Market Participation of Energy Storage and DER Aggregators: Energy Arbitrage, Retail Market Design, and Electricity Price Forecasting

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Acknowledgements

PSERC Support

- **M-41 [Ongoing]:** The Stacked Value of Battery Energy Storage Systems (BESSs)
- **M-42 [Starting Soon]:** Modeling and Coordinating DERs in Power Systems and Markets

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Battery Operation + Planning

Summer Intern @ Dominion

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Machine Learning + Price Forecasting

Available for Summer Intern

Mohammad Mousavi

Market Design + DER Aggregators

Challenges & Opportunities

- Source: Greentech Media
- Source: PJM
- Source: AutoGrid

Market Operation

- Energy arbitrage behavior of batteries?
- Batteries’ impact on market operation?
- Coordinate T&D, DER aggregators, and DERs?

Market Participation

- Market bidding/offering strategies?
- Forecast Electricity price?
- Offer multiple services?

Proposed Solutions

1

Market + Batteries:

Optimal Battery Participation in Energy & Ancillary Services Markets

2

Market + DER Aggregators:

A DSO Design for Wholesale & Retail Markets with DER Aggregators

3

Market Participation:

Machine Learning for System-Wide Electricity Price Forecasting

Proposed Solutions

1 ***Market + Batteries*:**

Optimal Battery Participation in Energy & Ancillary Services Markets

2 ***Market + DER Aggregators*:**

A DSO Design for Wholesale & Retail Markets with DER Aggregators

3 ***Market Participation*:**

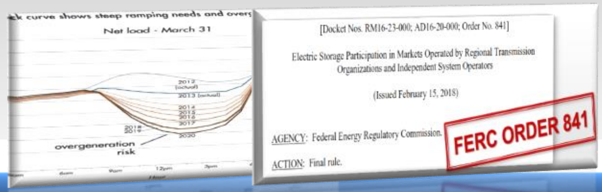
Machine Learning for System-Wide Electricity Price Forecasting

Background & Motivation

❖ Understand the role of **utility-scale batteries** in daily system operations and economics

Sustainability

- CO_2 Reduction
- Renewables



Policy

- FERC Order 841
- BESS → Markets

Technology

- BESS: fast ramping, multiple services

Background & Motivation

The Role of Utility-Scale Batteries in System Operations & Economics

- The impact of utility-scale batteries on daily market operations
- Utility-scale batteries' capability of multiple services provision (energy arbitrage, spinning reserve, frequency regulation services, etc.)
- Operating patterns of merchant batteries in energy, reserve, and pay-as-performance regulation markets
- Interaction between battery owner's profit maximization strategies and system operator's joint operating cost minimization activities (via the market clearing process)

Bi-Level Optimization: Battery Owner & System Operator

Problem Formulation: Bi-Level Optimization Framework

Upper-Level Problem – BESS Profit Maximization

$$\max \sum_{t=1}^{Time} \left\{ Rev_t^{RT-E} + Rev_t^{RT-Rs} + Rev_t^{RT-Rg,C} + Rev_t^{RT-Rg,M} \right\} \Delta t$$

$s.t.$ BESS output power limits

BESS state of charge (SOC) limits

BESS's Quantity and Price Bids

Real-Time Market Clearing Prices and Power Dispatched

Lower Level Problem – ISO Joint Market Clearing

$$\min \sum_{t=1}^{Time} \left(\sum_{g} \left[Cost_t^{GE} + Cost_t^{GRs} + Cost_t^{GRg,C} + Cost_t^{GRg,M} \right] + \left[Cost_t^{BE} + Cost_t^{BRs} + Cost_t^{BRg,C} + Cost_t^{BRg,M} \right] \right) \Delta t$$

$s.t.$ Operational limits of conventional generators

Operational limits of battery energy storage

Pay-as-performance regulation market constraints

System-wide reserve and regulation requirements

Power balance at each bus

- **Upper-level Problem:** Battery owner's profit maximization from real-time energy, reserve, and pay-as-performance regulation markets

- **Lower-level Problem:** System operator's joint market clearing process for real-time energy, reserve, and pay-as-performance regulation markets

The Upper-Level Problem

$$max \sum_{t\in T}\sum_{i\in B}\begin{bmatrix}\pi_{i,t}^{E}\left(P_{i,t}^{B,S}-P_{i,t}^{B,D}\right)+\pi_{t}^{Rs}P_{i,t}^{B,Rs}\\ +\pi_{t}^{RgC}P_{i,t}^{B,RgC}+\pi_{t}^{RgM}P_{i,t}^{B,RgM}\end{bmatrix}\Delta t$$

- **Upper-Level Objective:** Battery owner's profit maximization from real-time energy, reserve, and pay-as-performance regulation markets

Subject to:

$$0 \le Q_{i,t}^{E,S} \le u_i P_i^{Rate}$$

$$0 \le Q_{i,t}^{E,D} \le (1-u_i) P_i^{Rate}$$

$$0 \le Q_{i,t}^{Rs} \le P_i^{Rate}$$

$$0 \le Q_{i,t}^{RgC} \le P_i^{Rate}$$

$$-P_i^{Rate} + P_{i,t}^{B,RgC} \le P_{i,t}^{B,D} - P_{i,t}^{B,S} - P_{i,t}^{B,Rs} \le P_i^{Rate} - P_{i,t}^{B,RgC}$$

- **Constraints-1:** Battery output power limits

$$SOC_{i,t} = SOC_i^{Init} + \textstyle\sum_{k=1}^{t}\left(P_{i,k}^{B,S} - P_{i,k}^{B,D}\right)\Delta t$$

$$SOC_i^{Min} + \left(P_{i,t}^{B,Rs} + P_{i,t}^{B,RgC}\right)\Delta t \le SOC_{i,t} \le SOC_i^{Max} - P_{i,t}^{B,RgC}\Delta t$$

- **Constraints-2:** Battery state of charge (SOC) limits

The Lower-Level Problem

$$max \sum_{t \in T} \left(\begin{array}{c} \sum_{j \in G} \left[\begin{array}{c} \alpha_{j,t}^{E,S} P_{j,t}^{G,S} + \alpha_{j,t}^{Rs} P_{j,t}^{G,Rs} + \\ \alpha_{j,t}^{RgC} P_{j,t}^{G,RgC} + \alpha_{j,t}^{RgM} P_{j,t}^{G,RgM} \end{array} \right] \\ \sum_{i \in B} \left[\begin{array}{c} \beta_{i,t}^{E,S} P_{i,t}^{B,S} - \beta_{i,t}^{E,D} P_{i,t}^{B,D} + \beta_{i,t}^{Rs} P_{i,t}^{B,Rs} \\ +\beta_{i,t}^{RgC} P_{i,t}^{B,RgC} + \beta_{i,t}^{RgM} P_{i,t}^{B,RgM} \end{array} \right] \end{array} \right) \Delta t$$

- **Lower-Level Objective:** System operator's joint market clearing process for real-time energy, reserve, and pay-as-performance regulation markets

Subject to:

$$0 \leq P_{i,t}^{B,S} \leq Q_{i,t}^{E,S}$$
$$0 \leq P_{i,t}^{B,D} \leq Q_{i,t}^{E,D}$$
$$0 \leq P_{i,t}^{B,Rs} \leq Q_{i,t}^{Rs}$$
$$0 \leq P_{i,t}^{B,RgC} \leq Q_{i,t}^{RgC}$$

- **Constraints-1:** Operating limits of batteries

$$P_j^{Min} + P_{j,t}^{G,RgC} \leq P_{j,t}^{G,S} \leq P_j^{Max} - P_{j,t}^{G,Rs} - P_{j,t}^{G,RgC}$$
$$0 \leq P_{j,t}^{G,Rs} \leq P_j^{Rs,ramp}$$
$$0 \leq P_{j,t}^{G,RgC} \leq P_j^{Rg,ramp}$$

- **Constraints-2:** Operating limits of generators

The Lower-Level Problem

$$max \sum_{t\in T} \left(\begin{array}{c} \sum_{j\in G} \begin{bmatrix} \alpha_{j,t}^{E,S} P_{j,t}^{G,S} + \alpha_{j,t}^{Rs} P_{j,t}^{G,Rs} + \\ \alpha_{j,t}^{RgC} P_{j,t}^{G,RgC} + \alpha_{j,t}^{RgM} P_{j,t}^{G,RgM} \end{bmatrix} \\ \sum_{i\in B} \begin{bmatrix} \beta_{i,t}^{E,S} P_{i,t}^{B,S} - \beta_{i,t}^{E,D} P_{i,t}^{B,D} + \beta_{i,t}^{Rs} P_{i,t}^{B,Rs} \\ +\beta_{i,t}^{RgC} P_{i,t}^{B,RgC} + \beta_{i,t}^{RgM} P_{i,t}^{B,RgM} \end{bmatrix} \end{array} \right) \Delta t$$

- **Lower-Level Objective:** System operator's joint market clearing process for real-time energy, reserve, and pay-as-performance regulation markets

Subject to:

$$P_{j,t}^{G,RgC} \leq P_{j,t}^{G,RgM} \leq m_j P_{j,t}^{G,RgC}$$

$$P_{i,t}^{B,RgC} \leq P_{i,t}^{B,RgM} \leq m_i P_{i,t}^{B,RgC}$$

- **Constraints-3:** Operating constraints of pay-as-performance regulation markets

$$\sum_{i\in B} P_{i,t}^{B,Rs} + \sum_{j\in G} P_{j,t}^{G,Rs} \geq R_t^{Rs}$$

$$\sum_{i\in B} P_{i,t}^{B,RgC} + \sum_{j\in G} P_{j,t}^{G,RgC} \geq R_t^{RgC}$$

$$\sum_{i\in B} P_{i,t}^{B,RgM} + \sum_{j\in G} P_{j,t}^{G,RgM} \geq R_t^{RgM}$$

- **Constraints-4:** System-wide reserve and regulation requirements

$$\sum_{i\in B}\left(P_{i,t}^{B,S} - P_{i,t}^{B,D}\right) + \sum_{j\in G} P_{j,t}^{G,S} = P_t^{Load}$$

- **Constraints-5:** System power balance

Solution Procedure

Convert Bi-Level Problem to Single-Level Problem

- Lower-level problem: linear and convex
- Solve lower-level problem via solving the KKT equations of the lower-level problem
- Write KKT conditions of the Lower-level problem as constraints for the upper-level problem

Single-Level Problem after Conversion

$$\max \sum_{t \in T} \sum_{i \in B} \left[\pi_{i,t}^{E} \left(P_{i,t}^{B,S} - P_{i,t}^{B,D} \right) + \pi_t^{Rs} P_{i,t}^{B,Rs} + \pi_t^{RgC} P_{i,t}^{B,RgC} + \pi_t^{RgM} P_{i,t}^{B,RgM} \right] \Delta t$$

$s.t.$ **Battery power output limits**

Battery state of charge (SOC) limits

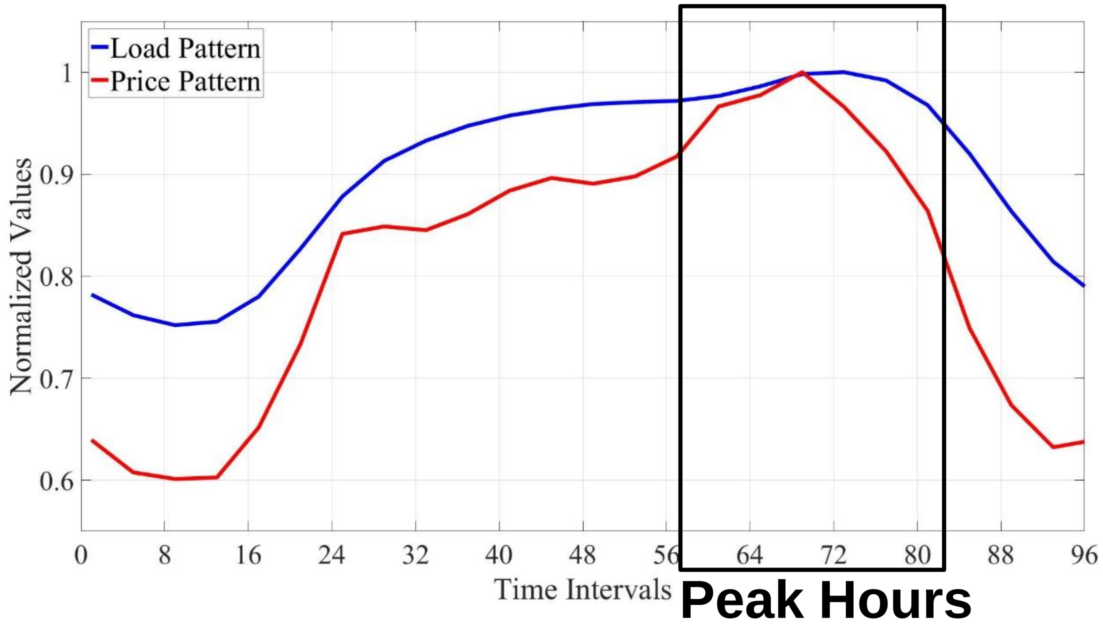
$\}$ Original Constraints of Upper-Level Problem

