Computational Algorithms for Power Systems Optimization

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Outline

1. Introduction
2. Optimization in Power Systems
3. Optimization in Fossil Fuel Industry
4. Optimization in Reducing Emission and Saving Energy
5. Conclusion

Energy and Civilization

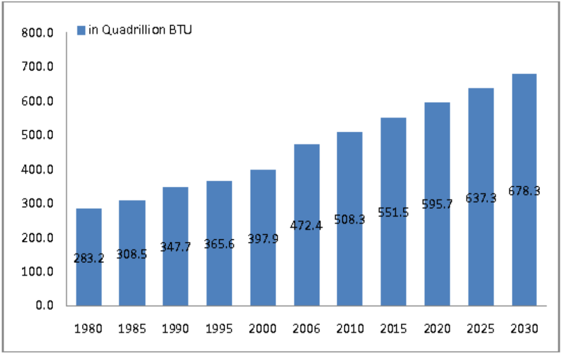
- Humans began to control fire about 1 million years ago.
  - Heating
  - Cooking
  - Protecting
- Ancient controllings of energy
  - Windmills, Sailboats
  - Waterwheels
- Industrial Revolution in 18th century started the age of steam and the dependence on fossil fuels.
- The foundation of the first power plant by Thomas Edison in New York in 1882 has brought the world into the Electricity age.

The progress of controlling energy = The advance of civilization = National Security

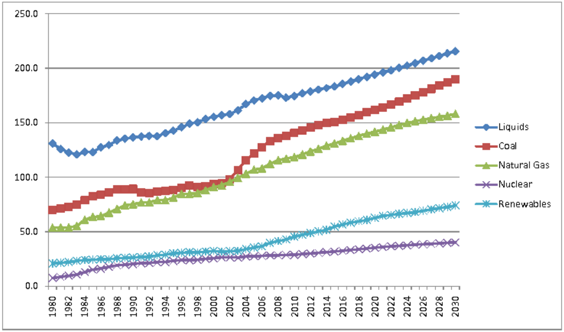
Energy and Human Society

- Both modern daily life and industrial production greatly rely on electricity.
- Electricity production and modern transportation heavily depend on fossil fuels.
- We cannot live without energy from either electricity or fossil fuels.

World Marketed Energy Consumption (in Quadrillion BTU)



World Marketed Energy by Fuel Type (in Quadrillion BTU)



Why Optimization?

- Energy demands grow very fast every year.
- The whole system is inefficient.
- New problems associated with energy usage, such as environment issues.
- Need better designs and rules.
- Optimization or Operations Research have been and will be the choice.

Contents

- Power Systems
  - Electricity Generation
  - Power Transmission
  - Electricity Market
- Fossil Fuels (Coal, Petroleum, and Natural Gas)
  - Production
  - Transmission
  - Market
- Protecting environment and saving energy.
  - Reducing Emissions (CO_2)
  - Saving Energy

Optimization in Power Systems

- Electricity Production
  - Unit Commitment Models
  - Hydro System
- Electricity Transmission
  - Optimal Power Flow Models
  - Transmission Network Expansion Models
- Electricity Market

Unit Commitment Models

Commitments of power generating units to meet the electricity demands with minimum cost. And UC models apply mostly to thermal power plants.

- Traditional Deterministic UC models in regulated market, where utility companies are the only ones to generate electricity.
- Stochastic UC models in deregulated market, where non-utility companies (renewable energy) also can sell electricity to customers through utility companies' networks.

Deterministic UC Models

- U_i^t: binary variable to denote whether unit i is committed;
- P_i^t: continuous variable to denote amount of energy generated by unit i at time period t;
- $c_i(P_i^t)$: cost function, which is nonlinear (quadratic);
- G_i^t: binary variable to denote whether the unit i start up at time t;
- s_i^t: start up cost;
- Objective Function:
  TotalCost$= \sum_{i\in I} \sum_{t=0}^{T} \left[c_i(P_i^t)U_i^t + s_i^t G_i^t\right]$

