# Demand-side Management over a Finite Time Horizon in a Co-optimized Energy and Reserve Market

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ISMP, 2018

# Outline

#### Problem Description

- Motivation
- NZEM
- Co-optimization of Electricity and Reserve over a Single Time Period
- Planning Demand over a Horizon

#### 2 Decomposition

- Decomposition
- Utility Consumption Curves
- Heuristics

### 3 Stochastic Versions

# Case Study

- In deregulated electricity markets, industrial consumers of energy may choose to purchase electricity from the wholesale market.
- The average wholesale prices is lower than the retail price, but with high volatility.
- In order to reduce the risk of high price fluctuations major consumers can use price-responsive consumption strategies.
- Our focus in this talk is on industrial demand response in the New Zealand Electricity Market (NZEM).

# New Zealand Electricity Market

- NZEM works as a uniform pricing auction with locational marginal pricing, at 285 nodes.
- NZEM has a co-optimized energy and reserve market.
- NZEM has several large consumers that together use up to 35% of generated electricity.
- Large consumers have dispatchable demand and can offer Interruptible Load Reserve (ILR).
- New Zealand Aluminium Smelter at Tiwai point uses approximately one third of the total power of the South Island and 15% of the total power countrywide (up to 610MW).

# Consumption Flexibility

- For aluminum smelters there are limitations on consumption.
- Shell Heat Exchanger is a new technology that is developed in UoA.
- SHE provides the cells with forced cooling/insulation equipment.



• SHE allows NZAS to respond to high and low prices of electricity via its flexibility in changing consumption levels in different time periods.

# Strategic Demand Response

- We focus on tools to assist major electricity users with consumption and reserve offer decisions.
- Given the hockey stick nature of the stacks, response to price saves on the cut back part but also reduces price for the amount that is consumed.



• The primary formulation is a bi-level optimization problem.

Maximize [Consumer's Profit] Subject to:

[Consumer's Consumption and ILR Constraints] vSPD:

Maximize [Social Welfare] Subject to: [Node Balance Constraints] [Reserve Constraints] [Network Constraints] [Generation/Demand Constraints]

#### Bi-level Optimization Strategic Consumer

• The single node equivalent is:

$$\begin{array}{ll} \text{Maximize} & u(q^c) - q^c . \pi^e + q^{ILR} . \pi^r \\ \text{s.t:} & 0 \leq q^c \leq C^c \\ & 0 \leq q^{ILR} \leq C_r \\ & q^c - q^{ILR} \geq V \\ & \text{Max.} & \sum_{i \in I} p_i^c x_i^c - \sum_{j \in J} p_j^g x_j^g - \sum_{k \in K} p_k^r x_k^r \\ & \text{s.t.} & \sum_{i \in I} x_i^c = \sum_{j \in J} x_j^g - q^c \quad [\pi^e] \\ & R - \sum_{k \in K} x_k^r = q^{ILR} \quad [\pi^r] \\ & [\text{Tranche and Bathtub Constraints}] \end{array}$$

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- We use KKT conditions of the dispatch problem, as well as big-M parameters to reformulate our bi-level problem to a MIP.
- We define our MIP in a generic form at time period t as below:

$$\begin{split} \left[\mathsf{MIP}\right]_{t,v} & \max \Pi_t(\mathbf{x}_t) = v x_t - \mathcal{C}_t(\mathbf{x}_t) \\ & \text{s.t. } \mathbf{x}_t \in \mathcal{S}_t \end{split}$$

- Here **x**<sub>t</sub> is a vector of decision variables at time t ( in our model it consists of consumption and ILR), and x<sub>t</sub> is the consumption level at time t.
- v is the value of consuming one unit of electricity, and C<sub>t</sub> is the cost function at time t.

# Stochastic Solution



Figure: Optimal single scenario bid.

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# Stochastic Solution



Figure: Optimal wait-and-see bids.

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# Stochastic Solution



#### Figure: Optimal monotone bid.

- The deterministic single stage problem ([MIP]<sub>t</sub>) has over 15,000 constraints and 2000 binary variables.
- Using standard reformulation methods, we can solve a stochastic version [S-MIP]<sub>t</sub>, where we optimize the strategic consumer's actions towards multiple scenarios and demand and generation offers.
- It takes about an hour to solve [S-MIP]<sub>t</sub> for 6 scenarios, which has over 100,000 constraints and 15,000 binary variables.

