On Applications of Stochastic Programming in Energy Systems

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Outline

• energy systems
  – electric power systems
  – won’t discuss: oil and gas; electric vehicles; building energy; etc.

• stochastic programming
  – two-stage model
  – multi-stage model
  – models with risk measures
  – adversarial models

• not a comprehensive survey of SP in electric power systems
  – rather: selected applications, with eye toward conference theme
Some Sources of Uncertainty in Electric Power Systems

- global warming (decades)
- long-term demand changes (decades/years)
- policy changes (years)
- fuel costs (years/months)
- hydro-electric inflows (months/weeks)
- short-term demand (days)
- solar irradiance and wind speed (hours/minutes)
- plant and line failures (seconds)
- electricity prices (various scales)
- attacks from state actors, terrorists, criminals (various scales)
Some Decisions in Electric Power Systems

- transmission line and power plant expansion (decade)
- hardening infrastructure (years)
- forward contracts for fuel (years)
- preventive maintenance scheduling (year)
- forward contracts for energy (years/months/weeks)
- long, mid, short-term hydro-thermal scheduling (years/months/weeks)
- day-ahead energy and ancillary services markets (day)
- day-ahead (security-constrained) unit commitment (day)
- transmission switching (day)
- intra-day market (hours)
- short-term market (5 minutes)
Important: Don’t Miss...
Important: Don’t Miss the Next Session...

10:00 am - 10:30 am
Coffee

10:30 am - 12:00 pm
FOCAPO: Young Investigators

Redesigning Decision-Making Architectures to Exploit Multi-Scale Electricity Markets
Victor M. Zavala
University of Wisconsin-Madison

CPC: Young Investigators

Advances and Opportunities in Optimization of Electrical Grid Operations
Carl Laird
Sandia National Laboratories
Two-stage Stochastic Program with Recourse

\[
\begin{align*}
\min_{x} \quad & cx + \sum_{\omega \in \Omega} p^\omega h(x, \omega) \\
\text{s.t.} \quad & x \in X
\end{align*}
\]

where

\[
\begin{align*}
h(x, \omega) = \min_{y} f^\omega y \\
\text{s.t.} \quad & D^\omega y = B^\omega x + d^\omega \\
& y \in Y^\omega
\end{align*}
\]

Classic example of a two-stage problem:

- \(x\) decision variables determine system design
- realization of \((B^\omega, d^\omega, D^\omega, f^\omega)\) is then observed
- \(y\) decision variables, adapted to scenario \(\omega\), operate system
A Stochastic Transmission Planning Model With Dependent Load and Wind Forecasts

Heejung Park, Member, IEEE, Ross Baldick, Fellow, IEEE, and David P. Morton

Abstract—This paper introduces a two-stage stochastic program for transmission planning. The model has two dependent random variables, namely, total electric load and available wind power. Given univariate marginal distributions for these two random variables and their correlation coefficient, the joint distribution is modeled using a Gaussian copula. The optimal power flow (OPF) problem is solved based on the linearized direct current (DC) power flow. The Electric Reliability Council of Texas (ERCOT) network model and its load and wind data are used for a test case. A 95% confidence interval is formed on the optimality gap of candidate solutions obtained using a sample average approximation with 200 and 300 samples from the joint distribution of load and wind.

Index Terms—Decomposition, Gaussian copula, stochastic optimization, transmission planning, wind power.

NOMENCLATURE

Data/Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_n )</td>
<td>Annualized cost of building line ( n ) ($).</td>
</tr>
</tbody>
</table>
A Stochastic Transmission Planning Model with Dependent Load and Wind Forecasts

- $x$: binary yes-no decisions to add a new transmission line at specific candidate locations in transmission network
- $d^\omega$: joint load and wind availability
- $y$: operates DC dispatch and power-flow system
- $D^\omega y = B^\omega x + d^\omega$: includes “you can’t use a line unless it’s installed”
- objective is to minimize sum of:
  - amortized cost of building new transmission lines
  - expected generation cost
  - expected penalty for curtailing wind power
  - expected penalty for shedding load
diagonal covariance term, denoted \( \rho \), and we describe how to determine this value shortly. First, however, we note that \( \rho \) and \( \rho' \) are uniformly distributed on the interval \((0,1)\). Thus, we can use the standard simulation technique of inversion \([29]\) to yield the desired marginals via

\[
(6)
\]

The idea behind the Gaussian copula technique is that the correlation between \( \rho \) and \( \rho' \) is at our disposal, and by properly selecting it we can achieve the desired correlation between \( \rho \) and \( \rho' \) as we now describe. The covariance between \( \rho \) and \( \rho' \) is given by

\[
(7)
\]

