Data-Enabled Modern Resource Management: From Risk Management to Socially-aware Solutions

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Presentation Outline

- Introduction
- A Data-Driven Approach for Analysis of Demand Response
- State-of-the-Art Artificial Intelligence for DER Management
- Chance Constrained Distribution System Scheduling
- Conclusions
- Key Notes
- Research Questions

The Midcontinent Independent System Operator (MISO) defined 3 Ds for the future grid:



Midcontinent Independent System Operator, MISO forward, March 2019.

There are, in fact, 5 Ds:



Distributed Energy Resources

- Increasing penetration level of DERs:
 - Renewables: Global movement towards clean, affordable, and sustainable energy
 - Energy democracy move: A person's desire to possess his or her own energy system

Energy democracy move is increasing the DER penetration level despite economies of scales for bulk generation.

Distributed Energy Resources

The key question is NOT: why move to a DER based system?



THE TRAIN HAS LEFT THE STATION!



The key question is: how to do it in a way that will continue to provide reliable service at affordable prices?



How to leverage DERs?

The potential of collective participation of prosumers has yet to be thoroughly achieved. Its pursuit is nontrivial as *the reliability, guarantees, and quality of grid services by end-users are not well understood and are more difficult to quantify than through conventional bulk generators.*

Disruptive opportunities are achievable when engineering solutions encapsulate the dynamic characteristics of prosumers via sociallyaware and risk-aware methods.

Existing challenges

• The existing strategy to manage the challenges of bulk renewables and DERs: more infrastructure and conventional generators.



In May 2019, CAISO curtailed 225GWh of solar and wind energy

How to leverage DERs?

Benefits of DERs for grid services (both energy and ancillary services):

- Prime location:
 - Infrastructure deferrals
 - Flexibility closest to demand

- Diversity in characteristics, capability, probability of defaulting on obligation, flexibility, geographical location
- Often seen as a hindrance
- But diversity is key to hedging when managing a system with stochastic resources

Design of operational plans to include DERs

- Expanded ISO/RTO to the distribution level
 - Not enough visibility
 - Computationally infeasible

• DERs aggregation through DSO and third party aggregators

- Scheduling, reliability, and retail settlements handled at DSO
 - Distribution markets
 - Trading platforms for peer to peer transactions

DER aggregation

• Aggregation has been discussed as a holistic approach to get rid of all complexities: large number of small resources, controllability, and scheduling



Indiscriminate aggregation makes the prediction of aggregated net load non-trivial.

Hawaiian Electric Company, Seams for Shines, Shines Program Review, SunShot Program, US Department of Energy, Feb. 2017. [Online]. Available: https://www.energy.gov/sites/prod/files/2017/05/f34/SHINES%20Program%20Review_HECO.pdf.

Energy as a technological, economical, and social phenomenon

- Social science research shows that energy is not merely a technological and economical phenomenon but is deeply embedded within social, geopolitical landscapes
- It is critical to account for social aspect of energy in design and operation of smart grids. Examples:
 - DER adoption
 - Different rate of EV adoption and use; higher trends in particular neighborhoods
 - Demand response participation
 - Distribution system upgrades
 - Uncertainty of participation in smart grid operation

[1] C.A. Miller, A. Iles, and C. F. Jones, "The social dimensions of energy transitions," *Science as Culture*, vol. 22, no. 2, pp.135-48, May 2013.

[2] T. Skjolsvold, M. Ryghaug, and T. Berker, "A traveler's guide to smart grids and the social sciences," Energy Res. Social Sci., vol. 9, pp. 1-8, Sep. 2015.

[3] K.S. Zimmerer, "New geographies of energy: Introduction to the special issue," Annals of the Association of American Geographers, vol. 101, no. 4, pp. 705-711, May 2011.

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Design of socially-aware solutions

- Analysis of customers' behavior has been classified to the domain of behavioral economics in research communities.
- Recent advances in AI algorithms empower characterizing prosumers' behaviors to enable design of socially-aware engineering solutions without modeling the behavior itself.

