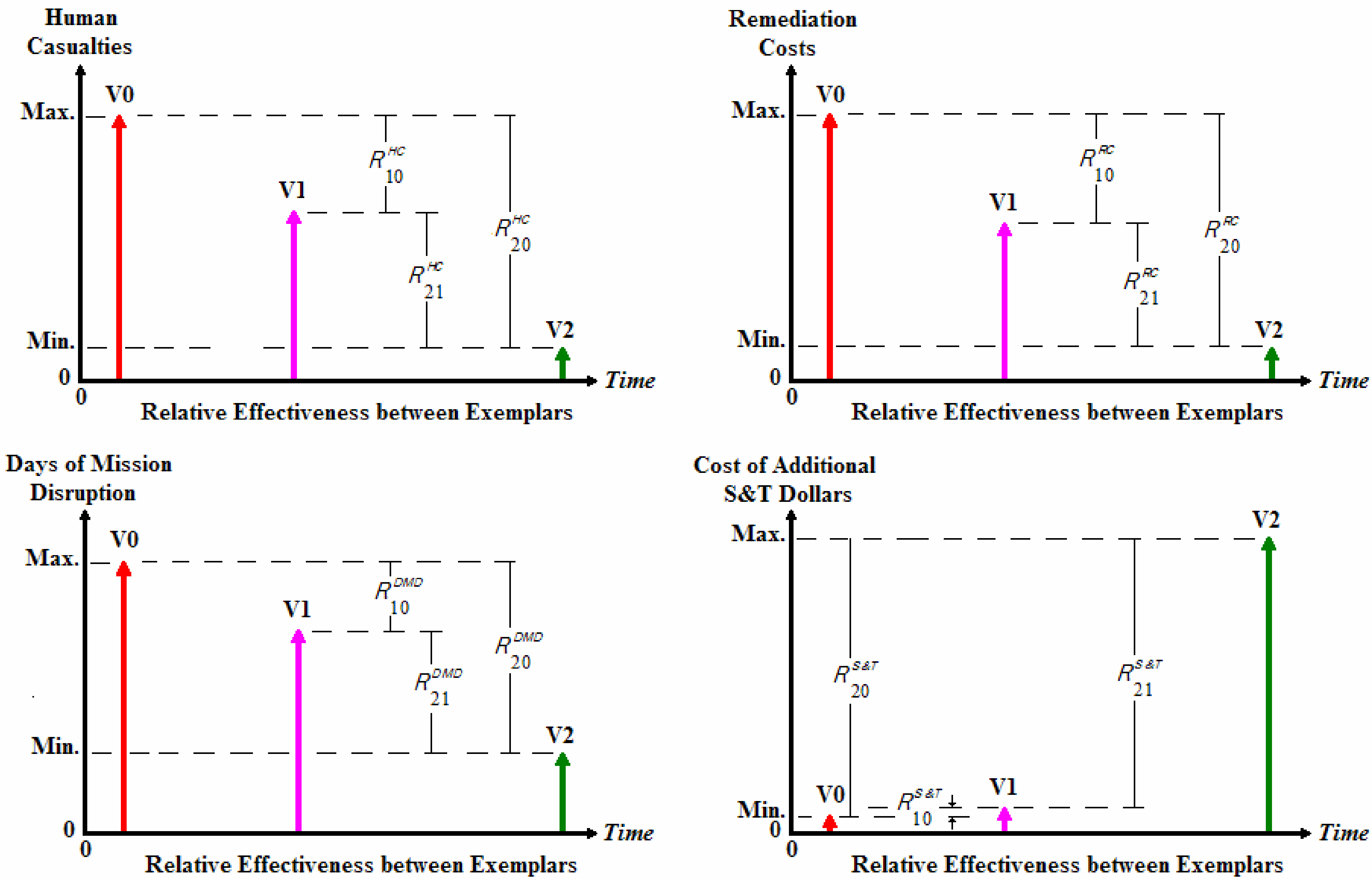
Adaptive Network Fuzzy Inference System (ANFIS)

- ANFIS is a set of fuzzy inference rules written in a neural network structure.
- Rules are extracted from exemplar data and learned.
- The resulting fuzzy-neural structure can be used to identify the effectiveness of mitigating factors on the consequences of *CB* attack scenarios.

