Understand the LMP$^1$-Load Coupling: Theoretical Analysis and An SVM$^2$-based Data-driven Approach

M.Sc Thesis Defense

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$^1$Locational Marginal Price
$^2$Support Vector Machine
Background and Motivations

1. Background and Motivations
   - Electricity Market Operations
   - An Illustrative Example
   - Locational Marginal Price (LMP)
   - Motivations of Understanding the LMP-Load Coupling

2. Understand the LMP-Load Coupling
   - Multi-parametric (Linear) Programming
   - Key Theoretical Results

3. A Data-driven Approach For Market Participants
   - A Classification Problem
   - A Data-driven Approach
   - Case Study

4. Conclusions and Future Works

5. Brief Summary of My M.Sc Years
Structure of Power Systems

**Electricity:**
Generators $\rightarrow$ Transmission Network $\rightarrow$ Distribution Network $\rightarrow$ Loads.

Generators:
- Coal Power Plants
- Wind Farms
- ...

Loads:
- Industrial Loads.
- Commercial Loads.
- Residential Loads.

Electricity Market

**Component:** generators, loads and transmission networks.

**Objective:** power systems operate safely and economically.

**Price:** locational differentiated prices.

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**Figure:** Transmission Network

**Figure:** ERCOT Price Contour
Security-constrained Economic Dispatch (SCED)

**Objective:** minimize total generation cost.

**Constraints:** supply-demand balance, transmission limits, generation capacity limits.

\[
\min_{P_G} \sum_{i=1}^{n_b} c_i(P_{Gi})
\]

s.t.

\[
\sum_{i=1}^{n_b} P_{Gi} = \sum_{j=1}^{n_b} P_{Dj} : \lambda_1
\]

\[
F^- \leq H(P_G - P_D) \leq F^+ : \mu^+, \mu^-
\]

\[
P_G^- \leq P_G \leq P_G^+ : \eta^+, \eta^-
\]

- $n_b$: number of buses.
- $P_G \in \mathbb{R}^{n_b}$: generation vector.
- $c \in \mathbb{R}^{n_b}$: cost of generators.
- $P_D \in \mathbb{R}^{n_b}$: load vector.
- $F^+, F^-$: transmission limits.

Assumptions:

- Quadratic Cost $\rightarrow$ Piecewise Linear (current practice).
- Assumptions (for simplicity)
  - Piecewise Linear $\rightarrow$ Linear (WLOG).
  - Each bus has (exactly) one load and one generator (WLOG).
An Illustrative Example (3 Bus System)

This 3-bus system serves as an illustrative example through this presentation.

\[ \min_{P_G_1, P_G_2, P_G_3} \quad 20P_G_1 + 50P_G_2 + 100P_G_3 \]  
\[ \text{s.t.} \quad P_G_1 + P_G_2 + P_G_3 = (P_{D_1}) + P_{D_2} + P_{D_3} \]  
\[ - \begin{bmatrix} 60 \\ 80 \\ 60 \end{bmatrix} \leq \begin{bmatrix} 0 & -2/3 & -1/3 \\ 0 & 1/3 & -1/3 \\ 0 & -1/3 & -2/3 \end{bmatrix} \begin{bmatrix} P_G_1 \ -P_{D_1} \\ P_G_2 \ -P_{D_2} \\ P_G_3 \ -P_{D_3} \end{bmatrix} \leq \begin{bmatrix} 60 \\ 80 \\ 60 \end{bmatrix} \]  
\[ 0 \leq P_{G_1} \leq 100, 0 \leq P_{G_2} \leq 150, 0 \leq P_{G_3} \leq 50 \]
Locational Marginal Price (LMP)

Definition

Locational Marginal Price (LMP) at bus (node) $i$ is the change of total system cost if the demand at node $i$ is increased by 1 unit.

$$\lambda_i = \frac{\partial f^*}{\partial P_{Di}}.$$  \hspace{1cm}  (5)

Calculation of Locational Marginal Prices (Two Methods)

