Understand Behind-the-meter Resources

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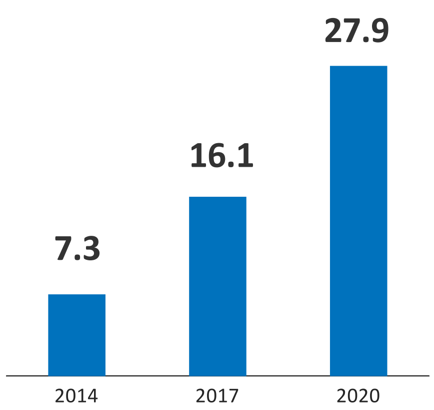
New Challenges on Load Forecasting

Rapid Growth of Behind-the-Meter (BTM) Assets and Huge Potentials

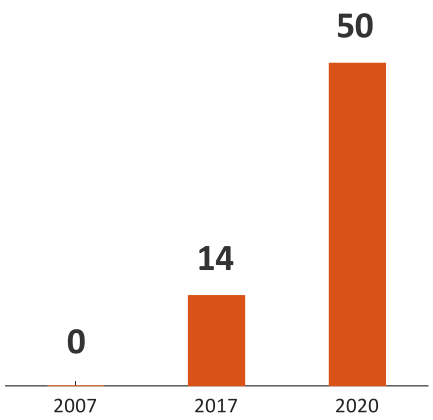
BTM PV
U.S. capacity, GW



Source: Energy Information Administration, 2020

20% annual growth

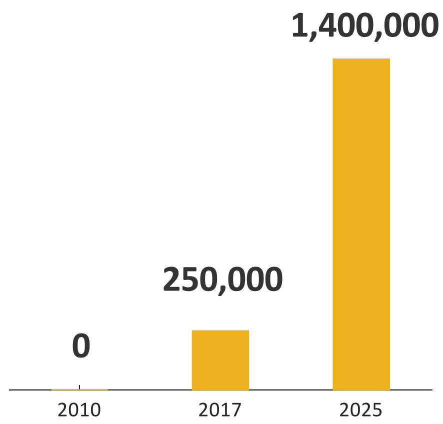
Smart Appliances
U.S. homes, millions



Source: Estimation by Brattle, 2019

53% annual growth

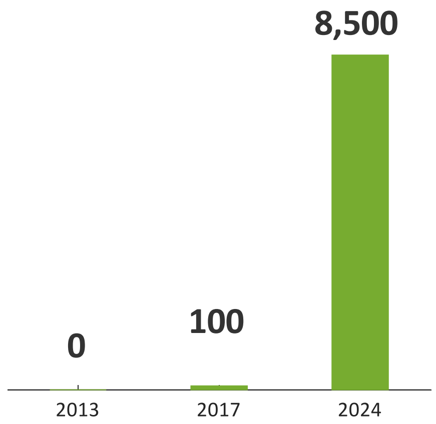
Electric Vehicles
