

# CS/ISyE 719: Stochastic Programming Modeling

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# Module Outline

## Stochastic Programming Modeling

- A little about stochastic modeling
- Crop planning example
- (Expected) Value of stochastic solution
- Expected value of perfect information
- Facility location example

# Stochastic Programming Modeling

## Optimization Modeling + Stochastic Modeling

- In this course, we tend to focus more on optimization modeling

## Stochastic Modeling

- Deriving the models of the random variables in the model
- Heavily problem/context dependent

# Data-Driven Stochastic Modeling

In short to medium-term problems, might be possible to use past data to construct stochastic model

- Forecasting, predictive modeling
- Ideally, build point and distribution estimates

# Data-Driven Stochastic Modeling

Many (most) stochastic programming methods only require ability to **sample** random variables appearing in model

- Used to construct a **scenario approximation** that is what is actually solved
- Or integrated into a stochastic algorithm
- Surprisingly “few” scenarios needed (relative to dimension of random vector)

⇒ Random variables can be generated from (possibly complicated) simulation models

- Key assumption: Simulation needs to be **independent** of decisions
- E.g., Weather simulation yields (correlated) wind power scenarios

## Example: Linear Regression

Example model for random demand of doughnuts:

- Assume you have estimated a linear regression model:

$$X = \sum_{i=1}^p w_i Y_i + \epsilon$$

- Assume that at time decision is made, independent variables  $Y_i, i = 1, \dots, t$  are known as  $\hat{Y}_i$  (e.g., current temperature, etc.)
- Other independent variables are unknown, but distribution estimates can readily be constructed from data (e.g., number of students who will attend the lecture)
- Obtaining random observation of  $X$ :
  - Sample  $\tilde{Y}_i$  from estimated distribution of  $Y_i, i = t+1, \dots, p$  and  $\tilde{\epsilon}$  from the error distribution
  - $\tilde{X} = \sum_{i=1}^t w_i \hat{Y}_i + \sum_{i=t+1}^p w_i \tilde{Y}_i + \tilde{\epsilon}$

# What you should (usually) NOT do

Some people use the term **Sample Average Approximation** for the following approach:

- Use past observations of demand **directly** as the scenarios in your stochastic model

**This is not (generally) Sample Average Approximation!**

- SAA uses scenarios generated from a stochastic model (which ideally is based on all available data)
- Key difference is the ability to use information that is known when making decision to build a better stochastic model (e.g., current weather conditions, most recent demand, etc.)

# “Expert” /case driven stochastic modeling

In some (many?) situations (e.g., long-term models), there may be no reasonable data to justify a stochastic model

What to do?

- Robust optimization: Just assume uncertain data lies in an “uncertainty set”, and optimize the worst-case
  - Better than assuming deterministic, but may be overly conservative
  - Also, **two-stage robust models** are generally intractable
- Constructed scenarios with subjective probability estimates:
  - Demand for a product is “low, medium, or high”.
  - Weather is “dry” or “wet”.
  - The market will go “up” or “down”



# George Box (Yes, again!)

“All models are wrong. Some models are useful.”

- Surely a subjectively constructed set of scenarios is **WRONG**
- But, the resulting stochastic programming model might be **USEFUL** in making better decisions

## Key insight (again)

Comparing solution expected values is easier than estimating each solution's individual expected value.

## Back to a Concrete Example



### Farmer Ted

- In this example, the farmer has (real) *recourse* that is, he can do after observing random outcome. Not just sell his newspapers.
- Farmer Ted can grow Wheat, Corn, or Beans on his 500 acres.
- Farmer Ted requires 200 tons of wheat and 240 tons of corn to feed his cattle
- These can be grown on his land or bought from a wholesaler.

## More Constraints

- Any excess production can be sold for \$170/ton (wheat) and \$150/ton (corn)
- Any shortfall must be bought from the wholesaler at a cost of \$238/ton (wheat) and \$210/ton (corn).
- Farmer Ted can also grow beans
  - Beans sell at \$36/ton for the first 6000 tons
  - Due to economic quotas on bean production, beans in excess of 6000 tons can only be sold at \$10/ton

# The Data

- 500 acres available for planting

	Wheat	Corn	Beans
Yield (T/acre)	2.5	3	20
Planting Cost (\$/acre)	150	230	260
Selling Price	170	150	36 ( $\leq 6000T$ ) 10 ( $>6000T$ )
Purchase Price	238	210	N/A
Minimum Requirement	200	240	N/A

## Formulate the LP – Decision Variables

- $x_{W,C,B}$  Acres of Wheat, Corn, Beans Planted
- $w_{W,C,B}$  Tons of Wheat, Corn, Beans sold (at favorable price).
- $e_B$  Tons of beans sold at lower price
- $y_{W,C}$  Tons of Wheat, Corn purchased.
- Note that Farmer Ted has *recourse*. After he observes the weather event, he can decide how much of each crop to sell or purchase!