1. Using Lagrange multipliers.
2. Solve the optimal solution $P_G^* = g(P_D)$, then $f^* = c^T P_G^* = c^T \cdot g(P_D)$. Locational Marginal Prices:

$$\lambda_i = \frac{\partial f^*}{\partial P_{Di}} = \frac{\partial c^T g(P_D)}{\partial P_{Di}}.$$  \hspace{1cm}  (6)
Locational Marginal Price (LMP) Calculation

An Illustrative Example: there is no congestion in the system

When there is no congestion in the system:

$$
\begin{bmatrix}
60 \\
80 \\
60
\end{bmatrix} <
\begin{bmatrix}
0 & -2/3 & -1/3 \\
0 & 1/3 & -1/3 \\
0 & -1/3 & -2/3
\end{bmatrix}
\begin{bmatrix}
P_{G_1}(-P_{D_1}) \\
P_{G_2} - P_{D_2} \\
P_{G_3} - P_{D_3}
\end{bmatrix} <
\begin{bmatrix}
60 \\
80 \\
60
\end{bmatrix}
$$

The SCED problem becomes:

$$
\min_{P_{G_1}, P_{G_2}, P_{G_3}} 20P_{G_1} + 50P_{G_2} + 100P_{G_3}
$$

s.t.

$$
P_{G_1} + P_{G_2} + P_{G_3} = (P_{D_1}) + P_{D_2} + P_{D_3}
$$

$$
0 \leq P_{G_1} \leq 100, 0 \leq P_{G_2} \leq 150, 0 \leq P_{G_3} \leq 50
$$

We will use the cheapest generation $P_{G_1}$, if not violating the generation capacity of $P_{G_1}$:

$$
P_{G_1}^* = P_{D_1} + P_{D_2} + P_{D_3}, P_{G_2}^* = P_{G_3}^* = 0
$$

Total Generation Cost:

$$
f^* = 20(P_{D_1} + P_{D_2} + P_{D_3}).
$$

Locational Marginal Prices:

$$
\lambda = [\lambda_1, \lambda_2, \lambda_3] = \left[\frac{\partial f^*}{\partial P_{D_1}}, \frac{\partial f^*}{\partial P_{D_2}}, \frac{\partial f^*}{\partial P_{D_3}}\right] = [20, 20, 20]
$$
Locational Marginal Price (LMP) Calculation

An Illustrative Example: when line 1 → 3 is congested

When line 1 → 3 is congested:

\[
[0, -1/3, -2/3] \cdot [P_{G_1} - (P_{D_1}), P_{G_2} - P_{D_2}, P_{G_3} - P_{D_3}]^T = 60 \quad (14)
\]

The SCED problem becomes:

\[
\begin{align*}
\min_{P_{G_1}, P_{G_2}, P_{G_3}} & \quad 20P_{G_1} + 50P_{G_2} + 100P_{G_3} \\
\text{s.t.} & \quad P_{G_1} + P_{G_2} + P_{G_3} = (P_{D_1}) + P_{D_2} + P_{D_3} \\
& \quad [0, -1/3, -2/3] \cdot [P_{G_1} - (P_{D_1}), P_{G_2} - P_{D_2}, P_{G_3} - P_{D_3}]^T = 60 \\
& \quad 0 \leq P_{G_1} \leq 100, 0 \leq P_{G_2} \leq 150, 0 \leq P_{G_3} \leq 50
\end{align*}
\]

From Eqn. (16) and Eqn. (17), assuming no output from the most expensive generation (#3):

\[
P_{G_1}^* = 180 - P_{D_3} + P_{D_1}, P_{G_2}^* = P_{D_2} + 2P_{D_3} - 180, P_{G_3}^* = 0 \quad (19)
\]

Total Generation Cost: \( f^* = 20(180 - P_{D_3} + P_{D_1}) + 50(P_{D_2} + 2P_{D_3} - 180) \)

Locational Marginal Prices:

\[
\lambda = [\lambda_1, \lambda_2, \lambda_3] = \left[ \frac{\partial f^*}{\partial P_{D_1}}, \frac{\partial f^*}{\partial P_{D_2}}, \frac{\partial f^*}{\partial P_{D_3}} \right] = [20, 50, 80] \quad (20)
\]
Motivations of Understanding the LMP-Load Coupling

The relationship between Locational Marginal Prices (LMPs) and Loads

- A fundamental question.
- Understand electricity market operations.
- Benefit both system operators and market participants.
Motivations of Understanding the LMP-Load Coupling

The relationship between Locational Marginal Prices (LMPs) and Loads

- A fundamental question.
- Understand electricity market operations.
- Benefit both system operators and market participants.

