Product Design Selection Under Uncertainty

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ENCE627 Decision Analysis for Engineering

Dec. 3rd 2002

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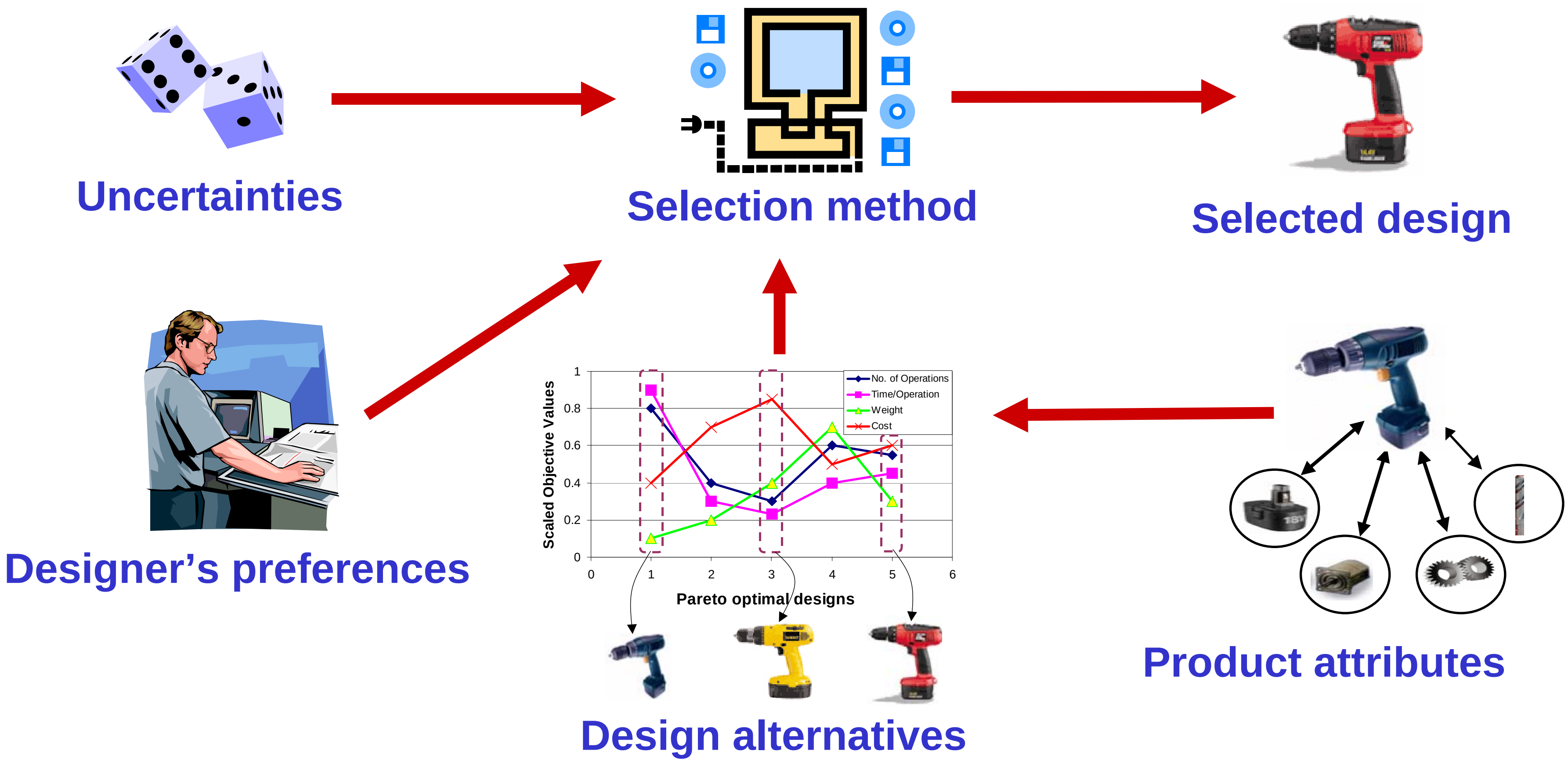
OUTLINE

