A Hybrid Metaheuristic / Benders Optimal Generation Coordination Method with Electric Vehicles as Stochastic Reservoirs

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What is generation coordination?

determining operational schedules, a few days ahead
Challenge: Renewable production does not coincide well with the demand!
Challenge: Wind (and other RES) power forecasting errors
Storages in Electric Power System

Storage idea: Decoupling electricity production from the demand
**Key trouble with introducing storages in the analysis**

The root of all the trouble in the analysis of power system WITH storages is the integration characteristic of the storage.

Energy storage “memorizes” past operational behavior, with its specific loss characteristics (and losses are not time invariant)

The value of stored energy depends on future decisions as well!

As a consequence, system can’t be adequately modeled using *snapshot* analyses!

Since the system state at the time t depends on the history, it can’t be analyzed out of context.

\[
E_t = \int_{-\infty}^{t} (P_t - P_{L,t}(P_t, E_t)) \, dt
\]

- $E_t$ – Stored energy
- $P_t$ – Power flowing from storage to the network or vice versa
- $P_L$ – Storage losses
Vehicle to grid (V2G) Concept

- Envisioned in 2005, extended in 2007
- IEEE and ISO standards and live functioning implementations exist
  - e.g. ISO 15118-1:2013
- Two way connection of EV to the electric power network
- Vehicles can return the energy to the grid
- Prerequisite: communication, ability of EV chargers to receive set points
Some examples of EV batteries

Citroën C-Zero – 16 kWh
joint venture PSA + Mitsubishi, also called Peugeot Ion / Mitsubishi i-MiEV,
approximately 35+ thousands of units sold from 2010-2015

Nissan Leaf – 24 kWh
best selling FEV, over 100 hundred thousands sold;
Norway has more than 7000

Renault Fluence Z.E. – 22 kWh

Tesla Model S – 60, 85, 90 kWh

Doking Loox (xD) – 33 kWh

Rimac Concept One – 86 kWh
**EV-based Stochastic Storage Concept**

- a group of vehicles connected to the grid comprises a stochastic storage

- all variables are time dependent and stochastic (incl. max and min energy storable in the reservoir)

- partial contributions from each electric vehicles as seen from the generation system form a cluster of vehicles = stochastic reservoir
EV-based Stochastic Storage Concept

The desired energy $Ed$: the difference between the final state of charge of an aggregated reservoir and the initial state.

The energy deficit is the difference between desired and actual SoC at the time of disconnection; analogous to ENS.
The constraints are formulated as flow constraints, decomposed per time period.

Energy that the power system can supply to / draw from the reservoir is limited: flow limits (aggregated interface limitations, grid limits etc).

After a group of vehicles is disconnected, the power cannot flow from the system to it (and vice versa) so there’s no connection (e.g. cluster 1 in t=3)
Transition to V2G: Three EV Charging Modes

- “dumb” charging:
  - time of disconnection is equal to the end of charging, no hourly arbitrage possible, inflexible demand (not flexible regarding power drawn from the grid)
    \[
    t_{\text{end}}(\text{cluster}) = t_{\text{charging}}
    \]
    \[
    E_r(t, c) = E_r(t, c), \quad \forall t
    \]
  - unlike additional load: the cost of failing to provide the desired amount of energy may be different from ENS!

- smart charging:
  - permits hourly arbitrage – delayed charging
  - charging amount controllable
  - does not permit the energy flow from the vehicle to the grid

\[
E_r(t, c) \leq \left[ E_d(c) - \sum_{t = t_0(c)}^{t = t - 1} E_r(t, c) \right], \quad \forall t_{\text{conn}}, t_0(c) \leq t_{\text{conn}} \leq t_f(c)
\]
\[
E_r(t, c) \geq 0, \quad \forall t
\]
\[
E_r(t, c) \leq E_r(t, c)
\]
Transition to V2G: Three EV Charging Modes

- **vehicle to grid interface charging:**
  - the real stochastic reservoir: EV pool is a stochastic storage
  - energy can flow in both directions
  - the equations link the time periods

\[
E_r(t, c) \leq E_r(t, c) \leq E_r(t, c) \\
E_r(t, c) < 0
\]

\[
E_r(t, c) \leq \left[ E_d(c) - \sum_{t=t_0(c)}^{t=t-1} E_r(t, c) \right], \quad \forall t_{conn}, t_0(c) \leq t_{conn} \leq t_f(c)
\]

\[
E_d(c) - \sum_{t=t_0(c)}^{t=t-1} E_r(t, c) \geq E_{min}(t, c), \quad \forall t
\]

