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Running TIMES in Stochastic Way: Policy Alternatives Under Uncertainty

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Outline

- Stochastic vs. Deterministic: assumptions
- Modeling techniques: approaches
- Implementation for TIMES: details
- An Example
- Some important issues
- Possible application
- Concluding remarks

Stochastic vs. Deterministic: assumptions

Deterministic

- **What** is optimal policy **if** future is known?
- **Input**:
  - Scenarios for uncertain parameters
- **Output**:
  - Minimal costs for each scenario

Stochastic

- **What** is optimal policy **if** we know risk?
- **Input**:
  - Distributions of uncertain parameters
  - Our risk aversion
- **Output**:
  - Trade-off between costs and risk scenario

Modeling techniques: approaches

- Review:
  - Bruce A. McCarl and Thomas H. Spreen, APPLIED MATHEMATICAL PROGRAMMING USING ALGEBRAIC SYSTEMS, 1997 http://agecon2.tamu.edu/people/faculty/mccarl-bruce/books.htm
- Methods implemented in TIMES:
  - Richard Loulou and Antti Lehtila, Stochastic Programming and Tradeoff Analysis in TIMES, 2007 http://www.etsap.org/Docs/TIMES-Stochastic.pdf

Stochastic Programming and Tradeoff Analysis in TIMES

