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Propagating Uncertainties in Simulation Assessments of Rockets, Artillery and Mortars Intercept Alternatives

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Abstract

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Simulations that support acquisition decisions are not free from error and uncertainty. Using an example from rockets, artillery and mortar (RAM) intercept development, this presentation applies sampling-based techniques from uncertainty analysis to assess simulation analysis errors within the broad context of decisions with risk. The presentation advocates a comprehensive inventory of sources of error, an expansion of uncertainty variables using designs of experiments, and results presentations using interactive probability distributions of uncertainties.

Errors in simulation-based analysis are not limited to Monte Carlo sampling errors. Simulations can have thousands of inputs and simulation-based studies depend on numerous assumptions. Current practice in modeling and simulation is to document fixed-value assumptions, to reach assumptions by consensus of authorities and experts and to perform extensive sensitivity analyses of uncertainty variables. Sensitivity analysis recognizes uncertainties in the problem, but inundates stakeholders with data without an integrating framework that supports decision making. Efficient designs of experiments enable enlarged sets of uncertainty variables compared to full factorial designs, but response surface and interpolating methods introduce additional estimation errors, which partially offset their benefits.

Uncertainties in the RAM defense problem include types of contingencies, threat capabilities, type and volume of threat attacks, types of forces that could be protected and weather and terrain that could be encountered. Any acquisition decision has the risk that the chosen alternative will not be adequate for the scenarios that actually emerge and also the risk that the “stressing scenario” never occurs so that consumed resources might have been used to pursue other capabilities. The presentation will illustrate the need to balance these types of risk in a notional analysis of alternatives (AoA) that compares a mature RAM intercept alternative with a developmental alternative.

The presentation will briefly refer to the prior work in uncertainty analysis. Sampling-based uncertainty propagation has already been applied successfully in cost and schedule risk modeling, infrastructure protection, environmental policy, pharmaceutical portfolio analysis and in energy exploration and production. The essential principles are that distributions, not expected values, of consequences are required to support decisions with risk, and that the current state of knowledge can be represented by subjective probabilities. Monte Carlo sampling against probability distributions over the uncertain variables leads to distributions rather than expected values of measures of effectiveness (MoE).

Application of risk principles to RAM intercept solutions requires overarching MoEs that portray long-run consequences, a set of control variables describing the alternatives, a comprehensive set of uncertainty variables and probability distributions on the uncertainty variables. The presentation will show how this might be pursued using example designs of experiments and analysis of outputs from EADSIM, a U.S. Army air and missile defense engagement simulation. The example will be used to illustrate ways of integrating and presenting measures of effectiveness as distributions rather than expected values.

Risk decision methodology acknowledges that stakeholders have different and changing preferences and attitudes towards risk. The use of meta-models enables fast-running response estimates, which allow the distributions of MoEs to be instantly updated. It provides a separation of sensitivity analysis from the uncertainty analysis and a way to trace how the distributions depend on subjective probabilities and sensitivities.

Contents

- Introduction: simulation errors within a risk framework
- Summarizing a sensitivity analysis with descriptive statistics
- Principles & past usage of uncertainty / risk analysis
- Comprehensive inventory of error sources
- Sources of uncertainty for life-cycle effectiveness
- Life-cycle cost & effectiveness with error & uncertainty for the rockets, artillery and mortars (RAM) intercept example
- Concluding observations

Simulation errors within a risk framework

Simulation analyses are not error-free

Sampling errors in Monte Carlo simulations can be estimated & controlled by sample size and designs of experiments

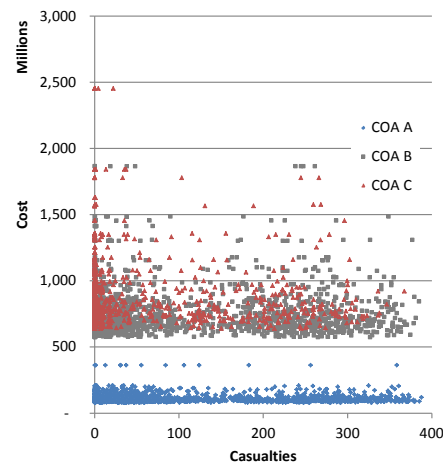
Analyses are subject to limited information imposed by schedule & limited resources

