Assessing market power in an electricity market using an agent based simulation model

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Day Ahead (DA) market

What is a DA Market?

Most power markets rely on a central **day-ahead auction** in which generators submit individual supply curves and the system operator uses these to determine the market price.

The Independent System Operator (ISO) is responsible for its operation and performs the following:

- Informs Power Producers of next day's demand
- Collects bidding schedules of all participating Power Producers
- Performs the market clearance for each hour
- Determines Power Producers' payments

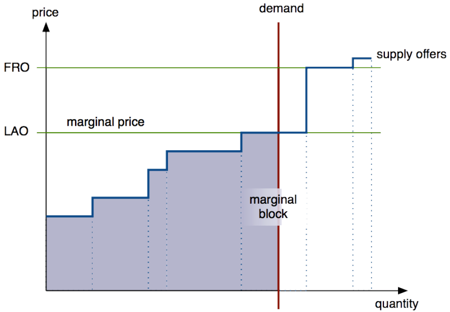
Market Clearance

Optimal Power Flow

Centralized determination of the production levels that minimize the total cost of production to meet the given load, respecting the network's physical constraints.

Auctions:

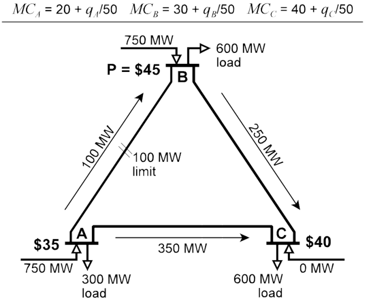
- Single-side
- Uniform
- LAO or FRO
- Marginal price



LMP & Market Power

Locational Marginal Price (LMP)

The locational marginal price is **the marginal surplus of an extra megawatt** of generation needed to serve the unit increase of the demand at that bus, **given all the physical constraints**.



Market Power

Market power is the ability to profitably alter prices away from competitive levels.

- Ask **higher price** than marginal cost
- **Withhold output** that could be produced

Literature

Relevant Papers:

i Skoulidas, Vournas, Papavassilopoulos: "An adaptive learning game model for interacting electric power markets"
- Effects of interconnection's capacity to coupled markets

ii Tellidou, Bakirtzis: "Multi-agent reinforcement learning for strategic bidding in power markets"
- Examine some variations of a sample network with constrains

iii Bach, Yao, Wang, Shengjie: "Research and application of the Q-learning for wholesale power markets"
- Study three cases which differ at the adopted learning technique

iv Ragupathi, Das: "A stochastic game approach for modeling wholesale energy bidding in deregulated power markets"
- Analyze the impact of constraints to producers' financial results

About the paper

What we do?

We use an agent based simulation model to replicate the market outcome in three different versions of the network so as to identify the effect of congestion to the market's outcome in the long run.

Key points:

- Market modeled as a Stochastic Game
- State space transformation technique used
- Players adopt Reinforcement Learning
- Three different network versions examined

Contributions

Main points:

- State space transformation technique
  - Adapted to concepts of incomplete information
  - Incorporate processed information
- R-Learning algorithm
  - Temporal difference (TD) control method
  - Off-policy generalized policy iterations (GPI) method
- Comparative study
  - Three indicative levels of transmission constraints
  - Transformation technique sufficient
  - Algorithm efficient (greedy action plans were identified)

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Market Structure

We consider:

- N individual production units, the players, $\mathcal{N} = \{1, \ldots, N\}$
- M available action functions, forming $\mathcal{A} = \{a_1, \ldots, a_M\}$
- K nodes, the transmission network's buses, $\mathcal{K} = \{1, \ldots, K\}$

For player $n \in \mathcal{N}$, action $a^h \in \mathcal{A}$ and bus $k \in \mathcal{K}$ we have:

Actions

$\alpha_n = \left[\alpha_n^1, \ldots, \alpha_n^{24}\right]$

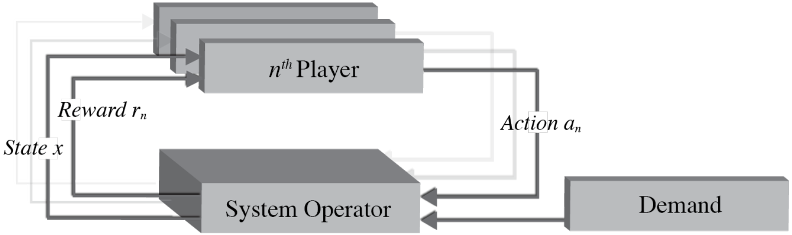
- daily bidding vector
- player's choice variables