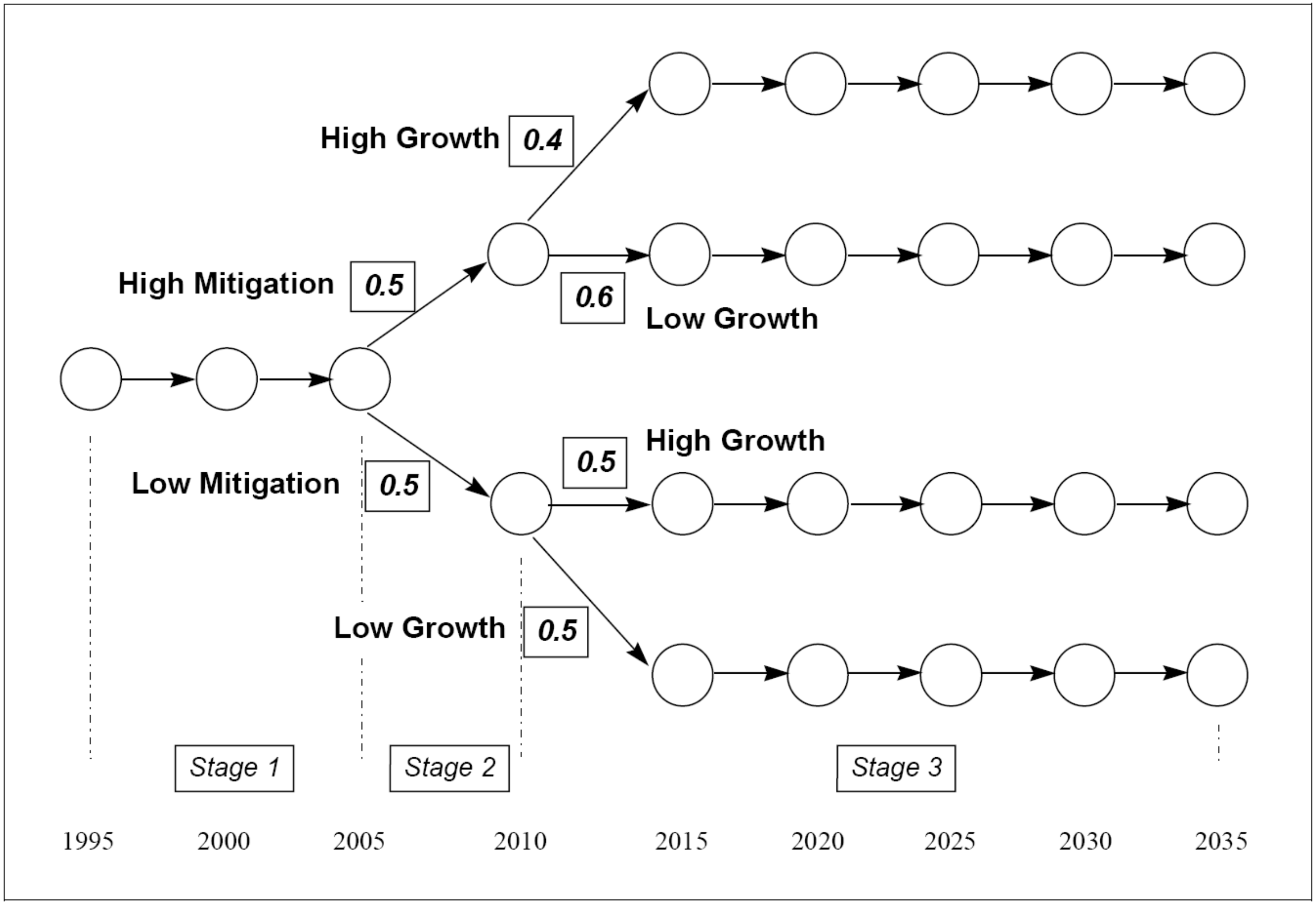


Figure 1. Event Tree for a three-stage stochastic TIMES Example.

Source: Richard Loulou, Antti Lehtila, 2007

EV model
(Expected Value - Variance)

EV Utility function:

$$U = EC + \lambda \cdot \sqrt{Var(C)}$$

Utility Function with Linearized Risk Aversion:

$$U = EC + \lambda \cdot UpsAbsDev(C)$$

$$UpAbsDev(Cost_k) = \sum_j p_j \bullet \left\{ Cost_{j|k} - EC_k \right\}^+$$

Source: Richard Loulou, Antti Lehtila, 2007

Interpreting results:

- Sensitivity analysis: How sensitive our results (costs and “optimal” policy) to possible future States of the World (SOW)

- Stochastic optimization: What is “optimal” policy if we know all the possible SOWs with probability (event tree) and if we are risk avers

Alternative three stages analysis:

Based on Monte Carlo sensitivity and EV/ROV analysis

Formulation

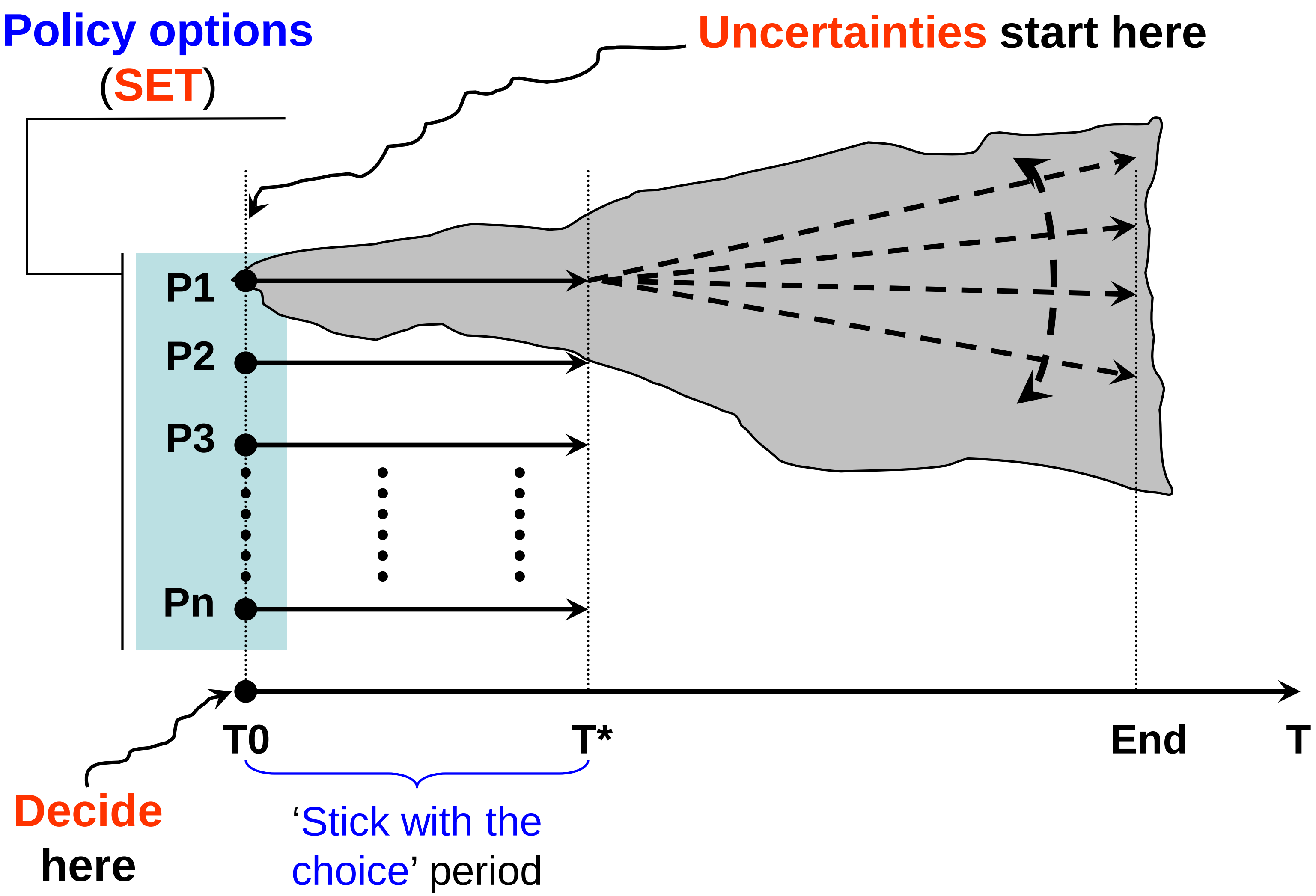
- Assume we have a finite set of alternative deterministic rational scenarios
- We can determine sources of uncertainties (prices, demands, technological parameters, etc.) and can characterize them with distributions
- Our goal is to pick scenario from the predetermined SET, taking to account the known risks and our risk aversion