Becoming more and more important...

*(In the background of Smart Grid):*

**Increasing Renewables:**

- increasing percentage of renewable energy in the electricity mix (e.g. California targets at 33% by 2020\(^a\)).
- (Usually regarded as) negative loads.

**Demand Response:** exploit the flexibility from end-users (loads).

\(^a\)http://www.energy.ca.gov/renewables/
Brief Literature Review

Sensitivity-based Method

- Widely used, calculate partial derivatives.
- Only valid for small changes.
- Requires the marginal generator stays the same.

Finding Critical Load Levels

- Assuming the system load is distributed to each bus proportionally
- Increasing total load in the system
- “Step Changes” of LMPs, Critical Load Levels.
Brief Literature Review

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- Widely used, calculate partial derivatives.
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Finding Critical Load Levels


- Assuming the system load is distributed to each bus proportionally
- Increasing total load in the system.
- “Step Changes” of LMPs, Critical Load Levels.

Multi-Parametric Programming

Preliminary Simulation Results

Get Some Intuition

Monte-Carlo Simulation on a Simpler 3-bus System

(1) Regard $P_{D_2}$ and $P_{D_3}$ as parameters, randomly generate $P_{D_2}$ and $P_{D_3}$; (2) solve the optimization problem (SCED); (3) record the Locational Marginal Prices.


Xinbo Geng (TAMU)
Preliminary Simulation Results
Get Some Intuition

Monte-Carlo Simulation on a Simpler 3-bus System

1. Regard $P_{D_2}$ and $P_{D_3}$ as parameters, randomly generate $P_{D_2}$ and $P_{D_3}$; (2) solve the optimization problem (SCED); (3) record the Locational Marginal Prices.

- There are some disjoint regions.
- When you solve the SCED problem given load vectors in the same region, you will get the same LMP vector.
Understand the LMP-Load Coupling

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Multi-parametric (Linear) Programming

Regard the load at each bus as parameters, understand the effects of parameters on the optimality of the problem.

Multi-parametric Programming

Multi-parametric Programming problem aims at exploring the characteristics of an optimization problem which depending on a vector of parameters.

Multi-parametric Linear Programming (MLP)

Focus on linear programming problems.

SCED in the Standard Form of MLP

$P_D$: load vector (parameters). $s$: vector of slack variables.

Primal: $\min_{P_G}\{c^T P_G : AP_G + s = b + WP_D, s \geq 0\}$ (21)

Dual: $\max_y \{- (b + WP_D)^T y : A^T y = -c, y \geq 0\}$ (22)
Key Definitions

Definition (Optimal Partition/System Pattern)

- Solve the Security-constrained Economic Dispatch, get the optimal solution $P^*_G$ and $s^*$.
- $\mathcal{J} = \{1, 2, \cdots, n_c\}$: the index set of constraints.

The **system pattern** $\pi = (\mathcal{B}, \mathcal{N})$ is defined as follows:

\[
\mathcal{B}(P_D) := \{i : s^*_i = 0 \text{ for } P_D \in \mathcal{D}\}
\]

\[
\mathcal{N}(P_D) := \{j : s^*_j > 0 \text{ for } P_D \in \mathcal{D}\}
\]

- **$\mathcal{B}$**: binding constraints
- **$\mathcal{N}$**: non-binding constraints
- $\mathcal{B} \cap \mathcal{N} = \emptyset$, $\mathcal{B} \cup \mathcal{N} = \mathcal{J}$

**System Pattern**: $\pi = (\mathcal{B}, \mathcal{N})$ represents the status of the system.

**system pattern** = **optimal partition** (in Multi-parametric Linear Programming theory).

3-bus system example (when there is no congestion:)

- $\mathcal{B}$ contains
  - Supply = Demand
  - Lower bounds of Generator#2 and #3.

