Moving Energy through Time
Storage and Demand Side Response

James Cruise
Department of Actuarial Mathematics and Statistics
Heriot-Watt University

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Research track organised by James Cruise and Golbon Zakeri

- 11\textsuperscript{th} to 15\textsuperscript{th} March
- Talks on range of related research topics.
- Working group developed modelling framework for future research direction.

Wide range of participation from programme participates.
Importance of Energy Shifting

Energy shifting can provide a large range of services

- Price smoothing
- Network reinforcement
- Operating reserve
- Fast response
- Voltage support
- …
A wide range of technologies can provide energy shifting services

- Wide range of capacities
- Wide range of temporal scales

Examples:
- Pumped hydro,
- Compressed gas,
- Industrial demand response,
- Battery storage,
- Domestic demand response.
Dinorwig: capacity: 9 GWh     rate: 1.8 GW   efficiency 0.75–0.80
Industrial Demand Response

Golbon Zakeri, Mahbubeh Habibian, Anthony Downward, Miguel F. Anjos, Michael Ferris

**Problem:** 
Control of industrial demand response in a Co-optimized Energy and Reserve Market

- Considers the response of large industrial consumers,
  - Aluminium smelters
  - Steal production facilities.
- Consumers large enough to be price maker.
- Co-optimizes consumption bids and interruptible load reserve offers.

- ‘Multistage Stochastic Demand-side Management for Price-Making Major Consumers of Electricity’ (M. Habibian, A. Downward and G. Zakeri),
Problem: Control of aggregated demand response and batteries

- Aims to develop a virtual energy storage through the control of flexible loads.
- Providing a useful service to the Grid.
  - eg. response and reserve services
- While respecting user QoS.
  - no frogs and algae in pools
  - privacy respected.
Tracking Grid Signal with Residential Loads
Example: 300,000 pools, 300 MW max load

Each pool consumes 1kW when operating
12 hour cleaning cycle each 24 hours

Power Deviation:

Nearly Perfect Service from Pools
Meyn et al. 2013 [CDC], Meyn et al. 2015 [IEEE TAC]
Local Control Design

Tracking performance
and the controlled dynamics for an individual load

Heterogeneous setting:
- 40 000 loads per experiment;
- 20 different load types in each case

Lower plots show the on/off state for a typical load
References: this talk


A. Bušić and S. Meyn. Passive dynamics in mean field control. *53rd IEEE Conf. on Decision and Control (CDC)* 2014.
Problem: Developing charging tariffs to utilise flexibility from EV fleet

- Increasing number of electric vehicles connected to the grid.
- Could provide flexibility services to the grid.
- Empirical study using charging data.
- Understand the business model to realise the flexibility.
Energimarked 2.0

- Tibber customers offer flexibility
- Flexible devices are controlled by Tibber
  - EVs and domestic appliances
- Potential value of flexibility
  - Price-optimization (day-ahead market)
  - Fast frequency reserves (TSO)
  - Local grid (DSO)
- What is a good business model in order to activate flexibility and realize value for all participants?
Lagrangian Approach to Storage Control (Arbitrage)

James Cruise and Stan Zachary

Problem: How to control energy storage to maximise profit?

- Energy shifting participating in markets.
- Help to equalise prices and hence net demand.
- Often contracted for other purposes as well.
- For example, providing capacity or link reinforcement.

How should the operator control the store in these circumstances?

- Impact of storage competition on energy markets (James R. Cruise, Lisa Flatley, Stanley Zachary), EJOR https://doi.org/10.1016/j.ejor.2018.02.036
- The Optimal Control of Storage for Arbitrage and Buffering, with Energy Applications (James Cruise, Stan Zachary), FRM 2017: Renewable Energy: Forecasting and Risk Management pp 209-227
Define the following (deterministic) optimisation problem: 

\( P: \) Choose \( s = (s_0, \ldots, s_T) \) with \( s_0 = s_0^* \) so as to minimise

\[
\sum_{t=1}^{T} \left[ C_t(x_t(s)) + A_t(s_t) \right]
\]

subject to the capacity constraints

\[
0 \leq s_t \leq E_t, \quad 1 \leq t \leq T,
\]

and the rate constraints

\[
x_t(s) \in X_t, \quad 1 \leq t \leq T.
\]
Theorem
Let $s^*$ denote the solution to the problem $P$. Then there exists a vector $\lambda^* = (\lambda_1^*, \ldots, \lambda_T^*)$ such that

$$\text{for all vectors } s \text{ such that } s_0 = s_0^* \text{ and } x_t(s) \in X_t \text{ for all } t \text{ (s is not otherwise constrained)},$$

$$\sum_{t=1}^{T} [C_t(x_t(s)) + A_t(s_t) - \lambda_t^* s_t] \geq \sum_{t=1}^{T} [C_t(x_t(s^*)) + A_t(s_t^*) - \lambda_t^* s_t^*].$$

(1)
Theorem

2. the pair \((s^*, \lambda^*)\) satisfies the complementary slackness conditions, for \(1 \leq t \leq T\),

\[
\begin{align*}
\lambda_t^* &= 0 \quad \text{if } 0 < s_t^* < E_t, \\
\lambda_t^* &\geq 0 \quad \text{if } s_t^* = 0, \\
\lambda_t^* &\leq 0 \quad \text{if } s_t^* = E_t.
\end{align*}
\]