- OVERVIEW OF THE PROJECT
- DESIGN VARIABLES AND ATTRIBUTES
- DESIGN ALTERNATIVE GENERATION
- THE UNCERTAINTY MODELING
- DESIGNER’S PREFERENCES
- DESIGN SELECTION APPROACH
- CONCLUSION

THE PROJECT OVERVIEW



Objective: Select the product design that accounts for both customer's requirements and designer's preferences

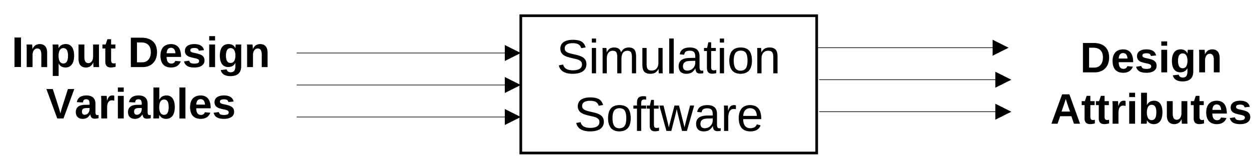
DESIGN VARIABLES & ATTRIBUTES

- **Design Variables**

  Set of input variables (parameters) to the design simulation software (e.g. Motor type, Gear type, Gear ratio, DC voltage, Ambient temperature)

- **Performance Attributes**

  Set of attributes that is the output of the simulation software,and identifies a product design (e.g. Manufacturing cost, Weight, Time per operation per battery charge)



DESIGN ALTERNATIVE GENERATION

Two methods for generating design alternatives:

- **Multiobjective Optimization**
  - Formulate a multiobjective optimization problem, solve for the alternatives that satisfy the objectives (performance attributes) the most.
  - There is no closed form representation of the objective functions
  - The design input parameters consist of both continuous and discrete variables
  - Multiobjective Genetic Algorithm is a good choice to handle this type of problems
  - The solution points constitute a non-dominated set w.r.t. all objective functions.

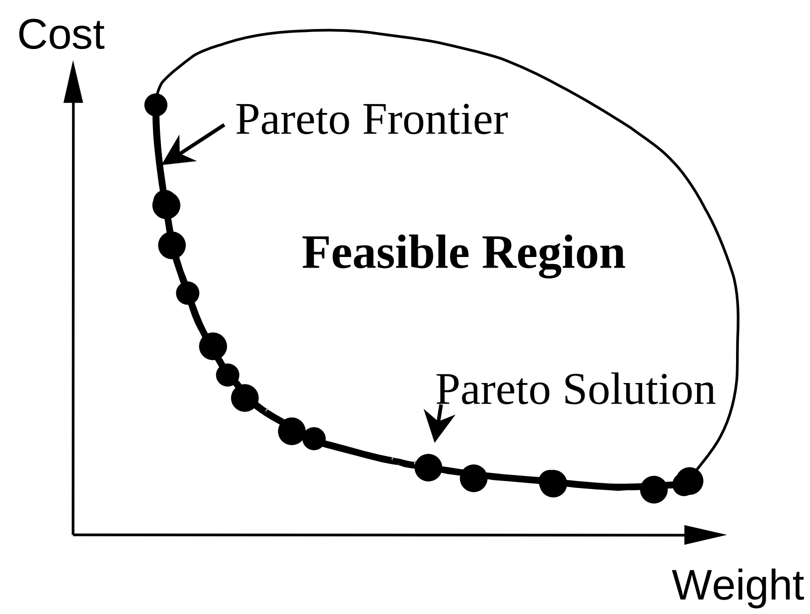
DESIGN ALTERNATIVE GENERATION

- **Multiobjective Optimization Contd.**

Example:

min Cost (Motor type, Gear type, Batter type, Skin material, Labor)
min Weight (Motor type, Gear type, Skin material)

s.t. Motor type integer between [1,20]
Gear type integer between [1,14]
Battery type integer between [1,5]
Gear ratio real between [10,20]
Skin Material integer [1,3]



DESIGN ALTERNATIVE GENERATION

- **Permutation Over Attributes**
  - Generating design alternatives by permuting the attributes over all (or certain) levels
  - Mapping between the attributes and the design variables is simple(i.e. we can easily obtain the corresponding design variables, once we get the attribute levels)
  - Very easy to implement but less likely to be able to handle real applications.