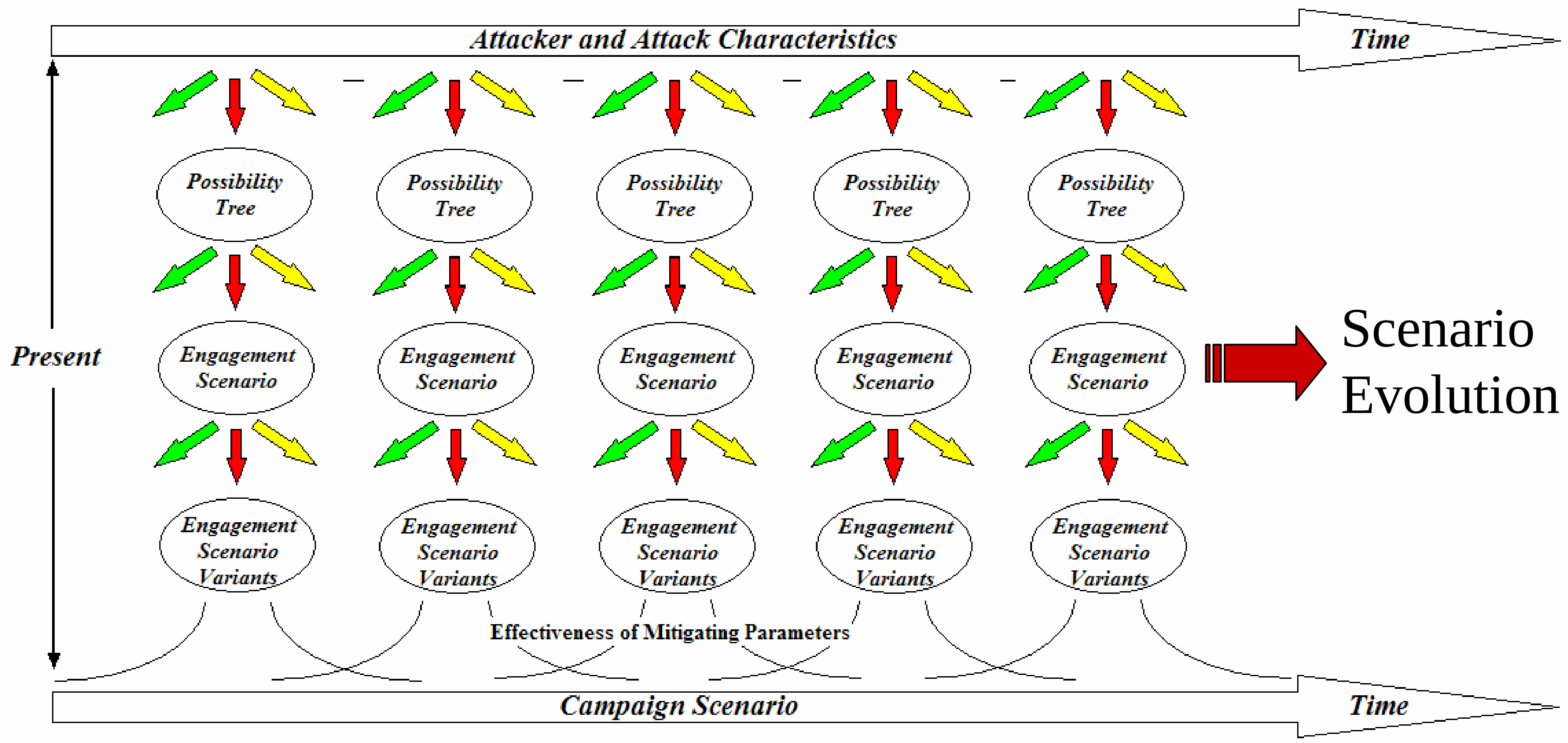
Scenario Variant Generation

- Exemplars of scenarios provided by *CB* Experts are used to train ANFIS rule-based structures and provide the means to generate hundreds and thousands of interpolated scenario variants.
- Large numbers of variants provide the means to Rank the effectiveness of mitigating factors on minimizing the overall consequences, and in identifying the total cost of additional S&T funds required.

