Tracking and Analyzing the Short-Run Impact of COVID-19 on the U.S. Electricity Sector

Le Xie

Texas A&M University

(le.xie@tamu.edu)

PSERC Webinar
September 1, 2020

PSERC Webinar Series, Fall 2020

Tracking and Analyzing the Short-Run Impact of COVID-19 on the U.S. Electricity Sector

Le Xie

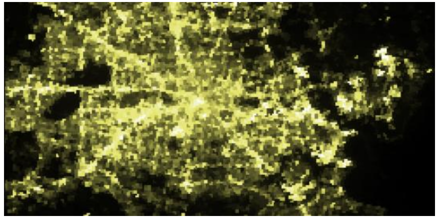
Professor, Electrical and Computer Engineering, Chancellor EDGES Fellow
Assistant Director-Energy Digitization, Texas A&M Energy Institute
September 1, 2020
le.xie@tamu.edu

Joint work with G. Ruan, D. Wu, X. Zheng, S. Sivaranjani, J. Wu, H. Zhong, C. Kang and M. A. Dahleh

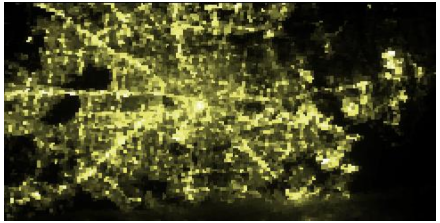
Outline

- **COVID-19 as a Public Health Crisis: A Brief Timeline**
- Short-run Impact on the U.S. Electricity Sector
- Cross-Domain Data-driven Analysis: Some Preliminary Insights
- What's Next? A Predictive Model
- Concluding Remarks

COVID-19 Timeline



Houston Night-Time Light image of 3/8 (left) and 4/25(right)



Jan. 21st

First confirmed case in the United States

Mar. 10th

1000 Confirmed cases in the U.S.

Universities start shifting classes to online format

Mar. 13th

The U.S. declares National emergency

50 total deaths in the U.S.

Mar. 16th

President Trump advices people to avoid massive gathering and restraint travels

Mar. 19th

Total number of COVID-19 cases in the U.S. exceeds 10,000

Apr. 20th

State of Texas starts the re-opening process to gradually restore economy

Apr. 27th

Total number of COVID-19 cases in the U.S. exceeds 1,000,000

Apr. 30th

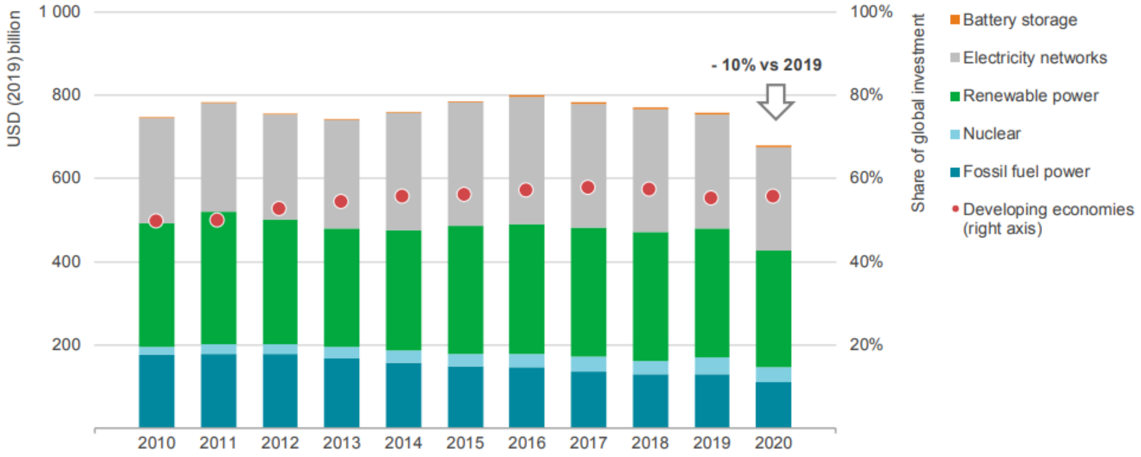
The Texas state stay-at-home order expired and retail businesses are allowed to reopen

May. 26th

Total number of COVID-19 deaths in the U.S. exceeds 100,000

Impact of COVID-19 to the Global Energy Sector

- According to the newly published IEA report[1], the global power investment fell to its lowest level in over a decade.
- Those investments are affected by policies, economic depression and mobilities restrictions due to COVID-19.
- The crisis is pushing the retirement of older and obsoleted plants, as the demand is dropping considerably.



International Energy Agency, World Energy Investment, https://www.iea.org/reports/world-energy-investment-2020

IEEE Spectrum News Report

IEEE SPECTRUM Topics Reports Blogs Multimedia

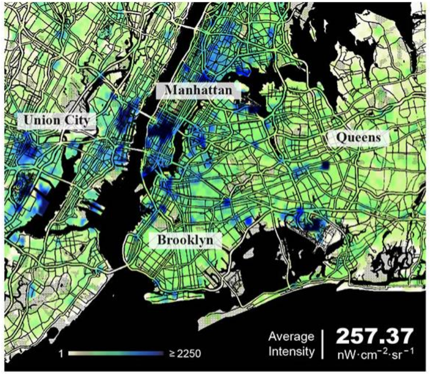
18 Jun 2020 | 18:17 GMT

How the Pandemic Impacts U.S. Electricity Usage

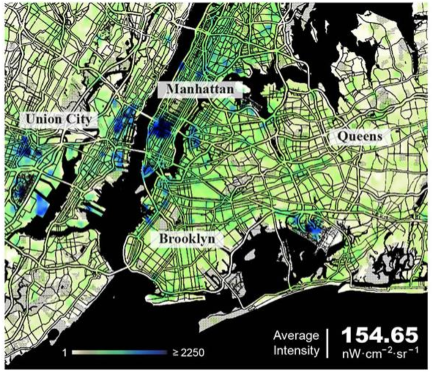
A big data project is analyzing social distancing's impact on U.S. electricity consumption during the pandemic

By **Jeremy Hsu**

Xie and his colleagues from Texas A&M, MIT, and Tsinghua University in Beijing, China, are publicly sharing their Coronavirus Disease-Electricity Market Data Aggregation (COVID-EMDA) project and the software codes they have used in their analyses in an online Github repository. They first uploaded a preprint paper describing their initial analyses to arXiv on 11 May 2020.



Night-time light in New York City before COVID-19 (Feb 8, 2020)



Night-time light in New York City during COVID-19 (April 25, 2020)

Images: Le Xie/Texas A&M Energy Institute, MIT, and Tsinghua University

Source: https://spectrum.ieee.org/energywise/energy/the-smarter-grid/how-the-pandemic-impacts-us-electricity-usage

Our Research Progress

Data Hub and Analysis Tools:

- Cross-domain Data Hub: COVID-EMDA+.
- Some open-source toolkits and tutorials are provided.
- Available: https://github.com/tamu-engineering-research/COVID-EMDA.

Research Papers:

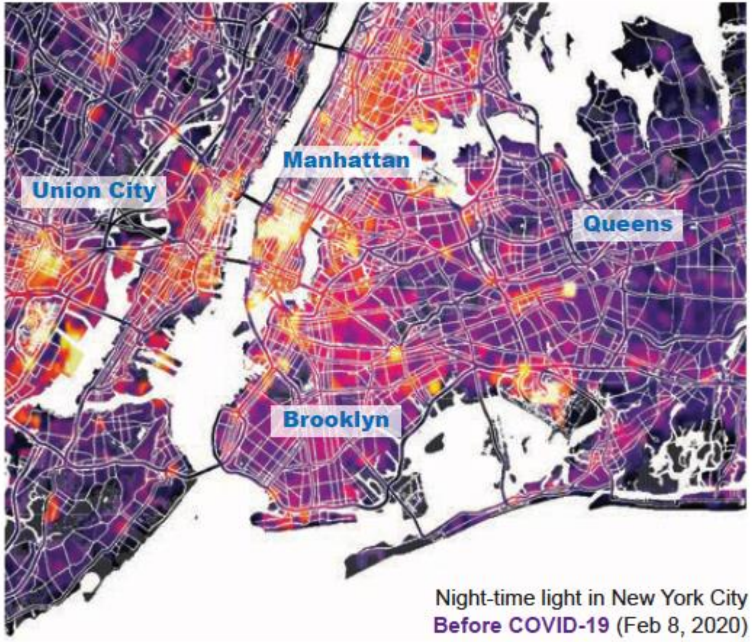
- G. Ruan, D. Wu, X. Zheng, H. Zhong, C. Kang, M. A. Dahleh, S. Sivaranjani, and L. Xie, "A Cross-Domain Approach to Analyzing the Short-Run Impact of COVID-19 on the U.S. Electricity Sector", Joule, 2020 (accepted, available: https://arxiv.org/abs/2005.06631 [Online])
- G. Ruan, J. Wu, H. Zhong, Q. Xia, and L. Xie, "Quantitative Assessment of U.S. Bulk Power Systems and Market Operations during the COVID-19 Pandemic", 2020 (in submission to Applied Energy, available: http://www.enerarxiv.org/page/thesis.html?id=2196 [Online])