Errors propagate when the outputs are used in another analysis or in decision making

The risk in errors & uncertainty in analysis is the consequence of a “wrong” decision

Error and uncertainty in analysis can be analyzed in a holistic framework that includes limited information and decisions with risk

Errors & uncertainties in analysis are also sources of risk



Any one course of action in a decision can have a myriad of potential consequences

Current practice in simulation analysis

Fixed-point assumptions conceal effects of unknowns on operational effectiveness analysis

- Likelihood of a "stressing scenario"
- Variations on the type of operation
- Variations in threat capabilities & tactics
- Variations in terrain and weather
- Unknown performance parameters for future solutions, threats and competitors

Assumptions should be transparent

Use authoritative sources to validate fixed-point assumptions

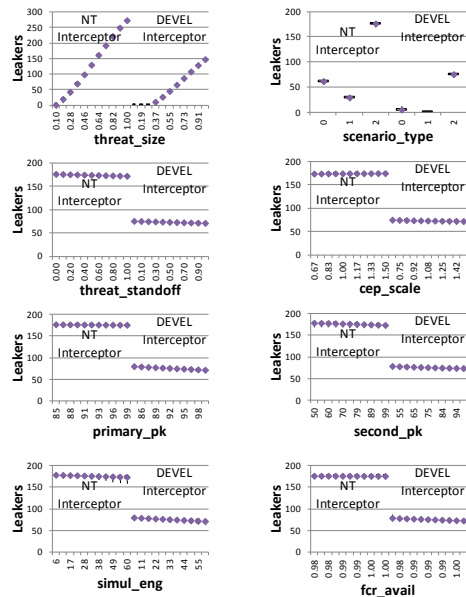
- Authoritative sources, study advisory groups, program direction, subject matter experts, peer review

Even when "validated", over-reliance on fixed-point assumptions can lead to an illusion of certainty (Janis 1973)

Employ extensive sensitivities to understand how assumptions affect the outcomes (Office of Aerospace Studies 2010, Morrow 2011)

Expose, document and estimate all sources of error

- Assumptions, inputs, modeling & simulation limitations, Monte Carlo sampling, response surface fit, generalization



Comparisons and sensitivity analysis for RAM intercepts simulation in EADSIM

The systems and threats in these examples are notional and presented for illustrative purposes

How to present comprehensive sensitivities in a way that recognizes risks and facilitates decisions?

Descriptive statistics summary of sensitivity studies

The graphics show summaries of 3600 engagement simulations and 600 cost outcomes

These show central location, spread and extreme-values of outcomes

Not a substitute for sensitivity graphs that link variation to particular factors

Cumulative probability graphs show more detail in the distributions but are less intuitive to some viewers

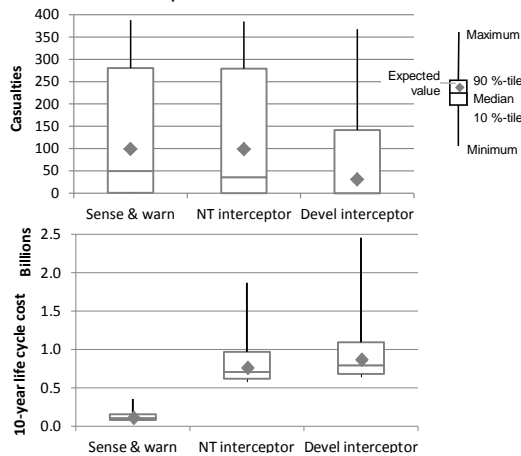
All sources of variation are included

- Sensitivity of 16 factors
- Monte Carlo variation within simulation

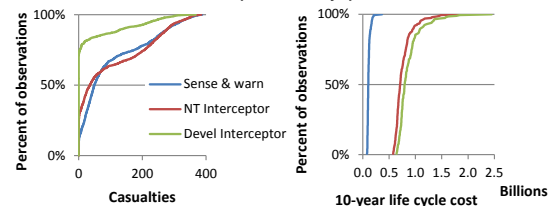
All points treated equally likely

A descriptive statistics summary shows distributions of the data without inference