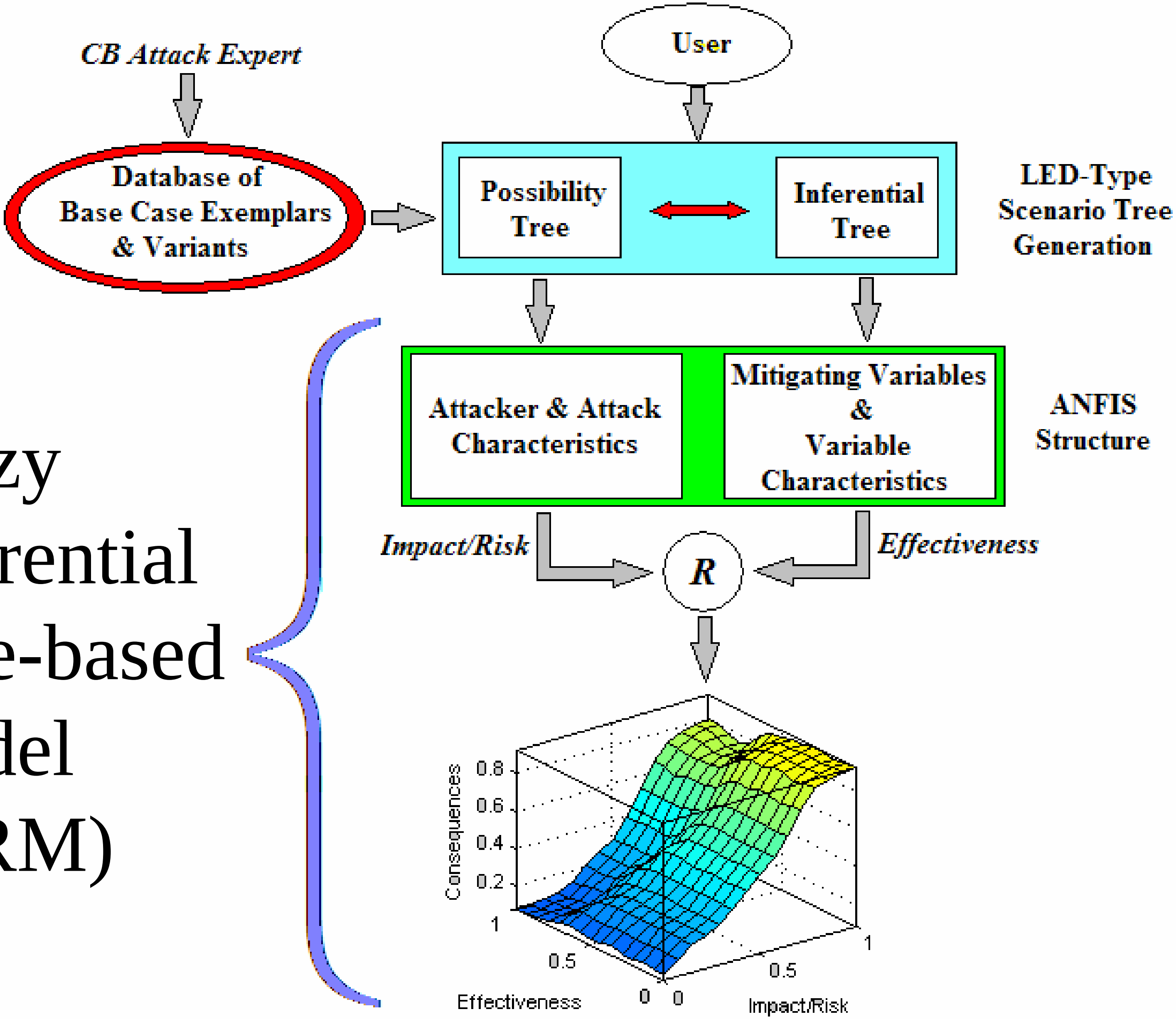
Relative Effectiveness Between Base Case Engagement Scenario and Variants