(the formulation is pretty standard; the main divergence from stochastic TIMES by this point is predetermined SET of rational scenarios and non-discrete distributions of risk)

Implementation

- Define the SET (deterministic rational scenarios) we want to analyze, parameters under risk and their distributions
- Define a ‘Stick with the choice’ period: where we cannot switch to another policy within the period
- Perform a sensitivity analysis for each deterministic rational scenario from the SET
- Compare the scenarios based on sensitivity results and EV or ROV analysis

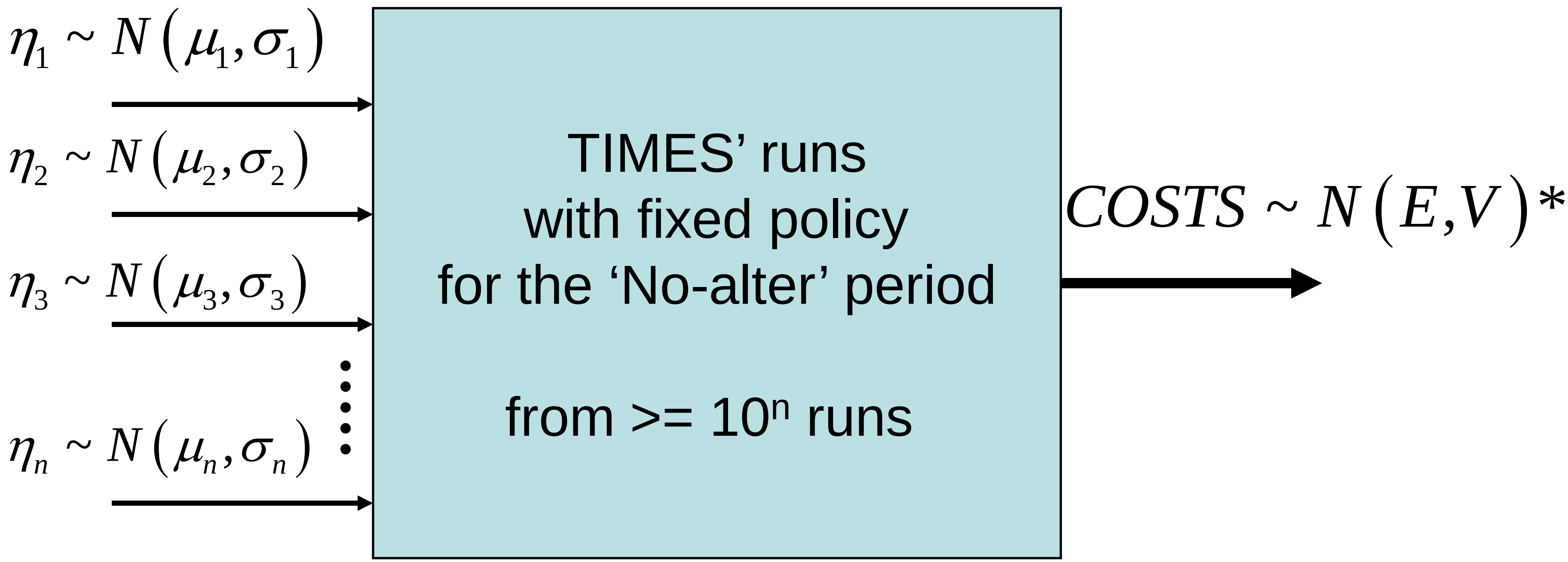
Formulation: schema



‘Stick with the choice’ period

- This is a period when we cannot change our decision to another one, after we have chosen one of the policy from our set of policy options.