Example:

$$\left.\begin{array}{l}\text{Motor type [1,5]}\\ \text{Gear type [1,3]}\\ \text{Battery type [1,2]}\end{array}\right\}\quad \text{5x3x2 = 30 design alternatives}$$

THE UNCERTAINTY

The uncertainty exists in the input design variables

- **Sources of Uncertainty**
  - The market price of the parts
  - The fluctuations in input voltage/current
  - The measurement error in the manufacturing of the parts
  - The quality of the material/parts
- **The Uncertainty Modeling**
  - Using presumed distributions for certain events (i.e. normal distribution for measurement error)
  - Collecting the historical/field data and fit the best distribution using BestFit® (Distribution of input design variables)

DISTRIBUTION OF ATTRIBUTES

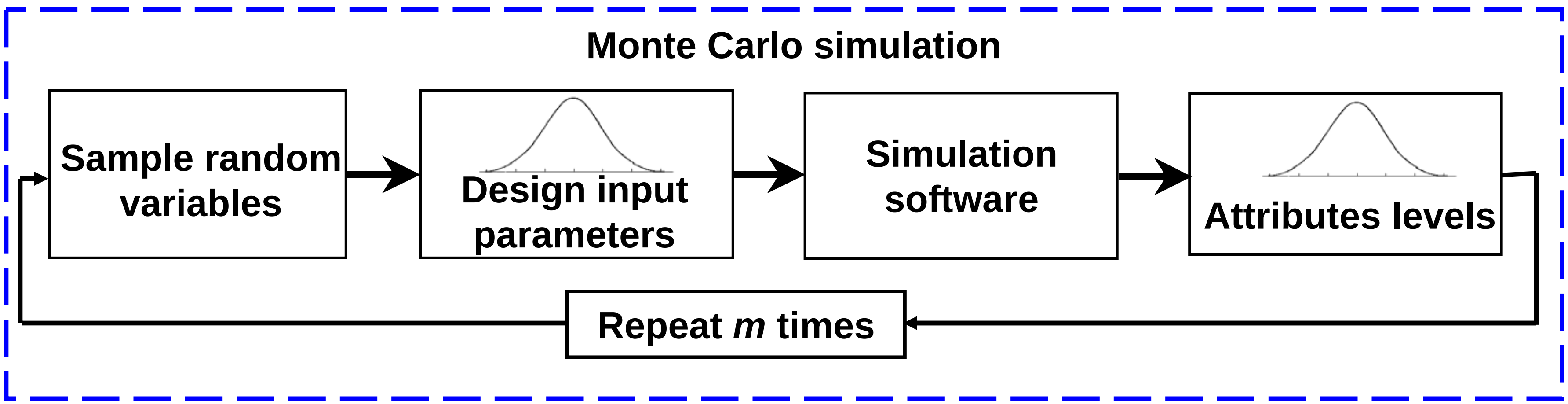
Monte Carlo Simulation

– Sample a random variable

– Construct the appropriate distribution for each design variable (i.e. Using @Risk or program that in Excel)