# Formulation

$$\begin{aligned} \max \quad & -150x_W - 230x_C - 260x_B - 238y_W + 170w_W \\ & -210y_C + 150w_C + 36w_B + 10e_B \end{aligned}$$

subject to

$$x_W + x_C + x_B \leq 500$$

$$2.5x_W + y_W - w_W = 200$$

$$3x_C + y_C - w_C = 240$$

$$20x_B - w_B - e_B = 0$$

$$w_B \leq 6000$$

$$x_W, x_C, x_B, y_W, y_C, e_B, w_W, w_C, w_B \geq 0$$

## Solution with (expected) yields

	Wheat	Corn	Beans
Plant (acres)	120	80	300
Production	300	240	6000
Sales	100	0	6000
Purchase	0	0	0

- Profit: \$118,600

# It's the Weather, Stupid!

- Farmer Ted knows well enough to know that his yields aren't always precisely  $Y = (2.5, 3, 20)$ . He decides to run two more scenarios
- Good weather:  $1.2Y$
- Bad weather:  $0.8Y$ .



# Creating a Stochastic Model

Here is a general procedure for making a (scenario-based) 2-stage stochastic optimization problem

- For a “nominal” state of nature (scenario), formulate an appropriate (deterministic) optimization model
- Decide which decisions are made before uncertainty is revealed, and which are decided after
- All second stage variables get “scenario” index
- Constraints with scenario indices must hold for all scenarios
- Second stage variables in the objective function should be summed and **weighted by the probability** of the scenario occurring

## What does this mean in our case?

- First stage variables are the  $x$  (or planting variables)
- Second stage variables are the  $y, w, e$  (purchase and sale variables)
- We have one copy of the  $y, w, e$  for each scenario!
- Attach a scenario subscript  $s = 1, 2, 3$  to each of the purchase and sale variables.
  - 1: Good, 2: Average, 3: Bad
- $w_{C2}$  : Tons of corn sold at favorable price in scenario 2
- $e_{B3}$  : Tons of beans sold at unfavorable price in scenario 3.

## Expected Profit

- The second stage cost for each submodel appears in the overall objective function weighted by the probability that scenario will happen

$$\begin{aligned} & -150x_W - 230x_C - 260x_B \\ & +1/3(-238y_{W1} + 170w_{W1} - 210y_{C1} + 150w_{C1} + 36w_{B1} + 10e_{B1}) \\ & +1/3(-238y_{W2} + 170w_{W2} - 210y_{C2} + 150w_{C2} + 36w_{B2} + 10e_{B2}) \\ & +1/3(-238y_{W3} + 170w_{W3} - 210y_{C3} + 150w_{C3} + 36w_{B3} + 10e_{B3}) \end{aligned}$$

# Constraints

$$x_W + x_C + x_B \leq 500$$

$$3x_W + y_{W1} - w_{W1} = 200$$

$$3.6x_C + y_{C1} - w_{C1} = 240$$

$$24x_B - w_{B1} - e_{B1} = 0$$

## Constraints (cont.)

$$2.5x_W + y_{W2} - w_{W2} = 200$$

$$3x_C + y_{C2} - w_{C2} = 240$$

$$20x_B - w_{B2} - e_{B2} = 0$$

$$2x_W + y_{W3} - w_{W3} = 200$$

$$2.4x_C + y_{C3} - w_{C3} = 240$$

$$16x_B - w_{B3} - e_{B3} = 0$$

$$w_{B1}, w_{B2}, w_{B3} \leq 6000$$

$$\text{All vars} \geq 0$$

# Optimal Solution

		Wheat	Corn	Beans
s	Plant (acres)	170	80	250
1	Production	510	288	6000
1	Sales	310	48	6000
1	Purchase	0	0	0
2	Production	425	240	5000
2	Sales	225	0	5000
2	Purchase	0	0	0
3	Production	340	192	4000
3	Sales	140	0	4000
3	Purchase	0	48	0