Deterministic UC Model

$$
\begin{aligned}
\textbf{D. UC:} \quad \text{Min} \quad & \sum_{i \in I} \sum_{t=0}^{T} \left[c_i(P_i^t) U_i^t + s_i^t G_i^t \right] \\
\text{s.t.} \quad & \sum_{i \in I} P_i^t \geq d_t, \quad t = 1, ..., T \\
& U_i^t - U_i^{t-1} \leq U_i^{\tau}, \quad \tau = t, ..., min\{t + L_i - 1, T\} \\
& U_i^{t-1} - U_i^t \leq 1 - U_i^{\tau}, \quad \tau = t, ..., min\{t + l_i - 1, T\} \\
& q_i U_i^t \leq P_i^t \leq Q_i U_i^t, \quad t = 1, ..., T \\
& G_i^t \geq U_i^t - U_i^{t-1}, \quad t = 1, ..., T
\end{aligned}
$$

This is a mixed nonlinear integer programming problem.

UC model solution algorithms

- Priority Listing (Heuristic)
- Dynamic Programming (Exhaustive search)
- Lagrangian Relaxation (Most widely used and efficient.)

Stochastic UC model

A dynamic programming formulation:

$$
\begin{aligned}
f(t) = f(t+1) + \text{Min} \quad & \sum_{i\in I}\sum_{j=1}^{J} \rho_j \left[c_i(P_i^t(j)) U_i^t(j) + s_i^t(j) G_i^t(j) \right] \\
\text{s.t.} \quad & \sum_{i\in I} P_i^t(j) \geq d_t(j), \\
& U_i^t(j) - U_i^{t-1}(j) \leq U_i^{\tau}(j), \\
& U_i^{t-1}(j) - U_i^t(j) \leq 1 - U_i^{\tau}(j), \\
& q_i U_i^t(j) \leq P_i^t(j) \leq Q_i U_i^t(j), \\
& G_i^t(j) \geq U_i^t(j) - U_i^{t-1}(j),
\end{aligned}
$$

where j denotes scenario.

Hydroelectric System

- Humans have been using hydro energy for a long time by using waterwheels.
- The first hydroelectric power plant was built on the Fox River in Appleton, Wisconsin in 1882, the same year when the first steam power plant was built by Thomas Edison.
- Hydro power plants have no fuel cost, and release almost no CO_2, but may affect the local ecosystem.
- Long time scheduling is a very important topic because of the water inflow is seasonal and stochastic.
- Coordination with thermal power systems.

Hydrothermal Dispatch models

A dynamic programming formulation,

$$
\begin{aligned}
z_t(v_t) = \beta z_{t+1}(v_{t+1}) + \text{Min} \quad & \sum_{j \in J} c(j) g_t(j) \\
\text{s.t.} \quad & v_{t+1}(i) = v_t(i) - u_t(i) - s_t(i) + a_t(i) \\
& \qquad + \sum_{m \in U(i)} [u_t(m) + s_t(m)], i \in I \\
& \sum_{i \in I} \rho(i) u_t i + \sum_{j \in J} g_t(j) = d_t, \\
& g_t(j) \leq g_{max}, i \in I, \\
& v_{t+1}(i) \leq v_{max}, i \in I, \\
& u_t(i) \leq u_{max}(i), i \in I.
\end{aligned}
$$

Hydrothermal Dispatch models

- $z_t(v_t)$: the total cost of time t through time T
- $c(j)$: the vector of thermal unit operating cost
- v_t: the vector of reservoir levels at time t
- u_t and s_t: turbined and spilled outflows
- a_t: precipitation inflow (seasonal, and stochastic)
- U: upper streams set
- $g_t(j)$: power generated by thermal plant j
- There is no cost for the hydroelectricity.

Solving the Hydrothermal Dispatch problem

- A multistage stochastic programming problem.
- A powerful method: Stochastic Dual Dynamic Programming
  - Proposed independently by Pereira and Pinto (1991) and Read and George (1990)
  - Widely used both in academic and industrial areas

Stochastic Dual Dynamic Programming (SDDP)

- Nicely avoid dimensionality explosion.
  - No need to generate all scenarios (billions, trillions)
  - Only need to generate some scenarios for one stage
- Forward and backward iterations.
- Monte Carlo forward simulation:
  - Generate some scenario of stage n.
  - Solve the generated scenarios (optimization problem).
- Backward iterations:
  - Construct Benders' cut for stage $n-1$ by using $\bar{\pi}_{n-1}$.
  - $\bar{\pi}_{n-1} = \sum_{j=1}^{m} p_n^j \pi_{n-1}^j$.
  - π_{n-1}^j is the optimal dual solution of stage n subproblem under scenario j, which happens with probability p_n^j.