By substituting (6) into the first term on the right-hand side (RHS) of (7), we obtain

\[
(8)
\]

where \( f_{\mathbf{Z}} \) is the probability density function for the bivariate normal, \( \mathbf{Z} \), with covariance, \( \mathbf{C} \). Note that the value on the left-hand side (LHS) of (8) is given as input to the copula procedure. All terms on the RHS of (8) are known except for the unspecified value \( \mathbf{u} \), where \( \mathbf{u} \) is a variable in (8) to be determined. We cannot solve this equation analytically, but by iteratively changing \( \mathbf{u} \) on the RHS, we can numerically match the given value on the LHS. It is known that the RHS of (8) is a monotonic function in \( \mathbf{u} \) (see \([32]\)) and hence we can perform a bisection search to determine the value of \( \mathbf{u} \) which forces the RHS to equal the given LHS. With a numerical tolerance of \( 10^{-6} \), and with a desired correlation coefficient between load and wind of \(-0.1721\) from our data set described above, bisection yields after 14 iterations. The bivariate integral on the RHS of (8) is evaluated numerically in MATLAB as part of the bisection search.

C. Summary of the Sampling Procedure

We summarize our procedure for generating i.i.d. observations from the bivariate distribution for load and wind. To generate the underlying correlated bivariate normal we require the Cholesky factorization of the covariance matrix:

\[
(9)
\]

where \( \mathbf{D} \). Summarizing the steps of our procedure:

1) Run bisection algorithm using (8) to determine \( \mathbf{u} \) as described in Section II-B.
2) Generate bivariate normal \( \mathbf{Z} \) as follows (e.g., \([33]\)):
   a) Generate random vector, \( \mathbf{Y} \), composed of two independent components, \( Y_1 \) and \( Y_2 \).
   b) Form the 2 \( \times \) 2 lower triangular matrix \( \mathbf{A} \) given by (9).
   c) Let \( \mathbf{Z} \) and \( \mathbf{u} \) from \( \mathbf{Z} = \mathbf{A} \mathbf{Y} + \mathbf{u} \).
3) Let \( \mathbf{Z} \) and \( \mathbf{u} \).
4) Goto Step 2) until we obtain number of samples. The procedure repeats \( T \) times to draw \( N \) samples. The two marginal distributions, denoted \( \mathbf{X} \) and \( \mathbf{W} \), along with the correlation coefficient \( \rho \) between load and wind, are both estimated from empirical data. The procedure provides i.i.d. samples of \( \mathbf{X} \).

Fig. 1 shows 200 and 300 i.i.d. observations generated using the Gaussian copula procedure and hourly load and wind data. All copulas samples are within the historical ranges we define for truncation of the marginal distributions.

III. MATHEMATICAL MODEL

In this section we first describe a two-stage stochastic integer program for our transmission system expansion planning problem. Transmission system expansion decisions are made in the first stage, and system operation decisions are made in the second stage. This model is suitable for application of the L-shaped decomposition method \([34]\) as we also describe.

A. Two-Stage Stochastic Integer Program

In the mathematical optimization model we describe, transmission system expansion decisions are represented by binary variables in the first stage. The linear objective function in the second stage models operating costs including thermal generation costs and a penalty cost on wind power curtailment and load. The Gaussian copula:

- lognormal load, bounded Johnson wind, correlation \(-0.17\)
Stochastic Transmission Planning: Joint Load and Wind Forecast

- 312-bus ERCOT (Texas) system
- 370 candidate locations for transmission lines
- 300-500 Monte Carlo scenarios; 10,000 scenarios to evaluate solution
- $\approx 100$ ($/\text{MWh}$) for wind curtailment and load shedding penalties
- 30 replications solved to within 1% using Benders’ decomposition implemented in GAMS modeling language in about 30 minutes
- consider increased wind penetration by factor of 3
- deterministic forecast: 12 new transmission lines
- stochastic forecast: 96 new transmission lines
- cost savings $\sim 10\%$
Toward scalable stochastic unit commitment
Part 2: solver configuration and performance assessment

Kwok Cheung\textsuperscript{1} · Dinakar Gade\textsuperscript{2} · César Silva-Monroy\textsuperscript{3} · Sarah M. Ryan\textsuperscript{4} · Jean-Paul Watson\textsuperscript{5} · Roger J.-B. Wets\textsuperscript{6} · David L. Woodruff\textsuperscript{7}