# The Value of the Stochastic Solution (VSS)

- Suppose we just replaced the “random” quantities (the yields) by their mean values and solved that problem.
- Would we get the same expected value for the Farmer’s profit?
- How can we check?
  - Solve the “mean-value” problem to get a first stage solution  $x$ .
  - Fix the first stage solution at that value  $x$ , and solve all the scenarios to see Farmer Ted’s profit in each.
  - Take the weighted (by probability) average of the optimal objective value for each scenario
- Alternatively (and simpler), we can fix the  $x$  variables and solve the stochastic programming problem we created.

# Computing FT's VSS

- Mean yields  $Y = (2.5, 3, 20)$
- (We already solved this problem).
- $x_W = 120, x_C = 80, x_B = 300$



# Fixed Policy – Average Yield Scenario

maximize

$$-150x_W - 230x_C - 260x_B - 238y_W + 170w_W - 210y_C + 150y_C + 36w_B + 10e_B$$

subject to

$$x_W = 120$$

$$x_C = 80$$

$$x_B = 300$$

$$x_W + x_C + x_B \leq 500$$

$$2.5x_W + y_W - w_W = 200$$

$$3x_C + y_C - w_C = 240$$

$$20x_B - w_B - e_B = 0$$

$$w_B \leq 6000$$

$$x_W, x_C, x_B, y_W, y_C, e_B, w_W, w_C, w_B \geq 0$$

## Fixed Policy – Average Yield Scenario Solution

	Wheat	Corn	Beans
Plant (acres)	120	80	300
Production	300	240	6000
Sales	100	0	6000
Purchase	0	0	0

- 
- Profit: \$118,600

# Fixed Policy – Bad Yield Scenario

maximize

$$-150x_W - 230x_C - 260x_B - 238y_W + 170w_W - 210y_C + 150y_C + 36w_B + 10e_B$$

subject to

$$x_W = 120$$

$$x_C = 80$$

$$x_B = 300$$

$$x_W + x_C + x_B \leq 500$$

$$2x_W + y_W - w_W = 200$$

$$2.4x_C + y_C - w_C = 240$$

$$16x_B - w_B - e_B = 0$$

$$w_B \leq 6000$$

- 
- Objective Value: \$55,120

# Fixed Policy – Good Yield Scenario

maximize

$$-150x_W - 230x_C - 260x_B - 238y_W + 170w_W - 210y_C + 150y_C + 36w_B + 10e_B$$

subject to

$$x_W = 120$$

$$x_C = 80$$

$$x_B = 300$$

$$x_W + x_C + x_B \leq 500$$

$$3x_W + y_W - w_W = 200$$

$$3.6x_C + y_C - w_C = 240$$

$$24x_B - w_B - e_B = 0$$

$$w_B \leq 6000$$

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- Objective Value: \$148,000

# What's it Worth to Model Randomness?

- If Farmer Ted implemented the policy based on using only “average” yields, he would plant  $x_W = 120, x_C = 80, x_B = 300$
- He would expect in the long run to make an average profit of...
  - $1/3(118600) + 1/3(55120) + 1/3(148000) = 107240$
- If Farmer Ted implemented the policy based on the solution to the stochastic programming problem, he would plant  $x_W = 170, x_C = 80, x_B = 250$ .
  - From this he would expect to make 108390

# VSS

- The difference of the values 108390-107240 is the **Value of the Stochastic Solution** : \$1150.
- 
- On average, it would pay off \$1150 per growing season for Farmer Ted to use the “stochastic” solution rather than the “mean value” solution.
  - \$1150 is precisely the (expected) “value” of **implementing a planting policy** based on the “stochastic solution”, rather than the mean-value solution.

# EVPI – Expected Value of Perfect Information

- The EVPI measures the maximum amount a decision maker would be willing to pay in return for complete and accurate information about the future.
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- How much could Farmer Ted make if he could “wait and see” what the weather was going to be before deciding on how to plant?