KKT conditions of the lower-level problem

Case Study: Test System

- **Modified PJM 5-bus test system (Market clearing interval = 15 min; Simulation time = 24 hours)**
- BESS Capacity: 400^{MWh} ;   BESS Output Power limit: 40^{MW}
- System's Load: 1000^{MW} mapped on 2018 PJM load pattern
- System's Spinning Reserve Requirements: 10% of load in each interval
- System's Regulation Capacity Requirements: 4% of load in each interval
- System's Regulation Mileage Requirements: 1.75 times regulation capacity requirements

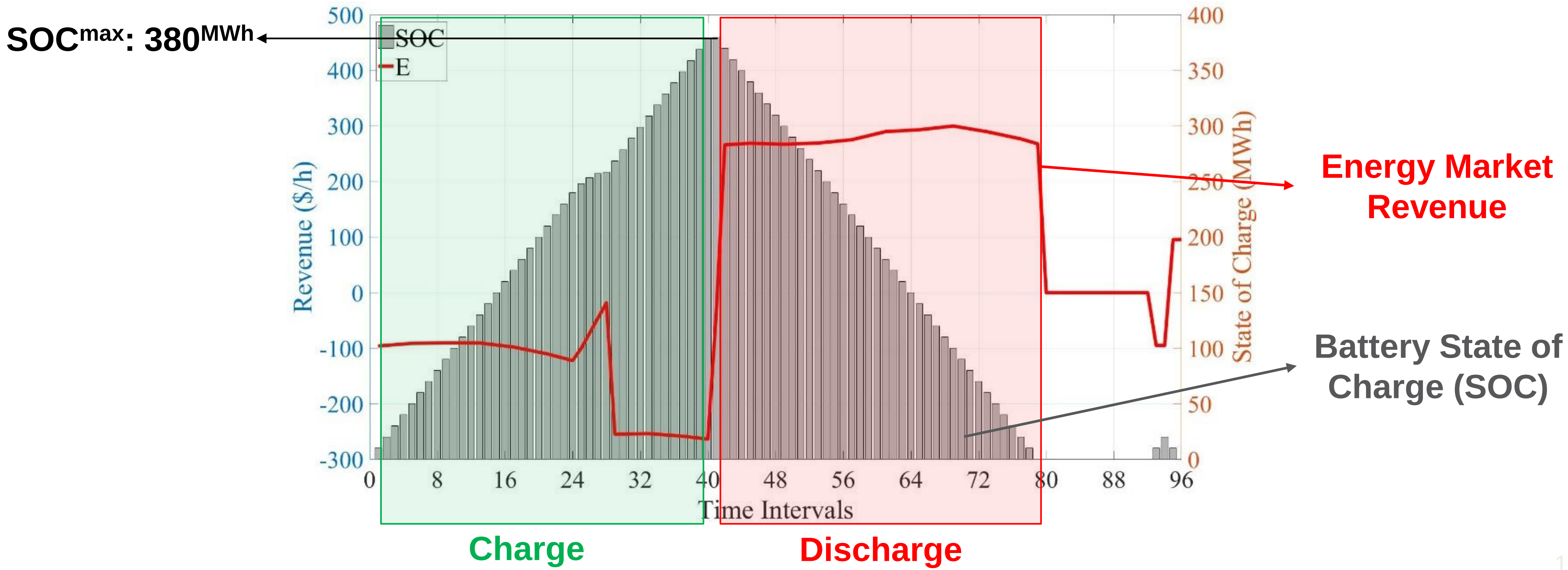
Generator No.	Base Price Bid ($/MWh)	P^{max} (MW)	$P^{Rg,ramp}$ (MW)	$P^{Rs,ramp}$ (MW)
G1	10	400	80	40
G2	14	300	60	30
G3	15	210	42	21
G4	30	350	70	35
G5	40	270	54	27



Case Study Results

[Case 1] Modeling Energy Market Only

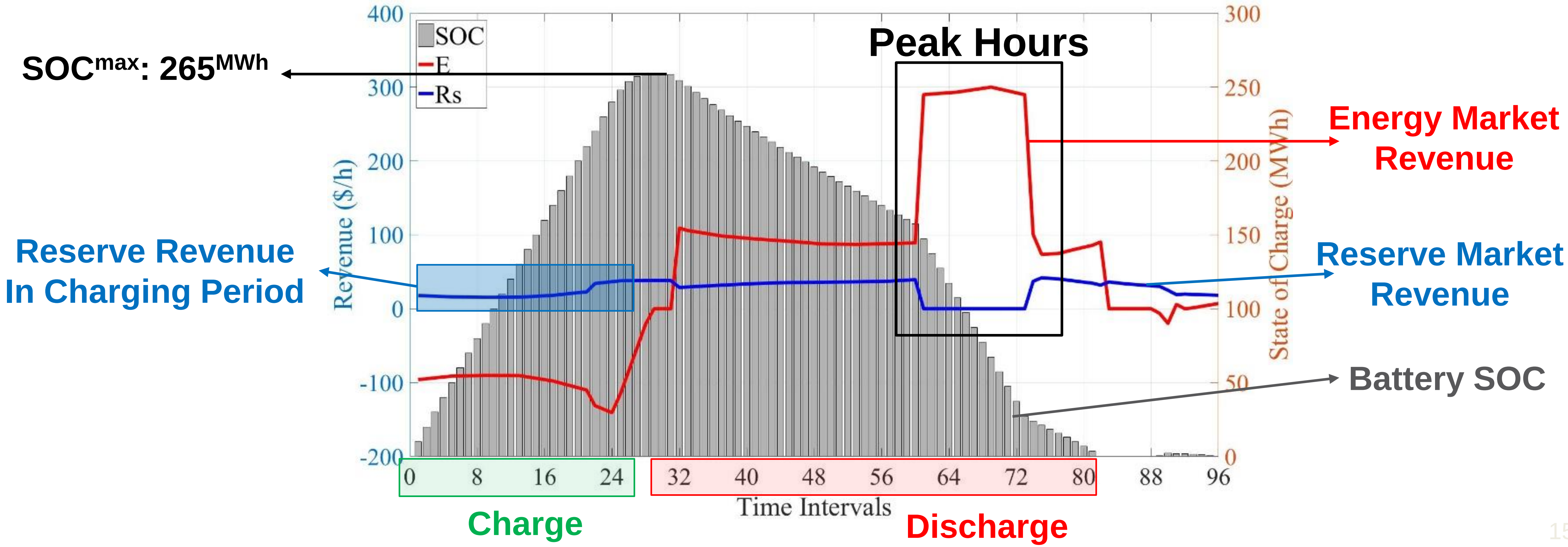
- Energy arbitrage between different market clearing intervals



Case Study Results

[Case 2] Modeling Energy & Reserve Markets

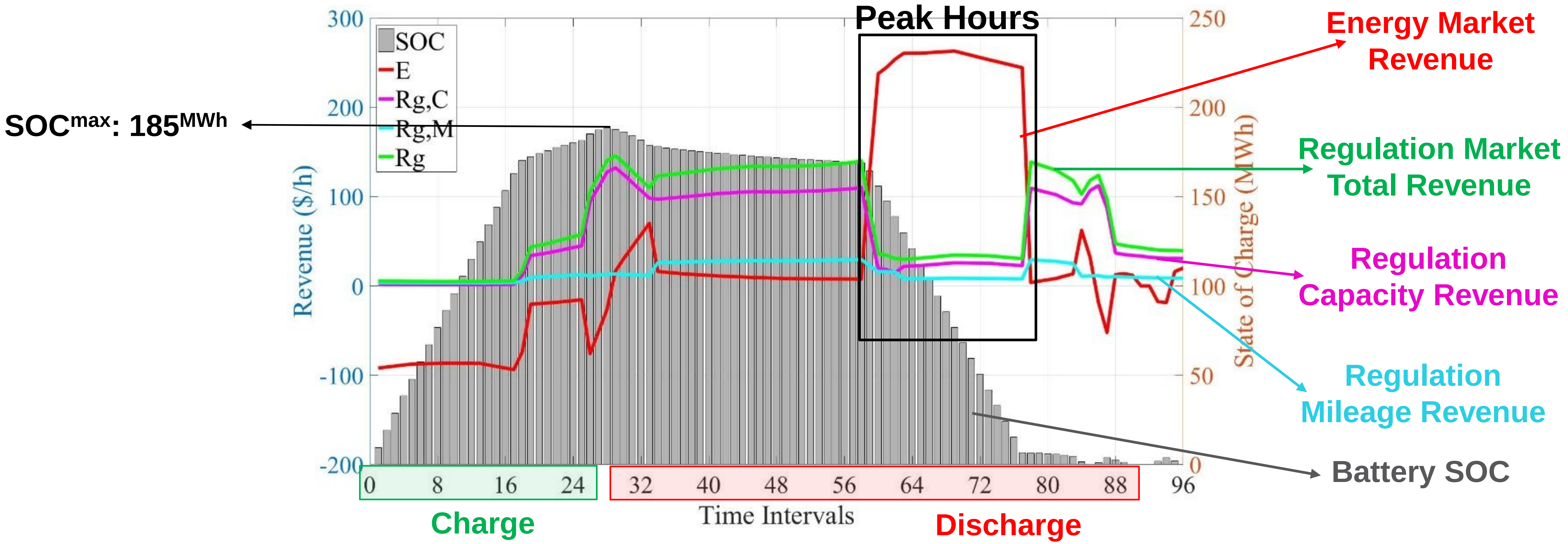
- Energy arbitrage between different market clearing intervals & between different markets
- Energy arbitrage between different markets at the same market clearing interval (during charging period)
- Lower state of charge (SOC) compared to Case 1 (with energy market only)



Case Study Results

[Case 3] Modeling Energy & Regulation Markets

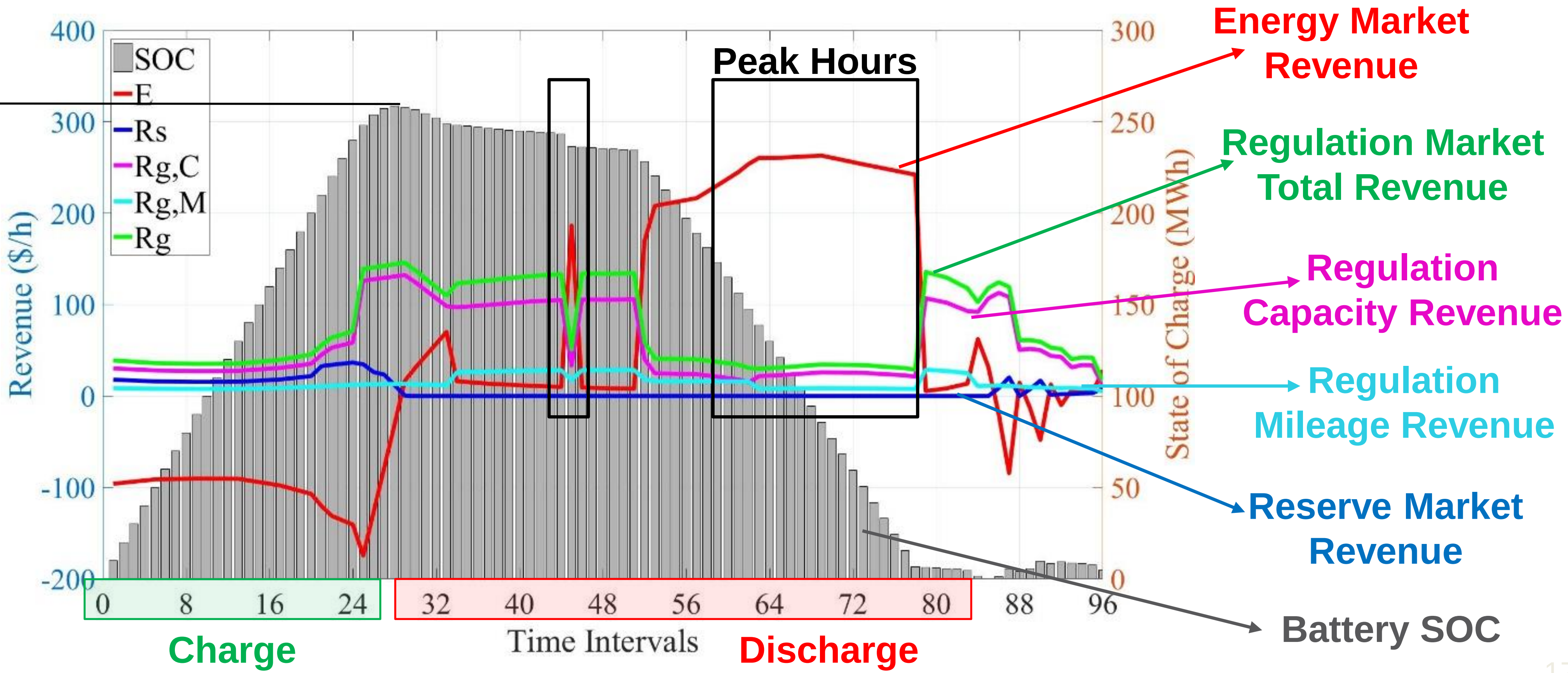
- Energy arbitrage between different market clearing intervals & between different markets
- Less revenue from the energy market