Outline

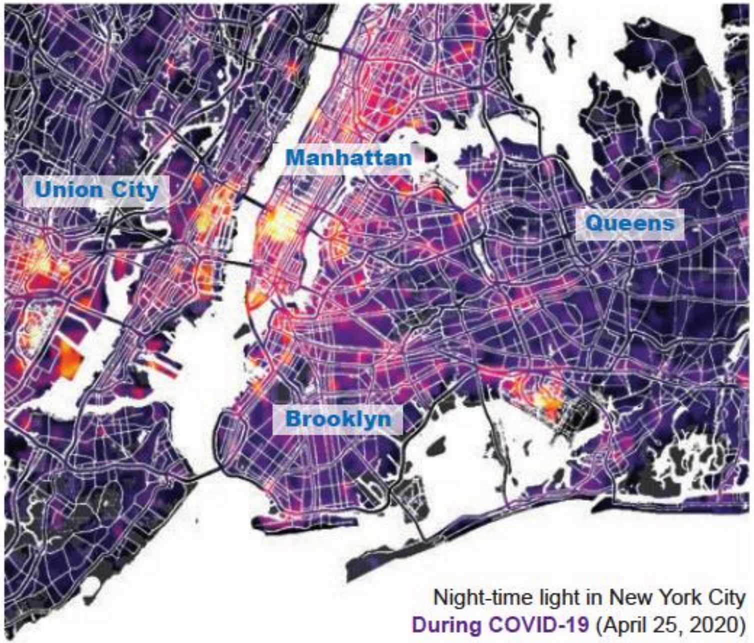
- COVID-19 as a Public Health Crisis: Timeline
- **Short-run Impact on the U.S. Electricity Sector**
- Cross-Domain Data-driven Analysis: Some Preliminary Insights
- What's Next? A Predictive Model
- Concluding Remarks

COVID-19's Impact from the Satellite View

Average intensity: 257

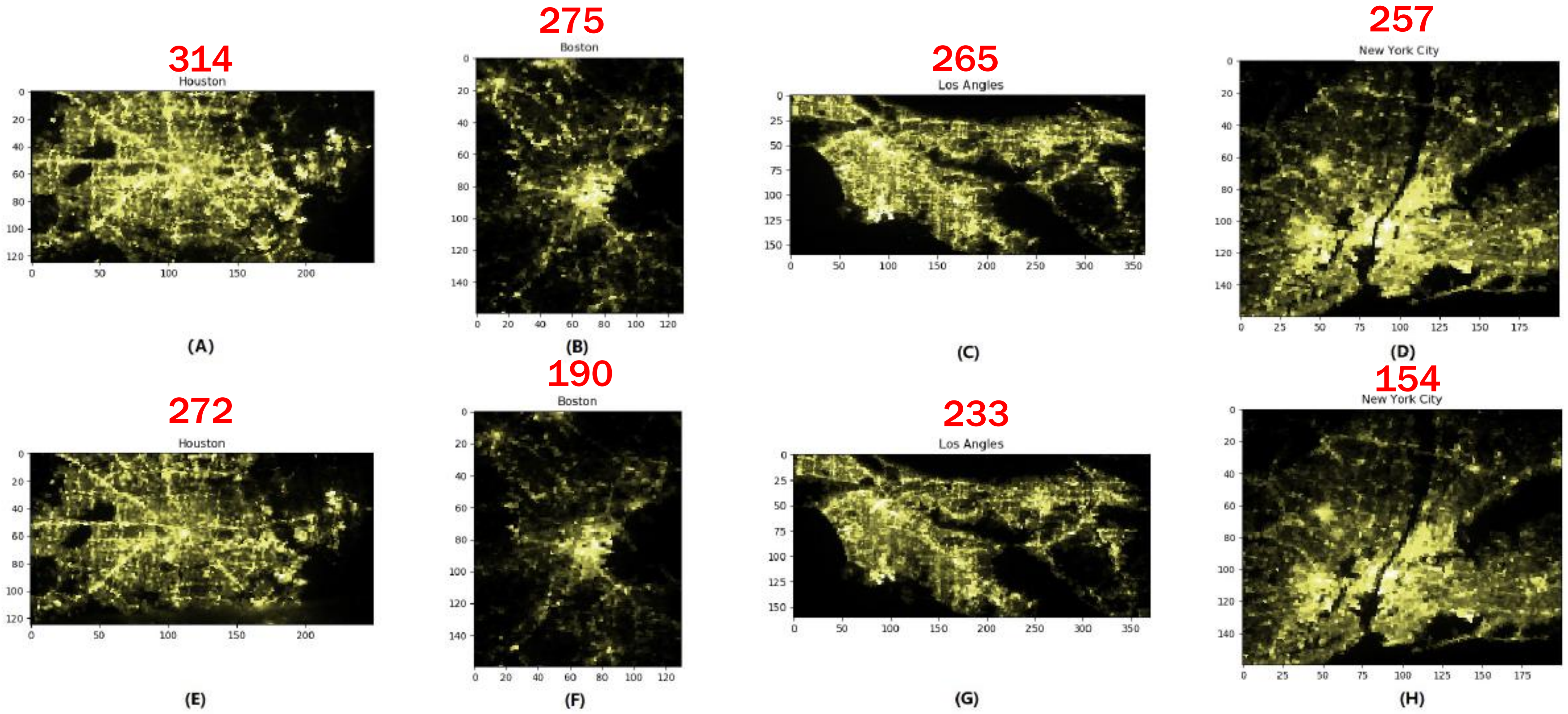


Average intensity: 154



G. Ruan, D. Wu, X. Zheng, H. Zhong, C. Kang, M. A. Dahleh, S. Sivaranjani, and L. Xie, "A Cross-Domain Approach to Analyzing the Short-Run Impact of COVID-19 on the U.S. Electricity Sector", Joule, 2020 (accepted, available: https://arxiv.org/abs/2005.06631[Online])