Box & whisker plots of RAM defense simulations



Alternative cumulative probability presentation



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Principles of an outcome-based risk analysis

A reality: decisions are made with incomplete information

Expected values of consequences are not sufficient to evaluate alternatives (Markowitz 1952, Kaplan & Garrick 1981)

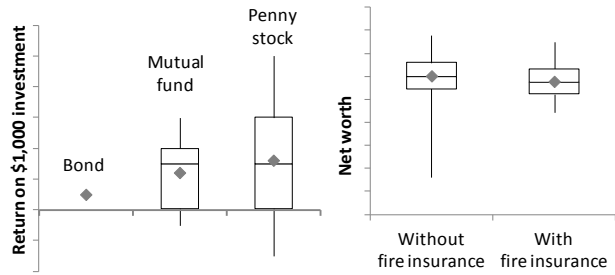
Subjective probabilities represent the current state of knowledge (Jaynes 1968)

Quantitative risk assessment approach: evaluate alternatives with probability distribution on a scale of outcomes (Garrick & Christie 2008)

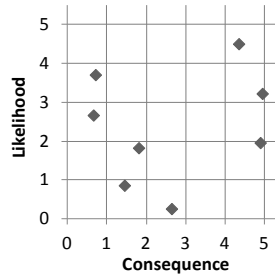
Transparency: the risk analysis should trace to the detailed sensitivities

The risk analysis should help identify the principal sources of risk

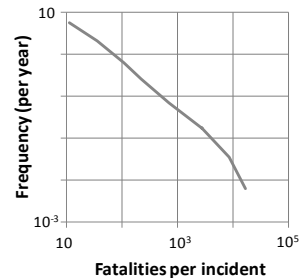
Risk is best understood in terms of a population of measurable consequences



Common risk decisions are evaluated on extreme value as well as expected outcome

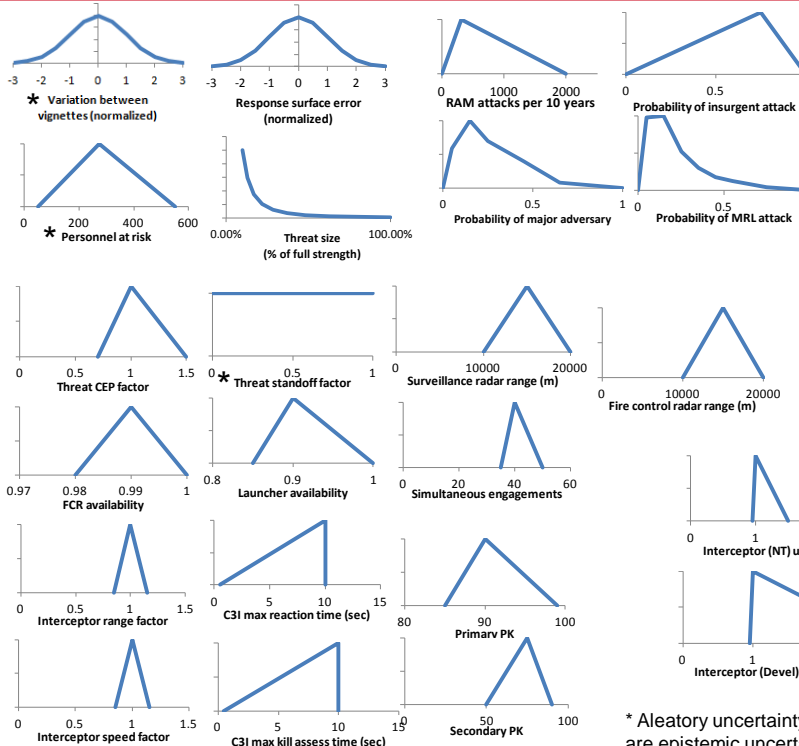


A risk reporting matrix (AMSAA Risk Team, 2013)



Frequency of man-caused disasters (fires, explosions, air crashes, dam failures, Kaplan & Garrick, 1981)

Identify *all* sources of error and uncertainty in the analysis



In Monte Carlo error analysis, all sources of error and uncertainties are assigned probability distributions for sampling

The distributions should represent the current state of knowledge

Capability to change distributions & update results in real time can facilitate presentation

* Aleatory uncertainty, subject to averaging. Others are epistemic uncertainties.