Optimization in Power Transmission

- Optimal Power Flow (OPF) problems.
- Transmission Network Expansion problems.

Optimal Power Flow (OPF)

- Three general formulations: linear, nonlinear, and mixed nonlinear programming problems.
- Minimizing the total generation cost, transmission loss, or both.
- With both equality and inequality constraints which could be either linear or nonlinear.
- Two types of variables: control and state variables.

OPF general formulation

$$
\begin{aligned}
OPF: \qquad \text{Min} \quad & f(x_c, x_s) \\
\text{s.t.} \quad & g(x) = 0, \\
& h(x) \leq 0, \\
& x^{MIN} \leq x \leq x^{MAX}.
\end{aligned}
$$

where x_c and x_s are the control and state variables respectively.

OPF models

Classification:

- Basic OPFs.
- SCOPF: additional security constraints.
- SCOPF-VS: SCOPF with voltage stability constraints.

OPF objectives

The objective of OPF could be any of the followings, a combination of them, or a multiple objective.

- Minimize the generating cost, $C_G = \sum_{i=1}^{n} a_{0i} + a_{1i} P_{gi} + a_{2i} P_{gi}^2$;
- Minimize real power loss and Volt-Ampere Reactive (VAR) power cost;
- Minimize the deviation from a specified point of control variables;
- Etc.

OPF constraints

- Power flow constraints (real and reactive power balance)
- Rotor-angle constraints
- Limits on both control and state variables
  - Real and Reactive power generation limits
  - PV and PQ bus voltage limits
  - Bus transient voltage limits
  - Transmission line flow limits
  - Transmission line power oscillation limits

OPF solution algorithms

- Deterministic methods
  - Generalized Reduced Gradient method
  - Successive Linear Programming (SLP) method
  - Successive Quadratic Programming (SQP) method
  - Lagrangian Newton method
  - Interior Point (IP) method
- Stochastic methods
  - Genetic Algorithm (GA)
  - Simulated Annealing (SA)
  - Particle Swarm Optimization (PSO)
  - Differential Evolution (DE)
  - Etc.

Transmission Network Expansion Planning

- Every year there are a lot of blackouts.
- Most of electricity networks are with some level of vulnerability.
- The demands are increasing very fast, and could become very huge when the era of electrical cars arrive.
- Mathematical programming is one of the most important methodologies to handle these problems.

A mixed integer nonlinear programming formulation

$$
\begin{aligned}
\text{Min} \quad & c_n^T n + c_p^T p \\
\text{s.t.} \quad & -\frac{1}{2}|S^T|(N+N^0)[S\theta]\Psi S\theta - S^T(N+N^0)YS\theta + p = d \\
& (N+N^0)(\frac{1}{2}[S\theta]\Psi S\theta + Y|S\theta| - \bar{f}) \leq 0 \\
& 0 \leq p \leq \bar{p}, 0 \leq n \leq \bar{n} \\
& n \text{ integer and } \theta \text{ unbounded}
\end{aligned}
$$

A mixed integer nonlinear programming formulation

c_n	cost vector of circuits that can be added;
c_p	cost vector of energy produced by the generators;
n	vector of circuits added;
$\bar{f}$	maximum power flow vector;
N	diagonal matrix with $n_i s$ as diagonal elements;
N^0	diagonal matrix with circuits in the base case as diagonal elements;
Ψ	diagonal matrix with conductance of the circuits as diagonal elements;
Y	diagonal matrix with susceptance of the circuits as diagonal elements;
S	branch-node incidence matrix from the electric system;
θ	angle phase vector;
p	generation vector with maximum value p;
$\bar{n}$	maximum number of vector circuits that can be added;
d	demand vector;
$[x]$	diagonal matrix with $x_i s$ as the diagonal elements.