- $\mathcal{N}$ contains the remaining:
  - transmission capacity constraints.
  - generation capacity constraints of generator#1.
Definition of System Pattern Region (SPR)

Definition (Critical Region/System Pattern Region)

System Pattern Region (SPR) refers to the set of load vectors which lead to the same system pattern \( \pi = (B_\pi, N_\pi) \):

\[
S_\pi := \{ P_D \in \mathcal{D} : B(P_D) = B_\pi \}
\]  \hspace{1cm} (25)

system pattern region = critical region (in MLP theory).

3 Colors \( \iff \) 3 SPRs.
E.g. Green: no congestion.
Complementary Slackness

Lemma (Complementary Slackness)

Given optimal solution \( P_G^* \) and system pattern \((B,N)\), according to complementary slackness:

\[
A_B P_G^* = (b + WP_D)_B
\]
\[
A_N P_G^* < (b + WP_D)_N
\]
\[
A_T y_B = -c, y_B > 0
\]
\[
y_N = 0
\]

where the \((\cdot)_B\) is the sub-matrix or the sub-vector whose row indices are in set \(B\), same meaning applies for \((\cdot)_N\).
Complementary Slackness

Lemma (Complementary Slackness)

Given optimal solution $P_G^*$ and system pattern $(\mathcal{B}, \mathcal{N})$, according to complementary slackness:

\begin{align*}
A_B P_G^* &= (b + W P_D)_B \quad (26) \\
A_N P_G^* &< (b + W P_D)_N \quad (27) \\
A_B^T y_B &= -c, \ y_B > 0 \quad (28) \\
y_N &= 0 \quad (29)
\end{align*}

where the $(\cdot)_B$ is the sub-matrix or the sub-vector whose row indices are in set $\mathcal{B}$, same meaning applies for $(\cdot)_N$.

Further Results (Details in backup slides.)

- Analytical form of SPRs.
- Conditions that different cost vectors lead to the same SPRs in the load space.

Other implications:

- linear relationship b/t LMPs and generation costs, b/t/ loads and generations.
- total generation cost is piecewise linear.

Abbreviations: SPR - System Pattern Region; LMP - Locational Marginal Price
The load space could be decomposed into many SPRs. Each SPR is a convex polytope. The relative interiors of SPRs are disjoint convex sets and each corresponds to a unique system pattern.

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Analyze the 3-bus system using the *Multi-parametric Programming Toolbox 3.0*:

- 10 SPRs.
- Every SPR is convex.
- SPRs are disjoint

E.g. SPR#5:
- No congestion.
- Marginal generator: gen#1.

E.g. SPR#3:
- Line 1 \(\rightarrow\) 3 is congested.
LMP-Load Coupling
Locational Marginal Prices (LMPs) and System Pattern Regions (SPRs)

Theorem (Distinct LMP Vectors)

Within each SPR, the vector of LMPs is unique\(^a\)\(^b\). Different SPRs have different LMP vectors.

\(^a\)Ji, Y., Tong, L., Thomas, R. J. Probabilistic Forecast of Real-Time LMP and Network Congestion


Each SPR has a unique LMP vector.

E.g. SPR#5:
- LMP: \(\lambda = [20, 20, 20]\).

E.g. SPR#3:
- LMP: \(\lambda = [20, 50, 80]\).

The boundary between two SPRs is linear.

Lemma (Separating Hyperplanes)

Because SPRs are convex sets, there exists a separating hyperplane between any two SPRs.
Overlapping System Pattern Regions (SPRs)
Example: When Transmission Limits Are Varying (dynamic line ratings)

- The load space decomposition is similar.
- SPRs are expanding or shrinking, and overlapping with each other.
- Analyzed using Multi-parametric Programming Toolbox 3.0.

Figure: Decreased by 10%

Figure: Increased by 10%
Overlapping System Pattern Regions (SPRs)

Monte-Carlo Simulation

- 3-bus system.
- Randomly change
  - transmission limits
  - load vectors
- Solve SCED problems, record LMPs.
- Blue and Red are overlapping.
- Blue and Green are overlapping.