Applications of uncertainty & risk analysis

Timson applies subjective probabilities and Monte Carlo simulation to model probability distributions for critical performance parameters in engineering program management (1968)

Cuff demonstrates how quantitative risk analysis in performance, cost and schedule can support program decisions (1973)

Armacost & Pet-Edwards incorporate uncertainty in ice flow reporting in ice patrol operations planning (1995)

Fredley (1995) includes uncertainty in numbers and types of future operations in a force structure analysis approach

Pate-Cornell & Guikema present a model for prioritizing terrorism threats and countermeasures in homeland security (2002)

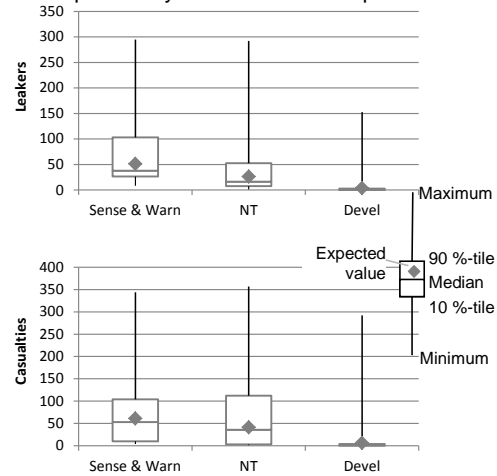
Monte Carlo sampling is used to propagate uncertainty of inputs in complex physics and environmental models (Christie, et al. 2005; Lloyd & Ries 2007)

Simulation-based sampling is used to propagate uncertainty through cost models (Anvari 2011)

Monte Carlo sampling has been used to propagate uncertainty in physical systems and cost modeling

Weighted distributions of outputs from EADSIM

Weights were derived from probability densities on the inputs



The systems and threats in these examples are notional and presented for illustrative purposes

Linking vignette results to life-cycle cost effectiveness

How will the acquisition will be judged after the fact?

The acquisition was well-matched to the threat and operations that actually occurred; the investment could not have achieved greater ends elsewhere

The acquisition was exceeded by the threat; high casualties and constraints on joint commander

The acquisition overmatched the actual threat to the extent that excess dollars could have been used to improve other capabilities

Sources of uncertainty for the life cycle

What types of global threats will emerge?

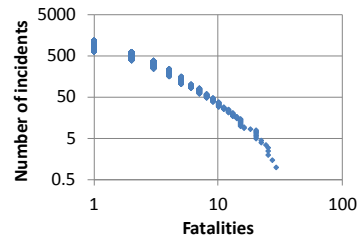
What types of operations will be undertaken?

How many vignettes will occur over the life cycle?

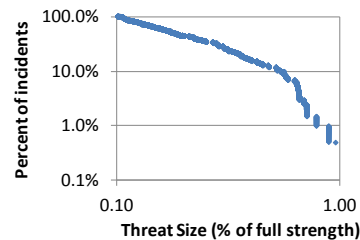
What is the distribution of "vignette intensity" (numbers of threat RAM employed)?

How should vignette to vignette variability be treated?

We can assign probability distributions to numbers of vignettes, threat size and intensity to derive a probability distribution of life-cycle casualties



Cumulative number of RAM incidents from March 2003 to March 2013 (Iraq Body Count, 2013)



Threat size distribution used in this RAM intercept illustration. Full strength is 100, 200 or 300 threats, depending on type of scenario.

Application to RAM intercept alternatives

Monte Carlo sampling of 3000 vignettes grouped into 200 futures



Grouping is necessary to separate epistemic and aleatory factors (epistemic factors should not be averaged over vignettes)