COVID-19's Impact from the Satellite View

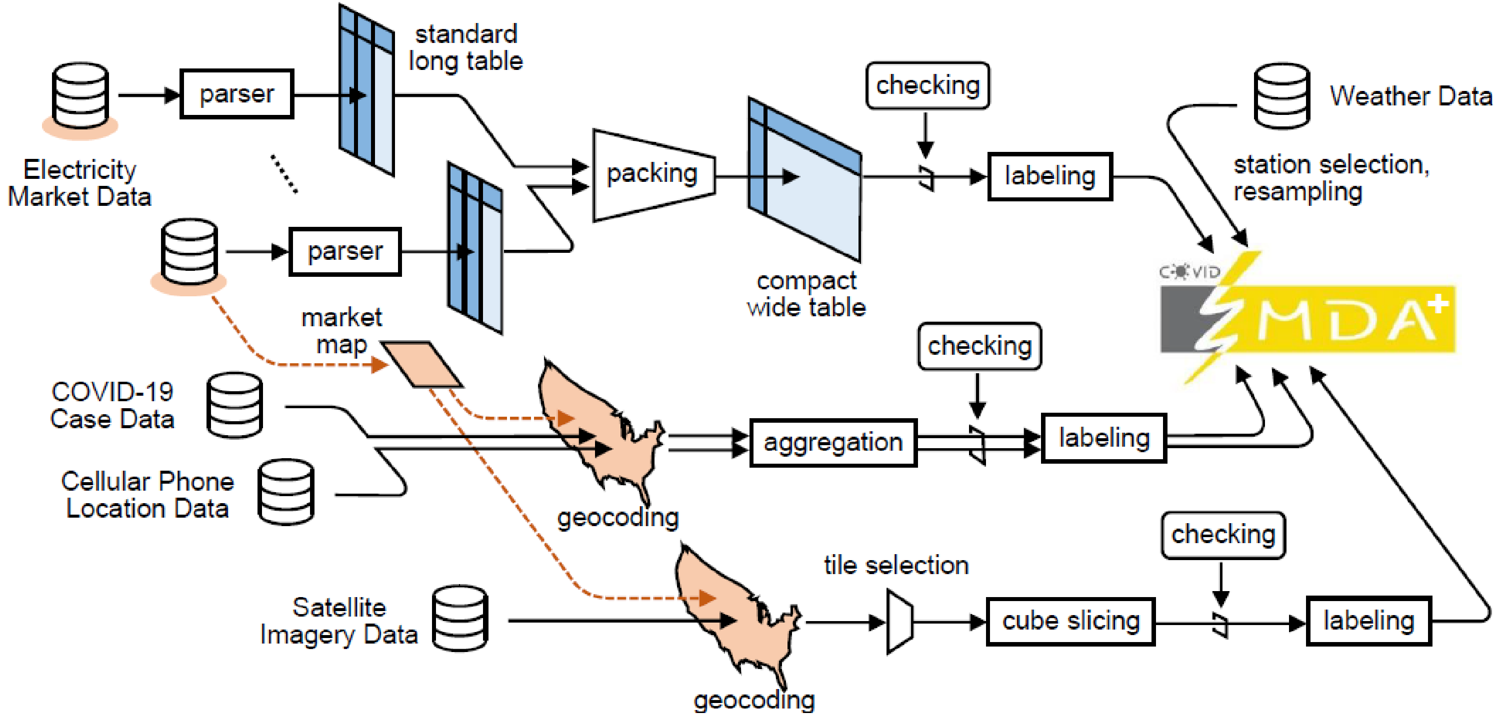


- Visible reduction in brightness for large cities across the U.S.

Red Numbers: Average Lighting Intensity

COVID-EMDA^{+} Data Hub

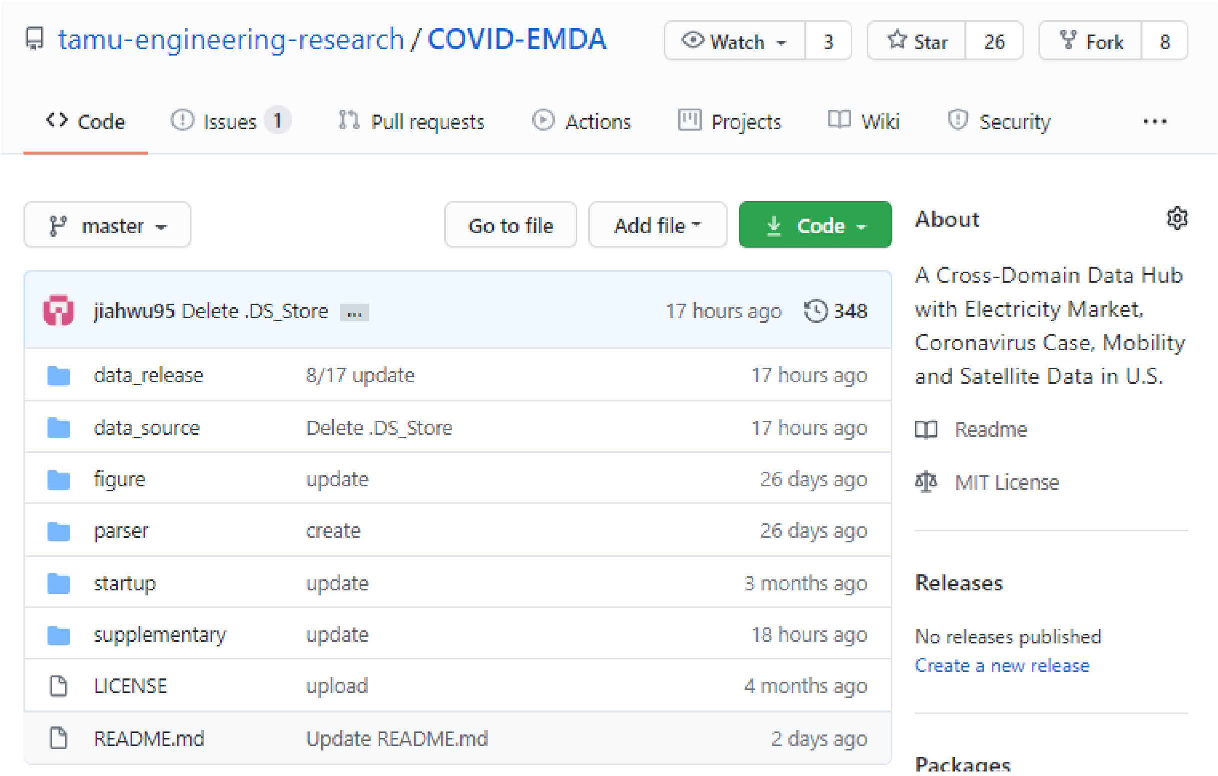
- **Features**: (1) Merge different data sources (2) Daily update and quality control (3) Open access



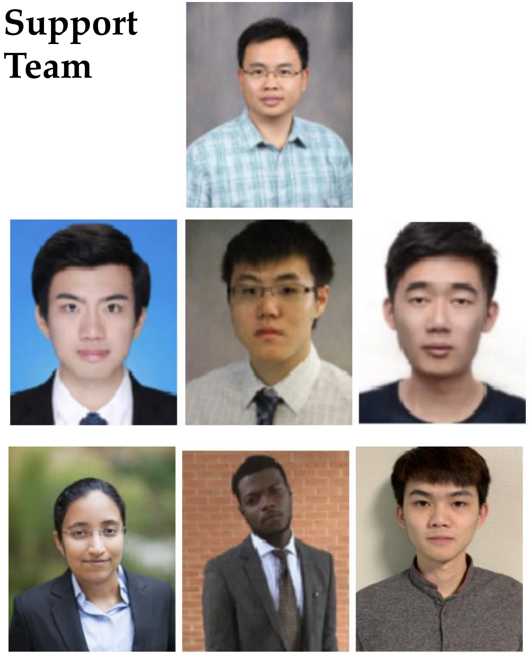
Open Access: https://github.com/tamu-engineering-research/COVID-EMDA

Data Hub: WE NEED YOUR SUPPORT!

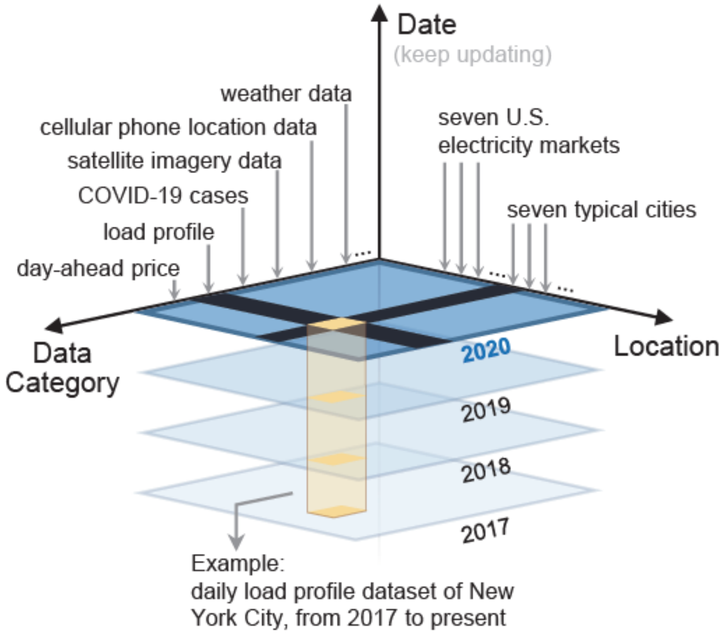
Public Release: https://github.com/tamu-engineering-research/COVID-EMDA



