The Deception Design Problem

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Introduction

Throughout history, deception has been used to change the outcome of a conflict. With the tremendous potential for gain and loss, many have undertaken the study of deception. Researchers have studied deception in fields as diverse as philosophy, law, psychology, and sociology. In economics, deception is used as a strategic tool to improve corporate performance [1].

*...little had been done to address the **tradeoff** between the **benefit, cost,** and **risk** of deception from a game theoretic perspective.*

Although there are serious ethical considerations, it has long been used in social and economic interactions, as well as throughout the domains of warfare. In fact, Sun Tzu stated that all warfare is based on deception [2, 3]. It has been described in battles from the conquest of Canaan to World War II and its employment continues into the emerging domain of cyberspace [4].

It is, therefore, no surprise that researchers apply mathematics to the study of deception. Game theory provides many tools to analyze mathematical models of conflict including those where uncertainty and deception are used. Although much work has been done to study deception from a *game theoretic* perspective, little had been done to address the trade off the between the benefit, cost, and risk of deception from a game theoretic perspective [5].

The omission of cost and risk is surprising in light of the current austere fiscal environment and the fact that risk assessment is a critical factor in deception planning doctrine. Furthermore, the ability to quickly plan and execute deceptive actions is increasingly important in domains where the latency between the start and end of an engagement is short.

In light of these research gaps, this research addresses deception in normal form games via payout manipulation and introduces a multiobjective optimization problem for designing efficient deceptive actions. The objective functions are used by a multiobjective evolutionary algorithm (MOEA) to automate the deception planning process. This is the first time a MOEA has been used to solve a game theoretic problem, and the first time benefit, cost and risk have been measured simultaneously in a single game theoretic modeled.

*The objective functions are used by a **multiobjective evolutionary algorithm** to automate the deception planning process*

Environmental Deception in action:

Rock, Paper, ~~Scissors~~ Doomsday Virus

Environmental deception causes the deceptive target (called the *mark*) to misperceive the game's payouts. Environmental deception does not change the true state of the conflict, only the mark's perception of it.

Suppose two players agree to a game of Rock, Paper, Scissors (RPS). The payouts for RPS are shown in blue in the top-right figure and represent the reality of the conflict: each round, the players receive either zero, one, or negative one points.

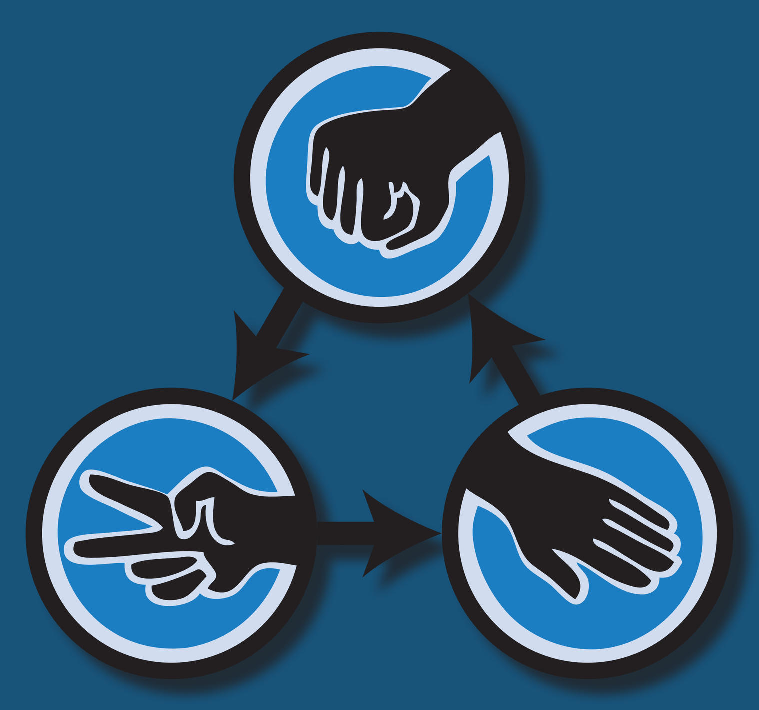
*The deceiving player is called the **Deceiver** and the target player is called the **Mark.***

But what if we deceived the mark into playing the wrong game? Instead of playing RPS, suppose the mark thought we were playing *Rock-Paper-Doomsday Virus* (RPDV). Rather than playing the optimal mix strategy according to reality, a rational player in RPDV would instead play a 50-50 mix between Rock and Paper 98% of the time. But since the reality is that the players are actually playing RPS, the deceiver can take advantage of the mark's off-equilibrium strategy.