State

$x_k = (q_k, p_k)$ formed by

- load vector $q_k = [q_k^1, \ldots q_k^{24}]$
- price vector $p_k = [p_k^1, \ldots p_k^{24}]$

Market Operation



Daily Operation:

1. ISO provides a forecast for load & price vectors ▸ (State x)
2. Players submit their bidding vectors to the ISO ▸ (Action α_n)
3. ISO clears the market given the faced demand ▸ (Transition)
4. Payments result from new load & price vectors ▸ (Reward r_n)

Market Operation

Assumptions:

- Demand is • Exogenous • Inelastic • Stochastic
- Players behave Non-cooperatively
- Markov Property imposed
  - ISO provides the current state as the forecast
  - Players make decision given only current state
  - $p(x' \mid x, a) = \Pr\{X_{t+1} = x' \mid X_t = x, A_t = a\}$
  - $p(x' \mid x, a)$ is independent of time, previous states & actions

Competitive Markov Decision Process (CMDP)

Since market's operation recurs daily, the **discrete process** observed at $t = 0, 1, 2, \ldots$, with state X_t, constitutes a **Competitive Markov Decision Process**, namely $\{\Gamma\}_t$.

Incomplete Information

The system's current state is $X_t = [x_{1,t}, \ldots, x_{K,t}]$ where $x_{k,t} = (q_{k,t}, p_{k,t})$ is the state of the k^{th} bus.

We assume that each player has **his own comprehension** about the state, so we define the vector $\widetilde{X}_t^n$ to be the **transformation** of the original state vector X_t that the n^{th} player uses as information set in decision making.

$$\varphi_n : X_t \rightarrow \widetilde{X}_t^n$$

Linear Examples ($\widetilde{X}_t^n = X_t A_n$) :

- A_n identity matrix (original state)
- A_n projection matrix (part of state)

Non-Linear Examples :

- The maximum price is
- included at the state

Reinforcement Learning (Algorithm)

Implemented R-Learning algorithm :

Initialization of learning parameters (λ, γ), action-value function $Q_n(\widetilde{x}_n, \alpha_n)$ and average reward $\bar{r}_n$.

Repeat:

$\widetilde{x}_n \leftarrow$ *linear transformation of the current state*
Player chooses action α_n under a policy
System transitions to the new state x'
Immediate reward $r(x, \alpha_n, x')$ is received
$D \leftarrow r_n(x, \alpha_n, x') - \bar{r}_n + \max_b Q_n(\widetilde{x}'_n, b) - Q_n(\widetilde{x}_n, \alpha_n)$
$Q_n(\widetilde{x}_n, \alpha_n) \leftarrow Q_n(\widetilde{x}_n, \alpha_n) + \lambda_t \cdot D$
$\bar{r}_n \leftarrow \bar{r}_n + \gamma_t \cdot [r_n(x, \alpha_n, x') - \bar{r}_n]$
Update the policy

The update rule:

$$Q_n(\widetilde{x}_n, \alpha_n) \leftarrow Q_n(\widetilde{x}_n, \alpha_n) + \lambda \left[r_n(x, \alpha_n, x') - \bar{r}_n + \max_b Q_n(\widetilde{x}'_n, b) - Q_n(\widetilde{x}_n, \alpha_n) \right]$$

Reinforcement Learning (Policy)

Implemented learning policy :

- As the learning policy we define a sequence of probabilities $\{c_t^n\}_{t \in N}$ for selecting a random action among the non-greedy available actions

$$c_t^n = \Pr\left\{a_n \neq \arg\max_b Q_n\left(x', b\right)\right\} \quad (1)$$

$$c_t^n = \left\{\mathcal{F}\left(t\right) \ : \ \lim_{t \to \infty} c_t^n = L\right\} \quad (2)$$

- L is the weakened exploring rate occurred at the end.
- The effect of further exploitation controlled by $\lambda_t, \gamma_t \in [0, 1]$.
- Step size parameters follow a descending course over time.