# Bi-parametric Sensitivity Analysis Reformulation Strategic Consumer

- The idea is to explicitly capture reserve and energy prices at the strategic node as functions of the actions of the strategic consumer, using the fundamentals of the simplex method
- We use sensitivity analysis on the right-hand sides of the two constraints that determine the nodal energy and reserve prices in the lower level problem for the major consumer.
- By employing an iterative algorithm, we define regions corresponding to optimal bases of the lower-level optimization problem (the OPF problem in our model)<sup>1</sup>.

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<sup>1</sup>Co-optimization of Demand Response and Reserve Offers for a Major Consumer, http://www.optimization-online.org/DB<sub>H</sub>TML/2017/03/5932.html  $\langle z \rangle \langle z \rangle$ 

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#### Bi-parametric Sensitivity Analysis Reformulation Strategic Consumer

• Utilizing this method we can solve our stochastic full-scale NZEM model for up to 22 scenarios in one hour.



# Stochastic Policy Simulation

Strategic Consumer



Figure: Winter peak profit for different values of electricity (u).

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- Our strategic consumer of energy needs to solve their problem over a 1-2 months period (duration of a contract with their clients).
- In order to fulfill their contracts, there will be a total consumption goal over the time horizon.

• We optimize the consumption and ILR levels for the strategic consumer, given a total consumption level *G* over a time horizon *T*.

• If we could price the total consumption constraint, the problem could be decomposed to each time period.

• Note that  $\sum_{t \in \mathcal{T}} v x_t^* = v G$ , where  $\mathbf{x}^*$  is the optimal solution to [MIP].

 We define [U-MIP]<sub>û</sub> as the problem with the total consumption constraint removed, and instead valued in the objective, with Lagrangian multiplier û.

$$\begin{aligned} [U-MIP]_u & \max U(\mathbf{x}) = -\sum_{t \in \mathcal{T}} C_t(\mathbf{x}_t) + \sum_{t \in \mathcal{T}} \hat{u} x_t - G \hat{u} \\ & \text{s.t. } \mathbf{x}_t \in \mathcal{S}_t \qquad \quad \forall t \in \mathcal{T} \end{aligned}$$

• Using Lagrangian sufficiency theorem, we prove that with the additional condition  $G = \hat{G}$  and  $\hat{G} \in \mathcal{G}$ , where  $G := \sum_{t \in \mathcal{T}} x_t^*$ , optimal solution of  $[U-MIP]_{\hat{u}}$  solves [CM-MIP].

# Utility-Consumption Curves

• We solve the  $[U-MIP]_{t,u}$ ,  $\forall u \in [0, u_{max}]$ , and plot  $(x^*, u)$ .

#### Lemma

Let  $\mathbf{x}^*$  be the optimal solution to  $[MIP]_{t,u}$ , for some t and u.  $x^*(u)$  is monotone  $\forall u \ge 0$ .

#### Proof.

Let  $\Pi(\mathbf{x}^*)$  be the optimal objective value of  $[MIP]_{t,u}$ . We define  $[MIP]_{t,u'}$ , for some  $u' \ge u$ , where  $\Pi'(\mathbf{x}^{*'})$  is the optimal objective value of  $[MIP]_{t,u'}$ .

$$[\mathsf{MIP}]_{t,u'} \max - \mathcal{C}(\mathbf{x}) + ux + (u' - u)x$$
  
s.t.  $\mathbf{x} \in \mathcal{S}$ 

 $\begin{aligned} \Pi(\mathbf{x}^*) &= \Pi'(\mathbf{x}^*) - (u'-u)x^* \text{ and } \Pi(\mathbf{x}^{*\prime}) = \Pi'(\mathbf{x}^{*\prime}) - (u'-u)x^{*\prime} \\ \Pi(\mathbf{x}^*) &\geq \Pi(\mathbf{x}^{*\prime}) \implies \Pi'(\mathbf{x}^*) \geq \Pi'(\mathbf{x}^{*\prime}) - (u'-u)(x^{*\prime}-x^*) \\ \text{If } x'^* &\leq x^* \implies \Pi'(\mathbf{x}^*) \geq \Pi'(\mathbf{x}^{*\prime}) \implies \bot \end{aligned}$ 

# Utility-Consumption Curves Price Maker Consumer

• If we solve the  $[U-MIP]_{t,u}$ ,  $\forall u \in [0, u_{max}]$ . We have the figure below:



• Scott and Read (1996) used demand curves for release in a hydro-scheduling setting.