Conversely, suppose that there exists a pair of vectors \((s^*, \lambda^*)\), with \(s_0 = s_0^*\), satisfying the conditions (1) and (2) and such that \(s^*\) is additionally feasible for the problem \(P\). Then \(s^*\) solves the problem \(P\).
Finding \((s^*, \lambda^*)\)

**Proposition**

Suppose that the functions \(A_t\) are differentiable, and that the pair \((s^*, \lambda^*)\) is such that \(s^*\) is feasible for the problem \(P\), while \((s^*, \lambda^*)\) satisfies the conditions of previous Theorem. For each \(t\) define

\[
\nu_t^* = \sum_{u=t}^{T} [\lambda_u^* - A'_u(s_u^*)].
\]  

(3)

Then the condition that \((s^*, \lambda^*)\) satisfies the condition (1) of previous Theorem is equivalent to the condition that

\[ x_t(s^*) \text{ minimises } C_t(x) - \nu_t^* x \text{ in } x \in X_t, \quad 1 \leq t \leq T. \]  

(4)
UK Market Example

\[ E/P = 5 \text{ hrs} \quad \text{Efficiency} = 0.85 \text{ (ratio of sell to buy price).} \]

\[ A_t(S) = \nu/S \text{ (Black: } \nu = 0.02, \text{ Red: } \nu = 0.2, \text{ Blue: } \nu = 1) \]
Problem: Using energy shifting to meet an energy shortfall.

Setup:

1. a nonnegative demand process \((d(t), t \in [0, T])\)
2. a set \(S\) of stores,

Each store \(i \in S\):

- serve energy at any rate \(r_i(t)\) for each time \(t \in [0, T]\)
- rate (power) constraint \(P_i\)
  \[
  0 \leq r_i(t) \leq P_i, \quad t \in [0, T],
  \]
- capacity (energy) constraint \(E_i\)
  \[
  \int_0^T r_i(t) \, dt \leq E_i.
  \]
Problem of optimally scheduling the use of the stores:

**P:** choose a policy \( (r_i(t), t \in [0, T]) \) to minimize

\[
E \int_0^T \left( d(t) - \sum_{i \in S} r_i(t) \right)^+ dt,
\]

subject to

\[
0 \leq r_i(t) \leq P_i, \quad t \in [0, T],
\]

\[
\int_0^T r_i(t) \, dt \leq E_i.
\]

‘Optimal scheduling of energy storage resources’ J.Cruise and S. Zachary
Also see work by M. Evans, D. Angeli, and S. H. Tindemans
Optimal Greedy Policy

Algorithm:
- For each store calculate $E/P$ ratio (time to empty).
- Order stores by this ratio.
- Allocate capacity in greedy fashion using this order.
- Proportionally allocate those with equal $E/P$ to maintain equality.

Notes:
- Looks to equalize $E/P$ ratio across stores.
- Note this is a myopic policy, has no care about the future.
- Optimal for both deterministic and random demand profiles.
Farther Results

Other results include:

- Classifying demand profiles which can be satisfied
- Determining marginal effective firm capacity in the presence of stores.
- Differences when considering weighted EEU.
Framework for storage and demand response

Model that is tool for thinking about a range of problems in which energy is moved through time.

Setup:

- Large population of users
- Single system operator
- Fixed time horizon $T$
- Each user has a utility function:

$$U_i(d_{i1}, d_{i2}, ... d_{iT})$$

where $d_{ij}$ is demand by user $i$ in time period $j$.

- Consider system operator and individual problem
Focus on two types of utility function:

1. Simple utility function with decoupling across time:

   \[ U_i(d_{i1}, d_{i2}, \ldots d_{iT}) = \sum_{t=1}^{T} u_{it}(d_{it}). \]

2. Utility depends on demand through a stock

   \[ s_{i,t+1} = s_{it} - \alpha_{it} + \beta_{it} d_{it}, \]

   then the utility function is

   \[ U_i(d_{i1}, d_{i2}, \ldots d_{iT}) = \sum_{t=1}^{T} u_{it}(s_{it}). \]

Here \( \alpha_{it} \) is the depletion through exogenous factors at time \( t \), and \( \beta_{it} \) corresponds to the efficiency. Examples include a factory carrying out demand response, a battery store, household thermal storage.
Choosing $X_t$ (total generation) and $d_{it}, \ i \in N, \ t = 1, 2, \ldots, T$, to

maximize $\sum_i U_i(d_{i1}, d_{i2}, \ldots d_{iT}) - \sum_t C_t(X_t)$

subject to $\sum_i d_{it} = X_t + W_t, \ t = 1, 2, \ldots, T$
$d_{it} \in D_{it}, \ i \in N, \ t = 1, 2, \ldots, T$

- $C_t$ is the generation cost function at time $t$,
- $W_t$ is the zero cost renewable generation at time $t$,
- $D_{it}$ is demand restriction for users.
Choosing $d_{it}, i \in N, t = 1, 2, \ldots, T$, to

$$\max_{d_{it} \in D_{it}} \left\{ U_i(d_{i1}, d_{i2}, \ldots d_{iT}) - \sum_t \pi_t d_{it} \right\}$$

where $\pi_t$ is the electricity price (this should be the shadow price from the system problem).
Directions to explore

- Exploring the value of heterogeneity in users.
- Small $N$ to large $N$ limit
- Incorporating a distribution network
Future directions of research

- How do we extend the work to consider multiple energy shifting resources?
  - Collaborative?
  - Competitively?
- Understanding the role of the network, where should such facilities be located?
- How do we better understand energy sources providing multiple services concurrently?