*What if we deceived the mark into **playing the wrong game?***

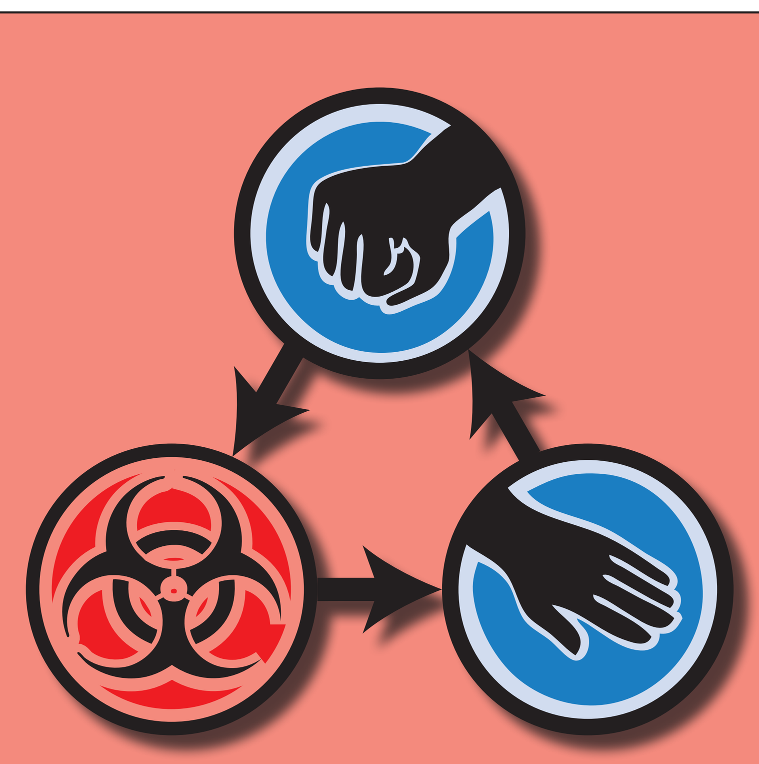
Reality

		Mark		
		R	P	S
Deceiver	R	0	-1	1
	P	1	0	-1
	S	-1	1	0



Perception

		Mark		
		R	P	Vir
Deceiver	R	0	-1	1
	P	1	0	-100
	Vir	-1	100	0



The Deception Design Problem (DDP) Definition

The Deception Design Problem is defined as follows: Given a payout matrix, A, that represents the reality of a conflict, compute a payout matrix, B, for the environmental deception game $G=\langle A,B\rangle$ that maximizes the deceiver's benefit (f_B) while minimizing cost (f_C) and risk (f_R).

Benefit

Benefit is the increase in expected utility for using environmental deception versus playing the deception-free game according to A, as in:

$$f_B=E(\langle A,B\rangle)-E(A)$$

where $E(\langle A,B\rangle)$ is the expected value in the environmental deception game $G=\langle A,B\rangle$, and $E(A)$ is the expected value in the original game.

Cost

Cost is the amount of effort that must be expended to cause the mark to believe the deception. This research assumes the amount of effort is proportional to the amount of change induced in the payout matrix. Thus, given a metric ***dist*** between payout matrices:

$$f_C=\boldsymbol{dist}(A,B)$$

Risk

Risk is the exposure to potential value loss:

$$f_C=Consequence\times Likelihood$$

where Consequence (R_C) is the magnitude of value loss if the mark plays the optimal counter-deception strategy

$$R_C=E(A)-\sum_{ij}\left(a_{ij}^{deceiver}\,(\sigma_D)_i\,(\sigma_{CD})_j\right)$$

and Likelihood (R_L) is the probability that the game's actual outcome and the mark's perception are inconsistent

$$R_L=\sum_{ij}I(a_{ij}^{mark},b_{ij}^{mark})\cdot p_{ij}\,(\sigma_D,\sigma_B^{mark})$$