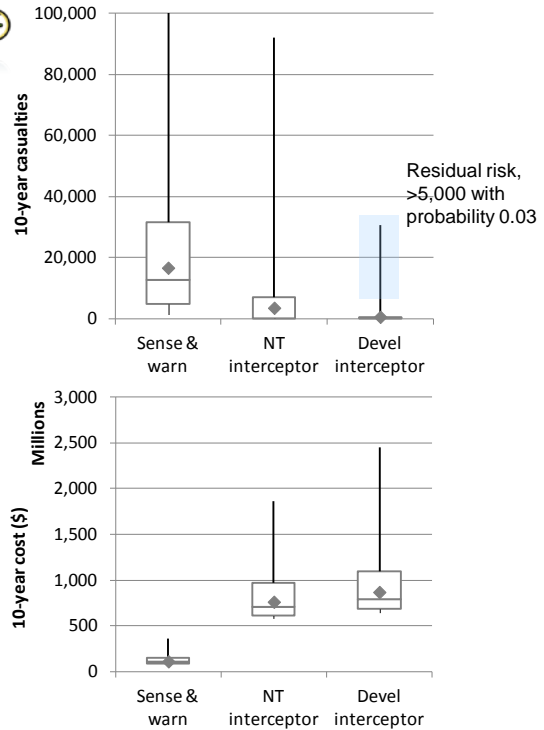
Discussion of alternatives can address extreme value as well as expected value outcomes

Distributions are highly skewed in this example

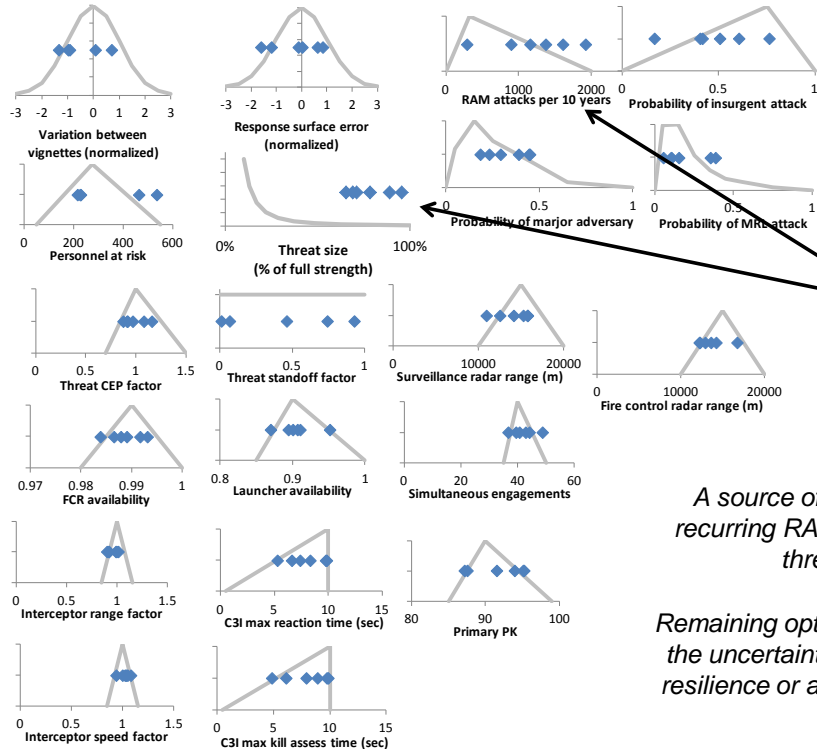
Ability to zoom the ordinate scale would help discriminate alternatives

A RAM intercept comparison showing life cycle effectiveness and cost as probability distributions

The systems and threats in these examples are notional and presented for illustrative purposes



Pulling the thread: cases resulting in >5,000 casualties for Devel interceptor



Six of 200 samples (3%) resulted in high 10-year casualties
 Except for Threat Size and Number of RAM Attacks, these samples are representative of uncertainty distributions

A source of risk is a decade of recurring RAM attacks at near full threat strength

Remaining options are to re-evaluate the uncertainty, improve alternative resilience or accept the residual risk

Some observations

The need for sensitivities of many uncertainty factors makes modern designs of experiments more attractive

The examples in this presentation used a space-filling design with 16 uncertainty factors and 410 scenarios

Replicate the DOE of uncertainty factors for each alternative; then there will be side-by-side simulations of the alternatives

Bayesian inference can produce posterior probability densities of some simulation inputs that are anchored to past observations

Example: use past data on RAM incidents to develop the probability density of future incidents

Whether or not to use surrogate models

It is possible to run simulations with directly sampled random inputs, directly summarizing outputs without surrogate models