Transmission Network Expansion Planning Solution Algorithms

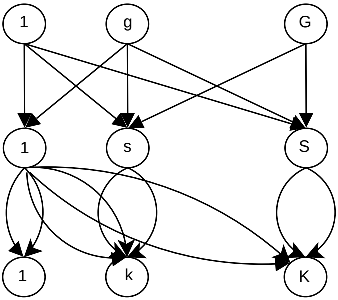
- Branch and bound
- Greedy Randomized Adaptive Search Procedure (GRASP)
- Genetic Algorithm (GA)
- Tabu Search

Equilibrium Models in Electricity Generation Network

The equilibrium can be defined as a set of prices, generation amounts, transmission flows, and consumption that satisfy each market participant's first-order conditions for maximization of its own net benefits while clearing the market.

- Nash-Cournot Models
- Supply Function Models

Electricity Generation Network



Power Generators

Power Suppliers

Transmission Service Providers

Power Generator Behavior

Each individual power generator is a profit-maximizer:

$$
\begin{aligned}
\text{Max} \quad & \sum_{s=1}^{S} \rho^*_{gs} q_{gs} - f_g(q_{gs}) - \sum_{s=1}^{S} c_{gs}(q_{gs}) \\
\text{s.t.} \quad & \sum_{s=1}^{S} q_{gs} = q_g, \quad \forall g \\
& q_{gs} \geq 0, \quad \forall s, g
\end{aligned}
$$

where ρ^*_{gs} is the unit price charged by power generator g for the transaction with power supplier s, q_g is the power generated by g, $c_{gs}(q_{gs})$ is the transaction cost incurred by power generator g in transacting with power supplier s and $f_g(q_{gs})$ is the power generating cost function of power generator g.

Formulation of the Equilibrium

Assuming all the function are continuously differentiable and convex, the equilibrium can be expressed by following Variational Inequalities (VIs):
Determining $(q^*, Q^*) \in K^1$ satisfying

$$\sum_{g=1}^{G} \frac{\partial f_g(q^*)}{\partial q_g} \times [q_g - q_g^*] + \sum_{g=1}^{G} \sum_{s=1}^{S} \left[\frac{\partial c_{gs}(q_{gs}^*)}{\partial q_{gs}} - \rho_{gs}^* \right] \times [q_{gs} - q_{gs}^*], \forall (q, Q) \in K$$

where $K^1 = \{(q, Q) | (q, Q) \in R_+^{G \times GS}, \sum_{s=1}^{S} q_{gs} = q_g, \quad \forall g.\}$

Other more advanced models

- Equilibrium with dynamic demands
- Equilibrium with concave demand functions
- Stochastic equilibrium problems

Optimization models in fossil fuel production

- Production Scheduling
- Reservoir Modeling
- Well placement
- Well and production facilities

Production Scheduling Considering Well Placement

- A mixed integer programming formulation
- Maximizing profit
  b_i^k to denote the benefit of one unit gas flow
- Considering well placement
  y_i to denote whether to drill the well at location i
- Considering the pressure loss due to withdraw
  q_i^k to denote the withdrawal rate from well i at time period k

The mixed integer programming formulation

$$
\begin{array}{lll}
\text{Max} & \displaystyle\sum_{k=1}^{m}\sum_{i=1}^{n} b_i^k q_i^k & \\
s.t. & \displaystyle\sum_{j=1}^{n} \Phi_{ij}^k q_j^k = p_i^k, & i=1,\ldots,n,\ k=1,\ldots,m, \\
& \displaystyle\sum_{j=1}^{n} \Phi_{ij}^k q_j^k \le \bar{p}_i^k, & i=1,\ldots,n,\ k=1,\ldots,m, \\
& \displaystyle\sum_{k=1}^{l}\sum_{j=1}^{n} \Phi_{ij}^k q_j^k \le \hat{p}_i^l, & i=1,\ldots,n,\ l=1,\ldots,m, \\
& \displaystyle\sum_{j=1}^{n} q_j^k \le d^k, & k=1,\ldots,m, \\
& q_i^k \le m_i y_i, & i=1,\ldots,n, \\
& q_i^k \ge 0, & i=1,\ldots,n,\ k=1,\ldots,m, \\
& y_i \in \{0,1\}, & i=1,\ldots,n,
\end{array}
$$

where from well i during time period k, $\bar{p}_i^k$ is the maximal pressure reduction at period k. $\hat{p}_i^l$ is the maximal total pressure drop allowed.