Case Study Results

[Case 4] Modeling Energy, Reserve, & Regulation Markets

- Energy arbitrage between different market clearing intervals & between different markets
- Battery collects the least revenue from reserve market
- Significant difference in battery revenue patterns and market outcomes

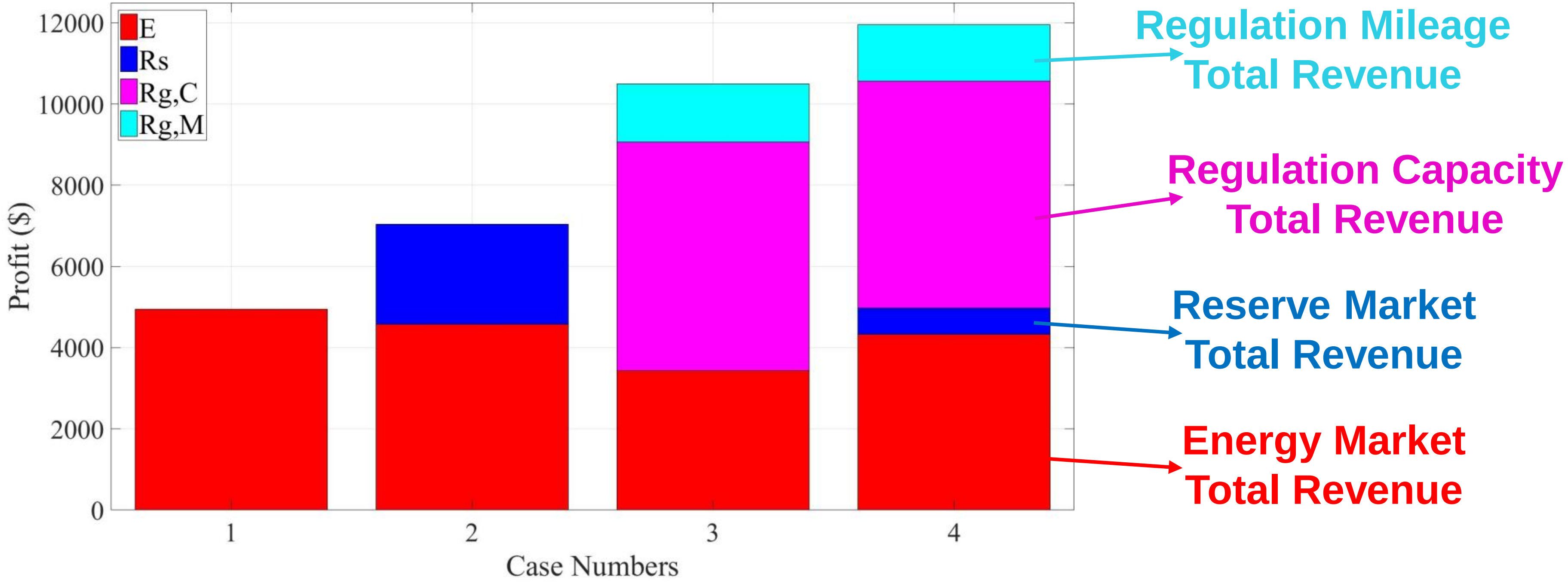


SOC^{max}: 265^{MWh}

Case Study Results

[Cases 1~4] Comparison of Battery Total Revenue

- Regulation market is the most profitable
- Gain more profit by participating in more markets
- Participating in reserve increases the revenue from energy market (Cases 3~4)



Part I: Conclusions & Future Directions

Conclusions

- **A bi-level optimization framework:**
  - ✓ Operating and revenue patterns of merchant batteries in energy, reserve, and regulation markets
  - ✓ Interactions between battery owner's profit maximization strategies and system operator's joint market clearing process

Future Directions

- **Incorporate more operating details in the bi-level optimization framework:**
  - ✓ AGC signal deployment
  - ✓ Battery degradation cost
  - ✓ Transmission system model
  - ✓ Battery charge/discharge efficiency, etc.

Proposed Solutions

1

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Optimal Battery Participation in Energy & Ancillary Services Markets

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A DSO Design for Wholesale & Retail Markets with DER Aggregators

3

Market Participation:

Machine Learning for System-Wide Electricity Price Forecasting

Background & Motivation

Impact of DER Aggregators on T&D Operations

- **DER aggregators**: control distribution-level DERs/loads + participate in transmission-level markets
- **Distribution operations**: cannot monitor DER aggregators' controls over DERs/loads ➔ security risks
- **Wholesale markets**: cannot observe DER locations/availabilities in distribution grids ➔ market uncertainties

Need an Entity to Coordinate DER Aggregators in T&D Operations

- **This entity can:**
  - ✓ Observe DER locations/availabilities in distribution grids
  - ✓ Monitor DER aggregators' controls over distribution-level DERs/loads
  - ✓ Coordinate DER aggregators' offers to wholesale markets

Background & Motivation

Need an Entity to Coordinate DER Aggregators in T&D Operations

Distribution System Operator (DSO) Framework

- Operate the retail market + distribution system
- Coordinate DER aggregators’ participation in day-ahead wholesale energy + pay-as-performance regulation markets and retail energy markets
- Collect offers from DER aggregators to operate the retail market, and coordinate these offers to construct an aggregated offer/bid for participating in the day-ahead wholesale market
- Consider distribution network security while coordinating DER aggregators’ wholesale market participation
- Consider various types of aggregators (for demand response resources, energy storage, EV charging stations, and dispatchable DGs)

Proposed DSO Framework

DSO Problem Formulation

$$min \sum_{t \in T} [\text{Total DSO Operating Cost}] \longleftrightarrow$$

Maximize total social welfare in the distribution grid

$s.t.$ **Operating constraints for demand response aggregators (DRAGs)**

Operating constraints for energy storage aggregators (ESAGs)

Operating constraints for EV charging stations (EVCSs)

Operating constraints for dispatchable DG aggregators (DDGAGs)

Linearized distribution power flow equations

DSO Framework: The Objective Function

$$\text{Min } \sum_{t\in T}[-P_t^{sub}\pi_t^e - r_t^{sub,up}\pi_t^{cap,up} - r_t^{sub,dn}\pi_t^{cap,dn}$$
$$-r_t^{sub,up}S_t^{up}\mu_t^{up}\pi_t^{mil,up} - r_t^{sub,dn}S_t^{dn}\mu_t^{dn}\pi_t^{mil,dn}$$

DSO Operating Cost for Participating in Wholesale Energy, Regulation Capacity & Regulation Mileage Markets

$$+\sum_{k\in\{K_2,K_4\}}P_{t,k}\pi_{t,k}^e - \sum_{k_3\in K_3}P_{t,k_3}\pi_{t,k_3}^e$$
$$+\sum_{k\in K}[\,r_{t,k}^{up}\pi_{t,k}^{cap,up} + r_{t,k}^{dn}\pi_{t,k}^{cap,dn} + r_{t,k}^{up}S_t^{up}\mu_t^{up}\pi_{t,k}^{mil,up}$$
$$+r_{t,k}^{dn}S_t^{dn}\mu_t^{dn}\pi_{t,k}^{mil,dn}] - \sum_{k_1\in K_1}\sum_{a\in A}P_{a,t,k_1}\pi_{a,t,k_1}^e\,]$$

DSO Operating Cost for Operating Retail Energy Markets with Various DER Aggregators

DSO Problem Formulation

$$min \sum_{t\in T}[\text{Total DSO Operating Cost}] \longleftrightarrow$$

Maximize total social welfare in the distribution grid

DSO Framework: The Constraints

Operating Constraints for Demand Response Aggregators (DRAGs)

$$\sum_{a\in A} P_{a,t,k_1} - r^{cap,dn}_{t,k_1} \geq 0; \quad \forall t \in T,\ \forall k_1 \in K_1$$

$$P_{t,k_2} = E_{t-1,k_2} - E_{t,k_2} + (1/\eta^{di}_{k_2}) r^{cap,up}_{t,k_2} \mu^{up}_t - (\eta^{ch}_{k_2}) r^{cap,dn}_{t,k_2} \mu^{dn}_t; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$P_{t,k_2} = (1/\eta^{di}_{k_2}) P^{di}_{t,k_2} - (\eta^{ch}_{k_2}) P^{ch}_{t,k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$r^{cap,up}_{t,k_2} = r^{cap,up,di}_{t,k_2} + r^{cap,dn,ch}_{t,k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$r^{cap,dn}_{t,k_2} = r^{cap,dn,di}_{t,k_2} + r^{cap,up,ch}_{t,k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$E^{min}_{k_2} \leq E_{t,k_2} \leq E^{max}_{k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$0 \leq P^{di}_{t,k_2} \leq b_{t,k_2} DR^{max}_{k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$0 \leq r^{cap,up,di}_{t,k_2} \leq b_{t,k_2} DR^{max}_{k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$0 \leq r^{cap,dn,di}_{t,k_2} \leq b_{t,k_2} DR^{max}_{k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$0 \leq P^{ch}_{t,k_2} \leq (1-b_{t,k_2}) CR^{max}_{k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$0 \leq r^{cap,up,ch}_{t,k_2} \leq (1-b_{t,k_2}) CR^{max}_{k_2}; \forall t \in T, \forall k_2 \in K_2$$

$$0 \leq r^{cap,dn,ch}_{t,k_2} \leq (1-b_{t,k_2}) CR^{max}_{k_2}; \forall t \in T, \forall k_2 \in K_2$$

$$r^{cap,dn,di}_{t,k_2} \leq P^{di}_{t,k_2} \leq DR^{max}_{k_2} - r^{cap,up,di}_{t,k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

$$r^{cap,dn,ch}_{t,k_2} \leq P^{ch}_{t,k_2} \leq CR^{max}_{k_2} - r^{cap,up,ch}_{t,k_2}; \quad \forall t \in T,\ \forall k_2 \in K_2$$

- Limitations for DRAG’s offers to energy, regulation capacity-up and capacity-down markets
- Real power offered at each demand block is limited within its permitted range
- The regulation capacity-up and capacity-down offers are lower than their maximum permitted values.