Advanced artificial intelligence algorithms, which account for demographic characteristics of prosumers, are required to enable accurate classification, aggregation, prediction, and uncertainty characterization of prosumers and their DERs.

A Data-Driven Approach for Analysis of Demand Response

Smart meter data study

- Data from an electric utility:
- Over 15,000 customers
- Demographic data includes income, household size, dwelling, start date of price plan, home ownership and family composition (e.g., age, marital status, children)
- Consumption, solar production, and DR
- 15-minute to 1-hour intervals for 1-2 years.
- Two Time-of-Use Plans:

DR Programs	On-Peak Time	On-Peak Price (\$/kWh)	Off-Peak Price (\$/kWh)	No. of Customers
E21 (Jul Aug)	3 - 6 p.m.	0.3588	0.0864	1776
E21 (May Jun Sep Oct)	3 - 6 p.m.	0.3033	0.084	1776
E26 (Jul Aug)	1 - 8 p.m.	0.2226	0.0741	1974
E26 (May Jun Sep Oct)	1 - 8 p.m.	0.1957	0.0738	1974

• Note: E21 has shorter on-peak period, more expensive on-peak price, and larger difference between on-peak and off-peak prices.

Conducted analysis



Predicted Consumption Baseline and Measured Data Comparision



Machine Learning algorithms

Three well-established machine learning algorithms are utilized to obtain customers' consumption baseline.

- Artificial Neural Network (ANN)
- K Nearest Neighbors (KNN)
- Ridge Regression (RR)

Evaluation Metrics:

$$R^{2} = 1 - \frac{\sum_{i} (y_{i}^{true} - y_{i}^{predict})^{2}}{\sum_{i} (y_{i}^{true} - y_{i}^{mean})^{2}} \qquad RMSE = \sqrt{\frac{\sum_{i=1}^{T} (y_{i}^{true} - y_{i}^{predict})}{T}}{T}$$
Coefficient of determination
$$Root-mean-square\ error$$

Artificial Neural Network



- A strong ability to fit into highly nonlinear functions
- Use Backpropagation to train the model
- Activation function: ReLu
- Number of layers: 3 hidden layers
- 85% Training set and 15% Testing set

K-nearest Neighbors

- Non-parametric method
- Uses k data points that are closest to the new data to predict the response
- Number of neighbors: 3
- Distance metric: Euclidean distance
- 85% Training set and 15% Testing set



Ridge Regression

This ML algorithm solves a regression model where the loss function is the linear least squares function and regularization is given by the l2-norm.



Consumption baseline

Trained model performances for testing samples.

Metrics	Number of Customers	ANN	KNN	RR
R2	30	0.943	0.932	0.948
RMSE (kW)	30	7.26	7.9	6.88
R2	50	0.959	0.944	0.962
RMSE (kW)	50	10	11.7	9.64
R2	100	0.982	0.974	0.983
RMSE (kW)	100	14.33	17	13.96

Accuracy of baseline load prediction model is high. The customers' consumption baselines predicted by these trained models are considered as their true baseline load in this study.

Trained model performances



On-peak load reduction



E21 price plan:

Clear load reduction and load shifting effect

E26 price plan:

On-peak hours: 1 p.m. to 8 p.m. from Summer Peak: On-peak: \$0.2226/kWh; Off-peak: \$0.0741/kWh



Long on-peak period and smaller price gap.

On-peak consumption reductions (E21)



On-peak load reduction

E21:

E26:



• Each point represents 15-min load reduction for the specified group.

Emergency Demand Response

- We received the dataset contains the customers who participate in emergency demand response (EDR) program.
- Nest thermostat
- Maximum of 15 EDR per year
- The electric utility pre-cools the customers' house one hour in advance.
- Customers have the right to readjust their air-conditioner setting during the event.

Emergency Demand Response

Here is an example showing the consumption baseline and actual consumption in the DR event day, Jun/22/2018.