## Formulation – Good yields

$$\begin{aligned} \max \quad & -150x_W - 230x_C - 260x_B - 238y_W + 170w_W \\ & - 210y_C + 150w_C + 36w_B + 10e_B \end{aligned}$$

subject to

$$x_W + x_C + x_B \leq 500$$

$$3x_W + y_W - w_W = 200$$

$$3.6x_C + y_C - w_C = 240$$

$$24x_B - w_B - e_B = 0$$

$$w_B \leq 6000$$

$$x_W, x_C, x_B, y_W, y_C, e_B, w_W, w_C, w_B \geq 0$$



## Solution with good yields

	Wheat	Corn	Beans
Plant (acres)	183.33	66.67	250
Production	550	240	6000
Sales	350	0	6000
Purchase	0	0	0

- Profit: \$167,667

## Formulation – Bad Yields

$$\begin{aligned} \max \quad & -150x_W - 230x_C - 260x_B - 238y_W + 170w_W \\ & - 210y_C + 150w_C + 36w_B + 10e_B \end{aligned}$$

subject to

$$x_W + x_C + x_B \leq 500$$

$$2x_W + y_W - w_W = 200$$

$$2.4x_C + y_C - w_C = 240$$

$$16x_B - w_B - e_B = 0$$

$$w_B \leq 6000$$

$$x_W, x_C, x_B, y_W, y_C, e_B, w_W, w_C, w_B \geq 0$$

## Solution – Bad Yields

	Wheat	Corn	Beans
Plant (acres)	100	25	375
Production	200	60	6000
Sales	0	0	6000
Purchase	0	180	0

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- Profit: \$59,950

# Computing Farmer Ted's EVPI

- With perfect information, Farmer Ted's Long Run Profit/Year would be:
  - $(1/3)(167667) + (1/3)(118600) + (1/3)(59950) = 115406$
  - The numbers 167667, 118600, 59950 are the **optimal** amounts of money he would make if he knew the yields beforehand.
- Without perfect information, using the stochastic programming solution, Farmer Ted can expected to make 108390.
- $EVPI = 115406 - 108390 = 7016$ .

Perfect information solution value is sometimes a useful bound on optimal stochastic programming value

# Farmer Ted: Final Thoughts

Model was obviously simple for illustrative purposes

- How might model of random yields be improved?
- What other types of uncertainty might Farmer Ted need to add to his model?
- Would you expect correlation between the different uncertain parameters?

# (General) Stochastic Programming

## General Stochastic Program

$$\min_{x \in X} \mathbb{E}_{\xi}[F(x, \xi)]$$

- $\xi$ : Random  $r$ -vector defined on some **probability space**  $(\Omega, \mathbb{P}, \Sigma)$ , i.e.,  $\xi : \Omega \rightarrow \mathbb{R}^r$
- Cumulative distribution function (cdf) of  $\xi$ :  $H_{\xi}(y) = \mathbb{P}[\xi \leq y]$
- Expected value<sup>1</sup>:  $\mathbb{E}_{\xi}[F(x, \xi)] = \int_{\Omega} F(x, \xi(\omega)) d\mathbb{P}$
- $X$ : Given set of **deterministic** constraints

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<sup>1</sup>Can just think of it as a weighted sum

# Two-stage Stochastic Programming

## Two-Stage Stochastic Program w/Recourse

$$\min_{x \in X} c^\top x + \mathbb{E}_\xi[Q(x, \xi)]$$

where:

$$\begin{aligned} Q(x, \xi) &:= \min q(\xi)^\top y \\ \text{s.t. } &W(\xi)y = h(\xi) - T(\xi)x \\ &y \geq 0 \end{aligned}$$

- $x$ : First-stage decisions (most important output of model)
- $y$ : Recourse decisions (implicitly depend on  $\xi$ )
- $Q(x, \xi)$ : Recourse function (AKA “value function”)

Fits general SP model with  $F(x, \xi) = c^\top x + Q(x, \xi)$

# Some Challenges in Stochastic Programming

## Two-Stage Stochastic Program w/Recourse

$$\min_{x \in X} c^\top x + \mathbb{E}_\xi[Q(x, \xi)] \quad (\text{here } F(x, \xi) = c^\top x + Q(x, \xi))$$

where:

$$\begin{aligned} Q(x, \xi) &:= \min q(\xi)^\top y \\ &\text{s.t. } W(\xi)y = h(\xi) - T(\xi)x \\ &\quad y \geq 0 \end{aligned}$$

- Evaluating  $\mathbb{E}_\xi[Q(x, \xi)] \Rightarrow$  Potentially high-dimensional integral
- Working with “implicit” definition of  $Q(x, \xi)$