- the model permits modeling gradual implementation of V2G connections
The Energy Deficit (in EV reservoirs)

- The unit commitment cost function becomes:

\[
\text{Minimize } \sum \text{Cost}(P(t)) + \sum \text{Cost}(\text{Def}(c))
\]

subject to system restrictions

- i.e. minimize the system operational cost plus the energy deficit “cost”: the price of not completely providing adequate charging to the EV owners

- the inclusion of the deficit makes the problem always mathematically feasible, favorable for cut generation and algorithm speed (only optimality cuts are generated)

- can be (and is) different from the cost of energy not being supplied (ENS)
  - aggregators may have different contractual obligations with the EV owners
  - this is the cost of customer insatisfaction
STRUCTURE OF THE PROBLEM

Benders and Dual Dynamic Programming: basics

\[ \text{Min} \quad C'X + D_1'Y_1 + ... + D_n'Y_n \]

\[ \text{Subj:} \quad AX + J_1X + K_1Y_1 \geq b \]

\[ \text{Subj:} \quad J_nX + K_nY_n \geq g_n \]

... a set of cascading “independent” problems:

\[ \text{Min} \quad C_1^tX_1 + C_2^tX_2 + ... + C_n^tX_n \]

\[ \text{Subj:} \quad A_1X_1 + A_2X_2 \geq b_1 \]

\[ \text{Subj:} \quad \cdots \geq b_2 - E_1X_1 \]

\[ \text{Subj:} \quad \cdots \geq \cdots \]

\[ \text{Subj:} \quad +A_nX_n \geq b_n - E_{n-1}X_{n-1} \]
BENDERS master and slaves

MASTER (Integer)

Slave 1 (LP)

Slave 2 (LP)

...

Slave n (LP)

New X values

New cut
Stochastic extension

Admit a problem with two time stages and with two scenarios for the second stage.

The structure of the problem may be

Min \( C_1^tX_1 + p_1C_2^tX_{21} + p_2C_2^tX_{22} \)

\[ A_1X_1 \geq b_1 \]

Subj: \( E_2X_1 + A_2X_{21} \geq b_{21} \)

\( E_2X_1 + A_2X_{22} \geq b_{22} \)

where \( p_1, p_2 \) are the probabilities of each scenario
The Benders trick

Primal and dual forms of the sub-problem:

\[ \alpha(X_{n-1}) = \min C_n^t X_n \]
Subj: \[ A_n X_n \geq b - E_{n-1} X_{n-1} \]
\[ X_n \geq 0 \]

\[ \alpha = \max (b - E_{n-1} X_{n-1})^t \pi \]
Subj.: \[ A_n^t \pi \leq C_n \]
\[ \pi \geq 0 \]

The domain of the dual does not depend on \( X_{n-1} \) !!!

The optimum of the dual may be found among the vertices of a fixed domain (if \( X_{n-1} \) changes, the optimum may change vertex, but the feasible region is constant)
Solving the dual

Searching for vertices

Two different slopes for the objective function, from different values of $X$

$$\alpha = \text{Max} \ (g - JX)^t \pi$$

Subj.: $K^t \pi \leq D$

$$\pi \geq 0$$

For a given $X^*$, each vertex defined by the dual variables $\pi$ will have an $\alpha$ value - and we wish to select the vertex $\pi^*$ with maximum $\alpha$

$$\min \ \alpha$$

$$\alpha \geq (g - JX)^t \pi^i$$

$$\alpha \geq (g - JX)^t \pi^{ii}$$

...$$\alpha \geq (g - JX)^t \pi^n$$
Adding a constraint to the master

Solving the sub-problem for a given $X^*$, we find a vertex of the dual, which corresponds to a valid constraint that can be added to the master:

\[
\begin{align*}
\text{Min} & \quad C^t X + \alpha \\
\text{Subj:} & \quad AX \geq b \\
\alpha & \geq (g - JX)^t \pi^* 
\end{align*}
\]

If we solve now the master, we get a new value for $X^*$ – which will allow finding another vertex $\pi$ in the sub-problem dual – which will allow a new constraint to be added to the master – which...

BUT

Adding a constraint to the problem may be replaced by adding a penalty to the Master objective function...