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Abstract In this second portion of a two-part analysis of a scalable computational approach to stochastic unit commitment (SUC), we focus on solving stochastic mixed-
Unit Commitment

- on-off decisions for generation units
- dispatch those units to satisfy demand
- constraints require that we satisfy
  - demand or shed load
  - transmission requirements: power flow, voltage angles, bounds
  - ramping limits
  - minimum up- and down-time limits
  - generation bounds
- objective: minimize sum of start-up, shut-down, and generation costs
Stochastic Unit Commitment

• of significant recent interest due to growing penetration of renewables and price-sensitive loads

• day-ahead unit commitment
  – takes as input: supply offers and demand bids from market participants
  – yields as output: committed units, hourly generation- and demand schedules, hourly location-dependent marginal energy prices
  – does not consider reserves

• security-constrained (or reliability) unit commitment
  – takes as input: day-ahead commitments, scenarios (e.g., outage scenarios, load scenarios, renewable availability scenarios)
  – yields as output: additional commitments, updates to dispatch

• security-constrained dispatch...
Stochastic Unit Commitment

• given prevailing market structures, a stochastic day-ahead unit commitment model won’t be directly used by an ISO

• thus, the emphasis is on stochastic programming models for security-constrained unit commitment

• robust optimization models and probabilistically constrained models are also of interest
Stochastic Security-Constrained Unit Commitment

- $x$: binary yes-no decisions to commit a generator at a particular hour, along with implied start-up and shut-down variables
- $d^\omega$: load and renewable availability
- $B^\omega$: forced outages
- $y$: operates DC dispatch and power-flow system
- objective is to minimize sum of:
  - start-up and shut-down costs
  - expected generation cost
  - expected load-shedding penalties
Toward scalable stochastic unit commitment
Part 2: solver configuration and performance assessment

Kwok Cheung1 · Dinakar Gade2 · César Silva-Monroy3 · Sarah M. Ryan4 · Jean-Paul Watson5 · Roger J.-B. Wets6 · David L. Woodruff7

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Abstract In this second portion of a two-part analysis of a scalable computational approach to stochastic unit commitment (SUC), we focus on solving stochastic mixed-
Toward Scalable Stochastic Unit Commitment

• from a DOE ARPA-E project in collaboration with NE-ISO

• goal: demonstrate the viability of stochastic unit commitment in a real-world applications context

• tractable: < 30-minute run times

• paper’s title says “Part 2”. Part 1 involves scenario generation

• test instance characteristics
  – 85-170-340 generators [WECC-240 test case]
  – all generators available for commitment
  – 48 one-hour time periods
  – 50-100 load scenarios

• model cross-validated with Alstom’s commercial e-terra-market unit commitment model
Towards Scalable Stochastic Unit Commitment

- progressive hedging algorithm: Lagrangian relaxation of nonanticipativity constraints, with a proximal term
- progressive hedging vs. Benders (heuristic, parallel implementation)
- Carrion and Arroyo (2006) unit commitment model
- implemented in PySP, open-source Python package for stochastic programming [https://software.sandia.gov/trac/pyomo](https://software.sandia.gov/trac/pyomo)
- 64-core workstation with 50 scenarios, WECC-240 test case
  - 15 minutes for 85 generators
  - 25 minutes for 170 and 340 generators
- solutions to within 1-2.5% of optimality
- generation cost savings over deterministic solution: 1.5% (base); 3-5% with generator outages; 4% (with 10% wind penetration)
Two-stage Stochastic Program with Recourse

\[
\begin{align*}
\min_x & \quad cx + \mathbb{E}_\omega h(x, \omega) \\
\text{s.t.} & \quad x \in X
\end{align*}
\]

where

\[
\begin{align*}
h(x, \omega) &= \min_y f^\omega y \\
\text{s.t.} & \quad D^\omega y = B^\omega x + d^\omega \\
& \quad y \in Y^\omega
\end{align*}
\]
Two-stage Stochastic Program with Recourse under CVaR Risk Measure

\[
\begin{align*}
\min_{x} & \quad cx + \lambda \mathbb{E}[h(x, \omega)] + (1 - \lambda) \text{CVaR}_\alpha[h(x, \omega)] \\
\text{s.t.} & \quad x \in X
\end{align*}
\]

where

\[
\begin{align*}
h(x, \omega) &= \min_{y} f^\omega y \\
\text{s.t.} & \quad D^\omega y = B^\omega x + d^\omega \\
y & \in Y^\omega
\end{align*}
\]
CVaR Risk Measure