Reasons of overlapping System Pattern Regions (SPRs):

- Varying Transmission Limits (dynamic line ratings).
- Not having load data of every bus in the system.
- ......
Understanding the System Pattern Regions

Understand the LMP-Load Coupling

Understanding the System Pattern Regions ⇔ understanding the LMP-Load Coupling.

For the System Operators

They know EVERYTHING (Confidential Information:)

- System Topology.
- Transmission Limits.
- Line Parameters.
- Generation costs.
- ...

They can analytically calculate the System Pattern Regions (SPRs). (e.g. Multi-parametric Programming Toolbox.)
From A Market Participant’s Viewpoint

How can the Market Participants Estimate the System Pattern Regions?
They know almost NOTHING about Confidential Information (e.g. System Topology, Transmission Limits, Line Parameters, Generation costs.....)
From A Market Participant’s Viewpoint

How can the Market Participants Estimate the System Pattern Regions?
They know almost NOTHING about Confidential Information (e.g. System Topology, Transmission Limits, Line Parameters, Generation costs.....)

Answer: Data!
From A Market Participant’s Viewpoint

How can the Market Participants Estimate the System Pattern Regions?

They know almost NOTHING about Confidential Information (e.g. System Topology, Transmission Limits, Line Parameters, Generation costs.....)

Answer: Data!

![Figure: Load Data]
From A Market Participant’s Viewpoint

How can the Market Participants Estimate the System Pattern Regions?

They know almost NOTHING about Confidential Information (e.g. System Topology, Transmission Limits, Line Parameters, Generation costs.....)

**Answer:** Data!

![Figure: Load Data](image1)

![Figure: Load Data and LMP Data](image2)
A Data-driven Approach For Market Participants

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5 Brief Summary of My M.Sc Years
SPR Identification Problem is a Classification Problem

Model the SPR Identification Problem as a Classification Problem

We proved:

- Load vectors within an SPR have the same LMP vectors.
- Different SPRs have different LMP vectors.

Load Data.
LMP Data.
SPR Identification Problem is a Classification Problem

Model the SPR Identification Problem as a Classification Problem

We proved:
- Load vectors within an SPR have the same LMP vectors.
- Different SPRs have different LMP vectors.

Classification Problem:
Given a feature vector $x$, label $x$ with a label vector $y$.

Load Data.
LMP Data.

Feature Vector: load vector.
Label Vector: label vector.

Identify SPRs $\leftrightarrow$ Identify the separating hyperplanes among SPRs
SPR Identification with SVMs

Binary, Separable Case

Not consider varying parameters (e.g. line limits): separable case.
SPR Identification with SVMs

Binary, Separable Case

Not consider varying parameters (e.g. line limits): separable case.

- Binary: only two classes \( y \in \{1, -1\} \).
- Separable: Eqn. (31) is feasible.
- Separating Hyperplane:
  \[
  w^\top P_D - b = 0.
  \]

- width of the margin: \( 2/||w|| \).

Support Vector Machine (Binary, Separable Case)

\[
\begin{align*}
\min_{w,b} & \quad \frac{1}{2} w^\top w \\
\text{s.t.} & \quad y^{(i)}(w^\top P^{(i)}_D - b) \geq 1, y^{(i)} \in \{-1, 1\}
\end{align*}
\]
When System Pattern Regions Are Overlapping
Binary, Non-separable Case

- $s^{(i)}$: slack variables (soft margins, tolerant errors).
- $C \sum_i s^{(i)}$: penalties of violation.

Support Vector Machine (Binary, Non-separable Case)

$$\min_{w,b,s} \quad \frac{1}{2} w^T w + C \sum_i s^{(i)}$$

$$\text{s.t.} \quad y^{(i)}(w^T P_D^{(i)} - b) \geq 1 - s^{(i)}, s^{(i)} \geq 0, y^{(i)} \in \{-1, 1\}$$
Multi-class SVM Classifier

Two kinds *multi-class* SVM classifiers (*n* classes):

- "one-vs-all" pick one class, the rest *n* − 1 classes becomes another class, train a *binary* SVM classifier. Get *n* *binary* SVM classifiers.