- It is important to do the sensitivity analysis with the ‘Stick with’ the policy period. It provides more realistic results from the analysis. F.i. if we started to build a hydro- or nuclear power plant, we should finish with no regard to the fuel prices fluctuations.
- Implementation in GAMS code: fix endogenous variables for the period on the level from deterministic run (NCAP(..).FX = NCAP(..).L, etc.).

Sensitivity: Monte Carlo



* In general case the resulting distribution is not normal

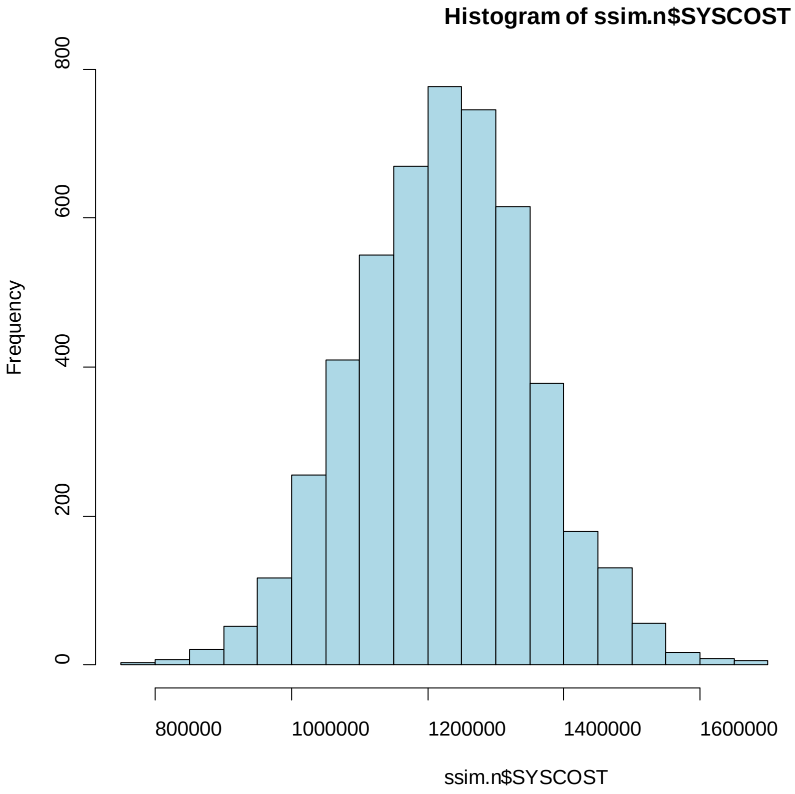
Example with RU-TIMES

- Small model:
  ~ 50 technologies: GAS, COAL, OIL, HYD, NUC …
  ELC, CHP, HPL plants
  2005 – 2030 time horizon
- Uncertainties:
  - Oil, Gas, Coal prices
  - Emissions permits (CO2) prices
- SET of policies:
  - Selected scenarios for CAP: -10%, -20%, -30% and -40% (4 scenarios with various fuel mix structure in ELC and HEAT production)