DSO Framework: The Constraints

Operating Constraints for Energy Storage Aggregators (ESAGs)

$$P_{t,k_2} = E_{t-1,k_2} - E_{t,k_2} + (1/\eta^{di}_{k_2}) r^{cap,up}_{t,k_2} \mu^{up}_t - (\eta^{ch}_{k_2}) r^{cap,dn}_{t,k_2} \mu^{dn}_t; \quad \forall t \in T, \forall k_2 \in K_2$$

$$P_{t,k_2} = (1/\eta^{di}_{k_2}) P^{di}_{t,k_2} - (\eta^{ch}_{k_2}) P^{ch}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$r^{cap,up}_{t,k_2} = r^{cap,up,di}_{t,k_2} + r^{cap,dn,ch}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$r^{cap,dn}_{t,k_2} = r^{cap,dn,di}_{t,k_2} + r^{cap,up,ch}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$E^{min}_{k_2} \leq E_{t,k_2} \leq E^{max}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$0 \leq P^{di}_{t,k_2} \leq b_{t,k_2} DR^{max}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$0 \leq r^{cap,up,di}_{t,k_2} \leq b_{t,k_2} DR^{max}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$0 \leq r^{cap,dn,di}_{t,k_2} \leq b_{t,k_2} DR^{max}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$0 \leq P^{ch}_{t,k_2} \leq (1 - b_{t,k_2}) CR^{max}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$0 \leq r^{cap,up,ch}_{t,k_2} \leq (1 - b_{t,k_2}) CR^{max}_{k_2}; \forall t \in T, \forall k_2 \in K_2$$

$$0 \leq r^{cap,dn,ch}_{t,k_2} \leq (1 - b_{t,k_2}) CR^{max}_{k_2}; \forall t \in T, \forall k_2 \in K_2$$

$$r^{cap,dn,di}_{t,k_2} \leq P^{di}_{t,k_2} \leq DR^{max}_{k_2} - r^{cap,up,di}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

$$r^{cap,dn,ch}_{t,k_2} \leq P^{ch}_{t,k_2} \leq CR^{max}_{k_2} - r^{cap,up,ch}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2$$

- Defining ESAG's power injection
- Decomposing offers to the energy, regulation capacity-up and capacity-down markets into charging and discharging terms
- Limitation for the charge level
- Ensure that ESAG's offers to the energy, regulation capacity-up and capacity-down markets are in their permitted ranges.
- Limitation for ESAG's offers to the energy, regulation capacity-up and capacity-down markets with respect to the charging and discharging rates.

DSO Framework: The Constraints

Operating Constraints for EV Charging Stations (EVCSs)

$$0 \le P_{t,k_3} \le ER_{k_3}^{max} b_{k_3}; \quad \forall t \in T', \forall k_3 \in K_3$$
$$0 \le r_{t,k_3}^{cap,up} \le ERR_{k_3}^{max} b_{k_3}; \quad \forall t \in T', \forall k_3 \in K_3$$
$$0 \le r_{t,k_3}^{cap,dn} \le ERR_{k_3}^{max} b_{k_3}; \quad \forall t \in T', \forall k_3 \in K_3$$
$$P_{t,k_3} + r_{t,k_3}^{cap,up} \le ER_{k_3}^{max}; \quad \forall t \in T', \forall k_3 \in K_3$$
$$P_{t,k_3} - r_{t,k_3}^{cap,dn} \ge 0; \quad \forall t \in T', \forall k_3 \in K_3$$
$$0.9CL_{k_3}^{max} b_{k_3} \le E_{k_3}^{int} b_{k_3} + \sum_{t \in T'} [P_{t,k_3} + r_{t,k_3}^{cap,up} \mu_t^{up} - r_{t,k_3}^{cap,dn} \mu_t^{dn}] \gamma_{k_3}^{ch} \le CL_{k_3}^{max} b_{k_3}; \forall k_3 \in K_3$$

- Limitation for EVCS's offers to the energy, regulation capacity-up and capacity-down markets.
- Ensuring that EVs are fully charged

Operating Constraints for Dispatchable DG Aggregators (DDGAGs)

$$P_{t,k_4} + r_{t,k_4}^{cap,up} \le P_{k_4}^{max}; \quad \forall t \in T, \forall k_4 \in K_4$$
$$P_{t,k_4} - r_{t,k_4}^{cap,dn} \ge P_{k_4}^{min}; \quad \forall t \in T, \forall k_4 \in K_4$$
$$0 \le r_{t,k_4}^{cap,up} \le RU_{k_4}; \quad \forall t \in T, \forall k_4 \in K_4$$
$$0 \le r_{t,k_4}^{cap,dn} \le RD_{k_4}; \quad \forall t \in T, \forall k_4 \in K_4$$

- Limitation DDAG's offers to the energy, regulation capacity-up and capacity-down markets.
- Ensure the regulation capacity-up/capacity-down offers are lower than maximum ramp-up/ramp-down rates.

DSO Framework: The Constraints

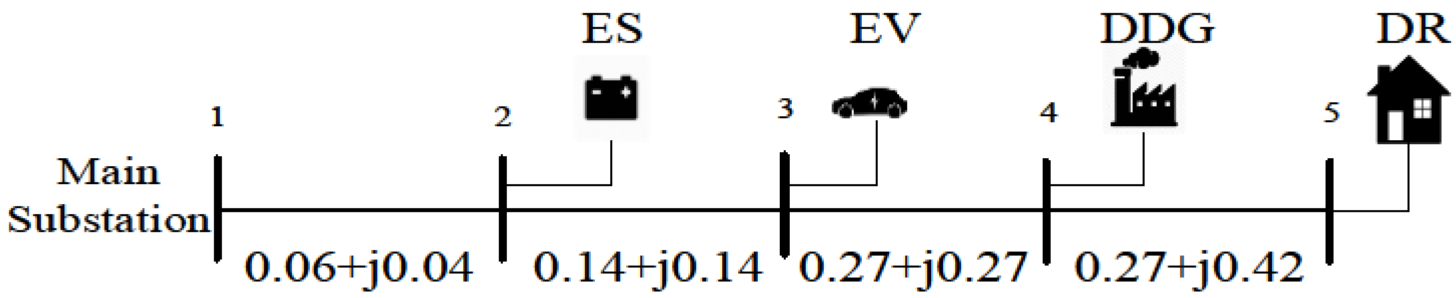
Linearized Distribution Power Flow Equations [1]

$$
\begin{aligned}
&\sum_{k_1 \in K_1} \sum_{a \in A} H_{n,k_1} P_{a,t,k_1} + \sum_{k_3 \in K_3} H_{n,k_3} P_{t,k_3} + P^D_{t,n} \\
&- \sum_{k_2 \in K_2} H_{n,k_2} P_{t,k_2} - \sum_{k_4 \in K_4} H_{n,k_4} P_{t,k_4} \\
&+ H^{sub}_n P^{sub}_t + \sum_{j \in J} Pl_{j,t} A_{j,n} = 0; \quad \forall t \in T, \forall n \in N \\
&\sum_{k_1 \in K_1} \sum_{a \in A} H_{n,k_1} P_{a,t,k_1} tan\phi_{k_1} + Q^D_{t,n} \\
&- \sum_{k_4 \in K_4} H_{n,k_4} P_{t,k_4} tan\phi_{k_4} \\
&+ H^{sub}_n Q^{sub}_t + \sum_{j \in J} Ql_{j,t} A_{j,n} = 0; \quad \forall t \in T, \forall n \in N \\
&V_{m,t} = V_{n,t} - (r_j Pl_{j,t} + x_j Ql_{j,t}); \quad \forall t \in T, \forall m \in N, \\
&\qquad \forall n \in N, \ C(m,n) = 1, \ A(j,n) = 1 \\
&V^{min} \le V_{n,t} \le V^{max}; \quad \forall t \in T, \forall n \in N \\
&-Pl^{max} \le Pl_{j,t} \le Pl^{max}; \quad \forall t \in T, \forall j \in J \\
&-Ql^{max} \le Ql_{j,t} \le Ql^{max}; \quad \forall t \in T, \forall j \in J \\
&r^{sub,up}_t = \sum_{k_2 \in K_2} r^{cap,up}_{t,k_2} + \sum_{k_4 \in K_4} r^{cap,up}_{t,k_4} \\
&\qquad + \sum_{k_1 \in K_1} r^{cap,dn}_{t,k_1} + \sum_{k_3 \in K_3} r^{cap,dn}_{t,k_3}; \quad \forall t \in T \\
&r^{sub,dn}_t = \sum_{k_2 \in K_2} r^{cap,dn}_{t,k_2} + \sum_{k_4 \in K_4} r^{cap,dn}_{t,k_4} \\
&\qquad + \sum_{k_1 \in K_1} r^{cap,up}_{t,k_1} + \sum_{k_3 \in K_3} r^{cap,up}_{t,k_3}; \quad \forall t \in T
\end{aligned}
$$

- Represent the real and reactive power flow
- Represent voltage drop at each line
- Represent real and reactive power limits at each line
- Represent DSO’s aggregated offers for participating in the wholesale energy, regulation capacity-up and capacity-down markets.

[1] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Trans. Power Del., vol. 4, no. 2, pp. 1401–1407, April 1989.

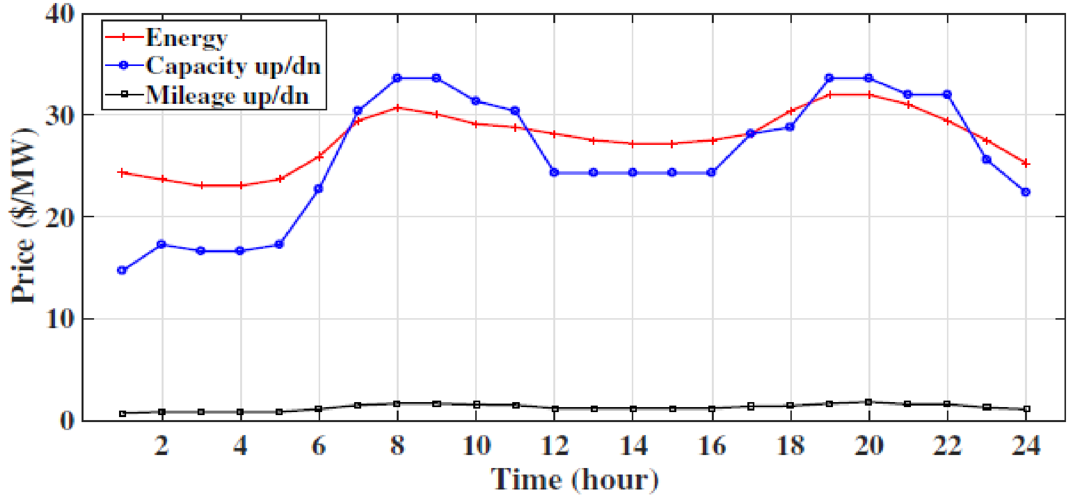
Case Studies: The Test System

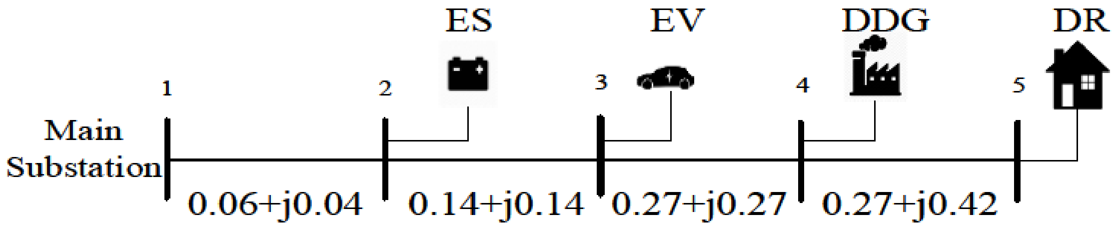


- A distribution test system with 5 nodes and 4 lines
- One demand response aggregator @ Node 5
- One dispatchable DG aggregator @ Node 4
- One EV charging station @ Node 3
- One energy storage aggregator @ Node 2

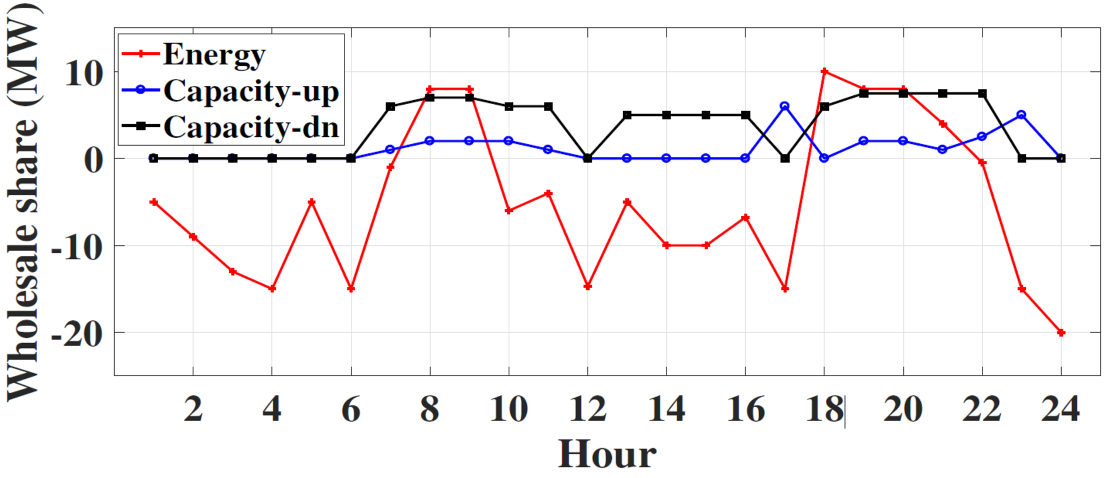
Case Studies: DSO's Wholesale Market Participation