Support Team



COVID-EMDA+ Data Hub



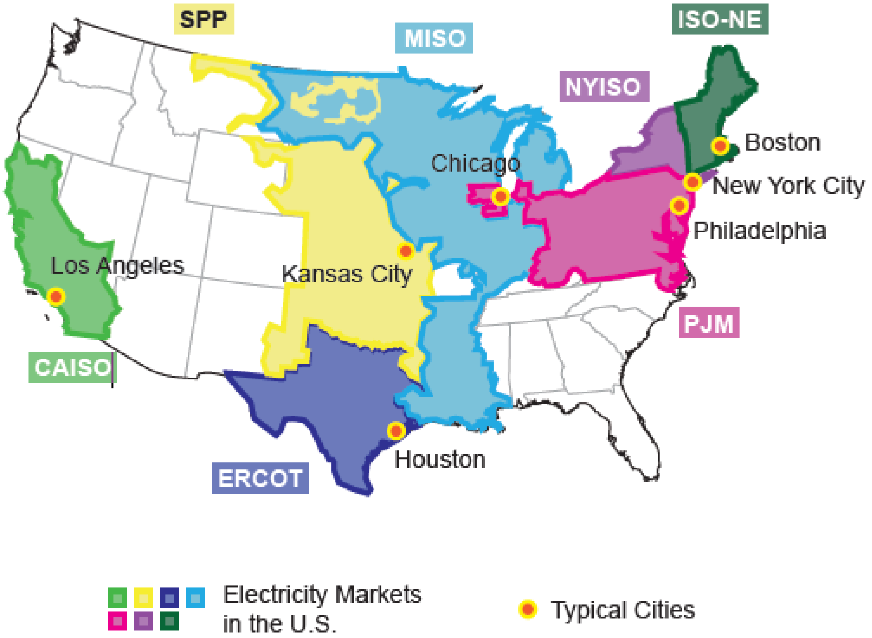
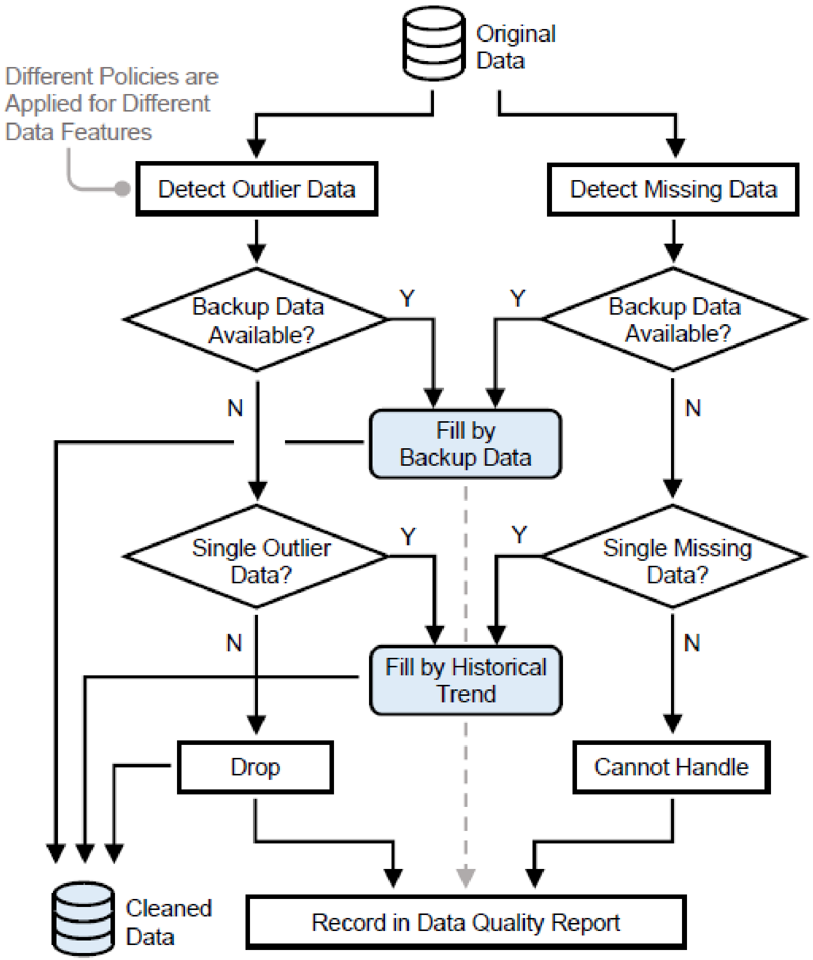


Figure. Architecture of COVID-EMDA+. Heterogeneous data from different sources are processed and aggregated to a consistent format along the time dimension.

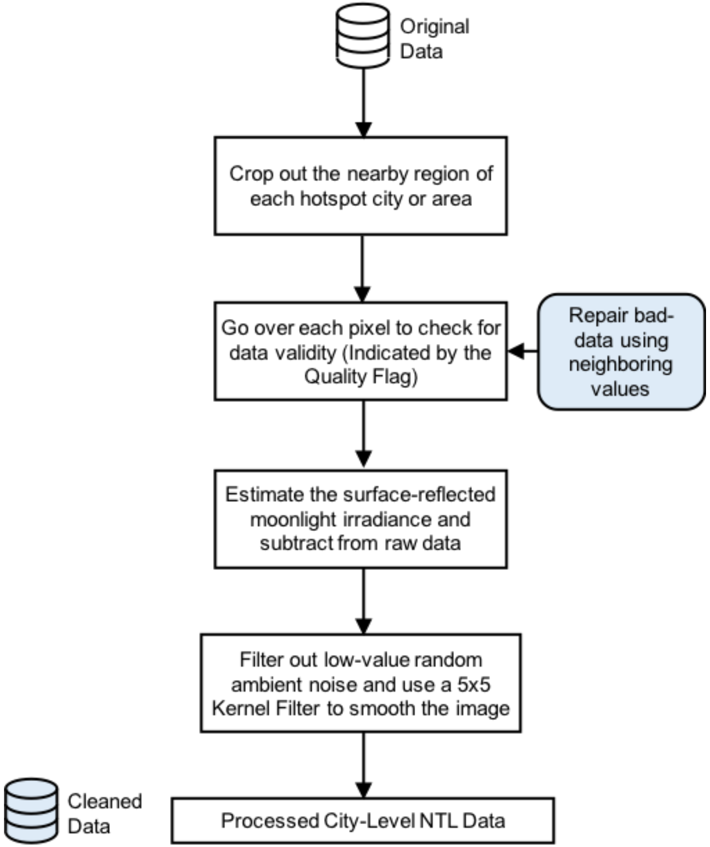
Figure. Map of United States representing the region of operation of market organizations/RTOs. Seven existing electricity markets and seven typical cities are highlighted.

Data Quality Control

- **Main issues**: handle the outlier and missing data. The flowchart is shown on the right hand side.
- **Key ideas**: fill possible problematic data by backup data sources or historical trend.
- Different polices are designed to consider different data features.



NASA's Night Time Lighting Data Processing Chart



Short-Run Impact – Demand Forecasting Accuracy

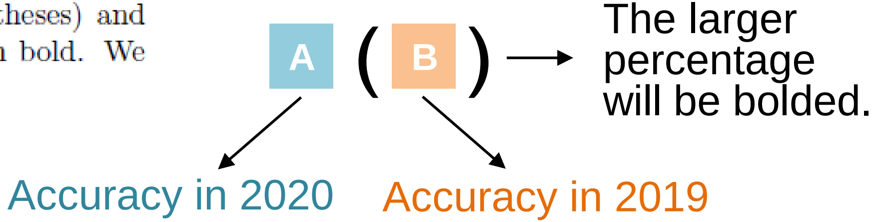
Table 1: Demand Forecasting Error in U.S. Electricity Markets [%].