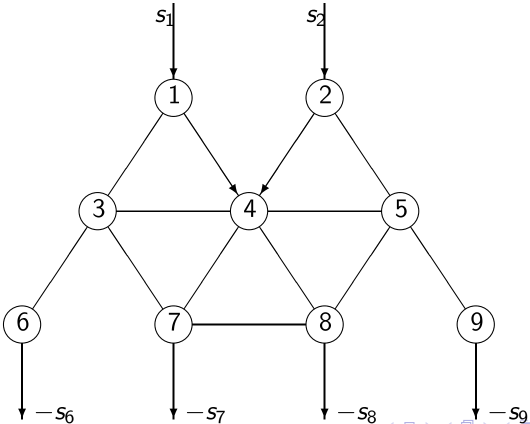
Natural Gas Pipeline Network Optimization

- Pipeline Network Design problems (location of pipelines)
- Optimal pipeline diameter problems
- Compressor station location problems
- Minimum pipeline network fuel consumption problems
- Usually the problems have nonlinear/nonconvex/nonsmooth constraints and objective functions
- Most common and troublesome (in the sense of computation) constraints: Panhandle Equations

$$\mathrm{sign}(f_{ij})f_{ij}^2 = p_i^2 - p_j^2, \qquad (i,j) \in A_p,$$

where f_{ij} is the flow rate of pipeline (i,j), p_i and p_j are the pressures at node i and j respectively.

Least Gas Purchase Problem and Optimal Dimensioning of Gas Pipelines



The nonlinear nonconvex network optimization problem

$$
\begin{aligned}
\text{Minimize} \quad & \sum_{i \in N_s} c_i s_i \\
s.t. \quad & \sum_{j \in A_i^+} f_{ij} - \sum_{j \in A_i^-} f_{ji} = s_i, && \forall i \in N, \\
& sign(f_{ij}) f_{ij}^2 = C_{ij}(p_i^2 - p_j^2), && \forall (i,j) \in A_p, \\
& f_{ij}^2 \geq C_{ij}(p_i^2 - p_j^2), && \forall (i,j) \in A_c, \\
& \underline{s}_i \leq s_i \leq \bar{s}_i, && \forall i \in N, \\
& \underline{p}_i \leq p_i \leq \bar{p}_i, && \forall i \in N, \\
& f_{ij} \geq 0, && \forall (i,j) \in A_c,
\end{aligned}
$$

where p_i is the gas pressure at node i, c_i is the purchase cost per unit gas from supplier i, and C_{ij} an coefficient for arc (i,j), which is determined by the length, diameter and so on.

Gas Contract Optimization Problem

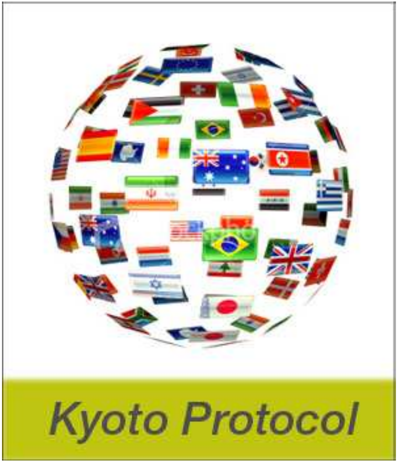
- Combined cycle power plants are very popular due to high efficiency and less CO_2.
- Take-Or-Pay (TOP) gas contract.
- Maintenance Scheduling of the power plants.
- Stochastic price of gas and electricity.
- A stochastic dynamic programming problem.