Let $Z$ be a continuous random variable with $\Phi(z) = \mathbb{P}(Z \leq z)$. Then,

$$\text{CVaR}_\alpha [Z] = \mathbb{E} [Z \mid Z > \Phi^{-1}(\alpha)]$$

$$= \min_u \left( u + \frac{1}{1 - \alpha} \mathbb{E}(Z - u)^+ \right)$$

- here, $\alpha = 0.90$ (say)
- $\lambda \mathbb{E} [\cdot] + (1 - \lambda) \text{CVaR}_\alpha [\cdot]$ is an example of a so-called coherent risk measure: Artzner et al. (1999)
- recently significant attention on multi-stage variants
- nuances for continuous versus discrete random variables
- two-stage and multi-stage implications
Multi-stage Stochastic Linear Program with Recourse

\[
\begin{align*}
\min_{x_1} & \quad c_1 x_1 + \mathbb{E}_{b_2 \mid b_1} h_2(x_1, b_2) \\
\text{s.t.} & \quad A_1 x_1 = B_1 x_0 + b_1 \\
& \quad x_1 \geq 0,
\end{align*}
\]

where for \( t = 2, \ldots, T \),

\[
\begin{align*}
h_t(x_{t-1}, b_t) &= \min_{x_t} c_t x_t + \mathbb{E}_{b_{t+1} \mid b_1, \ldots, b_t} h_{t+1}(x_t, b_{t+1}) \\
\text{s.t.} & \quad A_t x_t = B_t x_{t-1} + b_t \\
& \quad x_t \geq 0
\end{align*}
\]

- two-stage model, first stage is design and second stage is operations
- multi-stage model, same type of decision is repeated in each stage
- above, only \( b_t \) is random but this can be extended
- \( h_{T+1} \equiv 0 \), say
SOCRATES: A system for scheduling hydroelectric generation under uncertainty

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\textsuperscript{e}Cornell University, Ithaca, NY, USA

The Pacific Gas and Electric Company, the largest investor-owned energy utility in the United States, obtains a significant fraction of its electric energy and capacity from hydrogeneration. Although hydro provides valuable flexibility, it is subject to usage limits and must be carefully scheduled. In addition, the amount of energy available from hydro varies widely from year to year, depending on precipitation and streamflows. Optimal scheduling of hydrogeneration, in coordination with other energy sources, is a stochastic problem of practical significance to PG&E. SOCRATES is a system for the optimal scheduling of PG&E's various energy sources over a one- to two-year horizon. This paper concentrates on the component of SOCRATES that schedules hydro. The core is a stochastic optimization model, solved using Benders decomposition. Additional components are streamflow forecasting models and a database containing hydrological information. The stochastic hydro scheduling module of SOCRATES is undergoing testing in the user's environment, and we expect PG&E hydrologists and hydro schedulers to place progressively more reliance upon it.

I. Introduction

The Pacific Gas and Electric Company (PG&E) is one of the largest producers of hydroelectricity among American investor-owned utilities. PG&E's installed hydrogeneration capacity is nearly 3900 megawatts (MW), representing an investment of $1.3 billion in book value. Approximately 1200 of those megawatts are contributed by the Helms Pumped Storage Plant. The remaining 2700 MW represents conventional

1) Watts (W) and megawatts (MW) measure power, which is the rate at which energy is produced over time. The capacity of a generator is the maximum rate at which it can export energy (maximum power). Machine capability is rated in terms of power. Water (L), megawatthours (MWh) and gigawatthours (GWh) measure energy. The total production of a unit or generating system, over a period of time, is measured in terms of energy.

2) Statistics in this section are from [12].

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Multi-stage stochastic optimization applied to energy planning

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Application of CVaR Risk Aversion Approach in the Expansion and Operation Planning and for Setting the Spot Price in the Brazilian Hydrothermal Interconnected System

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Rio de Janeiro, Brazil
UERJ – State University of Rio de Janeiro
Rio de Janeiro, Brazil

Abstract
— Long-term hydrothermal generation planning typically requires the use of long-term hydrothermal generation planning models (LTHTP), which are well known to be complex and computationally demanding. In this paper, we present the CVaR approach, initially proposed by [4] with the use of artificial variables, later extended to include the CVaR term – can be evaluated directly as a straightforward way, based on the optimal value and Lagrange multipliers of the most critical scenarios at each node in the backward pass of the stochastic dual dynamic programming (SDDP) strategy [10],[7] applied to solve the problem. One of the main advantages of this approach is that we obtain a more intuitive recourse function, where future operation costs – must be applied.