Market	March	April	May	June	July
CAISO	3.4 (**2.7**)	3.9 (**2.8**)	6.0 (**2.7**)	4.3 (4.1)	3.9 (**3.1**)
MISO	2.9 (**1.6**)	3.0 (**1.3**)	1.7 (**1.3**)	2.4 (**1.8**)	1.7 (**1.6**)
ISO-NE	2.5 (**2.3**)	2.7 (**2.5**)	3.1 (**2.4**)	2.5 (**2.4**)	**2.1** (3.1)
NYISO	**2.3** (2.8)	**2.7** (3.1)	**2.0** (3.2)	**2.4** (3.1)	**2.0** (2.8)
PJM	2.9 (**1.9**)	2.8 (**2.3**)	2.4 (**1.7**)	2.7 (**2.0**)	**1.8** (2.4)
SPP	4.9 (4.0)	4.5 (**3.8**)	3.9 (**3.1**)	3.1 (**3.0**)	4.2 (**3.0**)
ERCOT	**1.8** (2.7)	2.3 (**2.2**)	2.9 (**2.3**)	**2.5** (3.0)	**1.4** (2.1)
Mean	3.0 (**2.6**)	3.1 (**2.6**)	3.1 (**2.4**)	2.8 (2.8)	**2.4** (2.6)

Note: The above data are forecasting errors in 2020 (outside parentheses) and 2019 (within parentheses). The smaller error items are highlighted in bold. We cover the results from March 1 to July 15 for both years.

- **Observations**: The forecasting accuracy is slightly dropped in March, April and May, and recovered in the next two months.

Illustration:



G. Ruan, J. Wu, H. Zhong, Q. Xia, and L. Xie, "Quantitative Assessment of U.S. Bulk Power Systems and Market Operations during the COVID-19 Pandemic", 2020 (in submission to Applied Energy, available: http://www.enerarxiv.org/page/thesis.html?id=2196 [Online])

Short-Run Impact – Renewable Energy

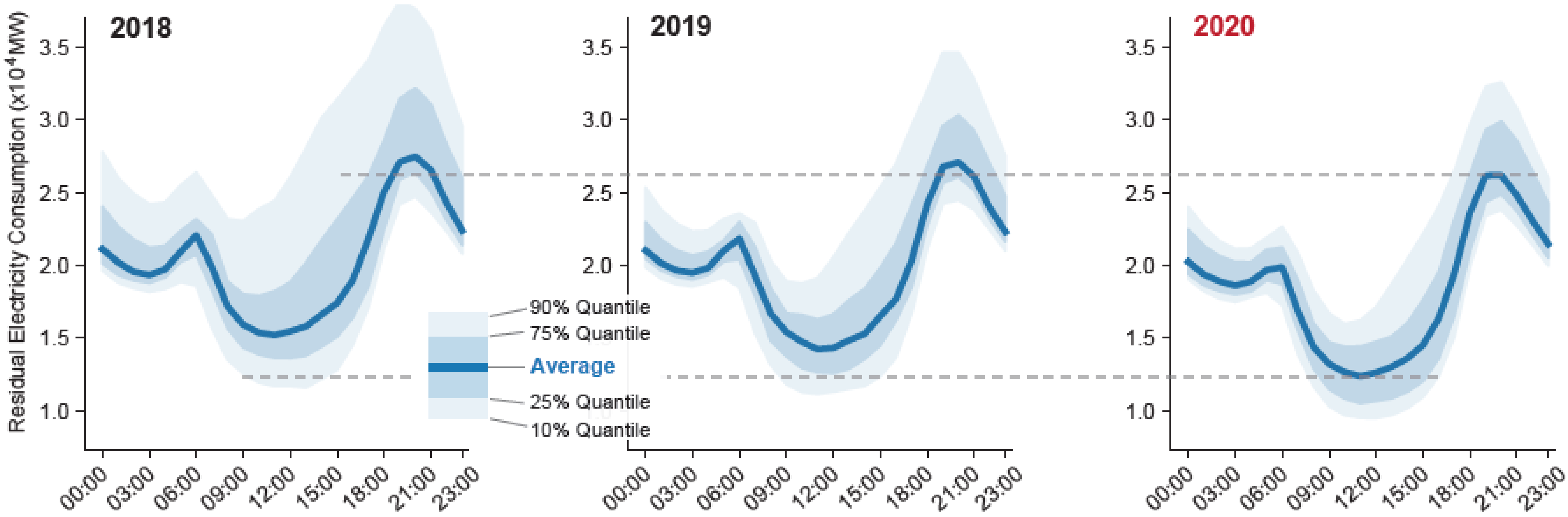
Table 2: Proportion of Renewable Generation in U.S. Electricity Markets [%].

Market	2017	2018	2019	2020
CAISO	21.0	23.8	25.5	26.1
MISO	8.3	7.4	9.1	12.3
ISO-NE	3.1	3.4	3.6	4.8
NYISO	3.2	2.6	3.2	3.4
PJM	2.7	2.6	3.2	3.9
SPP	22.6	23.7	27.1	33.1
ERCOT	18.6	20.5	21.3	27.8
Mean	11.4	12.0	13.3	15.9

- **Observations**: Slight increase can be observed in all electricity markets.
- **Further Analysis**: After eliminating the original growth trend, NYISO and CAISO are performing different from other markets --- the renewables in NYISO and CAISO are suffering extra decrease of their market shares.
- More details can be found in the reference below.

G. Ruan, J. Wu, H. Zhong, Q. Xia, and L. Xie, "Quantitative Assessment of U.S. Bulk Power Systems and Market Operations during the COVID-19 Pandemic", 2020 (in submission to Applied Energy, available: http://www.enerarxiv.org/page/thesis.html?id=2196 [Online])

Short-Run Impact – Duck Curve Profile



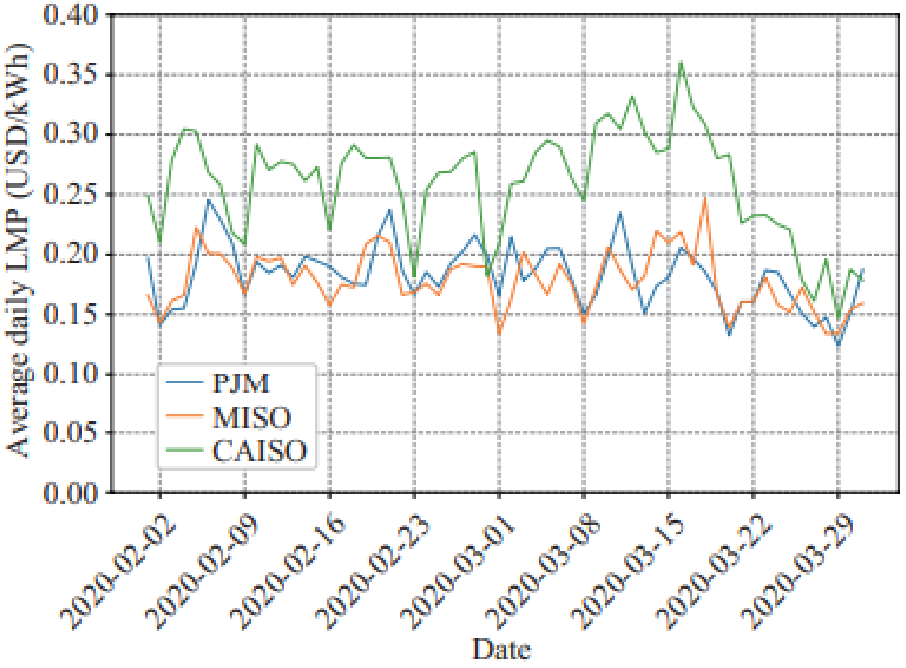
- The "Duck Curve" for California ISO is shifted lower compared to previous years during the COVID-19 outbreak.

G. Ruan, J. Wu, H. Zhong, Q. Xia, and L. Xie, "Quantitative Assessment of U.S. Bulk Power Systems and Market Operations during the COVID-19 Pandemic", 2020 (in submission to Applied Energy, available: http://www.enerarxiv.org/page/thesis.html?id=2196 [Online])

Short-Run Impact – Locational Marginal Price

- In addition to the load profile change, the electricity market is also under **unprecedented disturbances** as a result of the COVID-19 outbreak.

- **Observations**: Prices are going down severely in most electricity markets during the COVID-19 pandemic.
- Here, price refers to average daily locational marginal price.