- "one-vs-one" choose two classes out of *n*, train a *binary* classifier. Get *n(n − 1)/2* binary SVM classifier.

**Existence of Separating Hyperplanes between any two SPRs ⇒ “one-vs-one”**

**Max-vote-wins**

Given a load vector *P_D*, each *binary* SVM classifier gives a *vote* (the index of SPR that *P_D* belongs to), the SPR which gets the most vote is the final result.
Posterior Probabilities

**Posterior Probability**: $P(\text{class}|\text{input})$

*Binary Posterior Probability Calculation*

- **Binary Posterior Probability**: $P(y = 1|P_D$ and $y \in \{1, -1\})$ and $P(y^{(i)} = -1|P_D$ and $y \in \{1, -1\})$.
- Platt’s Algorithm\(^a\).


*Multi-class Posterior Probability Calculation*

- **Multi-class Posterior Probability**: $P(y = i|P_D$ and $y \in \{1, 2, 3, \cdots, n\})$
- Hastie & Tibshirani’s Algorithm\(^a\).
- Calculate *Multi-class* posterior probabilities based on the *binary* posterior probabilities.


**Max-posterior-wins**

Classification result: $\arg\max_i = P(y^{(i)} = i|P_D$ and $y^{(i)} \in \{1, 2, \cdots, n\})$
LMP Forecast Based on SPR Identification

- For any load vector $P_D$ belongs to an SPR, solving SCED will lead to the same LMP vector $\lambda$.
- Knowing SPR $\Rightarrow$ knowing LMP.

Max–vote-wins

$$\tilde{\lambda}(P_D) = \lambda^{(i^*)}$$ where $i^*$ is the index of the SPR winning the most votes.

Max-posterior-wins

Expectation of all the LMPs over all the SPRs.

$$\tilde{\lambda}(P_D) = \mathbb{E}[\lambda] = \sum_{i=1}^{n} \lambda^{(i)}P(y = i\mid P_D \text{ and } y \in \{1, 2, \cdots, n\}) \quad (34)$$
A Data-driven Approach to Identifying SPRs

1. **Training**: find out $n(n-1)/2$ optimal separating hyperplanes.
2. **Post-processing**: fit the posterior probabilities.
3. **Forecasting**: label a given load forecast $P_D$ (which SPR it belongs to).
A Data-driven Approach to Identifying SPRs

**Training:** find out $n(n-1)/2$ optimal separating hyperplanes.

**Post-processing:** fit the posterior probabilities.

**Forecasting:** label a given load forecast $P_D$ (which SPR it belongs to).

Characteristics of the Data-driven Approach

- From a market participant’s viewpoint.
- Without the knowledge of system topology or parameters.
- Purely data-driven.
- Considering varying parameters in the system.
- Provide posterior probabilities, which could be used to reduce risk.
An Illustrative Example

3-bus System

- Data generated using MatPower

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An Illustrative Example (Cont’d)

Posterior Probabilities (3-bus System)

\[ P(y = i | P_D \text{ and } y \in \{1, 2, \cdots, 8\}). \]

8 surfaces
Case Study
Performance Metrics

\textit{k-fold Cross Validation}
- To avoid overfitting
- To study the performance of the algorithm on an independent dataset.
- 3-fold cross validation (fold\#1, fold\#2, fold\#3).

\textit{Classification Accuracy}
- $\alpha_i$: classification accuracy of fold \#i.
- Average performance: $\bar{\alpha} = (\alpha_1 + \alpha_2 + \alpha_3)/3$.

\textit{LMP Forecast Accuracy}

$$\beta = \frac{1}{n_b n_v} \sum_{i=1}^{n_b} \sum_{j}^{n_v} \frac{|\tilde{\lambda}_i[j] - \lambda_i[j]|}{\lambda_i[j]}$$

(35)

The average forecast accuracy of all the validation data points over all the buses.
Case Study

IEEE 118-bus System

Test the proposed algorithm on a complicated system.

- Minor changes of settings about loads, generator costs and a line limit.
- 118 Bus.
- 186 Transmission Lines.
- 54 Generators.
- 91 Loads.