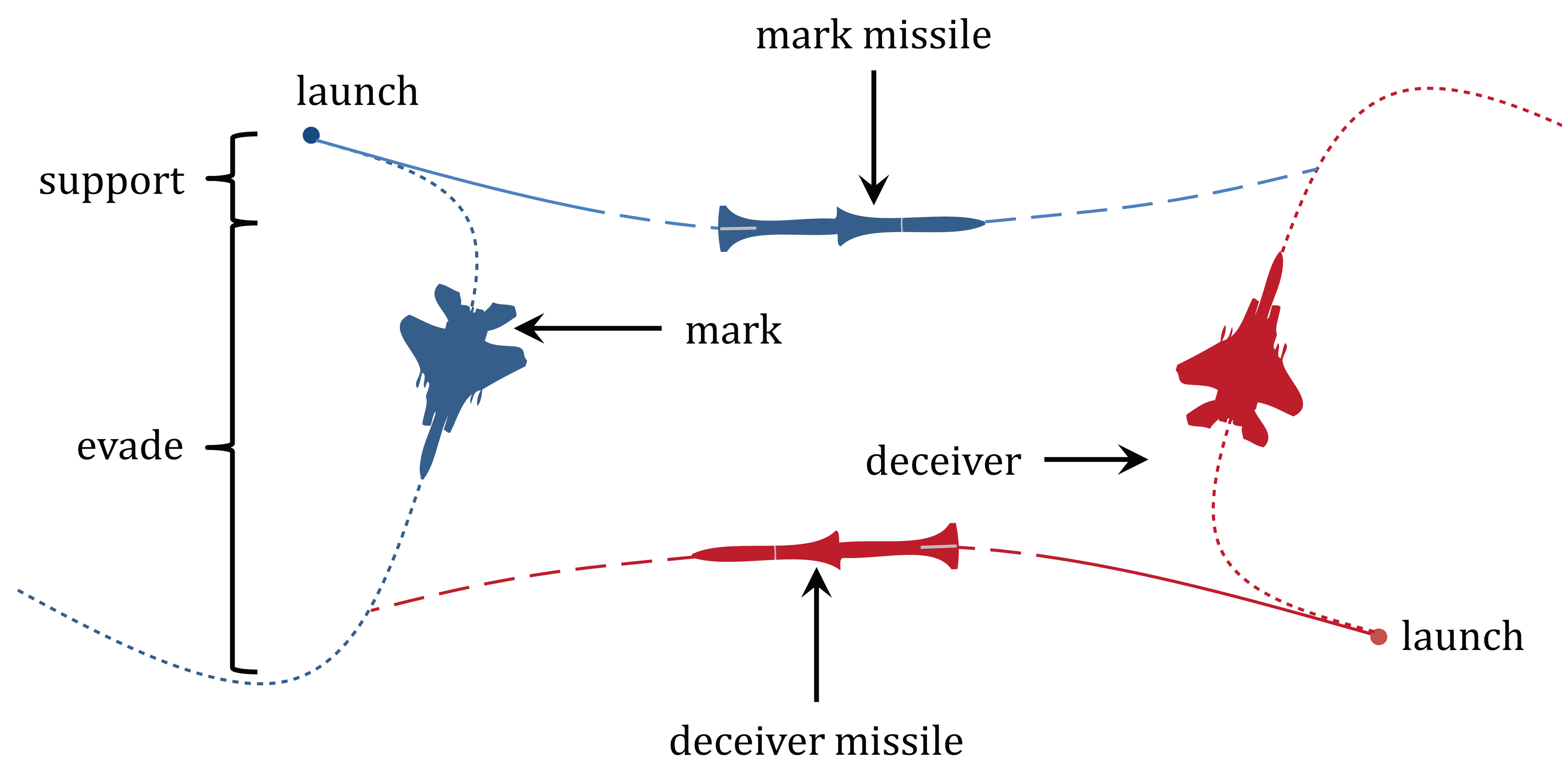
A multiobjective optimization problem for environmental deception design using game theory