Wholesale Energy and Regulation Markets Prices





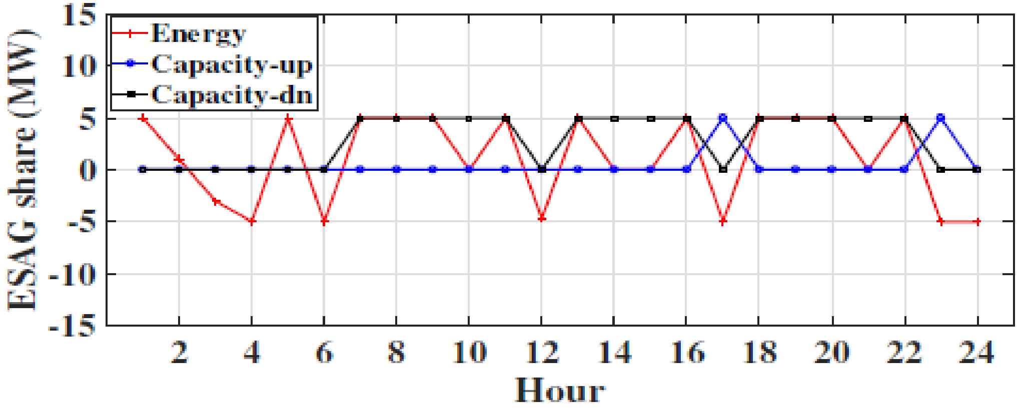
Trades between DSO and Wholesale Market



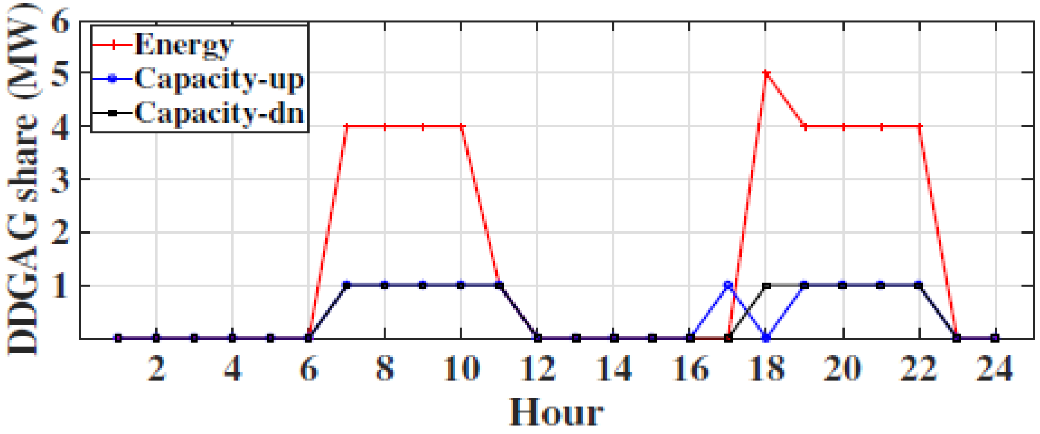
- DSO sells energy to the wholesale market @ hours 8~9 and 18~21 ➔ wholesale energy prices are high
- DSO buys energy from the wholesale market @ other hours

Case Studies: Aggregators' Market Participation

Hourly Awarded Energy & Regulation Services for The Energy Storage Aggregator



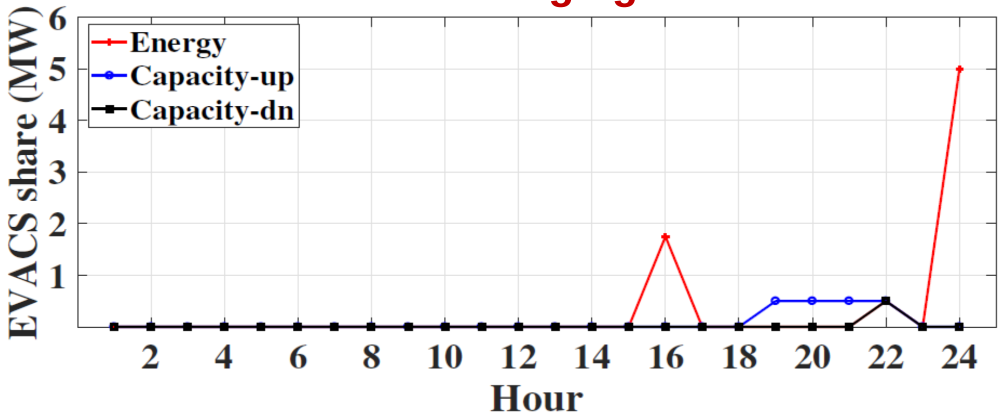
Hourly Awarded Energy & Regulation Services for The Dispatchable DG Aggregator



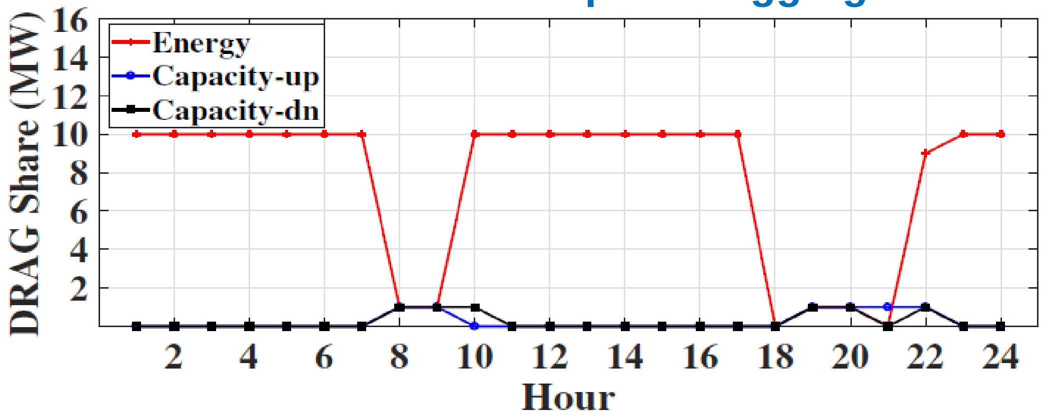
- Energy storage aggregator prefers offering regulation capacity-down service ➔ To increase its charging level
- Energy storage aggregator offers regulation capacity-down service at hours 13~16, when the regulation capacity-down price is lower than the energy price in wholesale market
- Dispatchable DG aggregator offers energy and regulation capacity services to the wholesale market during peak hours
- Dispatchable DG aggregator increases its energy provision (without offering regulation capacity-up services) @ hour 18, when wholesale regulation capacity price is lower than wholesale energy price

Case Studies: Retail Market Outcomes

Hourly Awarded Energy & Regulation Services for The EV Charging Station



Hourly Awarded Energy & Regulation Services for The Demand Response Aggregator



- EV charging station purchases energy @ hours 16 and 24 ➔ Wholesale energy price is the lowest of the day
- EV charging station offers regulation capacity-up service @ hours 19~22 ➔ Regulation capacity-up price is high, and EV charging station can increase EV charge levels by offering this service

- Dispatchable DG aggregator does not purchase energy from wholesale market at peak hours
- Dispatchable DG aggregator purchases energy for providing regulation capacity-down service

Part II: Conclusions & Future Directions

Conclusions

- **A DSO framework:**
  - ✓ Operate the retail energy market and participate in the wholesale energy and regulation markets
  - ✓ Collect offers from various DER aggregators via the retail market, and coordinate these offers to construct an aggregated offer/bid for participating in the day-ahead wholesale market
  - ✓ Consider distribution power flow constraints

Future Directions

- **Improve the proposed DSO framework:**
  - ✓ Three-phase unbalanced operations
  - ✓ Aggregators with mixed types of resources
  - ✓ Reactive power incentivization via the retail market, etc.

Proposed Solutions

1 *Market + Batteries*:

Optimal Battery Participation in Energy & Ancillary Services Markets

2 *Market + DER Aggregators*:

A DSO Design for Wholesale & Retail Markets with DER Aggregators

3 *Market Participation*:

Machine Learning for System-Wide Electricity Price Forecasting

Background & Motivation

Electricity Price Forecasting by Market Participants

- Critical for market participants to determine optimal bidding/offering strategies
- No confidential system model parameters/topology/operating conditions available to market participants

➔ Market participants need to forecast LMPs in a purely model-free/data-driven manor

Machine Learning for System-Wide Real-Time LMP Forecasting

- Purely model-free, using only public market data
- No confidential system modeling/operating details
- Spatio-temporal correlations among heterogeneous market data
- Inspired by video prediction techniques

Market Data Images & Videos (PJM AECO Price Zone)

Heterogeneous Market Data

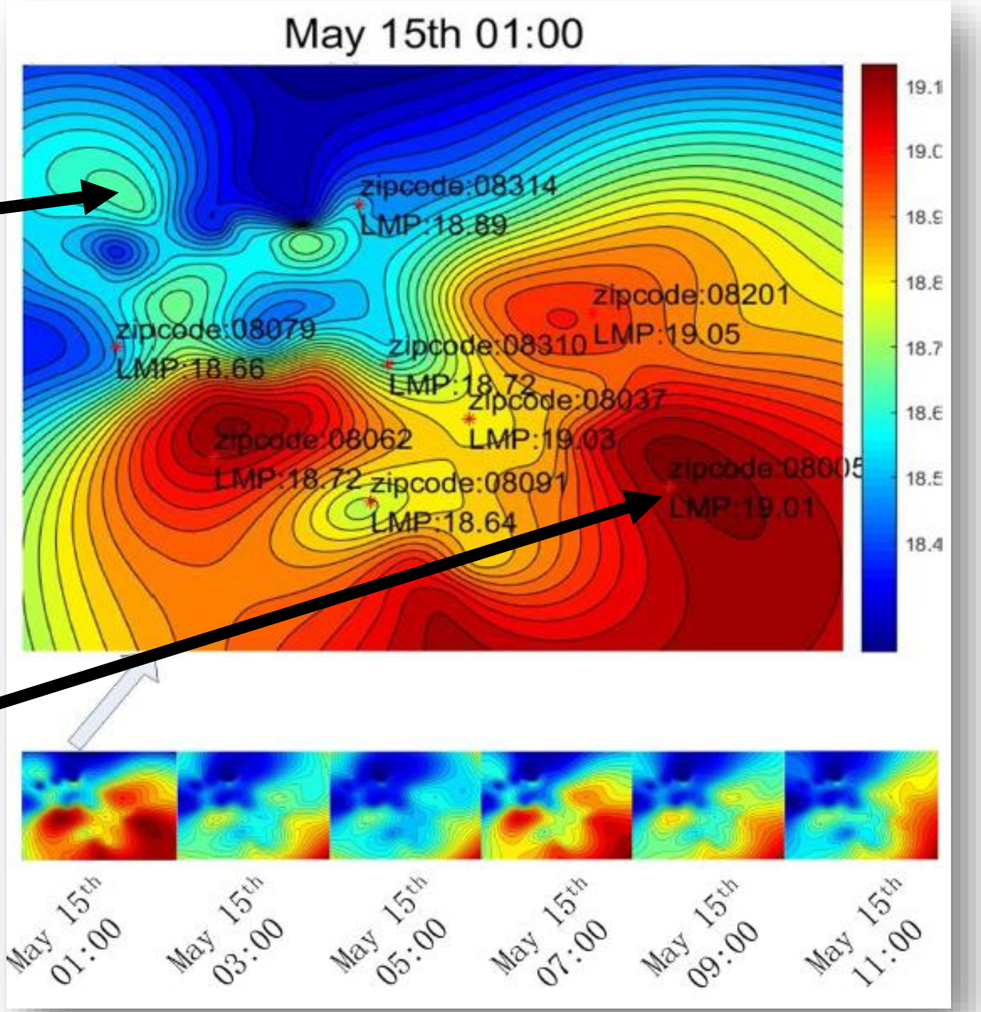
- Zipcode = 08014
- Hour = 1 AM, May 15, 2019