U.S. annual sales



Source: Edison Electric Institute and Institute for Energy Innovation, 2018

24% annual growth

BTM Storage
U.S. capacity, MW



Source: Estimated from Wood Mackenzie and Energy Storage Association, 2019

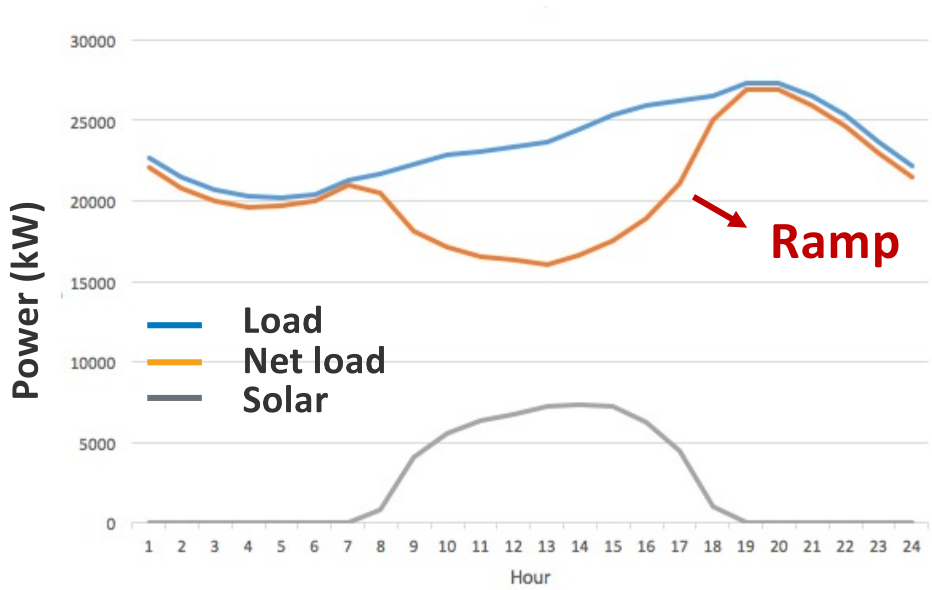
89% annual growth

200 GW (20% peak load) flexibility potential in U.S. by 2030 [1]

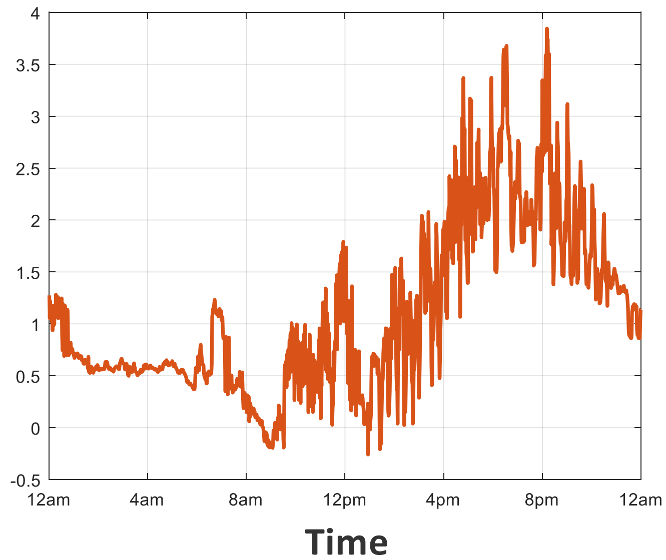
[1] R. Hledik, A. Faruqui, T. Lee, and J. Higham, "The National Potential for Load Flexibility: Value and market potential through 2030," The Brattle Group, 2019.