Emergency Demand Response

• Average percentage load reduction results for each income level and the number of occupants



Uncertainty characteristics



- These differences will be more severe when other smart grid technologies are integrated.
- If methods indiscriminately aggregate prosumers and use the same uncertainty model for all, then they fail to accurately capture prosumer behavior and response. ₂₉

State-of-the-Art Artificial Intelligence for DER Management

Necessity of advanced AI techniques

- Machine learning (ML) algorithms are helpful for a wide range of tasks.
 Black-box ML algorithms can make predictions; however, it is still critical to interpret the predictions.
- What if a different ML algorithm is applied? What if data from a different source is used? What if the data did not cover sufficient types of a particular behavior?
 Seen Context

 Observed Data

 Uncertainty Low

Unseen Context → Unseen Data → Uncertainty?

- Causal inference is defined with three levels: association, intervention, and counterfactuals.
- At the lowest level, no association implies no causation; consequently, association is the foundation for classical ML methods that learn basically association from data. Association methods may be useful; however, they are often inadequate and unreliable when correlations are spurious.
- Advanced AI algorithms are needed to capture prosumers' behavior.

Causal Learning for DER management

$$\begin{array}{c} p: \operatorname{Price} & b: \operatorname{Base \ consumption} \\ \hline n: \operatorname{No. \ of \ people} & r: \operatorname{Regular} \\ consumptions (e.g., \\ cooking, laundry) \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ conditioning} \\ \hline d: \operatorname{Day \ of \ week} & a: \operatorname{Air \ of \ week} \\ \hline d: \operatorname{$$

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Chance Constrained Distribution System Scheduling

Optimal scheduling of distribution systems: Bid-risk-dispatch model

Objective: Design an innovative operational paradigm that leverages the full flexibility of DERs while accounting for risk due to stochastic resources.

Optimal scheduling of distribution systems: Bid-risk-dispatch model

- Without adequate representation of uncertain factors, risk-driven models may fail if the realized scenario were not among the modeled uncertainty.
- The majority of risk driven methods in power system literature are dedicated to the bulk system. For distribution systems, there are many other complicating factors (multi-phase, unbalanced, mutual coupling).
- Prior work often considers uniform uncertainty characteristics for all resources. <u>The proposed model accounts for varying uncertainty across prosumer groups</u> <u>and operational time periods.</u>

ACOPF with Second Order Cone Programming

$$Min: \sum_{\forall t} \left[C_t^M (P_{M,t}, Q_{M,t}, R_{M,t}) + \sum_{\forall rg} (C_{rg}^{U_REN} (P_{rg,t}^{U_REN}, Q_{rg,t}^{U_REN}, R_{rg,t}^{U_REN})) + \sum_{\forall der} (C_{der}^{DER} (P_{der,t}^{DER}, Q_{der,t}^{DER}, R_{der,t}^{DER})) + \sum_{\forall der} (C_{ev}^{EV} (P_{ev,t}^{EV}, Q_{ev,t}^{EV}, R_{ev,t}^{EV})) + \sum_{\forall bess} (C_{bess}^{BESS} (P_{bess,t}^{BESS}, Q_{bess,t}^{BESS}, R_{bess,t}^{BESS})) \right]$$

 $g(P_{M,t}, P_{rg,t}^{U_REN}, P_{der,t}^{DER}, P_{ev,t}^{EV}, P_{bess,t}^{BESS}, Q_{M,t}, Q_{rg,t,c}^{U_REN}, Q_{der,t}^{DER}, Q_{ev,t}^{EV}, Q_{bess,t}^{BESS}) = 0$ $h(P_{M,t}, P_{rg,t}^{U_REN}, P_{der,t}^{DER}, P_{ev,t}^{EV}, P_{bess,t}^{BESS}, Q_{M,t}, Q_{rg,t,c}^{U_REN}, Q_{der,t}^{DER}, Q_{ev,t}^{EV}, Q_{bess,t}^{BESS}) \ge 0$