– Feed the design variables to the simulation software

– Obtain the distribution for the performance attributes

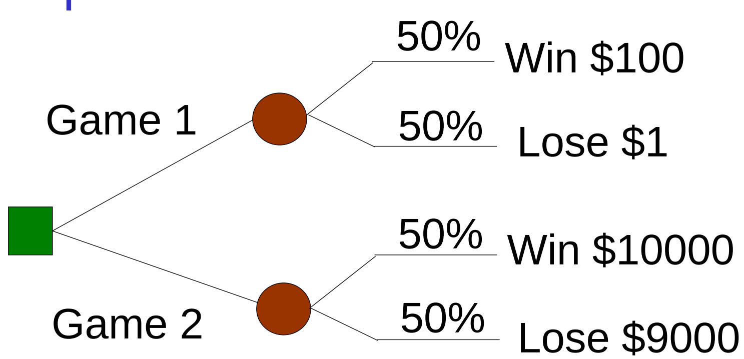


MODELING DESIGNER'S PREFERENCES

Utility Function

- Measure of the worth of a design alternative
- Accounts for the risk attitude of the designer
- Expected utility is a more realistic measure than expected value

Example:



EMV(Game 1) = $49.50

EMV(Game 2) = $500

UTILITY ASSESSMENT

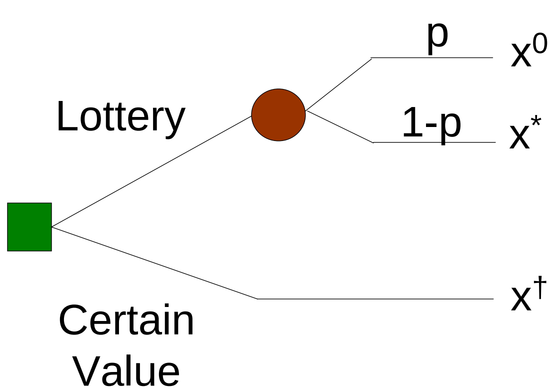
Certainty equivalent method

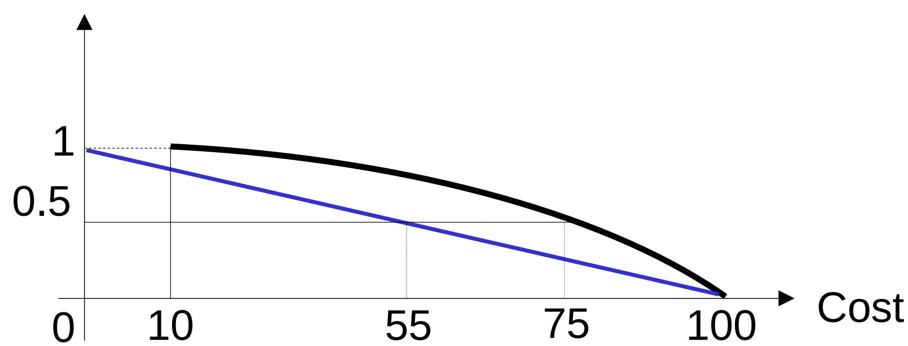
Decision maker is asked to provide a certain value that he believes, is equivalent to the lottery.

$$(x^0 , p ; x^*) \sim x^\dagger \quad \text{Or} \quad U(x^\dagger) = pU(x^0) + (1\text{-}p)U(x^*)$$

Probability equivalent method

Decision maker is asked to provide the probability in the lottery that makes him/her indifferent between the lottery and certain value.