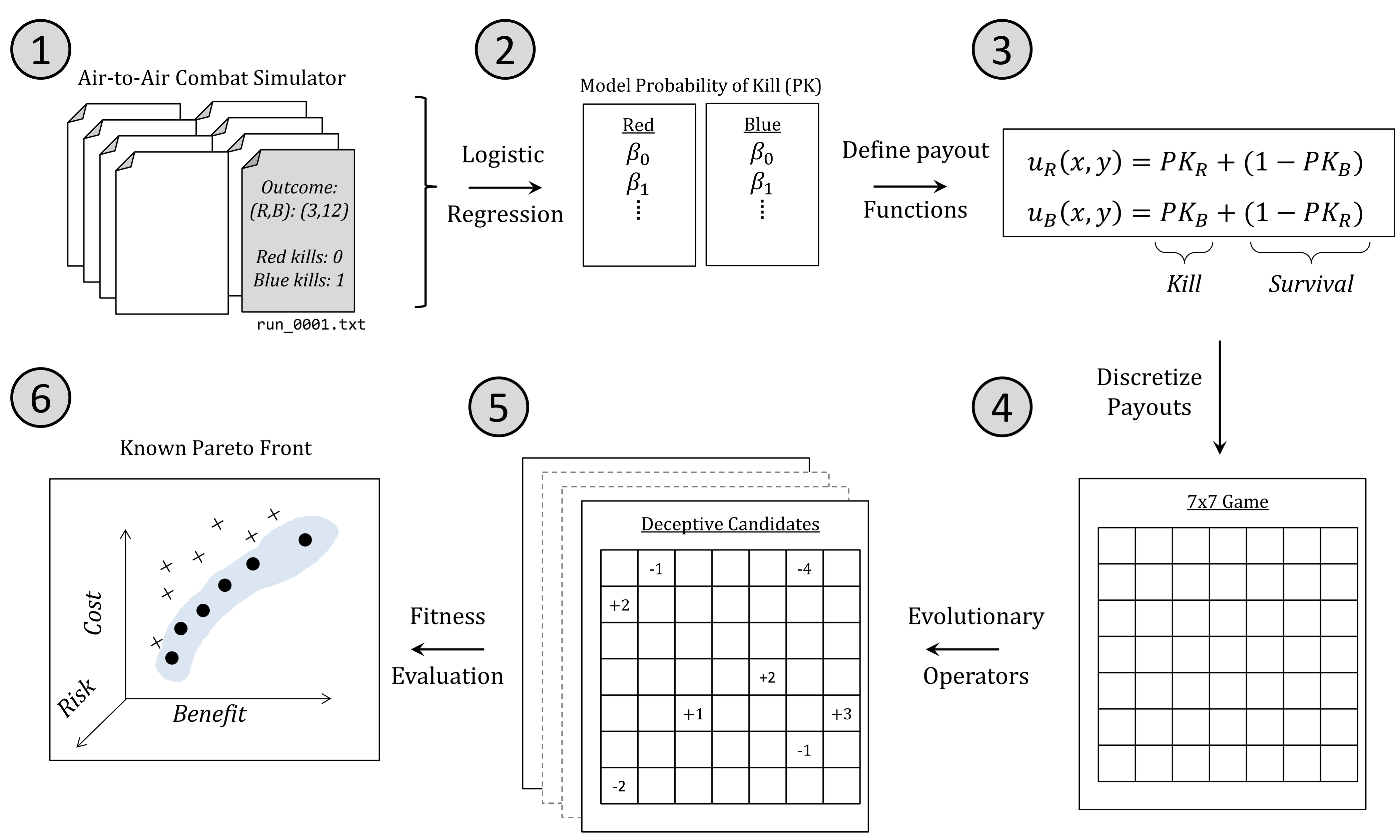
Case Study

The Missile Support Time (MST) game [6] involves two identical aircraft (AC) approaching each other at the edge of their engagement range. They each fire a missile at their opponent.

The longer they support, the more likely they are to kill their target, but this exposes them to ***a higher probability of being shot down***

The pilots can increase their probability of kill (PK) by supporting their missile with updates from their AC's guidance system. The pilots can enhance their chances of survival by performing evasive maneuvers. A pilot can either evade or support, but not both. To evade, the pilot must break his lock on the opponent and cease supporting his missile. So, the pilots must decide how long they will support before they evade. The longer they support, the more likely they are to kill their target, but this exposes them to a higher probability of being shot down themselves. Conversely, if they evade too soon, they are more likely to survive the engagement, but their missile will not likely hit their opponent. This case study investigates the possibility of using deception to cause one pilot to either support too long, or evade too soon. The payouts for each pilot are defined by a regression model fitted to the output of a discrete-event air combat simulator.