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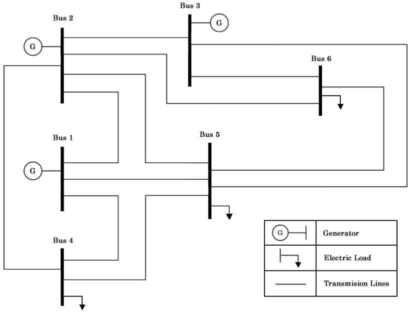
Simulations' Overview

- For the implementation we used a six-bus power network
- Half buses are generator buses, the rest are load buses
- Network's topology resembles one of Wood & Wollenberg's
- Simulations carried out with MATLAB (MATPOWER for OPF)

Cases

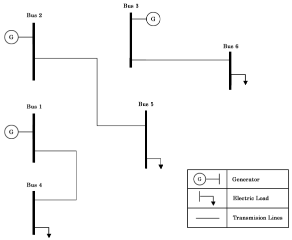
- A: Monopoly Market
- B: Uncongested Makret
- C: Congested Makret



Cases examined

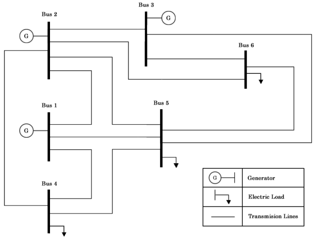
Non-competitive

- Monopoly, Case A
  (Direct and exclusive connection of production and demand buses)



Competitive

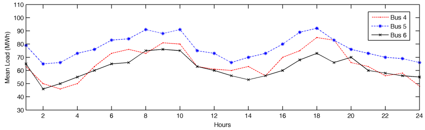
- Uncongested, Case B
  (Not constrained transmission lines)
- Congested, Case C
  (Uniform 50 MW line capacity constraint)



Stochastic Demand

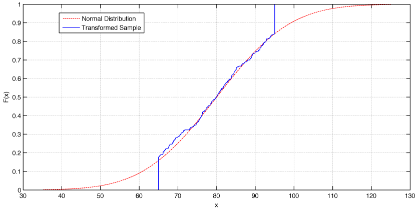
Mean Loads

- for each bus
- for every hour



Indicative Sample

- Bounded Normal distribution
- 32% at the boundaries



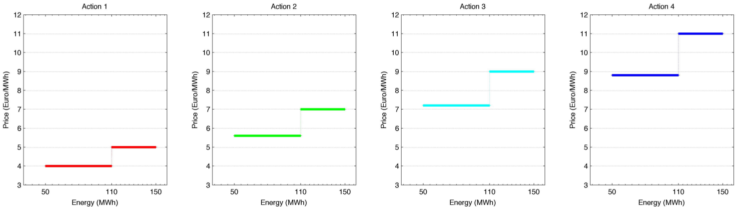
Bounding Function

$$\varphi(x) = \begin{cases} \mu - \sigma & , x < \mu - \sigma \\ \mu + \sigma & , x > \mu + \sigma \\ x & , \textit{otherwise} \end{cases} \qquad x \sim \mathcal{N}(\mu, \sigma^2)$$

Production side

- There is **a lower and an upper bound** in generation capacity, namely $Q^i_{min} = 50MW$ and $Q^i_{max} = 150MW$
- **Constant marginal cost**, equal with $4€/MWh$.

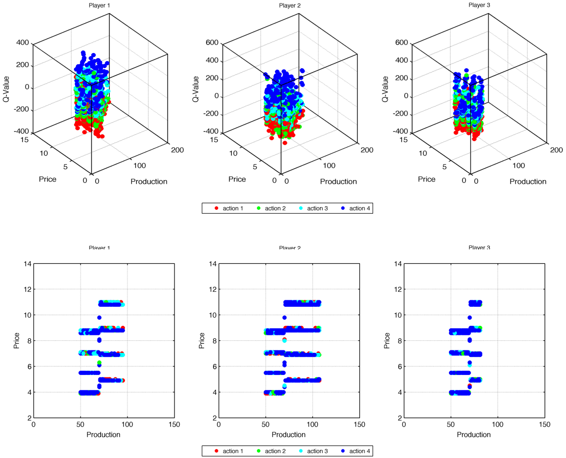
Available Actions :