UTILITY FUNCTION DISTRIBUTION

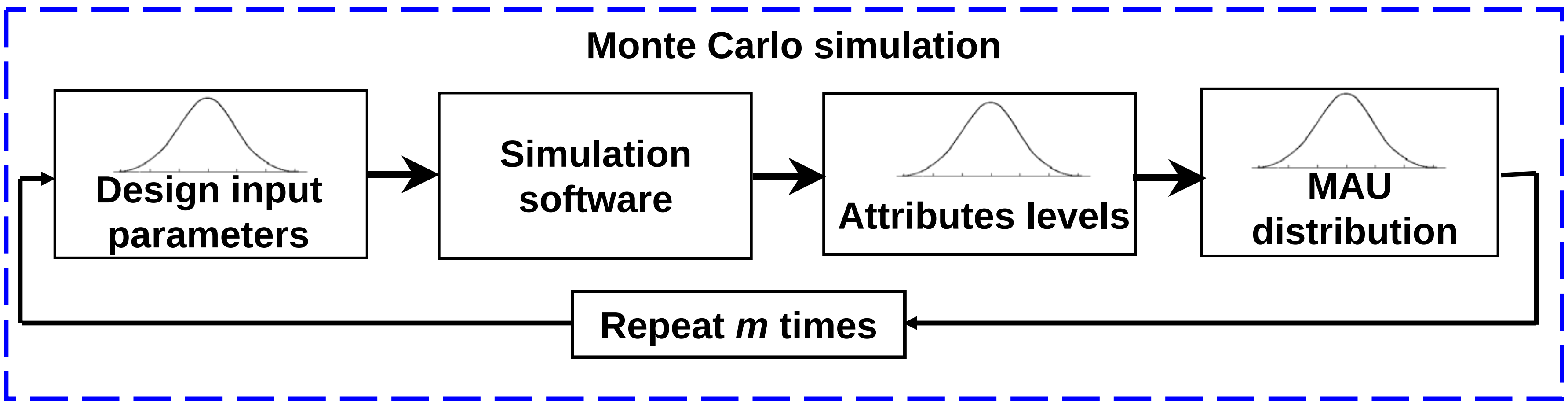
Multi Attribute Utility Function

– Measure for designer's preferences over all attributes of the product

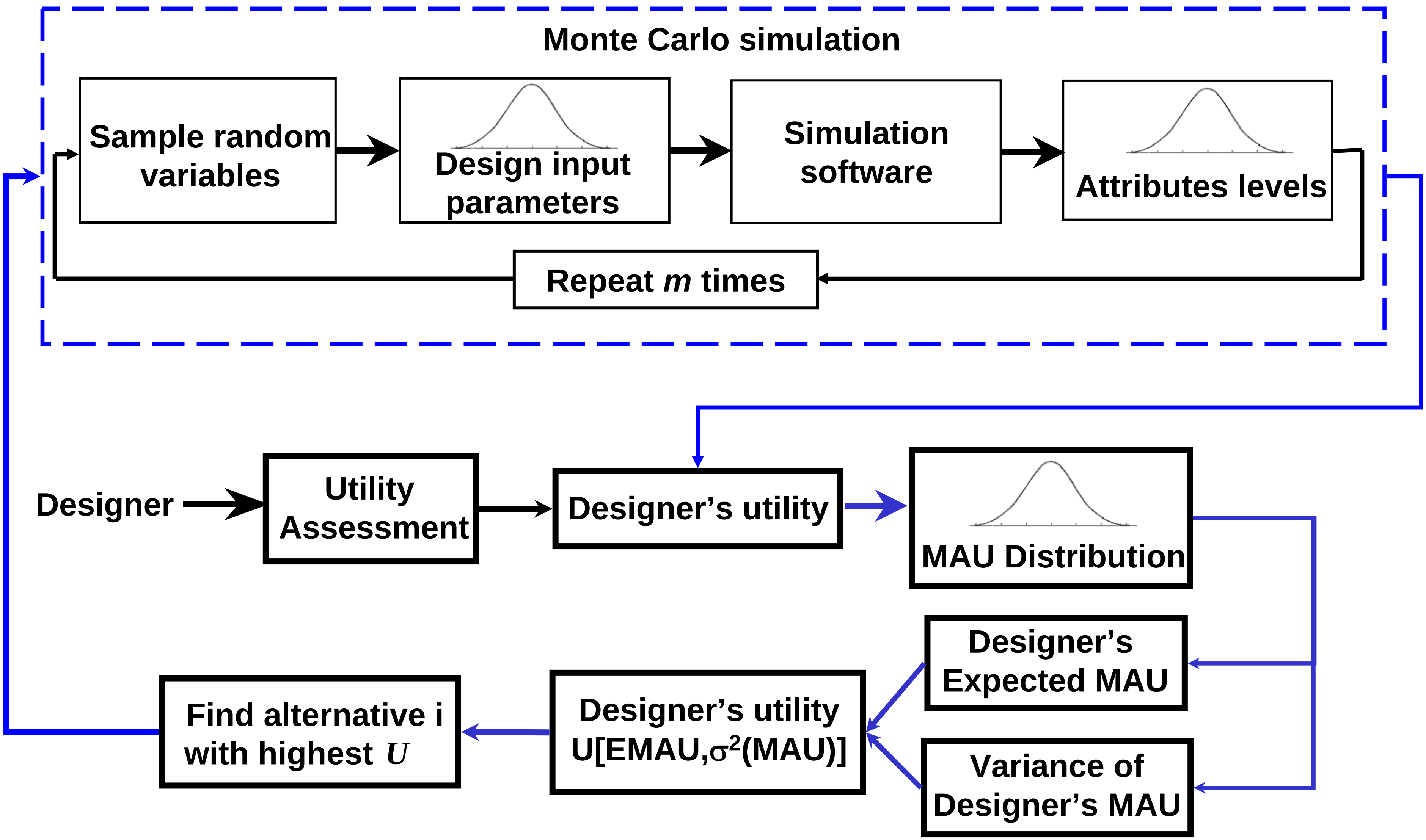
– Importance weights are required

– Obtain the MAU distribution by Monte Carlo simulation

– Estimate the Expected MAU and its variance for each design



DESIGN SELECTION APPROACH



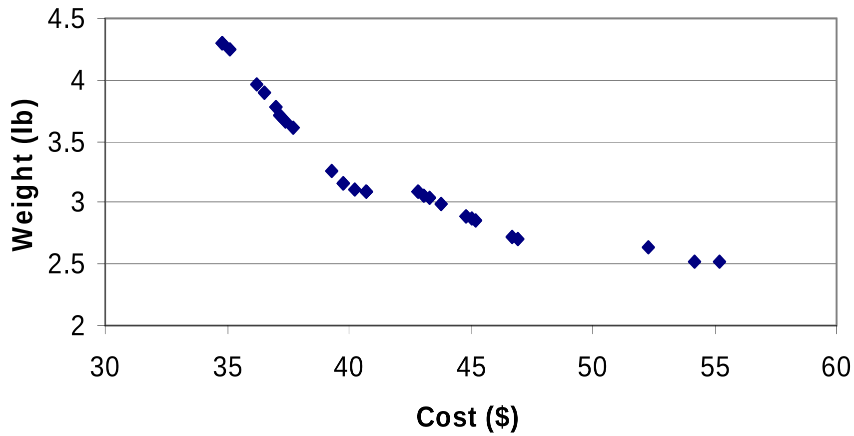
CONCLUSIONS

- The selection approach used in this project takes into account the uncertainties in the product design process
- The utility function accounts for the risk attitude of the decision maker, hence yields a better decision
- Evolutionary algorithms (such as GA) can handle the situations in which there are both continuous and discrete type of design variables and the closed form of the objective function(s) is not available
- Monte Carlo simulation is the main tool for modeling the uncertainty in this project
- The design attributes used (manufacturing cost and weight) are assumed to be statistically independent, however, this assumption may not hold in most of the real world applications

BACKUP SLIDES

SET OF DESIGN ALTERNATIVES & DESIGNER'S MAU

- **Attributes:**
  - Manufacturing Cost
  - Weight



Uncertainty assumption:

- Attributes are *statistically* independent

- **Designer's multi attribute utility:**
  - Cost is more important than time per operation