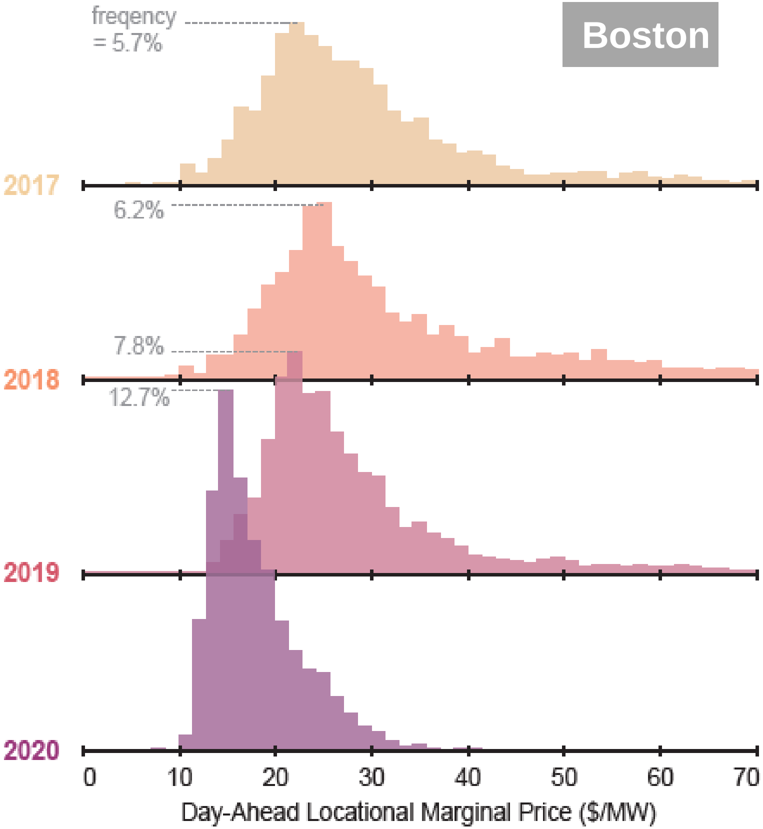
H. Zhong, Z. Tan, Y. He, L. Xie and C. Kang, "Implications of COVID-19 for the electricity industry: A comprehensive review", CSEE Journal of Power and Energy Systems, 2020.

Short-Run Impact – Locational Marginal Price

- The distribution of LMP in Boston Hub is showing an irregular shape with a **tighter spread and lower peak** compared to the same time period in previous years

- How to quantify: **Abnormal Price Index**.

  This index is based on the price distributions. More details are provided in the reference below.



G. Ruan, J. Wu, H. Zhong, Q. Xia, and L. Xie, "Quantitative Assessment of U.S. Bulk Power Systems and Market Operations during the COVID-19 Pandemic", 2020 (in submission to Applied Energy, available: http://www.enerarxiv.org/page/thesis.html?id=2196 [Online])

Outline

- COVID-19 as a Public Health Crisis: Timeline
- Short-run Impact on the U.S. Electricity Sector
- Cross-Domain Data-driven Analysis: Some Preliminary Insights
- What's Next? A Predictive Model
- Concluding Remarks

Cross-Domain Data-driven Analysis

A Cross-Domain Approach to Analyzing the Short-Run Impact of COVID-19 on the U.S. Electricity Sector

Guangchun Ruan[1,2], Dongqi Wu[1], Xiangtian Zheng[1], Haiwang Zhong[2,3], Chongqing Kang[2,3], Munther A. Dahleh[4], S. Sivaranjani[1,*], and Le Xie[1,5,*,†]

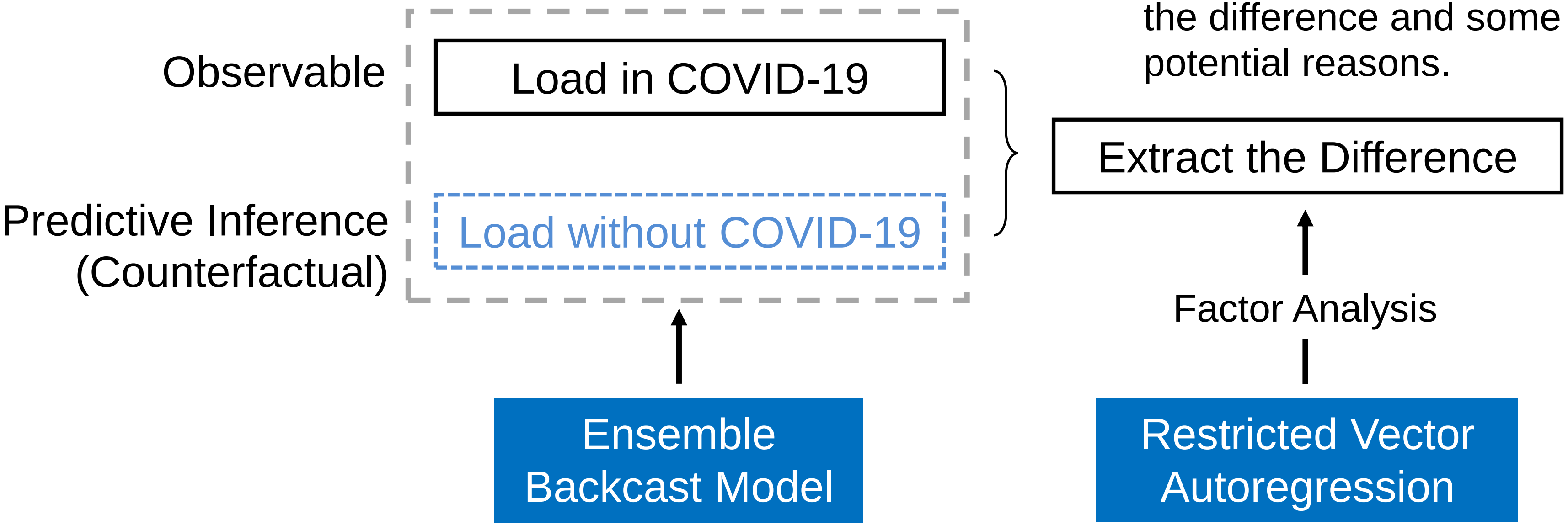
[1]Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843, USA.
[2]Department of Electrical Engineering, the State Key Lab of Control and Simulation of Power Systems and Generation Equipment, Tsinghua University, Beijing 100084, China.
[3]Institute for National Governance and Global Governance, Tsinghua University, Beijing 100084, China.
[4]Institute for Data, Systems, and Society, Massachusetts Institute of Technology, Cambridge, MA 02139, USA.
[5]Texas A&M Energy Institute, Texas A&M University, College Station, TX 77843, USA.
[*]Co-last author.
[†]Lead Contact, Corresponding author: le.xie@tamu.edu

G. Ruan, D. Wu, X. Zheng, H. Zhong, C. Kang, M. A. Dahleh, S. Sivaranjani, and L. Xie, "A Cross-Domain Approach to Analyzing the Short-Run Impact of COVID-19 on the U.S. Electricity Sector", ***Joule***, 2020 (accepted, available: https://arxiv.org/abs/2005.06631[Online])

Methodology to Track the Impact

▼ **STEP 01**: If different, we can verify the existence of the COVID-19's impact.

▼ **STEP 02**: Try to understand the difference and some potential reasons.



Ensemble Backcast Model

- This **Backcast model** is applied to eliminate the effect of weather, calendar and economics variables, and then providing **a more reliable estimation of the counterfactual**.

❶ **Base Model Design**

- Test different inputs combination, different preprocessing methods and different model architectures.
- Average accuracy is higher than 98%.

❷ **Random Search to formulate an ensemble model**

- Train 800 models ($\pm$20% fluctuation of hidden cell numbers) and select the top 200 with the highest estimation accuracy.
- Validation: apply this model for January and February 2020, the deviations are expected to be small (a basic hypothesis).