- LMP = $18.77 $/MWh
- Load = 1.05 MW
- Temperature = 39.59 F
- ……

Heterogeneous Market Data

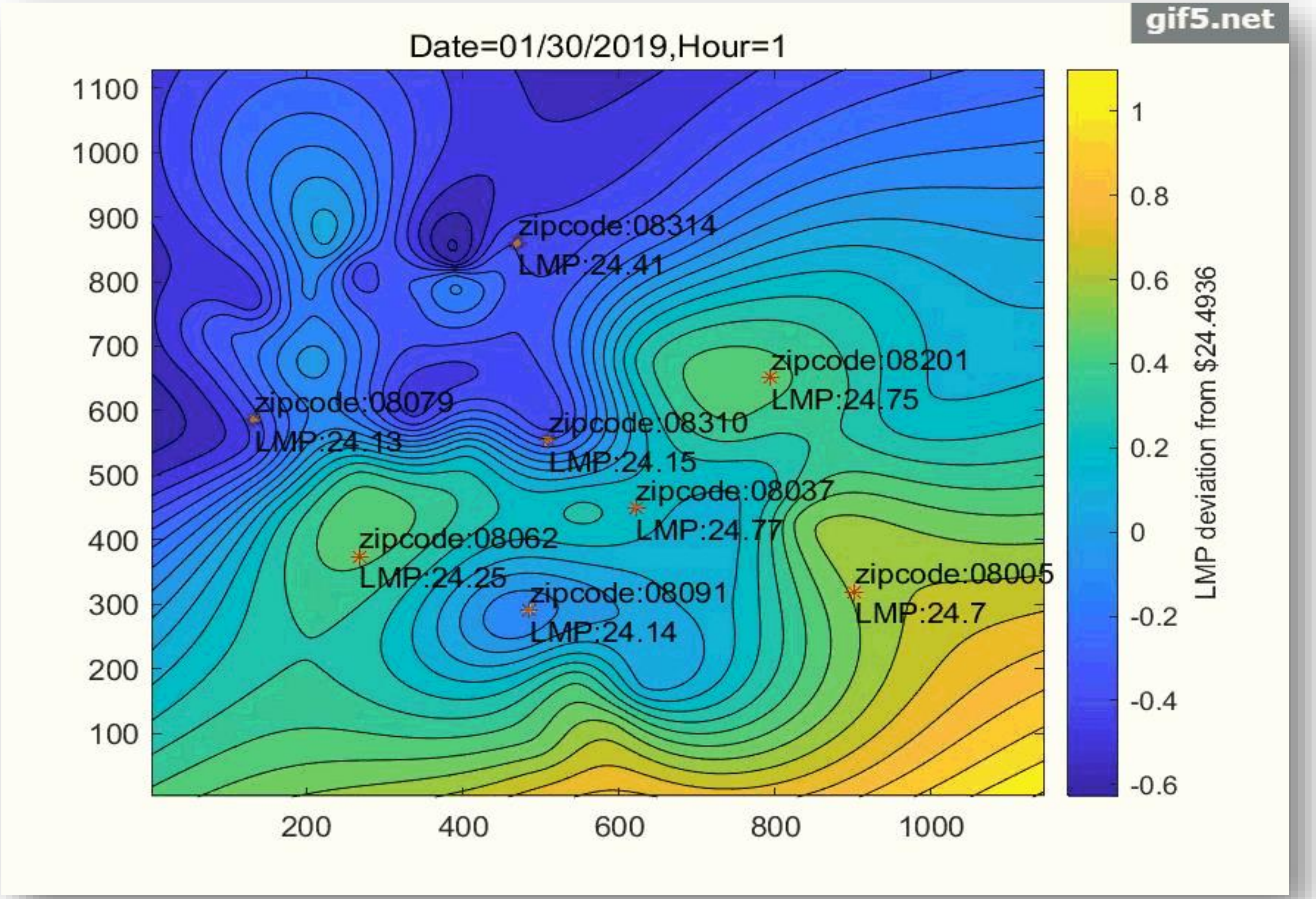
- Zipcode = 08005
- Hour = 1 AM, May 15, 2019

- LMP $19.01 $/MWh
- Load = 33.42 MW
- Temperature = 41.54 F
- ……



Spatio-Temporal Market Data → **Market Data Images & Videos**

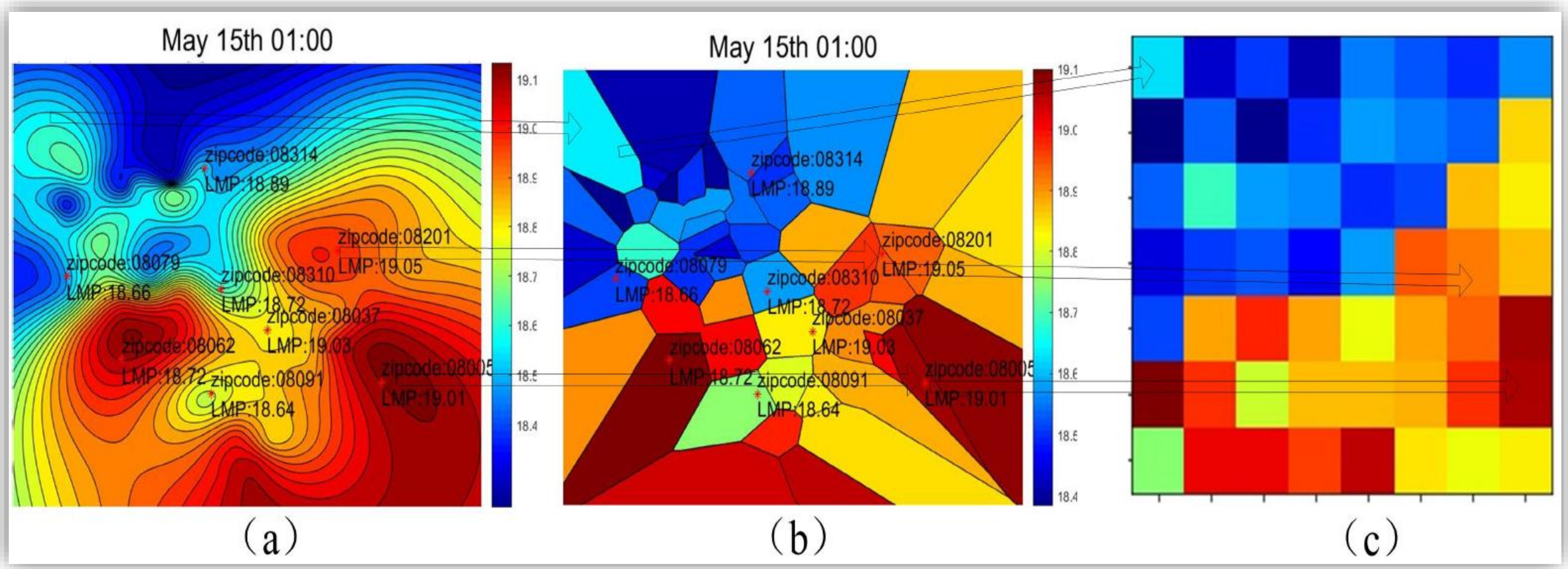
Example: Market Data Video (PJM AECO Price Zone)



Hourly LMPs @ PJM AECO Price Zone on 1/30/2019

General Data Structure: Market Data Pixels, Images, & Videos

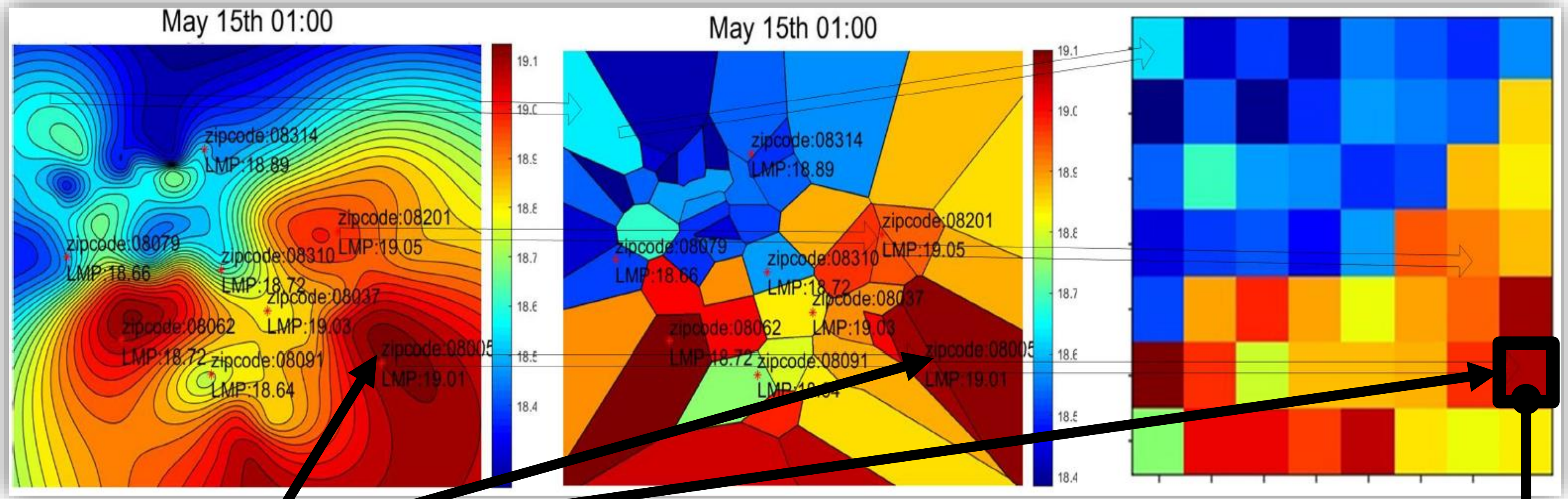
Different interpolation techniques applied to the same market dataset (56 price nodes)



PJM AECO Price Zone

- [a] Biharmonic spline interpolation ➔ smooth with many different colors
- [b] Nearest neighbor interpolation ➔ less smooth with exactly 56 different colors (1 color/price node)
- [c] Pixel representation ➔ 56 pixels with 56 different colors (1 color/price node)

General Data Structure:
Market Data Pixels, Images, & Videos



PJM AECO Price Zone

Heterogeneous Market Data

- Zipcode = 08005
- Hour = 1 AM, May 15, 2019
- LMP $19.01 $/MWh
- Load = 33.42 MW
- Temperature = 41.54 F
- ……

Data Normalization

RGB Color Codes

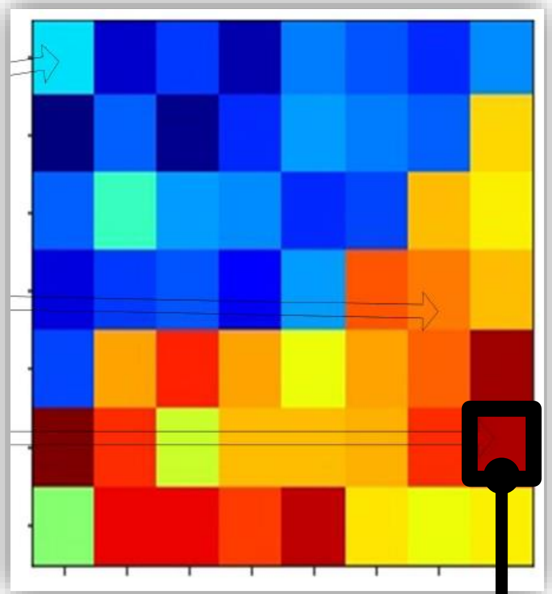
- Pixel Location = [6,8]
- Hour = 1 AM, May 15, 2019
- R = Normalized (LMP)
- G = Normalized (Load)
- B = Normalized (Temperature)
- Pixel Color = [R,G,B]

General Data Structure:
Market Data Pixels, Images, & Videos

Market Data Pixel

- The smallest addressable element of a market data image
- Pixel color is fully determined by the R, G, B color codes
- R, G, B color codes = percentages of red, green, blue colors in a pixel
- Let R, G, B color codes = Normalized heterogeneous market data

➔ Color of market data pixel = *f*(Normalized heterogeneous market data)