Pro: surrogate models allow reconstruction of sensitivities

Pro: surrogate models allow real-time changes in the input probability densities for collaborative workshops

Con: surrogate models introduce an estimation error that needs to be incorporated into the error modeling

If a surrogate model is used, Bayesian inference can produce a probability density of estimation error

Modern DOE and response surface methods facilitate simulation error & uncertainty analysis

Summary of Key Points

Errors & uncertainties in analysis are sources of risk

A descriptive statistics summary shows distributions of the data without inference

Risk is understood in terms of a population of measurable consequences

Identify all sources of error and uncertainty

Monte Carlo sampling can be used to propagate uncertainty through simulations

Assign probability distributions to numbers of vignettes, threat size and intensity to derive a probability distribution of life-cycle benefits

Risk-based error and uncertainty analysis presents effectiveness and cost as probability distributions

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Backup Material

Application to RAM intercept alternatives (zoomed in)

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Grouping is necessary to separate epistemic and aleatory factors (epistemic factors should not be averaged over vignettes)

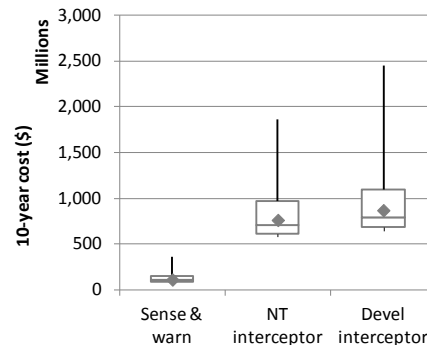
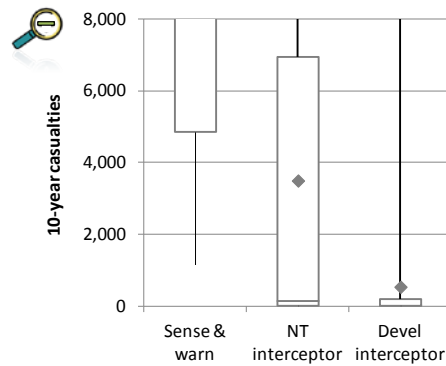
Discussion of alternatives can address extreme value as well as expected value outcomes

Distributions are highly skewed in this example

Ability to zoom the ordinate scale would help discriminate alternatives

A RAM intercept comparison showing life cycle effectiveness and cost as probability distributions

The systems and threats in these examples are notional and presented for illustrative purposes



Alternatives used in illustrative RAM defense risk analysis

	Sense & Warn	Near term (NT) interceptor	Developmental (Devel) interceptor
Development	Maintain other RAM defense pillars without intercept capability	In production Integrate in RAM defense system of systems	Develop new start interceptor & new fire control radar
Magazine (interceptors/launcher)		6	40
Nominal speed (m/sec)		525	430
Nominal range (m)		7000	5000
PK (<240 mm threats)		.85-.99	.85-.99
PK (≥240 mm threats)		.5-.9	.85-.99
Common elements		RAM intercept system consists of surveillance radar, fire control radar, C4I and four launchers	

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Error & uncertainty sources inventory

Source	Description	Source	Description
Threat size factor	% of threat full strength scenario	Interceptor range	Uncertainty scale factor of nominal range
Threat aiming accuracy	Uncertainty multiplier of CEP	PK	Actual PK will vary from program requirement
Threat standoff range	% between min & max range	Secondary PK	NT alternative PK vs large caliber rockets
Surveillance radar range	Types of radars available in future is uncertain	EADSIM internal sampling	PK success, threat & defense systems availability, impact points
Fire control radar range		Response surface error	Errors due to DOE & interpolation
C3I decision time	Uncertainty in time to clear engagement	Vignette rate of occurrence	Mean occurrence rate per year
Kill assessment time	Uncertainty in time to assess intercept	% of each type vignette	Occurrence rate as % of total
Simultaneous engagements	Number of interceptors in flight	Number of each type	Actual number, each type of vignette over 10 years
FCR availability	Actual availability will differ from program requirement	Personnel at risk	Number of personnel in defended area
Launcher availability		Cost growth	Uncertainty factors in program and ownership cost
Interceptor speed	Uncertainty scale factor of nominal speed		