Backcast Model Design

- A Deep Neural Network is used in developing backcast models
- The model is trained using existing data from 2017 to 2019 and verified using 2020 Jan. and Feb. Data

Inputs:

Month/Day/Time
Weekend/weekday flag
Current temperature and square
Temperature of previous 3 hours
Humidity
Wind speed
Economy factor corresponding to GDP

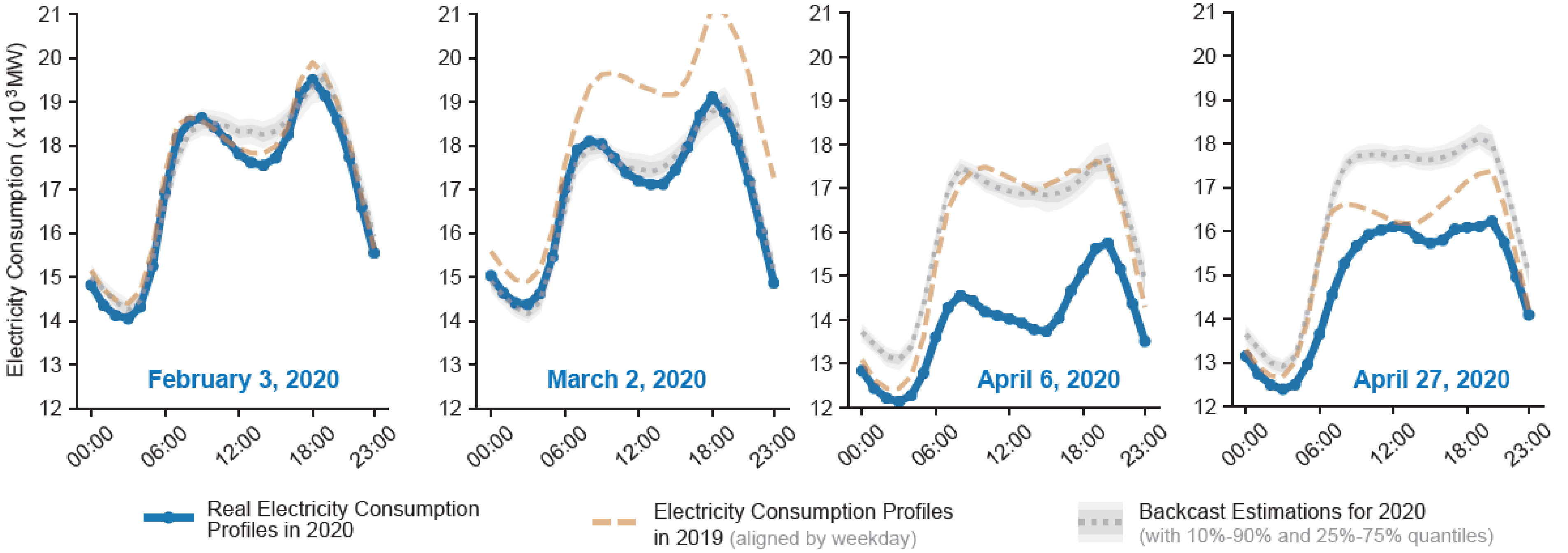
→ **Deep Neural Network** →

Output:

Predicted daily average load

Backcast Model

- The load profile of NYC during COVID-19 is **much lower** compared to backcast model prediction and previous year record



Key Findings

Visible Impact Across RTOs

Electricity Consumption Reduction (%)	CAISO	MISO	ISO-NE	NYISO	PJM	SPP	ERCOT
Average in February	**−1.31**	**−0.14**	**2.15**	**0.84**	**0.54**	**−0.90**	**−1.52**
	[−4.10, 1.24]	[−2.09, 1.77]	[−0.47, 4.58]	[−1.47, 3.14]	[−1.65, 2.57]	[−3.18, 1.27]	[−4.06, 0.86]
Average in March	**2.68**	**1.77**	**5.24**	**4.51**	**2.68**	**2.47**	**1.30**
	[0.52, 4.78]	[−0.41, 3.88]	[2.33, 7.88]	[2.01, 7.00]	[0.19, 5.02]	[0.36, 5.14]	[−1.00, 3.43]
Average in April	**9.24**	**10.24**	**9.47**	**10.20**	**9.44**	**7.72**	**6.36**
	[6.64, 11.72]	[7.88, 12.66]	[6.26, 12.32]	[7.26, 12.91]	[6.74, 12.07]	[4.49, 10.71]	[3.77, 8.80]
Average in May	**6.46**	**10.71**	**10.44**	**10.47**	**7.35**	**9.24**	**4.44**
	[3.24, 9.35]	[8.28, 13.16]	[6.70, 13.90]	[7.17, 13.54]	[4.45, 10.20]	[6.22, 12.07]	[2.10, 6.59]
Average in June	**0.29**	**3.49**	**1.79**	**5.72**	**0.14**	**2.66**	**2.41**
	[−2.74, 3.04]	[1.44, 5.54]	[−1.78, 5.06]	[2.37, 8.78]	[−2.57, 2.52]	[−0.05, 5.17]	[0.54, 4.06]

Electricity Consumption Reduction (%)	Boston	Chicago	Houston	Kansas City	Los Angeles	New York City	Philadelphia
Average in February	**0.40**	**0.09**	**−0.55**	**0.10**	**−1.12**	**0.43**	**0.75**
	[−1.93, 2.60]	[−2.41, 2.43]	[−3.02, 1.93]	[−2.76, 2.89]	[−4.27, 1.83]	[−2.12, 2.90]	[−1.98, 3.40]
Average in March	**7.12**	**2.95**	**−0.53**	**0.24**	**3.32**	**5.27**	**3.94**
	[4.63, 9.53]	[0.26, 5.49]	[3.01, 1.70]	[−3.44, 3.57]	[0.61, 5.85]	[2.60, 7.80]	[−0.96, 6.86]
Average in April	**11.32**	**9.81**	**5.33**	**9.04**	**11.06**	**14.10**	**8.93**
	[8.55, 13.93]	[6.70, 12.66]	[2.63, 7.79]	[5.00, 12.55]	[8.11, 13.82]	[11.26, 16.80]	[5.42, 12.18]
Average in May	**9.36**	**9.51**	**3.63**	**7.01**	**3.91**	**14.77**	**8.24**
	[6.02, 12.41]	[6.32, 12.51]	[0.86, 5.85]	[3.22, 10.67]	[0.59, 7.06]	[11.61, 17.76]	[4.58, 11.71]
Average in June	**0.41**	**3.24**	**4.41**	**0.21**	**−1.90**	**11.07**	**2.07**
	[−3.03, 3.38]	[0.36, 5.84]	[2.05, 6.48]	[−2.56, 2.62]	[−5.42, 1.34]	[7.60, 14.02]	[−1.20, 5.06]

Note: The regional transmission organizations are listed in an order from the Federal Energy Regulatory Commission, and the cities are given in an alphabetical order.

Significant Impact in Typical Cities

Next Question

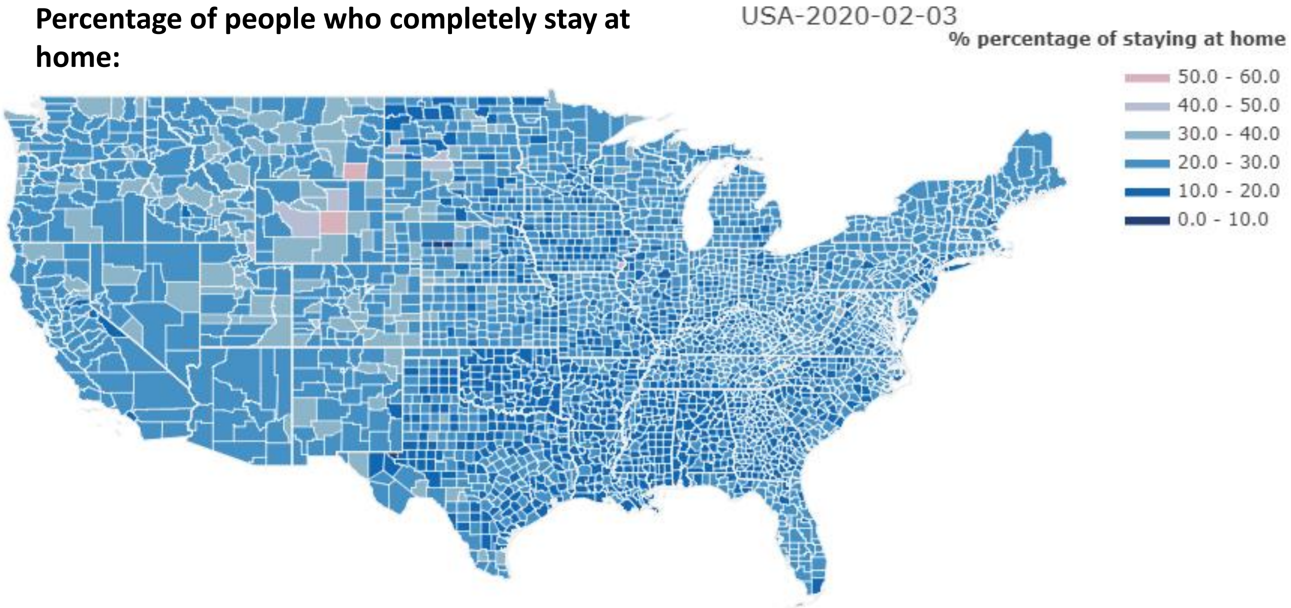
1. How to Explain the Load Change?