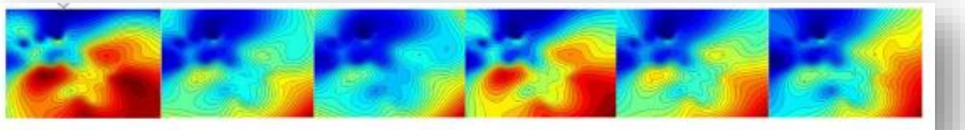


RGB Color Codes

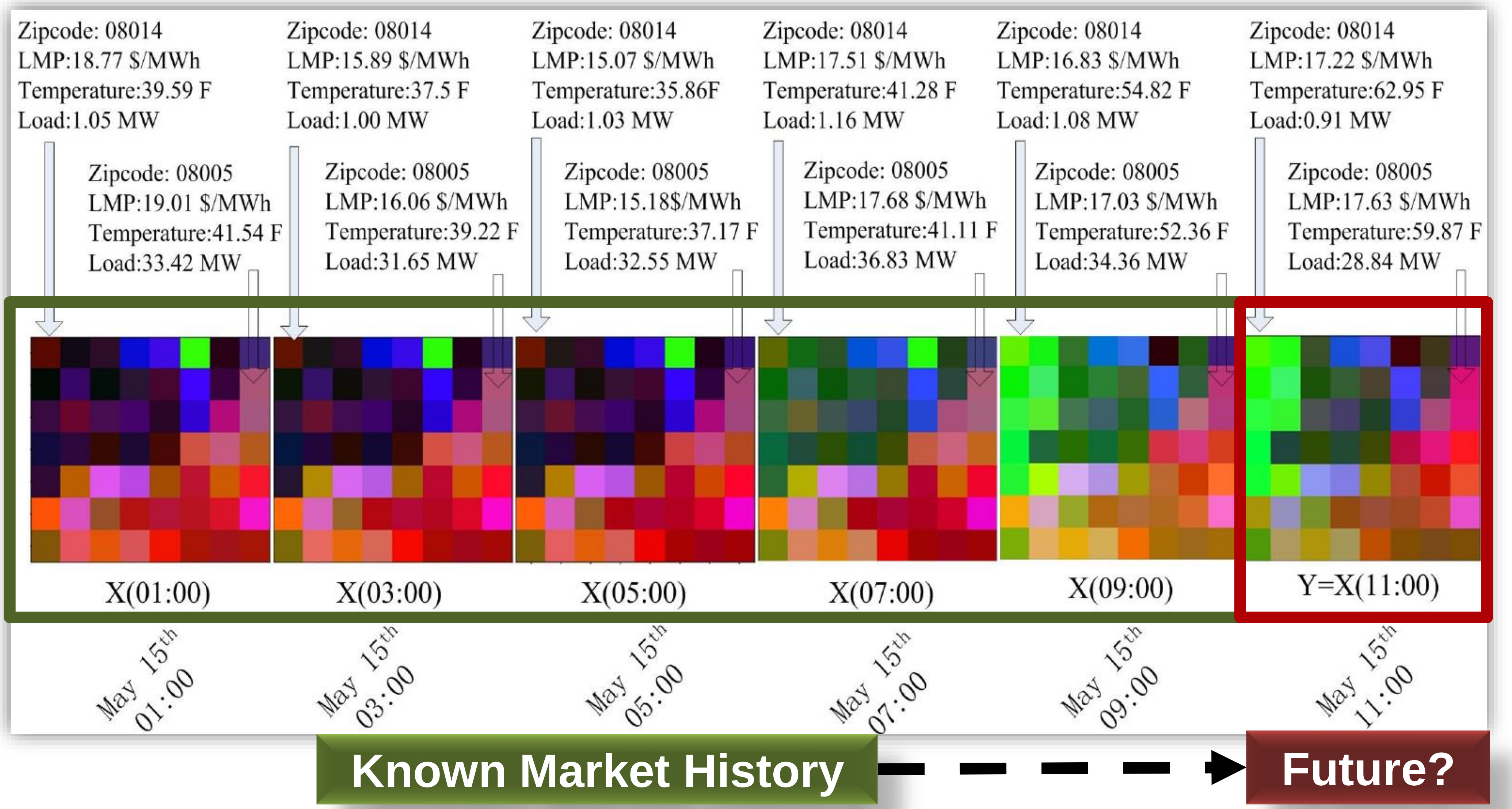
- **Pixel Location = [6,8]**
- **Hour = 1 AM, May 15, 2019**
- **R = Normalized (LMP)**
- **G = Normalized (Load)**
- **B = Normalized (Temperature)**
- **Pixel Color = [R,G,B]**

Market Data Image & Video

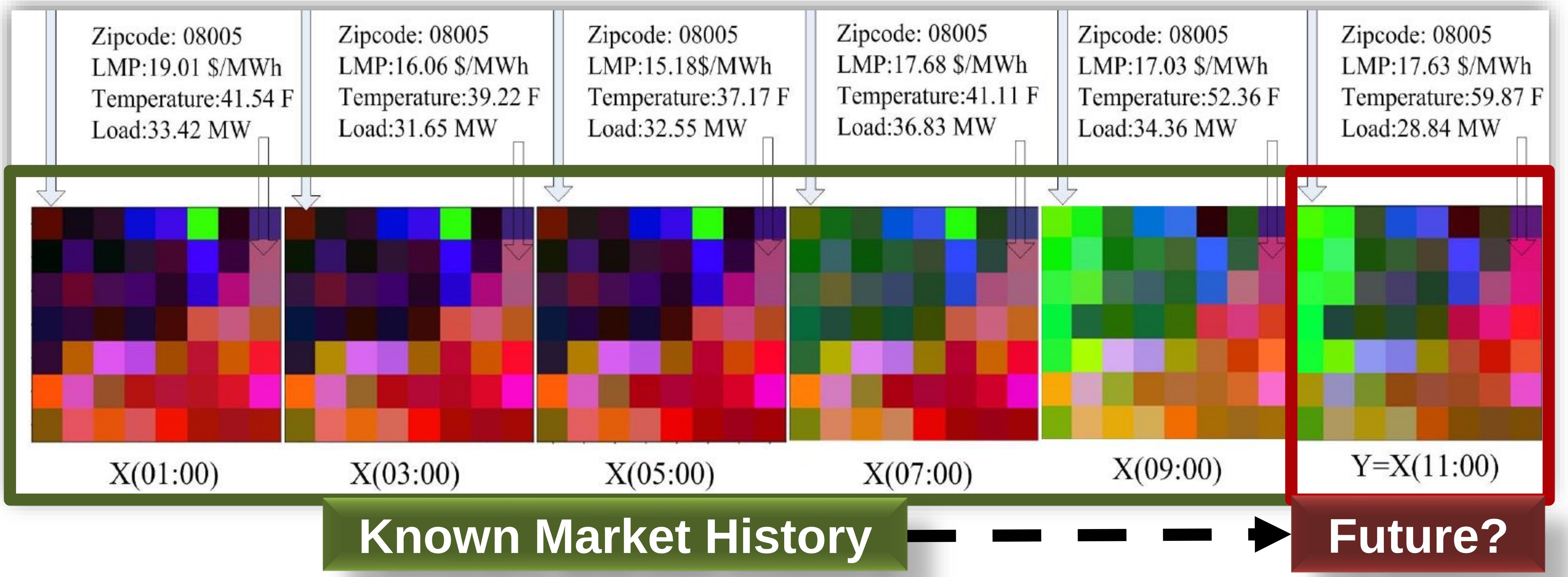
- **[Market Data Image]:** Spatioal variations of market data
- **[Market Data Video]:** Spatio-temporal variations of market data



Market Data Video: An Example (PJM AECO Price Zone, 56 Price Nodes)



Market Data Video: An Example
(PJM AECO Price Zone, 56 Price Nodes)



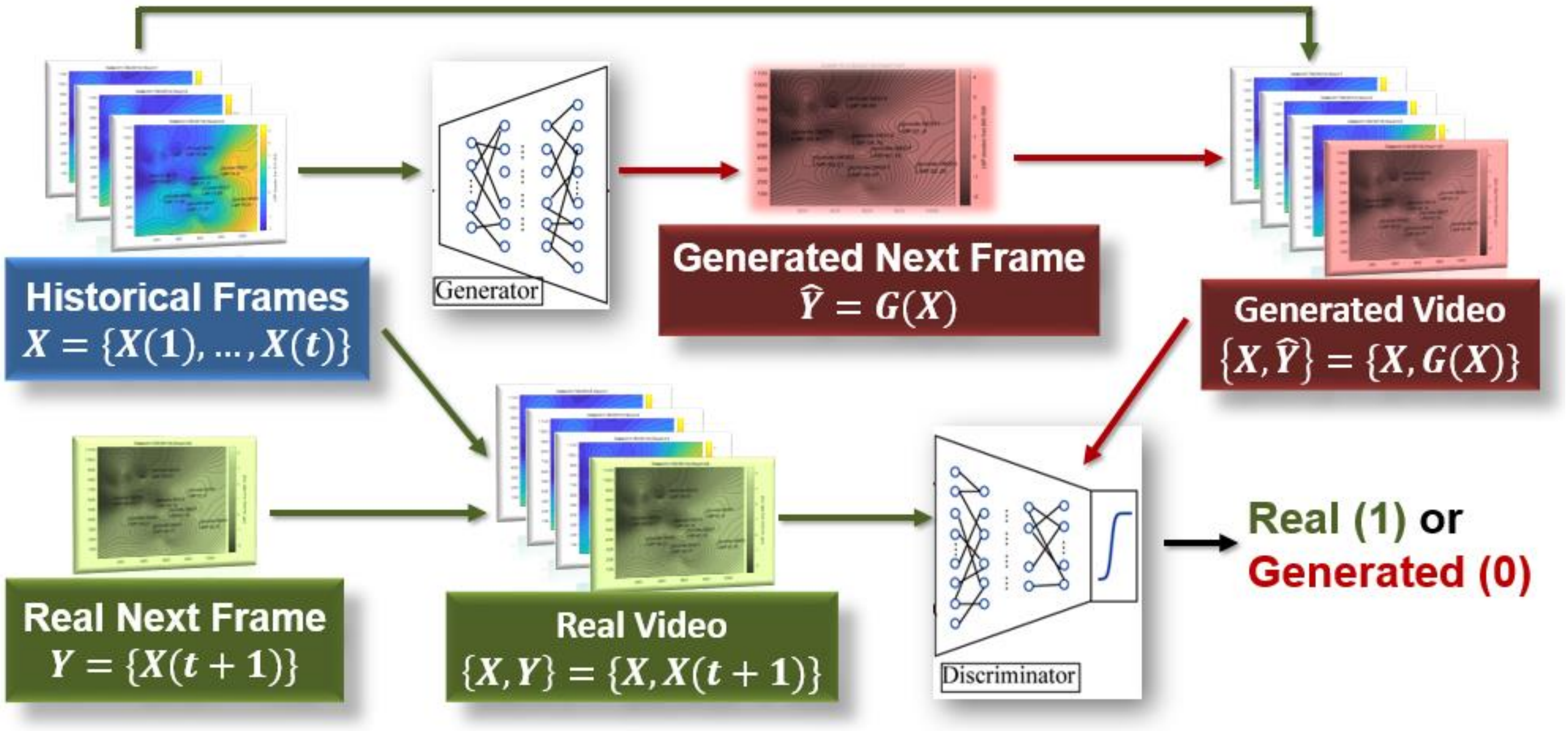
- **Market Data Pixel @ Location** $[i,j]$ **@ Time** t**:** $x_{i,j}(t) = \left[x_{i,j}^{R}(t), x_{i,j}^{G}(t), x_{i,j}^{B}(t)\right] = f(\text{Normalized Market Data})$
- **Market Data Image @ Time** t**:** $M \times N$ **matrix** $X(t) = \left[x_{i,j}(t)\right]$
- **Market Data Video @ Time 1~T : X** $= \{X(1), \ldots, X(t), \ldots, X(T)\}$

Deep Video Prediction for System-Wide LMP Forecasting

❖ **Problem Formulation:** Given the historical market data video $X = \{X(1), \dots, X(t)\}$, generate a future video frame $Y = \hat{X}(t+1)$, s.t. the conditional probability $p(\hat{X}(t+1)|X)$ is maximized.

❖ **Proposed Solution:** Conditional Generative Adversarial Network (GAN) with multiple loss functions.