Second Order Cone Programming:

$$\begin{aligned} R_{nj,x\phi,t} &= V_{n,x,t} V_{j,\phi,t} \cos(\theta_{n,x,t} - \theta_{j,\phi,t}), \qquad I_{nj,x\phi,t} = V_{n,x,t} V_{j,\phi,t} \sin(\theta_{n,x,t} - \theta_{j,\phi,t}), \qquad U_{n,x,t} = \frac{V_{n,x,t}^{2}}{\sqrt{2}} \\ P_{n,x,t}^{j} &= \sqrt{2} U_{n,x,t} G_{nj,xx} + \sum_{\substack{\phi=a \\ \phi \neq x}}^{c} R_{nn,x\phi,t} G_{nj,x\phi} + I_{nn,x\phi,t} B_{nj,x\phi} + \sum_{\substack{\phi=a \\ \phi \neq x}}^{c} -R_{nj,x\phi,t} G_{nj,x\phi} - I_{nj,x\phi,t} B_{nj,x\phi} \\ Q_{n,x,t}^{j} &= -\sqrt{2} U_{n,x,t} B_{nj,xx} + \sum_{\substack{\phi=a \\ \phi \neq x}}^{c} I_{nn,x\phi,t} G_{nj,x\phi} - R_{nn,x\phi,t} B_{nj,x\phi} + \sum_{\substack{\phi=a \\ \phi \neq x}}^{c} -I_{nj,x\phi,t} G_{nj,x\phi} + R_{nj,x\phi,t} B_{nj,x\phi} \\ 2U_{n,x,t} U_{j,\phi,t} \geq R_{nj,x\phi,t}^{2} + I_{nj,x\phi,t}^{2} \end{aligned}$$

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Chance constrained distribution system scheduling

$$P(V_{n,\min} \le |\tilde{V}_{n,t}| \le V_{n,\max}) \ge 1 - \varepsilon$$

$$P\left(\sqrt{(\tilde{P}_{n,t}^{j})^{2} + (\tilde{Q}_{n,t}^{j})^{2}} \le S_{n,j}^{max}\right) \ge 1 - \varepsilon$$

$$P(S_{M,t} - R_{M,t} \le \tilde{S}_{M,t} \le S_{M,t} + R_{M,t}) \ge 1 - \varepsilon$$

$$\begin{split} &\sum_{\forall rg} P_{rg,t}^{U_REN} + \sum_{\forall der} P_{der,t}^{DER} + \sum_{\forall ev} P_{ev,t}^{EV} \leq DNE\% \sum_{\forall l} P_{l,t}^{L} \\ &\sum_{\forall rg} Q_{rg,t}^{U_REN} + \sum_{\forall dr} Q_{der,t}^{DER} + \sum_{\forall ev} Q_{ev,t}^{EV} \leq DNE\% \sum_{\forall l} Q_{l,t}^{L} \end{split}$$

DNE: Do Not Exceed Limit

Chance constrained distribution system scheduling

Chance constrained distribution system scheduling: DR and PV uncertainty

- IEEE 33-bus system
- 9 solar PV units: various types of active and reactive power controllability settings
- Beta distribution for PV uncertainty
- Demographically diverse prosumers:

No. of Prosumer Groups	Income Level	No. of Occupants	Child	Average demand response (%)	Corresponding Variance
3	High	1-2	No	22.55	5.28
5	High	3-5	Yes	28.49	4.72
4	Low	1-2	No	11.34	7.26
4	High	3-5	Yes	3.92	6.81
1	Medium	1-2	No	0.99	8.12

Chance constrained distribution system scheduling: DR uncertainty

Operational scheduling: DR and PV uncertainty

 $P(\tilde{P}_{M,t} \leq \text{Compensated Power from Transmission System Threshold}) \geq 95\%$

Socially-aware aggregation, prediction, and uncertainty modeling

Compensated Power Threshold (kW)	Proportion of dispatched active power of DERs (%)	Proportion of dispatched reactive power of DERs (%)
100	20%	23%
200	29%	33%
300	66%	76%
400	82%	95%
500	84%	97%
600	84%	97%

Indiscriminate aggregation, prediction, and uncertainty modeling

Compensated Power Threshold (kW)	Proportion of dispatched active power of DERs (%)	Proportion of dispatched reactive power of DERs (%)
100	15%	17%
200	20%	23%
300	24%	28%
400	31%	36%
500	36%	42%
600	41%	47%