THE MASTER PROBLEM MAY BE SOLVED BY A META-HEURISTIC WITH EVOLVING LANDSCAPE!
Stochastic Modeling: Scenarios

- In systems with storage the decisions in a time step are reflected in other time steps.
- “snapshot” analysis - considering each time period as independent from others not adequate
  - sequence of marginal distributions also inappropriate!
  - missing temporal evolution of variables

- The chosen model of uncertainty: scenarios

- Sampled from an estimator model
  - for wind power: covariance matrix estimation
  - for EV behavior: Gaussian copula-based Monte Carlo model or extracting data from agent-based model simulations of traffic behavior

- Result: A large set of sampled scenarios -> Clustering to reduce the number of scenarios!
Stochastic modeling: Scenario reduction

- From a large set of Monte Carlo sampled scenarios clustering delivers a set of weighted scenarios according to the chosen similarity metric.

- Classic clustering problem: maximize entropy among clusters, minimize entropy within each cluster, assign relative weights.

- In the presented results the distance metric: absolute per-hour deviation.
The day-ahead stochastic UC problem decomposed into three stages:

**Stage 0: main problem**
- unit commitment decisions

**Stage 1**
- evaluation of wind power integration
- continuous variables (realizations)
- ramping constraints
- decomposed hydro constraints (max energy per day)
- max inclusion of renewable power
- min customer insatisfaction

**Stage 2**
- evaluation per stochastic storage scenarios
(Classic) UC Problem Formulation

- Quadratic fuel cost functions of thermal units, piecewise linearized per interval with a customizable number of intervals
  \[ C_g(t) = a \cdot uc_g(t) + bP_g(t) + cP_g(t)^2 \]

- Start-up and shut down costs
  \[ SU_g(t) = [uc_g(t) - uc_g(t - 1)]SU_g \]

- Hydro generators with large storages: total energy produced during the day is constrained (coming from longer-term optimization governing classic storages operation)
  \[ E_{g,\text{min}} \leq \sum_t P_g(t) \leq E_{g,\text{max}} \]

- Min up time and min down time constraints + unit initial conditions: \( s=1 \) if unit changed state, \( 0 \) otherwise
  \[ \sum_{t-t_{g,\text{on}} \leq i \leq t} s_{g,\text{on}}(i) \leq uc_g(t), \quad \sum_{t-t_{g,\text{off}} \leq i \leq t} s_{g,\text{off}}(i) \leq 1 - uc_g(t) \]

- Generation limits
  \[ P_{g,\text{min}} \leq P_g(t) \leq P_{g,\text{max}} \]

- Ramping limits
  \[ -R_{g,\text{down}} \leq P_g(t) - P_g(t - 1) \leq R_{g,\text{up}} \]
EPSO and the generalized version DEEPSO

The Master problem on integer variables is solved by a customized version of EPSO algorithm.

DEEPSO concept:

- **inertia**: moving in the same direction

- **perception**: sensing a local gradient (by the swarm)

- **cooperation**: attraction to the proximity of the global best

\[
X_{\text{new}}^{\text{new}} = X + V_{\text{new}}^{\text{new}}
\]

\[
V_{\text{new}}^{\text{new}} = w_I^* V + w_M^*(X_{r1} - X) + w_C^* P (b_G^* - X)
\]

* subject to mutation  \hspace{1cm} P – communication probability
EVOLVING SWARMS – EPSO AND DEEPSO

**EPSO** – the gradient perception is based on the particle self-memory term
\[ V^{\text{new}} = w_l^* V + w_M^* (b_i - X) + w_C^* P (b_G - X) \]

**DEEPSO** – a flavor of Differential Evolution added to EPSO
\[ V^{\text{new}} = w_l^* V + w_M^* (X_{r1} - X) + w_C^* P (b_G - X) \]

**Variants**: 
- sampled among the current generation \( : S_{\text{g}} \)
- sampled among the matrix \( b_i \) of individual past bests \( : P_{\text{b}} \)
- as a uniform recombination of the current generation \( : S_{\text{g-rnd}} \)
- as a uniform recombination within the matrix \( b_i \) \( : P_{\text{b-rnd}} \)

*for the latter 2:* 
- not taking in account the direction of \( (X_{r1} - X) \) \( : .^- \) minus
- taking in acc. the direction of \( (X_{r1} - X) \) \( : .^+ \) plus
- taking in acc. the direction of \( (X_{r1} - X) \) in each coordinate: \( .^0 \) zero

**DEEPSO**: winner of the 2014 IEEE competition of m-h for the OPF problem
Custom EPSO for UC (Stage 0)

- Initialization of unit commitment status:
  - Custom tailored heuristic, not general but with more insight into the problem
- Heuristic order-based rule to commit units and construct initial population of solutions
  - Commit enough units until \( \text{sum}(p) \) is enough to cover the max load
- Checks and repairs for violating of on/off restrictions (commiting and decommiting when violated)
- Each particle maps the \{0,1\} space of unit commitment decisions to fitness value