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#### Aggregate Utility-Consumption Curves Price Maker Consumer

• First we build the U-C curve for each  $t \in \mathcal{T}$ . Assume we have  $\mathcal{T} = \{1, 2\}.$ 



# Aggregate Utility-Consumption Curves

• In the aggregate U-C curve, the points on the G axis determine the set of total consumption values G that obtain optimal policies.



#### Aggregate Utility-Consumption Curves Price Maker Consumer

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• We can choose from total consumption values in *G*.

#### Aggregate Utility-Consumption Curves Price Maker Consumer

• In the aggregate U-C curve, the points on the G axis determine the set of total consumption values G that obtain optimal policies.



 After choosing the right G ∈ G, we can look up our U-C curve and find the right û for our model. • Therefore we can solve each  $[U-MIP]_t$  separately, given  $\hat{u}$ .



• But what if our designated total consumption  $\hat{G}$  is not in G?



#### Heuristics Price Maker Consumer

• We define the U-C curve for  $t \in \mathcal{T}$  as below:



 We connect the vertical lines with virtual horizontal lines, to make step functions.

- This step-wise function has the same attributes as a supply function for a generator in the dispatch model.
- We view each time period as a node, and the total consumption value is the demand.
- We introduce [HEU], where we minimize utility  $\times$  consumption.

$$\begin{array}{ll} \mathsf{HEU}] & \min \; \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{G}_t} u_t^i x_t^i \\ & \mathsf{s.t.} \; \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{G}_t} x_t^i = G & [\hat{u}] \\ & 0 \leq x_t^i \leq q_t^i - q_{t-1}^i & \forall i \in \mathcal{G}_t, \forall t \in \mathcal{T} \end{array}$$

- We model stochasticity by defining scenarios  $\omega \in \Omega_t, \forall t \in \mathcal{T}$ .
- We will maximize expected utility  $\mathbb{E}_{\omega \in \Omega_t, t \in \mathcal{T}} U(\mathbf{x})$ .
- Using Lagrangian sufficiency theorem, we prove that we can use the same decomposition method for the stochastic model with some adjustments<sup>\*</sup>.

• We use backward induction to aggregate the expected U-C curves, using the following algorithm:

• For 
$$t = T$$
:  $u_T(q) = \mathbf{E}_{\omega \in \Omega_T} u_T^{\omega}(q)$ .

- To aggregate the curves in backward induction, we use the intuition from the price taker model  $(C'(\mathbf{x}_t^{\omega}) = \mathbf{E}'_{\nu \in \Omega^{t+1}}[C_{t+1}^{\nu}(g_{t+1}^{\omega})] = u_t^{\omega}).$
- For t ≠ T: if u<sub>t</sub><sup>ω</sup>(q̂<sub>t</sub>) = E<sub>ω∈Ω<sub>t+1</sub>u<sub>t+1</sub><sup>ω</sup>(q̂<sub>t+1</sub>), we aggregate the consumption levels q = q̂<sub>t</sub> + q̂<sub>t+1</sub> to build the U-C curve for time t and scenario ω (u<sub>t</sub><sup>ω</sup>(q)).
  </sub>
- For  $t \neq T$ :  $u_t(q) = \mathbf{E}_{\omega \in \Omega_t} u_t^{\omega}(q)$ .

# Case Study

- We implemented this approach for a large consumer of electricity in South Island.
- We simulated the optimal policies, using historic data of winters 2016 and 2017.
- We simulated our policy for 200 sample paths, which resulted in %14 reduction in average cost.
- For the monthly scheduling the time horizon consists of 1440 trading periods.

	Expected cost	Average Price
Standard U-C Policy	42321019.1	62.6
Fixed Policy	50998360.2	82.4

Table: Monthly Scheduling Comparison

### Case Study **Consumption - Price Comparison**



#### • Thank you.

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