- **Piece-wise linear** bidding functions

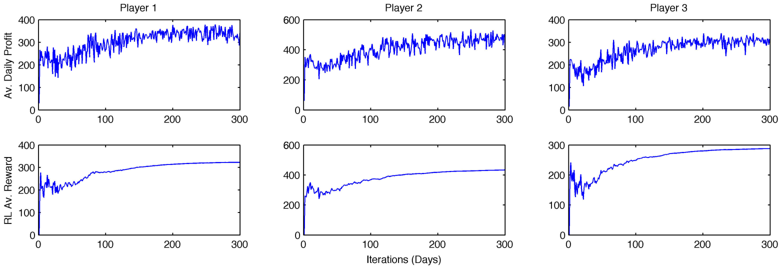
Results - Case A (Monopoly market) - 1/2

Action Space



Results - Case A (Monopoly market) - 2/2

Av. Daily Profit & RL Av. Reward

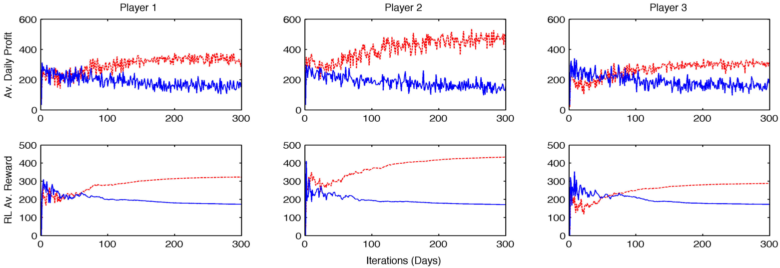


Case A (Monopoly market)

- Players **identify the lack of competition**
- Players **adopt the highest price action**

Results - Case B (Uncongested Case)

Av. Daily Profit & RL Av. Reward

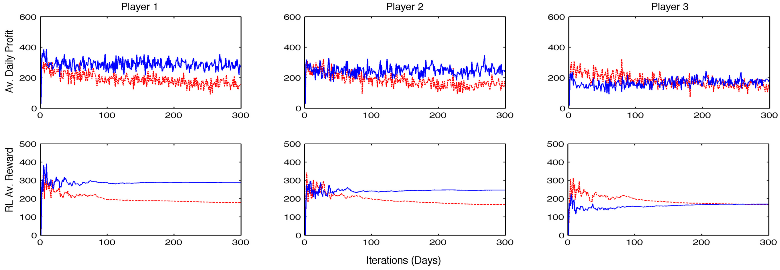


Case B (Uncongested Case) - Case A (Monopoly market)

- Players adopt a **mixed strategy** action plan
- It's the **most competitive** outcome (**symmetric**)
- **Unconstrained transmission** enforces competition

Results - Case C (Congested Case)

Av. Daily Profit & RL Av. Reward



Case C (Congested Case) - Case B (Uncongested Case)

- Lines equally constrained, Outcome not symmetric (**topology**)
- Players identify the potential - Exert market power

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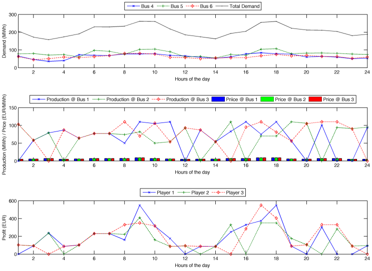
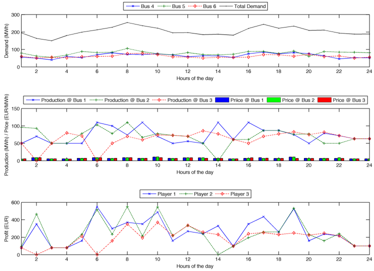
Conclusion

- **State space transformation** (incomplete information) proved to be both **sufficient** and **efficient**.
- **R-Learning algorithm** enabled players to **identify greedy action plans** so as to maximize their profits
- Cases examined aligned with intended purpose, **three levels** of transmission constraints offered **thorough benchmark**



Case B (Uncongested Case)



Case C (Congested Case)

Relevant work

Different **market structures** & Different **informational concepts**

We study the implementation of

- State space transformation technique
- R-Learning algorithm

under

- two informational concepts
  - only private information
  - private information + aggregated demand + max price
- two different cases of ownership
  - 3 firms own 3 units
  - 2 firms own 3 units

Thank you for your attention!!

Any questions?

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