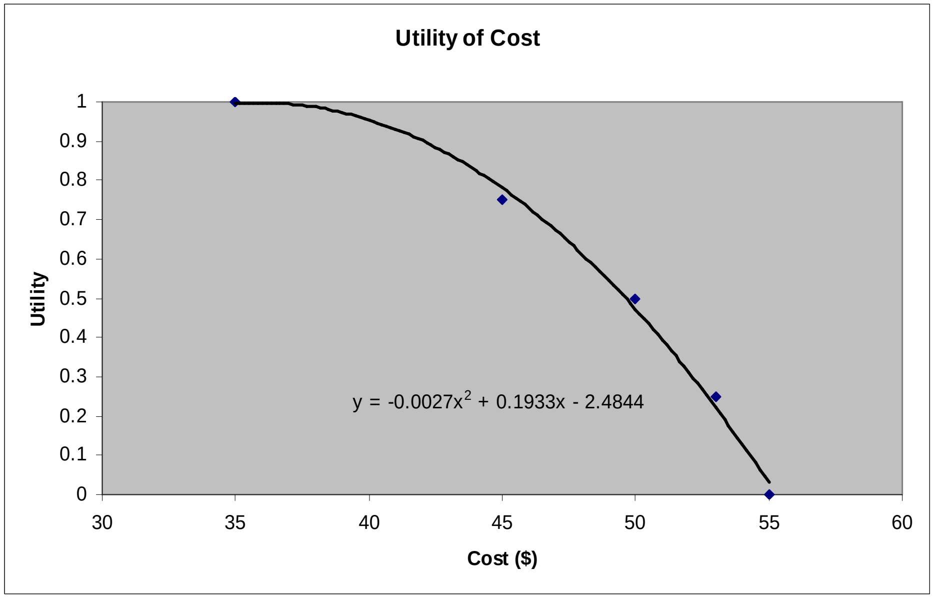
- **Additive MAU:**

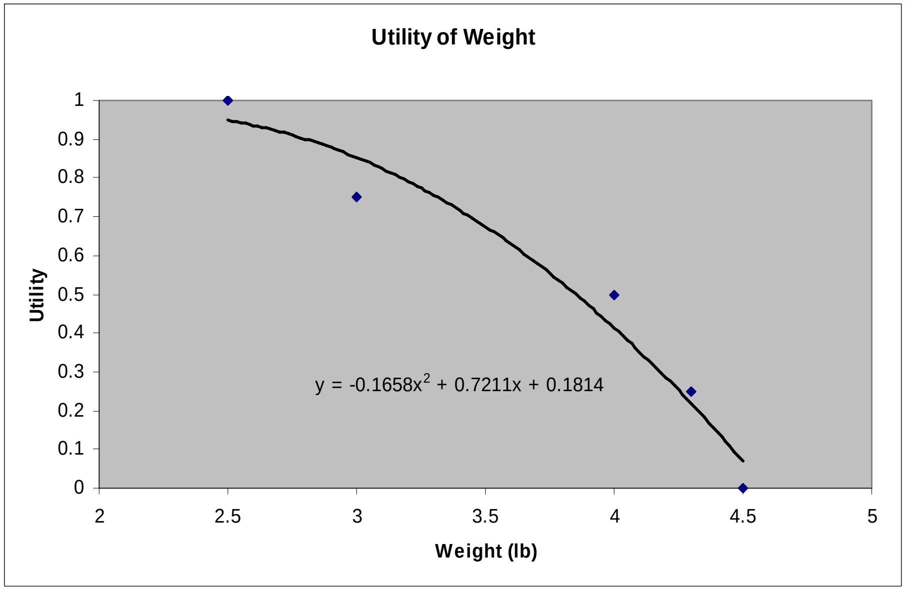
$$u_c(x_c) = -0.0027x_c^{\ 2} + 0.1933x_c - 2.4844 \qquad k_c = 0.65$$

$$u_w(x_w) = -0.1658x_w^{\ 2} + 0.721x_w + 0.1814 \qquad k_w = 0.35$$

$$U(x_p, x_t) = k_c u_c(x_c) + k_w u_w(x_w)$$

UTILITY ASSESSMENTS





Cost	Utility
35	1
45	0.75
50	0.5
53	0.25
55	0

Weight	Utility
2.5	1
3	0.75
4	0.5
4.3	0.25
4.5	0