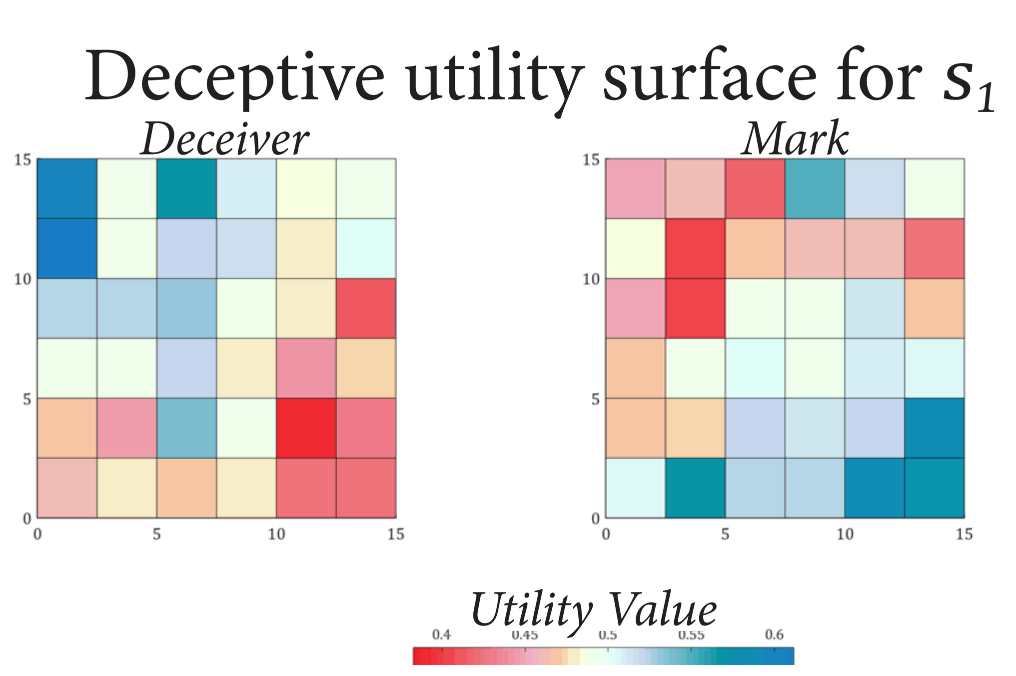


Methodology

After executing the air combat simulator (1), logistic regression is applied to the pilots' PK (2). The payouts are defined as a weighted-sum of PK and the probability of survival (3). The utility functions are then discretized into a normal form representation (4). The Speed-constrained Multiobjective Particle Swarm Optimization (SMPSO) [7] is a multiobjective particle swarm optimization algorithm; it is used to generate deceptive candidates (5). The fitness of each deceptive candidates is evaluated and dominated candidates are eliminated from the solution set (6).

The resulting known Pareto front contained ***only seven efficient solutions***

Results and Future Work



Steps 1-6 were executed 1,000 times. The resulting known Pareto front contained only seven solutions, summarized in the table below. The deceptive utility surface is shown to the left. In all cases, the deceiver benefited from deception (since $f_B>0$). Many of the efficient solutions were zero-risk to the deceiver (since $f_R=0$). Several techniques for reducing the deceptive cost are discussed in [5]; evaluating these techniques as well as developing an adaptation for continuous games are open areas for future research.

Solutions for the MST Case Study

Index	Fake Game Strategy Profile of Mark (σ_B^{mark}) 0s	2.5s	5s	7.5s	10s	12.5s	15s	σ_D	σ_{CD}	f_B	f_C	f_R	R_C	R_L
s_1	1.00	-	-	-	-	-	-	15s	10s	**0.095**	3.263	-	0.048	-
s_2	1.00	-	-	-	-	-	-	15s	10s	**0.095**	3.159	0.048	0.048	1.000
s_3	0.70	-	0.30	-	-	-	-	12.5s	10s	0.076	3.152	0.008	0.008	1.000
s_4	-	-	-	-	-	-	1.00	10s	10s	0.056	3.151	-	-	1.000
s_5	-	-	0.67	-	-	-	0.33	10s	10s	0.039	3.148	-	-	0.328
s_6	-	-	0.67	-	-	0.01	0.32	10s	10s	0.039	3.133	-	-	1.000
s_7	-	-	0.64	0.30	-	0.06	-	10s	10s	0.024	**3.103**	-	-	1.000

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