**Test System:** IEEE 118-Bus, 54 Unit, 24-Hour System. Retrieved from motor.ece.iit.edu/data/JEAS_IEEE118.doc

8640 (30 days, 5min-based) Points Generated using MatPower.
A Data-driven Approach For Market Participants

Case Study

Simulation Results (118-bus System)

- Implemented using Matlab.
- Simulated on a PC with Intel i7-2600 8-core CPU@3.40GHz and 16GB RAM memory.

Table: Average Computation Time of the Data-driven Approach (average of 3 folds, in seconds)

<table>
<thead>
<tr>
<th>Steps</th>
<th>Computation Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) training</td>
<td>4.93s</td>
</tr>
<tr>
<td>(b) data post-processing</td>
<td>45.47s</td>
</tr>
<tr>
<td>(c1) max-vote-wins</td>
<td>184.79/2880 = 0.064s per forecast</td>
</tr>
<tr>
<td>(c2) max-posterior-wins</td>
<td>1033.78/2880 = 0.359s per forecast</td>
</tr>
</tbody>
</table>

Table: Classification Accuracy (118 Bus System)

<table>
<thead>
<tr>
<th>Method</th>
<th>Fold#1</th>
<th>Fold#2</th>
<th>Fold#3</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max-Vote-Wins</td>
<td>95.14%</td>
<td>94.31%</td>
<td>94.32%</td>
<td>94.59%</td>
</tr>
<tr>
<td>Max-Posterior-Wins</td>
<td>95.24%</td>
<td>93.99%</td>
<td>94.79%</td>
<td>94.67%</td>
</tr>
</tbody>
</table>

Table: LMP Forecast Accuracy (118 Bus System)

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<tr>
<th>Method</th>
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<th>Fold#2</th>
<th>Fold#3</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max-Vote-Wins</td>
<td>95.24%</td>
<td>99.15%</td>
<td>96.55%</td>
<td>96.98%</td>
</tr>
<tr>
<td>Max-Posterior-Wins</td>
<td>98.68%</td>
<td>98.70%</td>
<td>97.02%</td>
<td>98.13%</td>
</tr>
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Conclusions and Future Works

1 Background and Motivations
   - Electricity Market Operations
   - An Illustrative Example
   - Locational Marginal Price (LMP)
   - Motivations of Understanding the LMP-Load Coupling

2 Understand the LMP-Load Coupling
   - Multi-parametric (Linear) Programming
   - Key Theoretical Results

3 A Data-driven Approach For Market Participants
   - A Classification Problem
   - A Data-driven Approach
   - Case Study

4 Conclusions and Future Works

5 Brief Summary of My M.Sc Years
Conclusions

We examine the fundamental coupling between Locational Marginal Prices and loads:

- Analysis based on Multi-parametric Linear Programming theory.
- The load space can be partitioned into convex system pattern regions (SPR).
- Each SPR is one-to-one mapped with a unique LMP vector.

We propose a data-driven approach to identifying SPRs.

- Identifying SPRs is modeled as a classification problem.
- a “one-vs-one” multi-class SVM classifier.
- estimating SPRs purely from historical data, without knowing confidential system information
- Visualize the results on a 3-bus system, case study on IEEE 118-bus system.

Possible Future Works:

- Investigate the LMP volatility due to the renewables in the system.
- LSEs could use demand response to shift from SPRs with high prices.
Brief Summary of My M.Sc Years

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Brief Summary of My M.Sc Years

Journals:


Conferences:


Awards:

- Best Master Student, Oct.2015, Dwight Look College of Engineering, Texas A&M University.
- Best Master Student, Aug.2015, Department of Electrical & Computer Engineering, Texas A&M University.
- Department Scholarship, 2014, Department of Electrical & Computer Engineering, Texas A&M University
Any Questions?

Understand the LMP\textsuperscript{4}-Load Coupling: Theoretical Analysis and An SVM\textsuperscript{5}-based Data-driven Approach

M.Sc Thesis Defense

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October 1, 2015

\textsuperscript{4}Locational Marginal Price
\textsuperscript{5}Support Vector Machine