Operational scheduling: DR and PV uncertainty

$P(\tilde{P}_{M,t} \leq 300) \geq Probablity of violation\%$

Socially-aware aggregation, prediction, and uncertainty modeling

Probability of	Proportion of dispatched active	Proportion of dispatched
violation (ε) (%)	power of DERs	reactive power of
	(%)	DERs (%)
1	32%	37%
3	36%	42%
5	66%	76%
7	68%	79%
9	71%	82%
11	73%	84%

Indiscriminate aggregation, prediction, and uncertainty modeling

Probability of violation (ε) (%)	Proportion of dispatched active power of DERs (%)	Proportion of dispatched reactive power of DERs (%)
1	16%	18%
3	19%	22%
5	24%	28%
7	27%	31%
9	30%	35%
11	31%	36%

Chance constrained distribution system scheduling: DR uncertainty

- IEEE 33-bus system
- 9 solar PV units: various types of active and reactive power controllability settings
- No PV uncertainty
- Demographically diverse prosumers:

No. of Prosumers Groups	Income Level	No. of Occupants	Child	Average demand response (%)	Corresponding Variance
3	High	1-2	No	22.55	5.28
5	High	3-5	Yes	28.49	4.72
4	Low	1-2	No	11.34	7.26
4	High	3-5	Yes	3.92	6.81
1	Medium	1-2	No	0.99	8.12

Operational scheduling: DR uncertainty

 $P(\tilde{P}_{M,t} \leq \text{Compensated Power from Transmission System Threshold}) \geq 95\%$

Socially-aware aggregation, prediction, and uncertainty modeling

Compensated Power Threshold (kW)	Proportion of dispatched active power of DERs (%)	Proportion of dispatched reactive power of DERs (%)
100	26%	30%
200	36%	42%
300	83%	96%
400	84%	97%
500	84%	97%
600	84%	97%

Indiscriminate aggregation, prediction, and uncertainty modeling

Compensated Power Threshold (kW)	Proportion of dispatched active power of DERs (%)	Proportion of dispatched reactive power of DERs (%)
100	20%	23%
200	27%	31%
300	32%	37%
400	37%	43%
500	42%	48%
600	45%	52%

Operational scheduling: DR uncertainty

$P(\tilde{P}_{M,t} \le 300) \ge (1 - \varepsilon)\%$

Socially-aware aggregation, prediction, and uncertainty modeling

Probability of violation (ε) (%)	Proportion of dispatched active power of DERs (%)	Proportion of dispatched reactive power of DERs (%)
1	70%	81%
3	72%	83%
5	83%	96%
7	84%	97%
9	84%	97%
11	84%	97%

Indiscriminate aggregation, prediction, and uncertainty modeling

	Proportion of	Proportion of
Probability of	dispatched active	dispatched
violation (ϵ) (%)	power of DERs	reactive power of
	(%)	DERs (%)
1	27%	31%
3	29%	33%
5	32%	37%
7	34%	39%
9	35%	40%
11	36%	42%

Conclusions

- With increasing penetration level of DERs, socially-aware engineering solutions can improve smart grid design and operations.
- Recent advancements in Artificial Intelligence empower characterizing prosumers' behaviors to enable design of socially-aware engineering solutions without modeling the behavior itself.
- Advanced artificial intelligence (AI) algorithms, which account for demographic characteristics of prosumers, are required to enable accurate classification, aggregation, prediction, and uncertainty characterization of prosumers and their DERs.
- Risk-aware and socially-aware operational solutions can enable efficient utilization of DERs.

Key Notes

• In the era of energy democracy, it is critical to consider the interplay of social, behavioral, technological, and engineering aspects, while designing smart grid solutions.

• This is essential for the existing system to the transition period and to the future grid.

Research Questions

- How to design operational protocols to enable efficient use of DERs while accounting for risk?
- How can we aggregate prosumers in a way to enable efficient prediction and utilization of DERs?
- How will this help with the design of distribution markets?
- What is a good approach for risk-aware scheduling?

Questions?

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