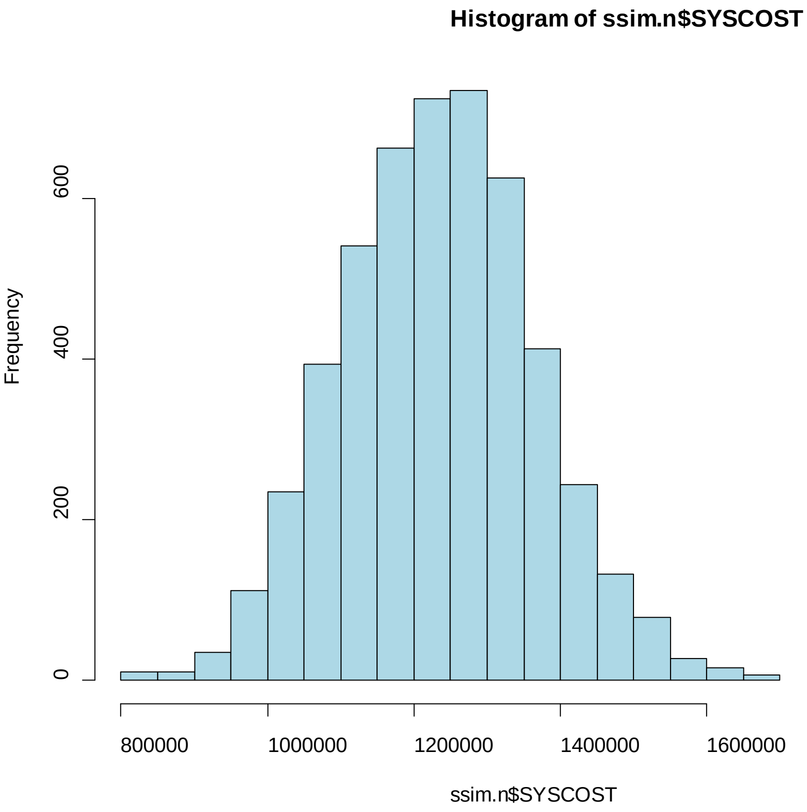
Monte Carlo simulations:

- The model was generated with VEDA-FE, then GAMS code was adopted for the experiments (some minor changes were required to fix endogenous capacity variables after the first run).
- One run of the model's GAMS code takes 30 sec…1 min depending on scenario.
- GAMS's OPTION Savepoint=1 reduces time of repeated runs up to 10 times.
- For each of the four scenario we run the RU-TIMES model 5000 times.
  - it takes ~ 3 hours (for 4*5000 runs)
  - on 4-core Intel 2.66, 8Gb RAM
  - and 4 threats (separate threat for each scenario)
- The results are stored in CSV file for analysis with statistical software (R, STATA, etc.) or in MS Excel.

MC results for CAP10 & CAP40



CAP -10%



CAP -40%

Monte-Carlo results: Total costs

	CAP	Mean	Median	SD
1	-10%	1,223.5	1,229.3	128.7
2	-20%	**1,217.0**	**1,220.6**	128.4
3	-30%	1,224.8	1,229.2	**127.1**
4	-40%	1,233.4	1,236.4	131.2

EV analysis

E + RAP * SD

(lowest value ≡ ‘optimal’ scenario)

	CAP	E+1SD	E+2SD	E+3SD	E+5SD	E+7SD	E+10SD
1	-10%	1,352.2	1,480.9	1,609.6	1,867.0	2,124.5	2,510.6
2	-20%	**1,345.4**	**1,473.8**	**1,602.2**	**1,859.1**	2,115.9	2,501.1
3	-30%	1,351.9	1,479.1	1,606.2	1,860.5	**2,114.8**	**2,496.2**
4	-40%	1,364.6	1,495.8	1,626.9	1,889.3	2,151.7	2,545.3

More risk averse agent will chose more stringent CAP (-30% starting with RAP=7)

Some important issues

- Monte Carlo simulations:
  - Are the uncertain parameters independent? (f.i. oil and gas prices, coal prices and CCS costs, weather conditions for solar and wind, and demand for heat and electricity, carbon permits and fossil fuels prices, etc.)
  - We need to estimate or assume covariance matrix for the uncertain parameters: historical econometric estimates or theoretical assumptions
  - Bayesian econometrics might be useful for the covariance matrix estimates (if the parameters are observable)

- RAP (Risk Averse Parameter)
  - depends on our goal and might vary from one project to another (what is more important for us: minimal coasts or stability?)