# Discrete r.v.'s: The easy life!

- Assume  $\xi \in \{\xi^1, \dots, \xi^K\} \subseteq \mathbb{R}^r$  with  $P(\xi = \xi^k) = p_k, k = 1, \dots, K$
  - $T_k \stackrel{\text{def}}{=} T(\xi^k), h_s \stackrel{\text{def}}{=} h(\xi^k), q_k \stackrel{\text{def}}{=} q(\xi^k), W_k = W(\xi^k)$
- 

$$\begin{aligned} \min \quad & c^\top x + \sum_{k=1}^K p_k Q_k(x) \\ \text{s.t.} \quad & Ax = b \\ & x \in \mathbb{R}_+^{n_1} \end{aligned}$$

where for  $k = 1, \dots, K$

$$\begin{aligned} Q_k(x) \stackrel{\text{def}}{=} Q(x, \xi^k) &= \min q_k^\top y \\ \text{s.t.} \quad & W_k y = h_k - T_k x \\ & y \in \mathbb{R}_+^{n_2} \end{aligned}$$

# Extensive Form

- When we have a finite number of scenarios, or if we **approximate the problem** with a finite number of scenarios<sup>2</sup>, we can write an equivalent **extensive form** linear program:

$$\begin{aligned} \min_{x,y} \quad & c^\top x + \sum_{k=1}^K p_k q_k^\top y_k \\ \text{s.t.} \quad & Ax = b \\ & T_k x + W_k y_k = h_k, \quad \forall k = 1, \dots, K \\ & x \geq 0, \quad y_k \geq 0, \quad \forall k = 1, \dots, K \end{aligned}$$

Note: Model works same with integer restrictions on any of the variables

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<sup>2</sup>Stay Tuned for Sample Approximation Module

# Extensive Form: Structure

$$\begin{array}{llllllll} c^\top x & + & p_1 q_1^\top y_1 & + & p_2 q_2^\top y_2 & + & \cdots & + & p_K q_K^\top y_K \\ \text{s.t.} & & & & & & & & \\ Ax & & & & & & & & = & b \\ T_1 x & + & W_1 y_1 & & & & & & = & h_1 \\ T_2 x & & & + & W_2 y_2 & & & & = & h_2 \\ \vdots & & & & & \ddots & & & & \vdots \\ T_K x & & & & & & & + & W_K y_K & = & h_K \\ x \geq 0 & & y_1 \geq 0 & & y_2 \geq 0 & & & & & & y_K \geq 0 \end{array}$$

# The Upshot

- This is just a larger linear program (or linear integer program)
- Might be VERY large, but it has special structure
- Stochastic programming algorithms exploit this structure

$$\begin{array}{llllllll} c^T x & + & p_1 q_1^T y_1 & + & p_2 q_2^T y_2 & + & \cdots & + & p_K q_K^T y_K & & \\ \text{s.t.} & & & & & & & & & & \\ Ax & & & & & & & & & = & b \\ T_1 x & + & W_1 y_1 & & & & & & & = & h_1 \\ T_2 x & & & + & W_2 y_2 & & & & & = & h_2 \\ \vdots & & & & & \ddots & & & & \vdots & \\ T_K x & & & & & & & + & W_K y_K & = & h_K \\ x \geq 0 & & y_1 \geq 0 & & y_2 \geq 0 & & & & & & y_K \geq 0 \end{array}$$

# Building the Extensive Form

- 1 Write a nominal (one scenario) model
- 2 Decide which variables are first stage, and second stage
- 3 Give  $s$  scenario index to all second stage variables and random parameters
- 4 “Give context” to all scenarios

# Facility Location and Distribution

- Facilities:  $I$
  - Customers:  $J$
  - Fixed cost  $f_i$ , capacity  $u_i$  for facility  $i \in I$
  - Demand  $d_j$ : for  $j \in J$
  - Per unit Delivery cost:  $c_{ij} \forall i \in I, j \in J$
- 

$$\min \sum_{i \in I} f_i x_i + \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ij}$$

$$\sum_{i \in I} y_{ij} \geq d_j \quad \forall j \in J$$

$$\sum_{j \in J} y_{ij} - u_i x_i \leq 0 \quad \forall i \in I$$

$$x_i \in \{0, 1\}, y_{ij} \geq 0 \quad \forall i \in I, j \in J$$

# Evolution of Information

- 1 Build facilities **now**
- 2 Demand becomes known. One of the scenarios  $d^k, k = 1, \dots, K$  happens
- 3 Meet demand from open facilities