Changing Load Patterns

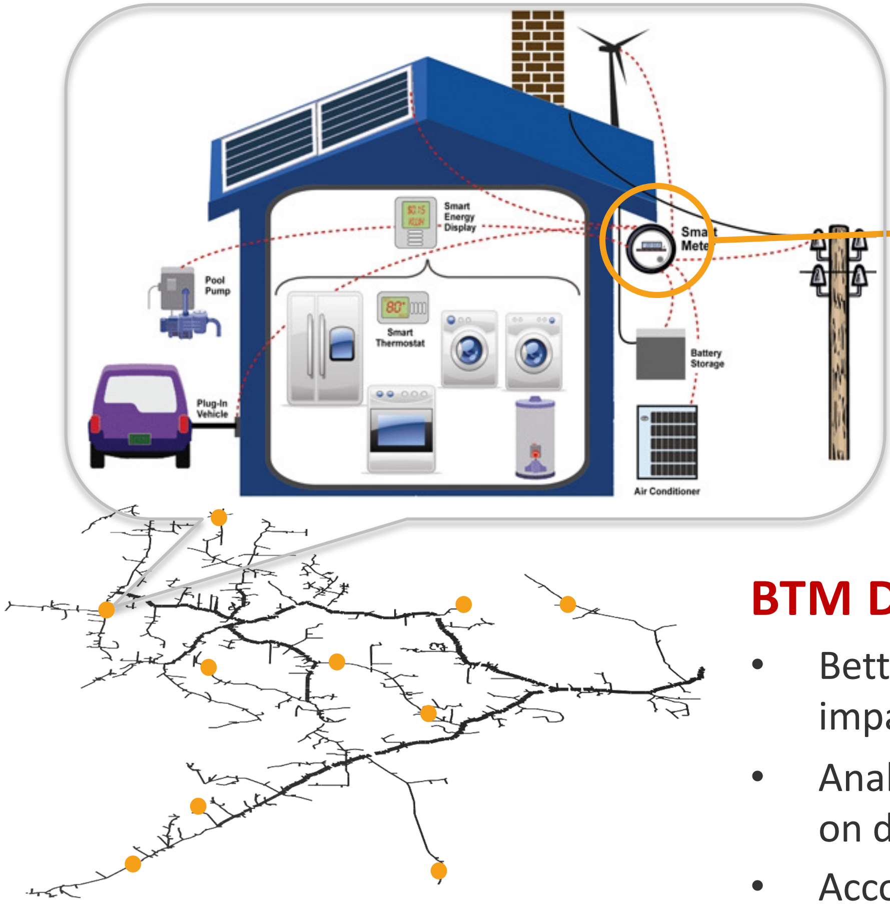
Net-Load Shapes



Volatility and Uncertainty

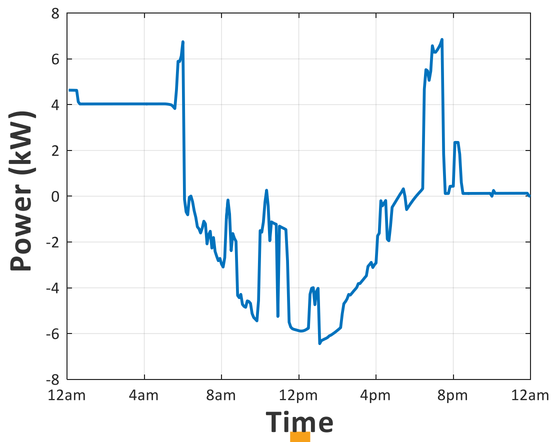


Visibility of BTM DERs

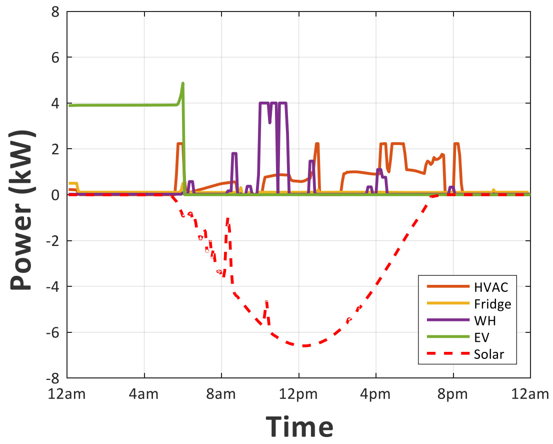


Smart Meter

Whole House Power Consumption



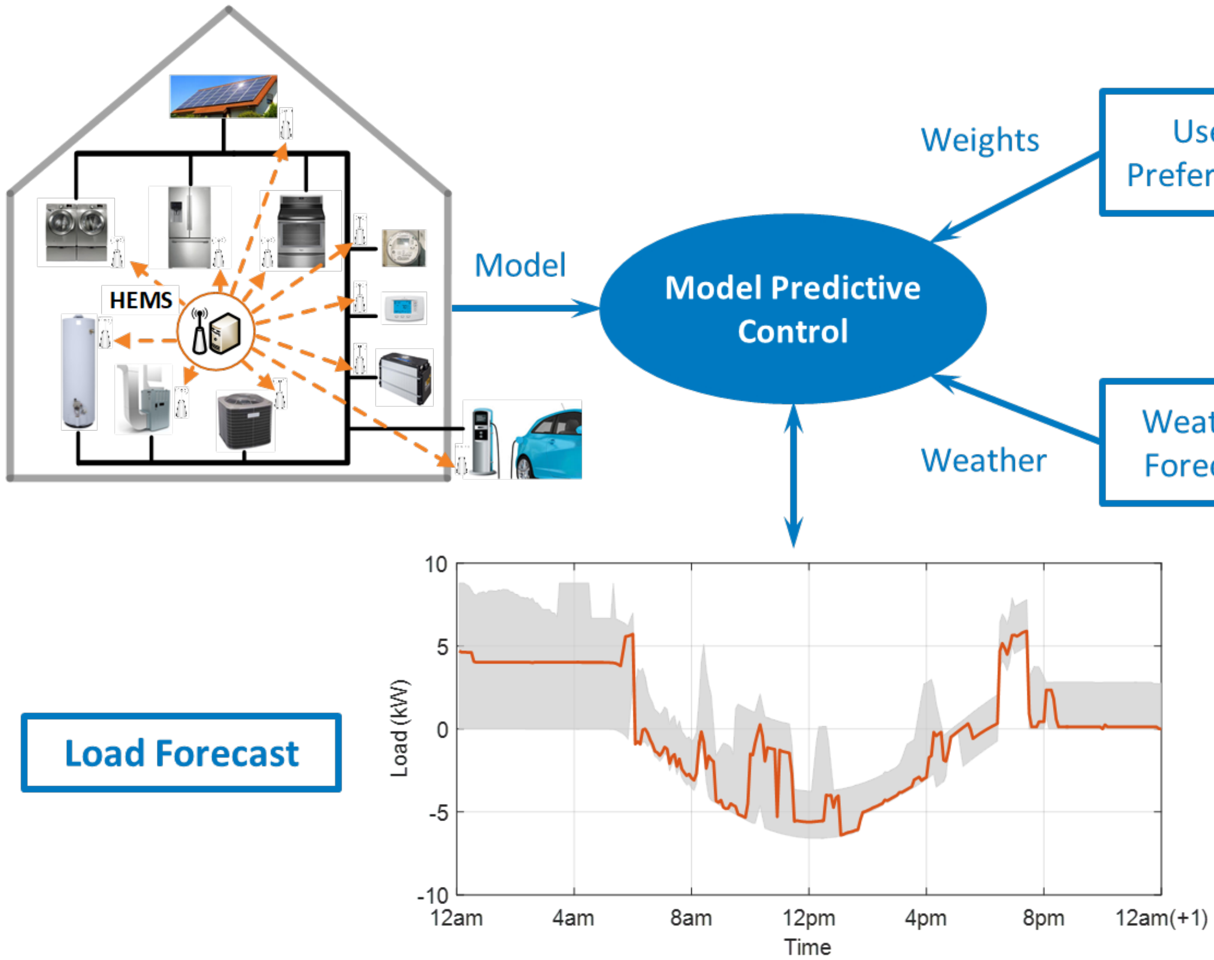
Asset Consumption/Generation



BTM DER Visibility

- Better quantify the impact on net load
- Analyze impact of DERs on distribution systems
- Accommodate DER integration

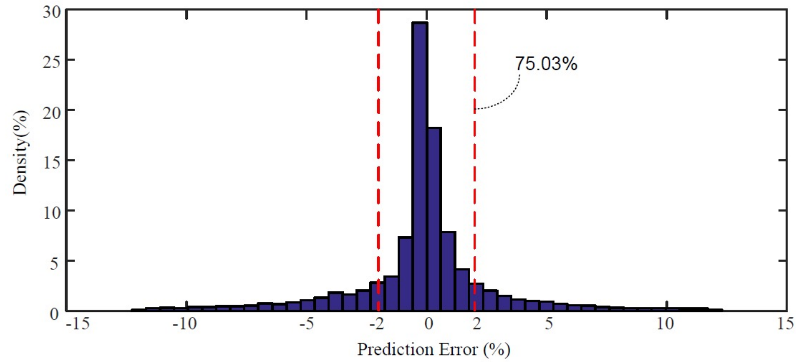
Model-Based Load Forecasting



- **Model-based load forecasting**
  - Model predictive control
  - Weather forecasts as input
  - Load consumption and flexibility forecasting
- **Home energy management system**
  - Real-time control of appliances
  - Improve energy efficiency
  - Reduce energy cost

Data-Driven Forecasting

- Motivation
  - Load profiles close to end users have more abrupt variations
- Approach [2]
  - Support vector regression
  - Two-step hybrid parameters optimization
- Simulation Results
  - 80 days of load captured from a partner utility's distribution feeder



Minutes-ahead Forecasting

Methods	Max. Error (%)	MAPE (%)
ARIMA	31.25	11.21
GA based SVM	21.16	5.27
ANN	25.97	6.62
Proposed	14.11	2.53