EACH OF THE SCENARIOS IN STAGES 1 and 2 ESSENTIALY REPRESENTS AN ADDITIONAL PENALTY TO THE FITNESS LANDSCAPE!
Linearized subproblems in stages 1 and 2

- The subproblems involving wind power and storages are formulated as LP problems

- Solved using an industry standard LP solver to optimality
  - the dual value of the system equality is easily obtained

- The linear formulations in stage 1 have PNS and in stage 2 energy deficit:
  - There always exists a mathematically feasible solution
    - Faster to solve to (mathematical) feasibility even if technical feasibility is not obtained
  - The cuts generated by the subproblems: they are optimality cuts and not feasibility, so no distortion in the EPSO search space
Scenarios as penalties to fitness function: Risk handling

In the expected value formulation, the fitness function is

\[ Cost = E(Cost) = \frac{1}{N_s} \sum_{s \in S} Cost_s \]

For a robust optimization (worst case) fitness value formulation, the worst case defines the cost

\[ Cost = \max_{s \in S} Cost_s \]

For a minimax regret formulation, the cost is the maximum cost deviation from what would be the cost with perfect foresight (if the particular scenario occurred exactly)

\[ Cost = \max_{s \in S} [Cost_s - C_{pf}(s)] \]
Scenarios contribute as penalties to fitness function

An adaptive scheme handles the constraint contributions to the fitness function

\[ f = \sum_s \lambda_s p_s \text{Cost}_s \]

- Weight factors for each scenario cost are adapted according to the risk model and the probability of a certain scenario
  - remember the scenarios have a relative probability as a result of clustering

- Exponential decay is used to „forget” scenarios that do not discriminate between the current population of solutions
  \[ \lambda_{s,i+1} = \mu \lambda_{s,i}; \mu < 1 \]

- In the initial phase of the algorithm a limited subset of scenarios is used to speed up convergence and then resampling is used
Finishing an iteration of the algorithm

- In the classic EPSO, the location information is shared between individuals; here, the solutions also share scenario values
  - Optimal cost values for stage 2 and reduced cost coming from the equality constraint are shared!
  - This way the stage 2 solutions can be approximately calculated using the Benders decomposition cost-to-go principle!

- Cut calculation includes historical values: no recalculation if not necessary

- After each iteration, binary solutions of stage 0 repaired if there are violations of startup and shutdown time
Results: comparison with a MILP solver

- classic formulation with 1000 wind power scenarios and 5 units

- can be solved both with MILP solver directly
  - the same solver used within EPSO for LP problems used here for the whole problem

- stable and consistent results of EPSO with comparable performance
  - approx 20% loss in performance provides more flexibility

Average run times: 5 unit 1000 wind scenarios (no reduction), 100 repeated runs, expected value formulation:

Pure MILP UC: 121 seconds
EPSO UC: 163 seconds

(On a i7-3820QM laptop computer, same solver used for linear subproblems as well as full MILP)
Results: 10 Unit illustration problem (1)

- 1000 wind power scenarios reduced to a set of 20 scenarios
- 500 scenarios of EV integration reduced to a set of 20 scenarios
- 10 unit thermal system, enough power but relatively constrained with regard to flexibility (ramps)
- no electric vehicles, wind power integration only:

![Graph showing power output over time with various scenarios labeled gen_00 to gen_08 and wind]
Results: 10 Unit illustration problem (2)

- 33,000 vehicles with 16 kWh average desired energy, on avg 550 MWh of additional energy required throughout the day
- 80% of vehicles dumb charging, 20% smart charge, no V2G

no PNS, wind not spilled, energy deficit at bay ...

smart chargers help avoiding wind spill but the resulting additional load not favorable... most covered by expensive generator 7

1.8% additional energy
-> 3.1% increase in system cost!
Results: 10 Unit illustration problem + strong V2G (3)

- 20% of vehicles have smart charging and 80% V2G no dumb charging

- system cost reduced due to more charging in cheaper valley hours
- some extra demand still occurs in peak hours; 2.0% increase in overall cost compared to NO EV case
- 6.81% lower overall cost compared to dumb charging case - 35% less increase in system costs
CONCLUSIONS

A hybridization of the Benders decomposition with customized EPSO as master solver and LP slave problems is successful!

- A stochastic model with high number of scenarios (wind + EV use), keeping track of relation of time instants
- Metaheuristic nature of main solver allows including risk management strategies directly within the problem
- EV storage model allows modeling and evaluating different strategies of EV integration
- For smaller scale problems solver performance not far off from MILP:
- The algorithm suitable for planning purposes for system operators or EV aggregators (through modeling responses to tariffs)