Besides describing the actual implementation of the CVaR methodology, two parameters must be defined and properly evaluated, with the objective of enhancing system security at reasonable operational cost overhead and to replace the previous mechanisms: Conditional Value at Risk (CVaR) [5] and Risk Aversion Surface (SAR) [8], [9]. The CVaR approach is applied to five years; provided as a constraint on minimum storage of reservoirs (but not for spot price setting), based on energy supply studies performed externally to the optimization models. In this paper we present the CVaR approach, initially proposed by [4] with the use of artificial variables, later extended to include the CVaR term – can be evaluated directly as a straightforward way, based on the optimal value and Lagrange multipliers of the most critical scenarios at each node in the backward pass of the stochastic dual dynamic programming (SDDP) strategy [10],[7] applied to solve the problem. One of the main advantages of this approach is that we obtain a more intuitive recourse function, where future operation costs – must be applied.

References

Multi-stage Hydro-Thermal Scheduling

minimize expected system operation cost (or a CVaR risk measure)
subject to

• satisfy load
• bounds on thermal generation
• bounds on hydro releases, reservoir volumes, and spills
• hydro network-flow constraints
• side constraints, e.g., decrees

with

• stochastic natural inflows of water
• nonlinear (typically piecewise linear) thermal cost function
• weekly and then monthly time periods
Multi-stage Hydro-Thermal Scheduling
Brazilian Electrobras NEWAVE model

Model size:

- 10-year horizon, 120 monthly stages
- autoregressive model governs hydro inflows
- \( \approx 30 \) scenarios per stage
- four aggregate reservoirs
- uses nested CVaR as a risk measure

Applications:

- hydro- and thermal generation dispatch
- calculate spot prices in wholesale market
- evaluate 10-year capacity expansion plan
- calculate power-plant assured energy (for long-term contracts)
Disaggregated Variant of CEPEL’s Model

• 10-year horizon, 120 monthly stages
• autoregressive model governs hydro inflows with lag of two
• 85 reservoirs with storage; 160 reservoirs total
• \(85 + 2 \cdot 160 = 405\) state variables
• 30 scenarios per stage
• 3 load blocks
• solution time: 90 minutes using 25 servers with 16 processors each
Stochastic Dual Dynamic Programming (SDDP)

(a) Forward Pass

(b) Backward Pass

Computational effort per iteration grows linearly in: number of stages, number of scenarios per stage (with the other fixed)
Analysis of Electric Grid Security
Under Terrorist Threat
Javier Salmeron, Kevin Wood, and Ross Baldick, Member, IEEE

Worst-Case Interdiction Analysis
of Large-Scale Electric Power Grids
Javier Salmeron, Kevin Wood, and Ross Baldick, Fellow, IEEE

OR: CATALYST FOR GRAND CHALLENGES
Opportunities in security
The infrastructure of the United States, and the world, is increasingly interconnected. The ongoing integration of systems— including transportation, energy, water, communications, finance and more— has been central to their growth in scale and reach and has facilitated increases in their functional efficiency. At the same time, these interdependencies make systems more vulnerable to both intentional threats and unintentional...
Security for Adversarial and Stochastic Scenarios

1. model system operation, both under nominal conditions, and when some components are disabled or degraded
   – cannot enumerate threat scenarios; require operational model, which we will systematically query

2. distinguish unintentional hazards (malfunctions, natural disasters, human error) and intentional threats (criminals, saboteurs, terrorists)
   – model hazards via scenarios / stochastic programming
   – model threats via adversary with limited resources

3. allocate scare resources to optimally improve system performance
   – we’re supposed to be good at this...
Concentrating Solar Power

- system design: tower, heliostats
- (single) unit commitment and dispatch with energy storage
- maintenance scheduling
- uncertainty: direct normal irradiance and energy prices

DOE: M. Wagner (NREL), S. Leyffer, J. Larson (Argonne), R. Braun, A. Newman (Colorado School of Mines)
Microgrid Design and Dispatch

- system design: diesel generators, batteries, and PV arrays
- dispatch over a year with uncertain load and solar irradiance
- nonlinear battery dynamics

ONR: Colorado School of Mines, Ga Tech, MIT, Naval Postgraduate School, NREL, DOD
Summary

• Uncertainty pervasive in electric power systems

• Stochastic programming plays important role
  – system design; system security
  – long- and mid-term hydro-thermal scheduling
  – day-ahead operations
  – bilateral contracts for large consumers

• Further work and challenges
  – competitive equilibrium models
  – self-scheduling versus bidding into markets
  – grid-scale energy storage
  – AC versus DC optimal power flow
  – complex, interconnected decisions at disparate time scales and by different market participants