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- First stage variables:  $x_i$
  - Second stage variables:  $y_{ij\mathbf{k}}$

# The Extensive Form

$$\min \sum_{i \in I} f_i x_i + \sum_{k=1}^K p_k \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ijk}$$

$$\sum_{i \in I} y_{ijk} \geq d_{jk} \quad \forall j \in J, k = 1, \dots, K$$

$$\sum_{j \in J} y_{ijk} - u_i x_i \leq 0 \quad \forall i \in I, k = 1, \dots, K$$

$$x_i \in \{0, 1\}, y_{ijk} \geq 0 \quad \forall i \in I, j \in J, k = 1, \dots, K$$



# Modeling Discussion



- Do we **always** need to meet demand?
  - Regardless of the outcome  $d^k$ ?
- What happens on the off chance that our product is **so popular** that we can't **possibly** meet demand, even if we opened all of the facilities?
  - Does the world end? (Recourse problem is infeasible  $\rightarrow$  infinite cost!)

## Two Ideas

- 1 We could penalize not meeting demand of customers.
- 2 We only want to meet demand “most of the time”. (Chance constraint)

# SP Definitions

Let  $\Xi$  be the support<sup>3</sup> of random vector  $\xi$

- A 2-stage stochastic optimization problem has **complete recourse** if for every possible outcome, there always exists a feasible recourse solution:

$$Q(x, \xi) < +\infty \quad \forall x \in \mathbb{R}^n, \quad \xi \in \Xi$$

- A 2-stage stochastic optimization problem has **relatively complete recourse** if for every outcome, *and for every feasible first stage solution*, there is always feasible recourse:

$$Q(x, \xi) < +\infty \quad \forall x \in X, \quad \xi \in \Xi$$

Good modeling practice: Include sufficiently flexible recourse to ensure model has relatively complete recourse.

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<sup>3</sup>Support of  $\xi$ : smallest set  $\Xi$  such that  $\mathbb{P}[\xi \in \Xi] = 1$

# Penalize Shortfall: A Recourse Formulation

New parameter:  $\lambda_j$  = Per unit “cost” of not meeting demand of customer type  $j$

$$\min \sum_{i \in I} f_i x_i + \sum_{k=1}^K p_k \left[ \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ijk} + \sum_{j \in J} \lambda_j z_{jk} \right]$$

$$\sum_{i \in I} y_{ijk} + z_{jk} \geq d_{jk} \quad \forall j \in J, k = 1, \dots, K$$

$$\sum_{j \in J} y_{ijk} - u_i x_i \leq 0 \quad \forall i \in I, k = 1, \dots, K$$

$$x_i \in \{0, 1\}, y_{ijk} \geq 0 \quad \forall i \in I, j \in J, k = 1, \dots, K$$

# VSS: Value of the Stochastic Solution

- Let  $z_S$  be the optimal solution value to

$$z_S \stackrel{\text{def}}{=} \min_{x \in X} \mathbb{E}[F(x, \xi)]$$

- Let  $x_{MV}$  be an optimal solution to the “mean-value” problem:

$$x_{MV} \in \arg \min_{x \in X} F(x, \mathbb{E}[\xi])$$

- Let  $z_{MV}$  be the long run cost if you **plan** based on the policy obtained from the ‘average’ scenario:

$$z_{MV} \stackrel{\text{def}}{=} \mathbb{E}[F(x_{MV}, \xi)]$$

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## Value of Stochastic Solution

$$\text{VSS} \stackrel{\text{def}}{=} z_{MV} - z_S$$

- 
- Simple HW: Prove  $\text{VSS} \geq 0$

# EVPI

- Let  $z_S$  be the optimal solution value to a stochastic program

$$z_S = \min_{x \in X} \mathbb{E}[F(x, \xi)]$$

- Let  $z_{PI}$  be the expected value of the optimal “wait and see” solution(s)

$$z_{PI} = \mathbb{E}[\min_{x \in X} F(x, \xi)]$$

## Expected Value of Perfect Information

$$EVPI = z_S - z_{PI} \geq 0$$

- 
- Simple HW: Prove  $EVPI \geq 0$