Performance Comparison

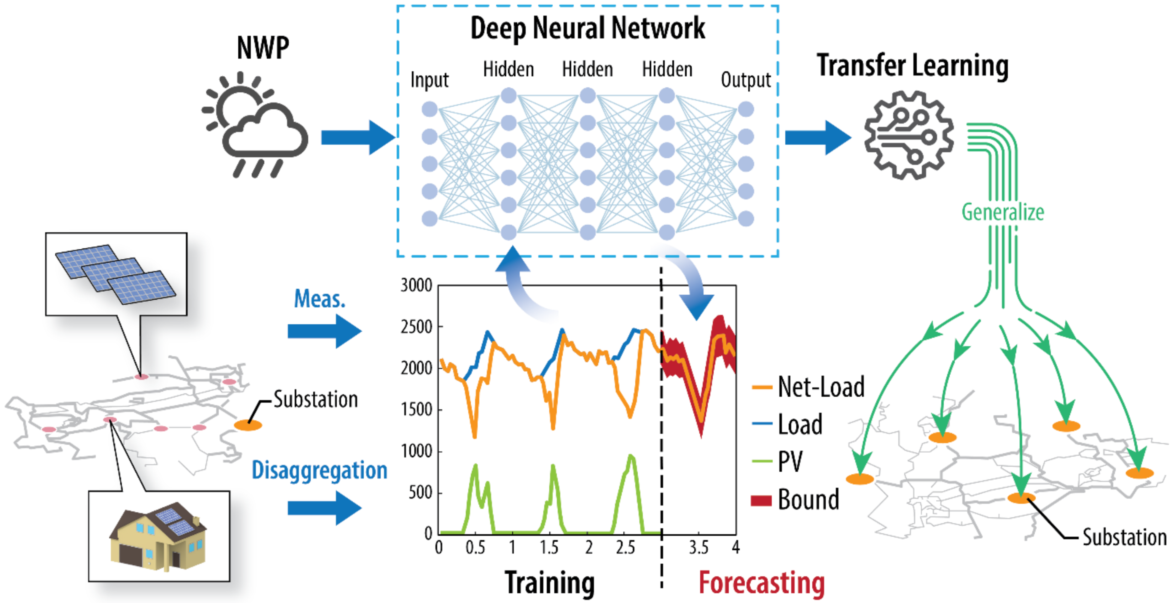
Methods	20 minutes (S)	4 hours (S)
ARIMA	11.25	77.21
GA based SVM	45.16	1412.7
ANN	40.9	683.62
Proposed	12.89	83.53

Time Consumption Comparison

[2] H. Jiang, Y. Zhang, E. Muljadi, J. J. Zhang, and D. W. Gao, "A Short-Term and High-Resolution Distribution System Load Forecasting Approach Using Support Vector Regression With Hybrid Parameters Optimization," IEEE Transactions on Smart Grid, vol. 9, no. 4, July 2018.