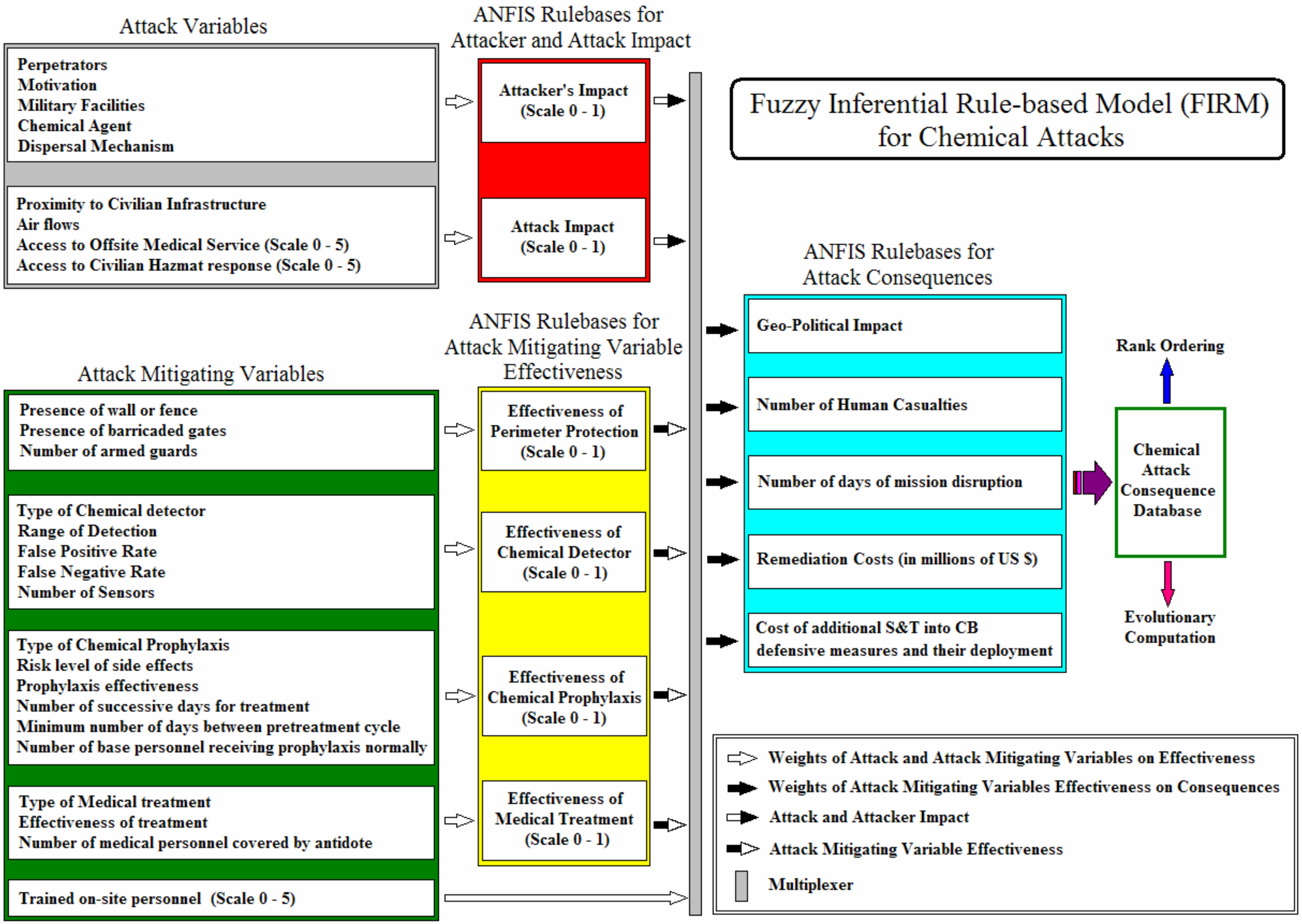
Evolution of Possibility Trees & Engagement Scenario Variants