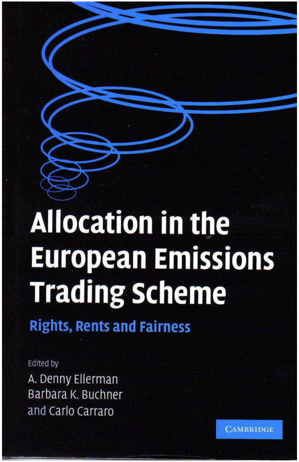
The dynamic programming formulation of Gas Contract Optimization

$$
\begin{aligned}
& && FBF_t^k(VA_t, VB_t, \{VH_t^{i,j}, i = 1, \ldots, n, j = 1, \ldots, m\}, \pi_t^k) \\
= & \quad \text{Max} && RI_t + \sum_{s=1}^{S} p_{t+1}(k,s) FBF_{t+1}^s(VA_{t+1}, VB_{t+1}, \{VH_{t+1}^{ij}, i = 1, \ldots, n, j = 1, \ldots, m\}, \pi_{t+1}^k) \\
& \quad s.t. && VA_{t+1} = VA_t + ARM_t - GToP_t + GTR_t - GD_t, \\
& && VB_{t+1} = VB_t - GTR_t \\
& && VH_{t+1}^{i,j} = VH_t^{i,j}(1 - x_t^{i,j}) + \overline{VH}^j x_t^{i,j} - \gamma EG_t^i, \quad i = 1, \ldots, n, j = 1, \ldots, m, \\
& && \sum_{i=1}^{n} \psi_t^i EG_t^i = H_c(CToP_t + GToP_t + \nabla G_t)
\end{aligned}
$$

- GP_t is the amount of gas actually used to generate electricity;
- GS_t is the amount of gas purchased or sold to the gas spot market;
- ARM_t is amount of gas purchased from the gas distributor, an should be bounded below by $X\%M$;
- VA_t and VB_t is the remaining gas in reservoir A and B respectively;
- GTR_t is the amount of gas transfer from A to B;
- GD_t is the amount of gas discarded when it is in the reservoir more than the maximum storage time, N.

Emission Quotas vs. Emission Market





CO_2 emissions: What should we do?

Sins of emission
Economist, March 12, 2009

"...all this (...) would complement Mr. OBAMA's broader ambition to tackle global warming through a cap-and-trade scheme, whereby the government would set steadily declining annual limits on emissions, and would then auction permits to pollute up to that level. The president has consistently called for such a scheme..."

CO_2 Allowances Modeling

The CO_2 allowances can then be modeled as follows

$$\sum_{t|y} \sum_{j \in J} B_j \mathbf{g}_{tj}(\omega) - \mathbf{f}_y(\omega) \leq E_y^{\mathrm{CO_2}}, \quad y \in Y$$

where $y \in Y \subseteq T$ is the set of stages when the CO_2 allowances are issued.

$j \in J$	set of thermal plants
$t \in T$	set of stages
$y \in Y \subseteq T$	set of stages when CO_2 allowances are issued (e.g., yearly)
$t\|y$	stages t belonging to the CO_2 emissions issue period $y \in Y$
B_j	CO_2 emissions coefficient per plant $j \in J$
g_{tj}	thermal plant power generation per period t
$\mathbf{f}_y$	fine for exceeding CO_2 emissions per year y
$\omega \in \Omega$	random event
$E_y^{\mathrm{CO_2}}$	CO_2 emission allowances per year y

CO_2 Emission Allowances Modeling via Reservoirs

$$\mathbf{e}_{t+1} = e_t - \sum_{j \in J} B_j \mathbf{g}_{tj} + \mathbf{f}_t, \quad t \in \mathbf{T} \setminus \mathbf{Y} \tag{1}$$

$$\mathbf{e}_{t+1} = \widetilde{e}_t - \sum_{j \in J} B_j \mathbf{g}_{tj} + \mathbf{f}_t + E_t^{\mathrm{CO}_2}, \quad t \in \mathbf{Y} \tag{2}$$

$$\mathbf{e}_{t+1} \geq 0, \quad \mathbf{f}_t \geq 0, \quad t \in T, \tag{3}$$

CO_2 Emission Allowances Modeling via Reservoirs

$$\mathbf{e}_{t+1} = e_t - \sum_{j \in J} B_j \mathbf{g}_{tj} + \mathbf{f}_t, \quad t \in \mathbf{T} \setminus \mathbf{Y} \tag{1}$$