- Training Procedure: GAN-Based Real-Time LMP Forecasting



Loss Functions: Learning Spatio-Temporal Correlations

Discriminator: A CNN trained by minimizing the following loss (distance) function:

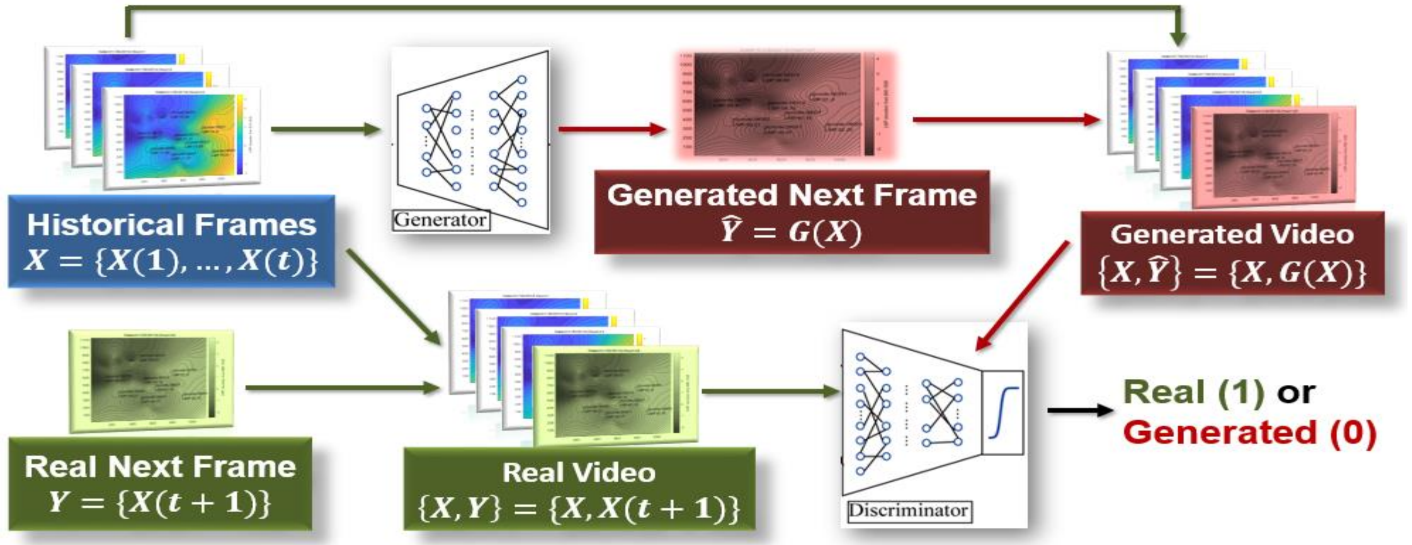
$$\mathcal{L}_{adv}^{D}(X,Y) = \mathcal{L}_{bce}(D(\{X,Y\}),1) + \mathcal{L}_{bce}(D(\{X,\hat{Y}\}),0) \quad (4)$$

where $\mathcal{L}_{bce}$ is the binary cross-entropy:

$$\mathcal{L}_{bce}(K,S) = -\sum_{i}[K_i log(S_i) + (1-K_i) log(1-S_i)] \quad (5)$$

where $K_i \in [0,1]$ and $S_i \in \{0,1\}$.

- **Objective:** Classify input videos $\{X,Y\}$ as real (1) and $\{X,\hat{Y}\}$ as generated/fake (0).
- **Upon Convergence:** Generator produces realistic $\hat{Y}$, s.t. Discriminator cannot classify $\hat{Y}$ as generated/fake.



Loss Functions: Learning Spatio-Temporal Correlations

Generator: A CNN trained by minimizing the following loss (distance) functions:

$$\mathcal{L}^G(X,Y) = \lambda_{adv}\mathcal{L}^G_{adv}(X,Y) + \lambda_{\ell_p}\mathcal{L}_p(X,Y) + \lambda_{gdl}\mathcal{L}_{gdl}(X,Y) + \lambda_{dcl}\mathcal{L}_{dcl}(X,Y)$$

$$\mathcal{L}_p(X,Y) = \ell_p(G(X),Y) = \|G(X) - Y\|_p^p$$

$$\mathcal{L}^G_{adv}(X,Y) = \mathcal{L}_{bce}(D(\{X,G(X)\}),1)$$

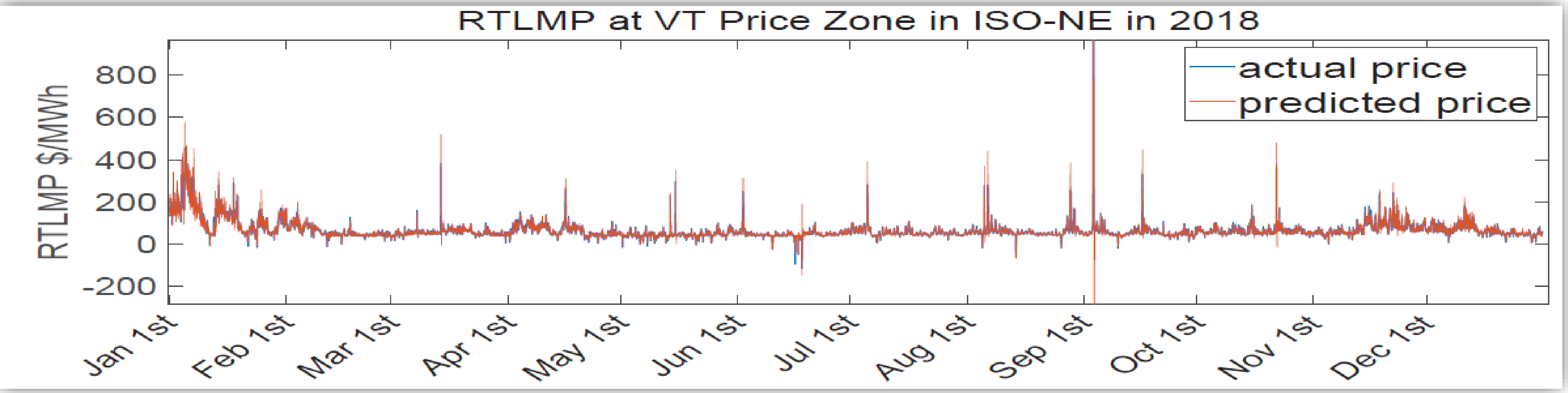
$$\begin{aligned}\mathcal{L}_{gdl}(X,Y) &= \mathcal{L}_{gdl}(\hat{Y},Y)\\ &= \sum_{i,j} \left||Y_{i,j} - Y_{i-1,j}| - |\hat{Y}_{i,j} - \hat{Y}_{i-1,j}|\right|^\alpha \\ &+ \left||Y_{i,j-1} - Y_{i,j}| - |\hat{Y}_{i,j-1} - \hat{Y}_{i,j}|\right|^\alpha\end{aligned}$$

$$\mathcal{L}_{dcl}(X,Y) = \sum_{i,j} |sgn(\hat{Y}_{i,j} - X_{i,j}(t)) - sgn(Y_{i,j} - X_{i,j}(t))|$$

- **Objective**: Generate $\hat{Y} = G(X)$, s.t. the distance b.t. Y and $\hat{Y}$ (quantified by $\mathcal{L}^G(X,Y)$) is minimized.
- $\mathcal{L}_p(X,Y)$: p-norm distance b.t. Y & $\hat{Y}$
- $\mathcal{L}^G_{adv}(X,Y)$: temporal coherency of generated video $\{X,\hat{Y}\} = \{X, X(G)\}$
- $\mathcal{L}_{gdl}(X,Y)$: spatial correlations among market data at neighboring price nodes.
- $\mathcal{L}_{dcl}(X,Y)$: market data changing directions (increment/decrement)

Case Study 1: ISO New England

- **Training Data for Case 1:** Hourly zonal real-time LMPs, day-ahead LMPs, and demands in the entire years of 2016 and 2017 @ 9 price zones of ISO-NE
- **Testing Data for Case 1:** Hourly zonal real-time LMPs in 2018 @ 9 price zones of ISO-NE

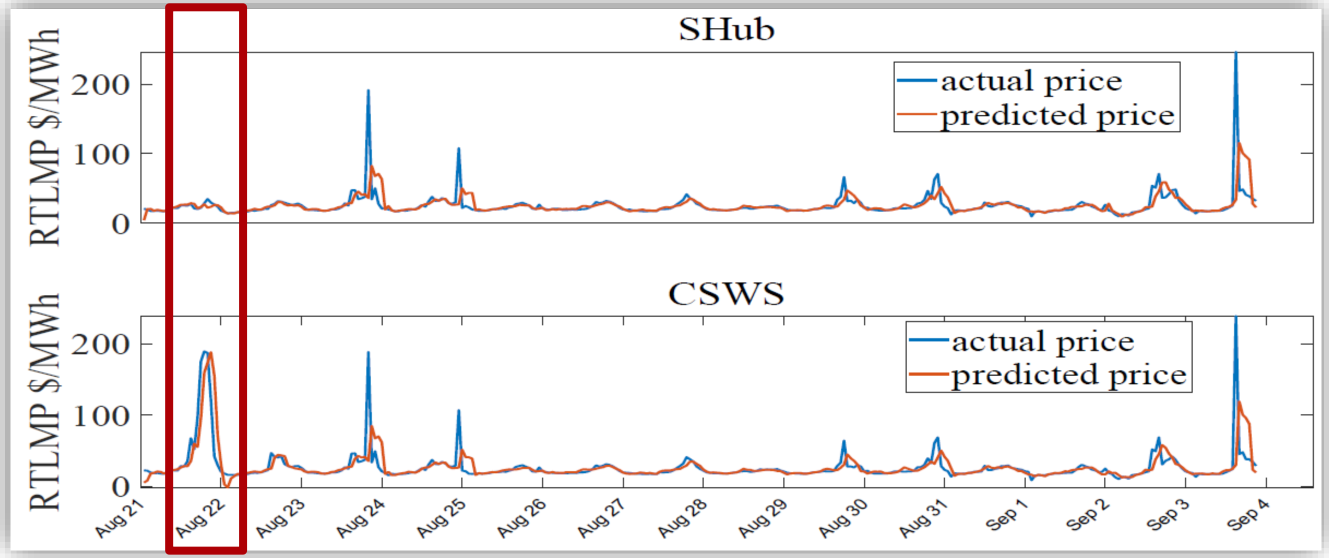


Real-Time LMP Forecasting Error @ 9 Price Zones of ISO-NE

Price Zone	VT	HN	ME	WC MA	Sys-tem	NE MA	CT	RI	SE MA
MAPE (%)	11.03	11.25	11.82	10.99	11.06	11.05	11.04	11.01	11.05

Case Study 2: Southwest Power Pool

- **Training Data for Case 2:** Hourly zonal real-time LMPs, day-ahead LMPs, demands, and generation resource mix data from 6/1/2016 to 7/30/2017
- **Testing Data for Case 2:** Hourly zonal real-time LMPs during 7/31/2017-8/13/2017, 8/21/2017-9/3/2017, 9/18/2017-10/1/2017, 10/2/2017-10/15/2017



Real-Time LMP Forecasting Error @ SHub & NHub Price Zones of SPP

Approach	MAPE (%) for SHub Price Zone	MAPE (%) for NHub Price Zone
ALG+$\hat{M}^1$	25.4	36.9
Genscape^2	21.7	28.2
Case 2	17.7	19.1

1: Best LMP forecasting result with method proposed in [2]
2: Baseline LMP forecasting from commercial predictor Genscape [2]

[2] A. Radovanovic, T. Nesti, and B. Chen, “A holistic approach to forecasting wholesale energy market prices,” IEEE Transactions on Power Systems, pp. 1–1, 2019.

Part III: Conclusions & Future Directions

Conclusions

- **A General Data Structure:** Organizing heterogeneous spatio-temporal electricity market data into market data pixels, images, and videos
- **Real-Time LMP Forecasting:** Formulated as a video prediction problem and solved using conditional GAN with multiple loss functions
- **A General Framework:** Incorporating video/image processing techniques for power system spatio-temporal data analytics

Future Directions

- **Improve LMP Forecasting:** electricity price spike forecasting, market (dc OPF) model/parameters recovery, etc.
- **Other Spatio-temporal data analytics:** Apply the general data structure and video/image processing techniques to other power system spatio-temporal data analytics

Related Publications

[Market + Batteries]: R. Khalilisenobari and M. Wu, "Optimal Participation of Price-Maker Battery Energy Storage Systems in Energy, Reserve and Pay as Performance Regulation Markets," *2019 North American Power Symposium (NAPS)*, Wichita, KS, USA, 2019, pp. 1-6.

[Market + DER Aggregators]: M. Mousavi and M. Wu, "A DSO Framework for Comprehensive Market Participation of DER Aggregators," *2020 IEEE Power & Energy Society General Meeting*, Montreal, Canada, 2020, Accepted.

[Price Forecasting]: Z. Zhang and M. Wu, "Predicting Real-Time Locational Marginal Prices: A GAN-Based Video Prediction Approach," *IEEE Transactions on Power Systems*, Submitted.

Market Participation of Energy Storage and DER Aggregators: Energy Arbitrage, Retail Market Design, and Electricity Price Forecasting

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