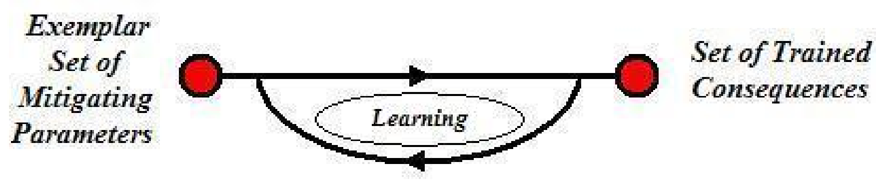
Fuzzy Inferential Rule-based Model (FIRM)



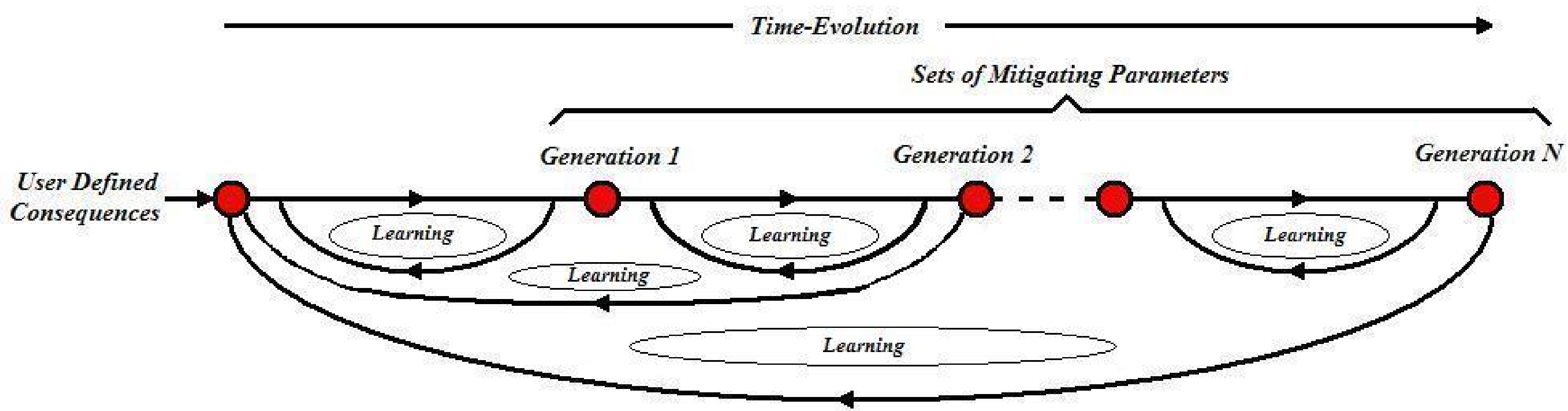
Scenario Variant Generation Using FIRM



Learning Systems