$$\mathbf{e}_{t+1} = \widetilde{e}_t - \sum_{j \in J} B_j \mathbf{g}_{tj} + \mathbf{f}_t + E_t^{\mathrm{CO_2}}, \quad t \in \mathbf{Y} \tag{2}$$

$$\mathbf{e}_{t+1} \geq 0, \quad \mathbf{f}_t \geq 0, \quad t \in T, \tag{3}$$

and

$$\widetilde{e}_t := \begin{cases} 0, & \text{if the emissions expire} \\ e_{t-1}, & \text{if the emissions do not expire} \end{cases}, \quad t \in \mathbf{Y} \tag{4}$$

e_t CO_2 emission allowances left at the beginning of period t (quota level)

Saving Energy

- By principles of physics, energy is always saved by itself (Law of Energy Conservation).
- In the economic sense, saving energy means using less money and human power.
- In the environmental sense, saving energy means making less or no damages to mother nature.
- By saving energy, we mean to design a better way to exploit energy economically and environmentally.
- 2008 US Energy Consumption by sector
  - Residential and Commercial: 41% (Mostly within buildings)
  - Industrial: 31%
  - Transportation: 28% (passenger cars contribute two thirds)
- Using energy more efficiently in buildings means a lot of savings: optimize the energy cost of buildings.

A mathematical model of multi-energy resource building system optimization

$$
\begin{aligned}
\text{Min} \quad & f(E_{in}, P_k) \\
\text{s.t.} \quad & E_{in} = \mathbf{D} E_{out} \\
& P_{in} = \mathbf{F} P_{out} \\
& E_{in} \geq 0 \\
& P_{in} \geq 0 \\
& 0 \leq d_{ij} \leq 1, \forall i, j \\
& 0 \leq f_{kl} \leq 1, \forall k, l \\
& \sum_j d_{ij} = 1, \forall i \\
& \sum_l f_{kl} = 1, \forall k
\end{aligned}
$$

Notations of the above model

- E_{in} Energy Supply Vector of all types.
- E_{out} Energy demands of all types.
- **D** The coupling matrix which depends on systems and plants installed and on their conversion efficiencies. $\mathcal{D} = (d_{ij})$
- P_k The design power of each converter k.
- $f(E_{in}, P_k)$ The cost function, which could be either of the following, or combination, multiple objectives,
  - The running and capital costs
  - The amount of energy consumed
  - The environmental costs (such as emissions, etc)

Conclusion

- Optimization models are everywhere in the energy systems.
- Several optimization techniques are used in the energy systems.
- With help of optimizers, the energy system can perform better.
- The demands are increasing and the systems are changing, more modeling and optimization are needed.

Our Energy Group

Our current research areas:

- Optimal Power Flow problems (OPF).
- Transmission Network Expansion Planning.
- Electricity market equilibrium modeling.
- Natural gas contract optimization and network expansion.
- Electricity network blackout modeling and optimization.
- Wind Power Modeling and optimization.
- CO_2 market modeling and optimization.

Our Books

- Published:
  "*Optimization in the Energy Industry*," Springer, 2009, ISBN: 978-3-540-88964-9
- Coming soon:
  "*Handbook of Power Systems*", Springer.
- In progress:
  - "*Handbook of Networks in Power Systems*";
  - "*Handbook of CO_2 in Power Systems*";
  - "*Handbook of Renewable Energy Sources*";
  - "*Handbook of Wind Power Systems*".

Call for Papers

New Springer Journal: "**Energy Systems**"
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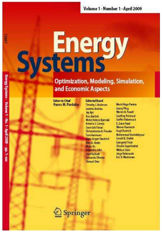
Editor-in-Chief: **Panos M. Pardalos**



INFORMS Conference on Optimization

Conference on "*Energy, Sustainability and Climate Change*"

February 26 - 28, 2010
University of Florida
Gainesville, Florida, USA

http://www.ise.ufl.edu/cao/escc2010/

Conference Organizer: **Panos M. Pardalos**

Thanks and Questions

Thank you all!
Questions?

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