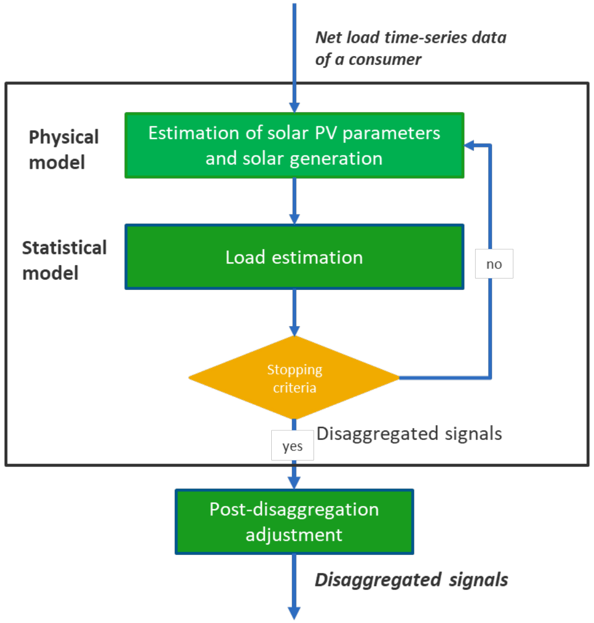
Deep Learning with BTM PV Visibility

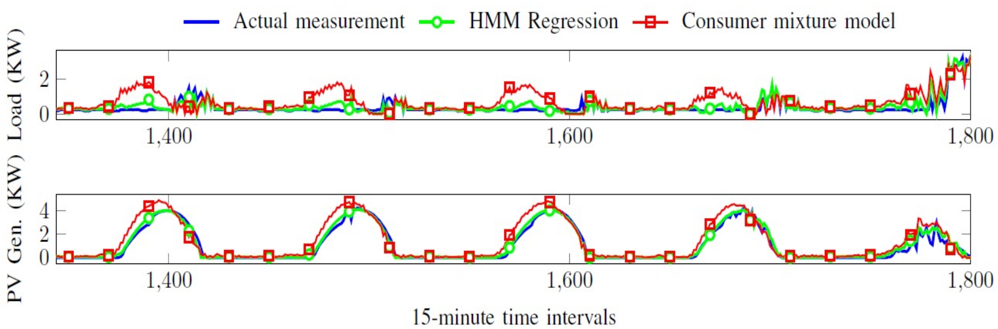
- Probabilistic net-load forecasting with BTM PV disaggregation
  - Visibility into the BTM PV systems through disaggregation
  - Point and probabilistic forecasting through deep learning
  - Transfer learning to ensure generalization to diverse locations with different sensor data availability



Estimation of BTM PV

- **Key innovation: Physical + statistical models**
- Estimation of solar generation (S)
  - Estimation of solar PV parameters θ_S
  - Physical PV system performance model g
- Estimation of load (L)
  - Statistical hidden Markov model regression
  - Variables: hour of the day, temperature, weekday/weekend
- Iterative method [3]





[3] F. Kabir, N. Yu, W. Yao, R. Yang, and Y. Zhang, "Estimation of Behind-the-Meter Solar Generation by Integrating Physical with Statistical Model," *IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids*, Beijing, China, Nov. 2019.

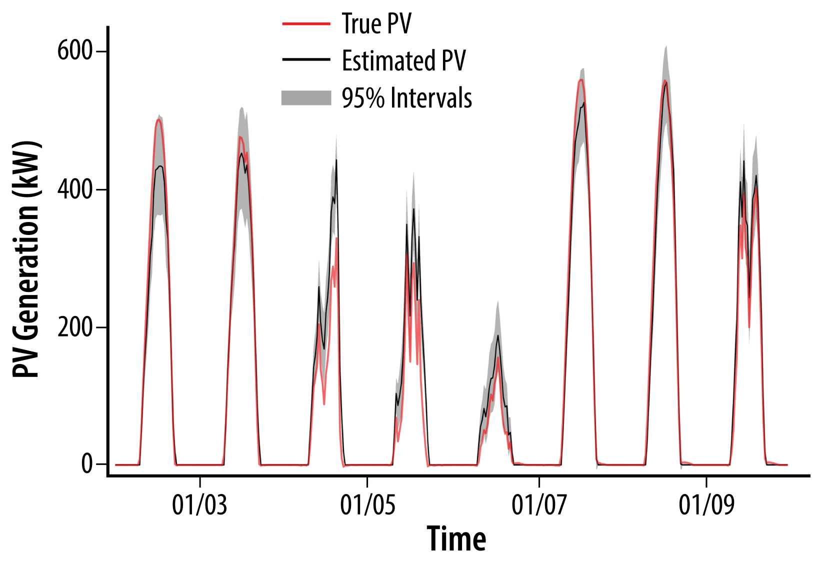
Probabilistic Estimation of BTM PV

- **Key innovation: Probabilistic estimation with uncertainty quantification**
- Method: Bayesian structural time series (BSTS) model [4]
- Model:

$$\boldsymbol{y}_t = \boldsymbol{Z}_t(\gamma)\boldsymbol{y}_{t-1} + \omega_t$$
$$P_t = \boldsymbol{A}\boldsymbol{y}_t$$

Synthetic state space model

- Fitting is performed by combining Kalman Filtering and Markov Chain Monte Carlo.



[4] S. Shaffery, R. Yang, and Y. Zhang, "Bayesian Structural Time Series for Behind-the-Meter Photovoltaic Disaggregation," *The Eleventh Conference on Innovative Smart Grid Technologies*, Washington D.C., Feb. 2020.

Conclusion

Key takeaways:

- Understanding BTM resources is crucial yet challenging
- Model-based and data-driven methods

Challenges:

- Lack of visibility of BTM DERs
- Volatility and uncertainty at more granular spatiotemporal scales
- Generalization of machine learning methods

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Thank you!

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