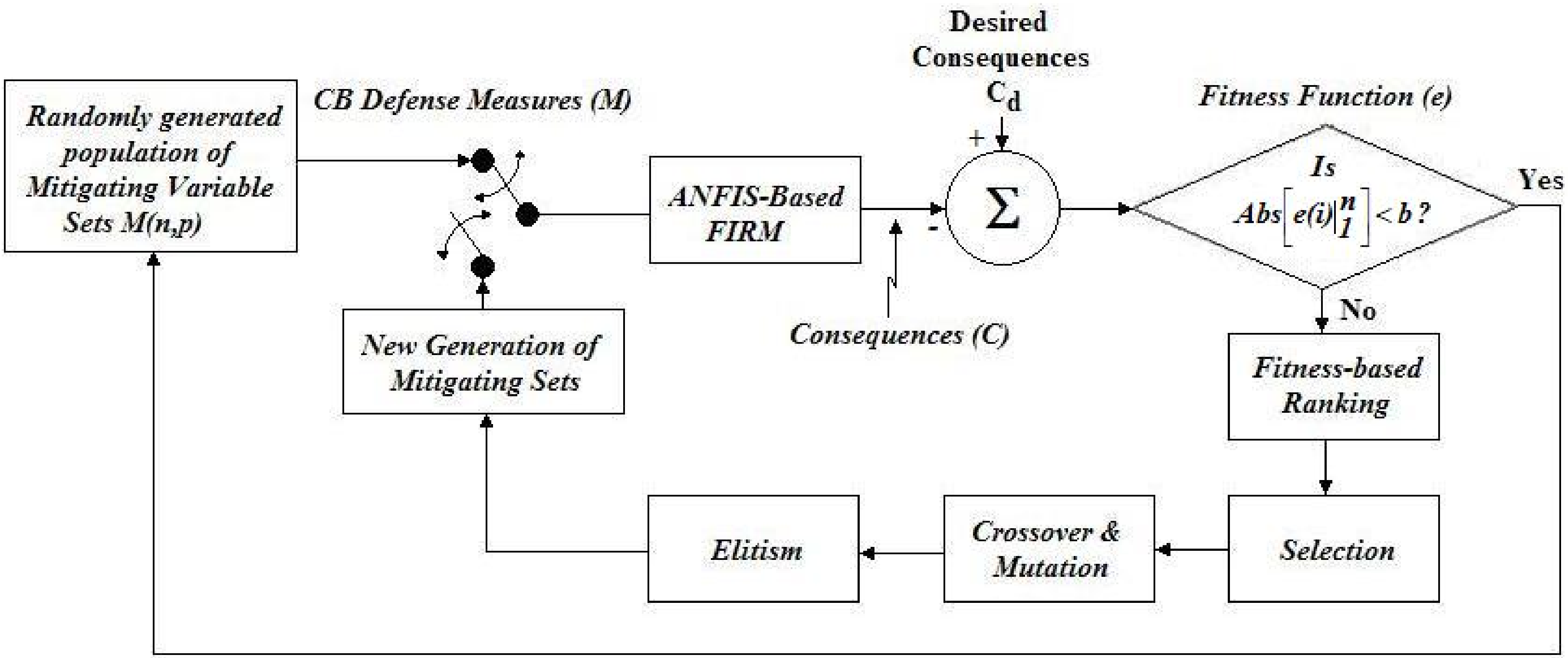


(a) Iterated learning through supervision

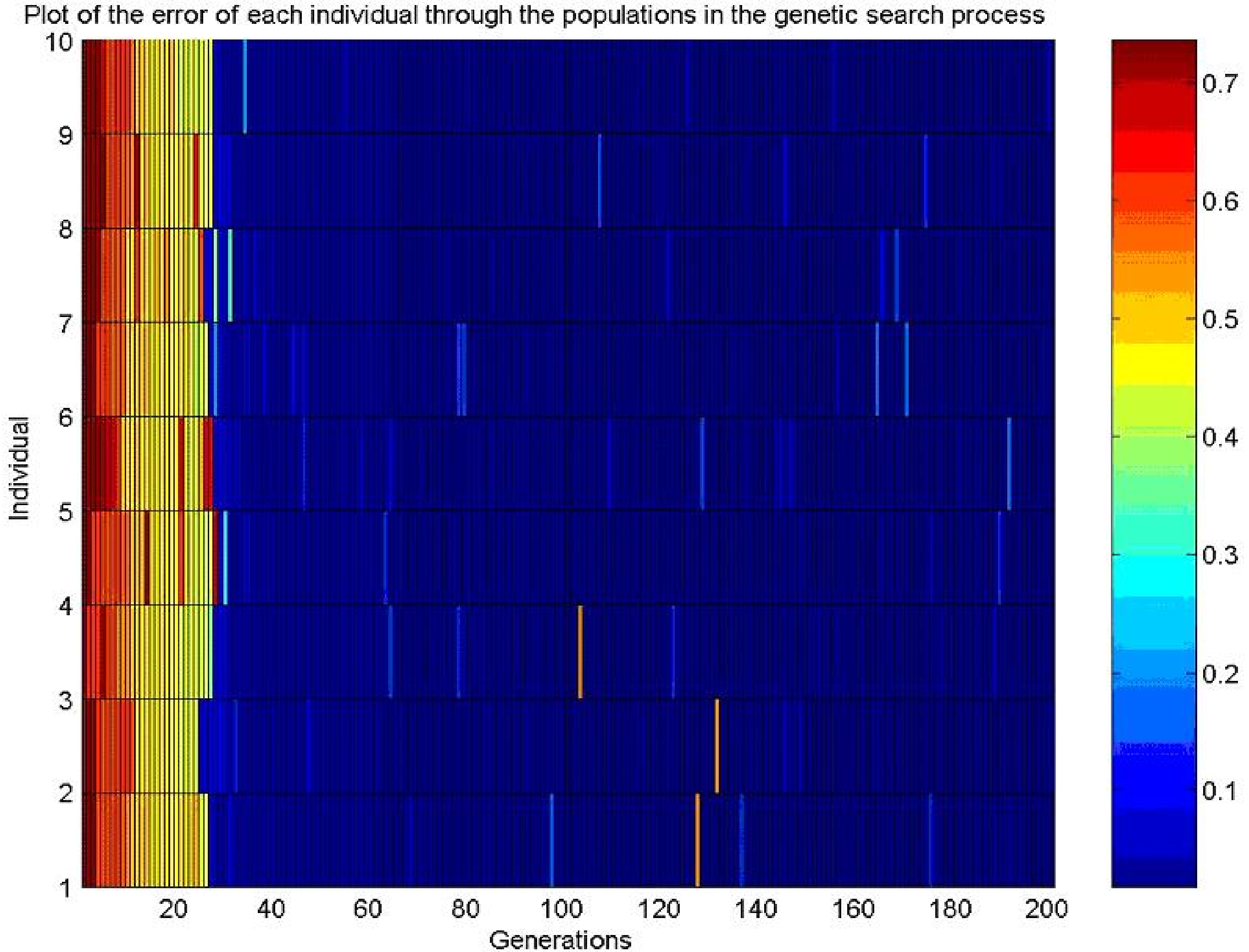


(b) Iterative learning through evolution

Evolutionary FIRM (E-FIRM)



Spectrograph of Variant Evolution



Cost Model

$$[\theta_1, \theta_2] = f[\text{Eff}_1, \text{Eff}_2, \text{Eff}_3, \text{Eff}_4, \text{Eff}_5, \text{Eff}_6, t_1, t_2]$$