Bayes' rule

$$p(\theta|y) \propto p(\theta)p(y|\theta).$$

θ - parameters

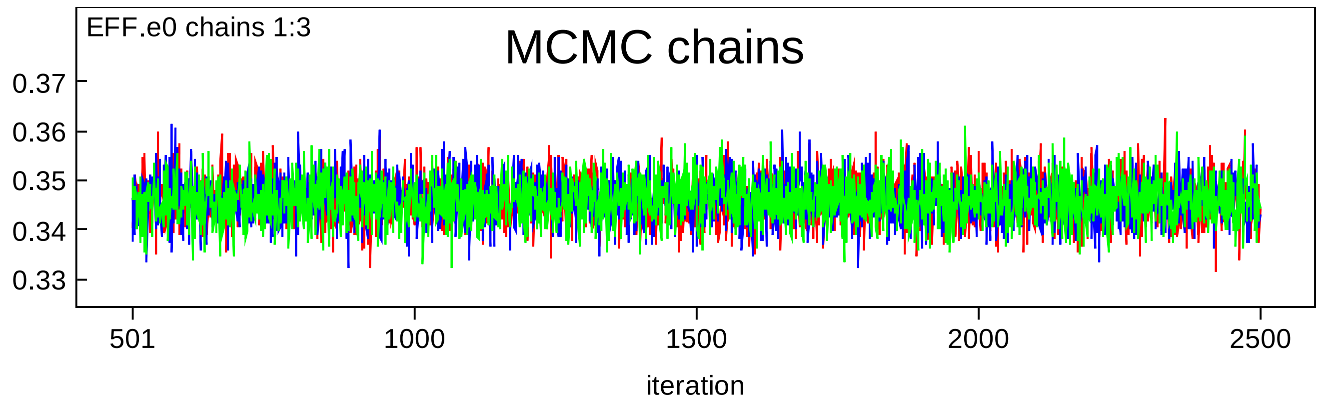
y - data

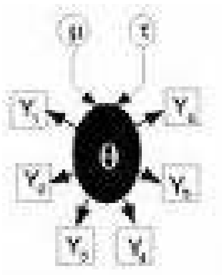
$p(\theta)$ - Prior distribution of parameters (our believes)

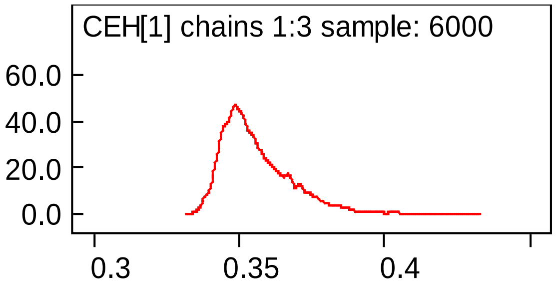
$p(y|\theta)$ - Likelihood function

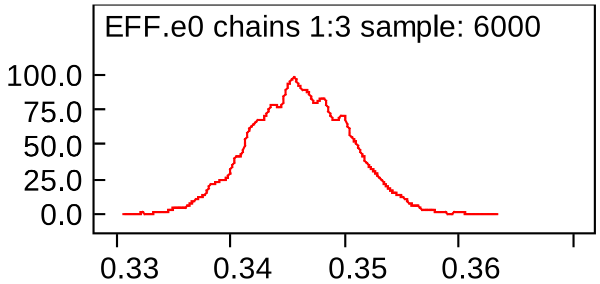
$p(\theta|y)$ - Posterior distribution of parameters (combination of information in data and our believes)

Estimation of CHP parameters with Bayesian MCMC (in WinBUGS)









The distribution of estimated parameters are results from Bayesian econometrics - they might be used as input parameters for the sensitivity analysis stage.

Possible application

- Useful when a set of rational plans have been already set up, and we need to chose one of them.
- Future prices (fossil fuels, emissions permits, …)
- Investment costs (CCS, conventional technologies' costs variation, …)
- New techs parameters (efficiency, availability, costs,…)
- Demand fluctuations (LR growth, by time slices: seasonal, day/night, etc.)
- Other agents decisions and their affect on all the other parameters (CAP, limits on nuclear, etc.)

Concluding remarks

- The discussed methodology provides additional information for researchers and policymakers: estimation of risk coupled with particular policy.
- Stages of the approach provide transparency. No additional optimization is required on the last-step analysis (EV or ROA) which can be made manually with basic statistical software.

Thank you!

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