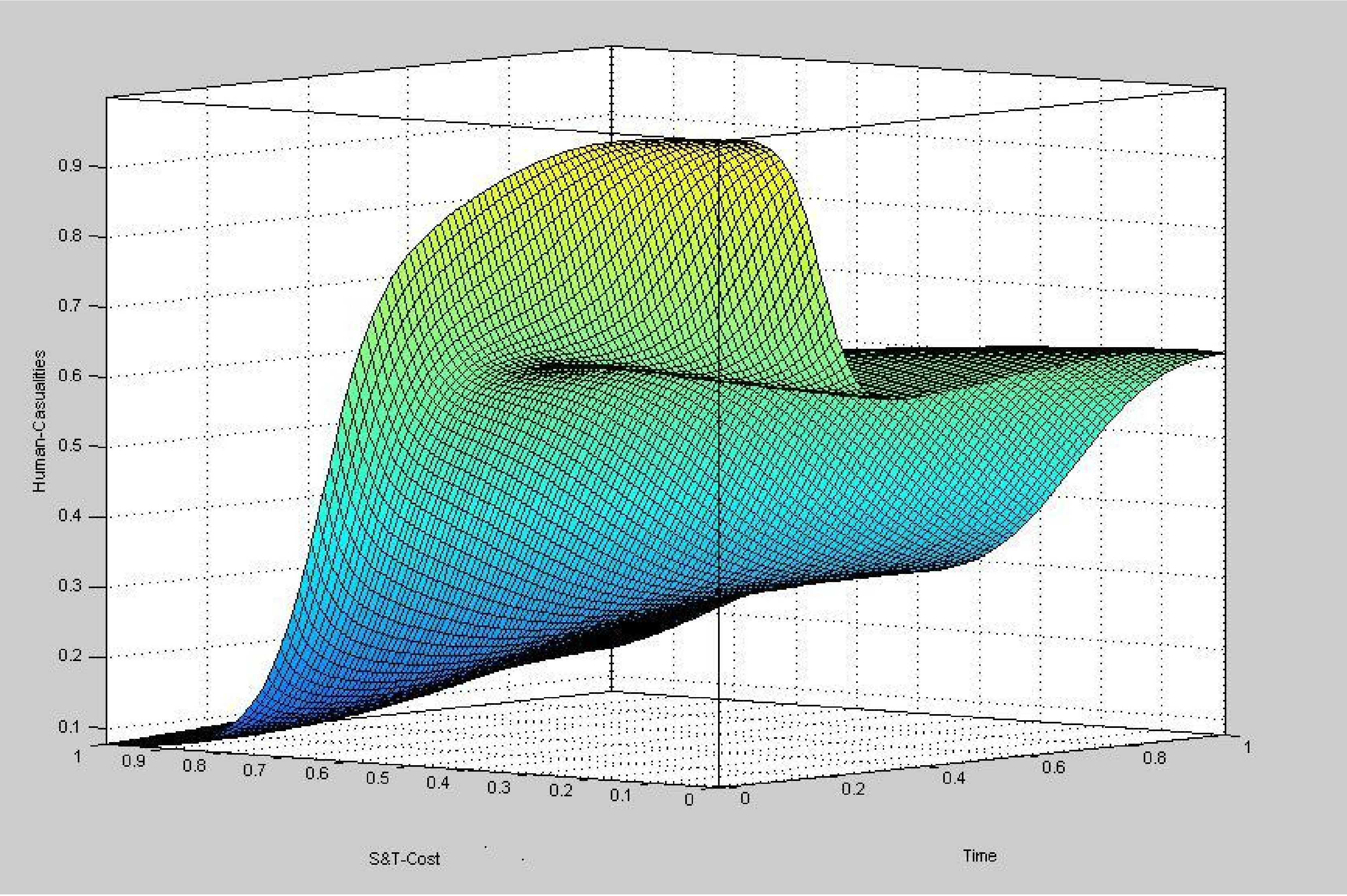
θ_1, θ_2 are the Cost of S & T and the Cost of Deployment

$\text{Eff}_i \big|_{i=1}^{6}$ are the mitigating factor effectiveness

t_1, t_2 are the time required to achieve the desired effectiveness

This is a nonlinear mapping for which a Radial Basis Function Neural Network with dynamic allocation of neurons has been applied

S&T Cost to minimize Human Casualties based solely upon Expert generated Engagement Scenario exemplars



Advances in *CB* Attack Analysis

- It is shown that a "**rule-based**" inferential method with ability to "***learn***" CB attack scenarios and consequences, and "***evolve***", is necessary for machine intelligence in decision-making (*MInD*) where multitudes of scenario variants can be generated on demand
- The structure of *MInD* is explored within an evolutionary framework to emulate Human-like learning and decision making for *CB* attack analysis
- A fuzzy-neural system embedded in the Fuzzy Inferential Rule-based Model (FIRM) exhibits learned decision-making abilities to predict the effectiveness of mitigating factors on consequences

More ……

Advances in *CB* Attack Analysis

- An evolutionary structure (E-FIRM) allows the examination of multitudes of mitigating factor variants using FIRM as a kernel to yield a desired set of consequences
- The evolutionary structure allows the formulation of appropriate neural network-based Cost Models that provide a basis for ranking alternatives and for optimizing on the cost of S&T funding and cost of deployment over the desired time horizons

Q & A

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