2. What may be the best indicator?

➔ Important and unexplored resources: cross-domain data.

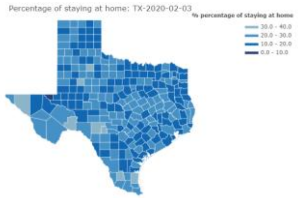
Social Distancing in the U.S.

Percentage of people who completely stay at home:

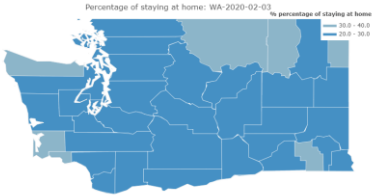


CA

NY



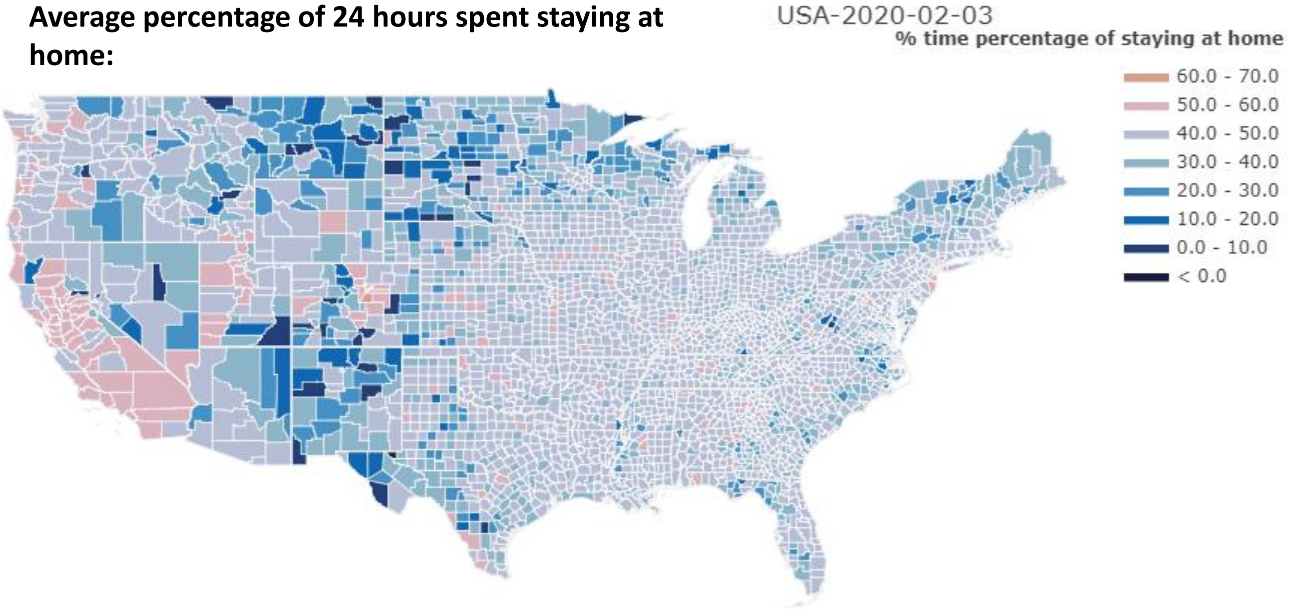
TX



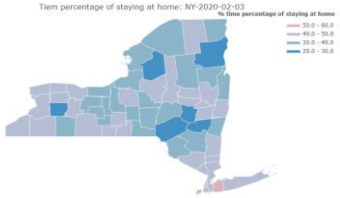
WA

Stay-at-home Rate in the U.S.

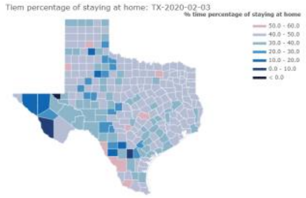
Average percentage of 24 hours spent staying at home:



CA



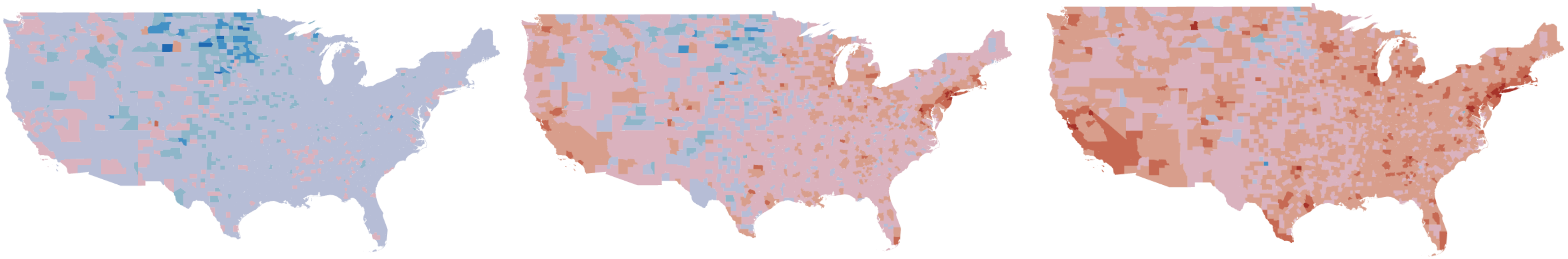
NY



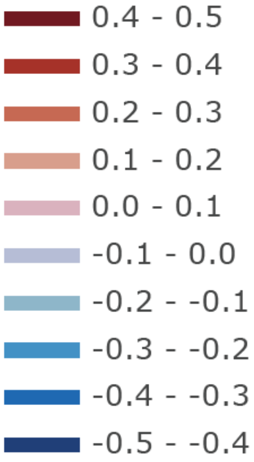
TX

WA

Social Distancing Patterns in the USA



March 11, 2020 | March 25, 2020 | April 08, 2020



- The increased proportion of complete stay-at-home population compared to Feb. 12, 2020, before the COVID-19 outbreak
- All days are Wednesdays and non-holidays

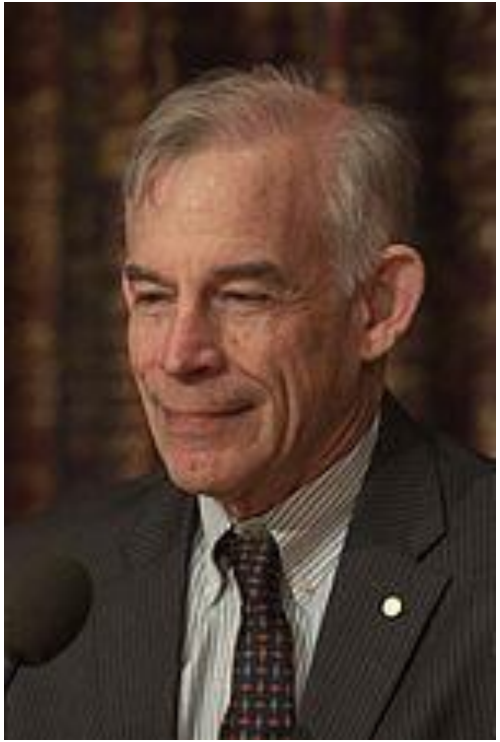
Outline

- COVID-19 as a Public Health Crisis: Timeline
- Short-run Impact on the U.S. Electricity Sector
- Cross-Domain Data-driven Analysis: Some Preliminary Insights
- **What's Next? A Predictive Model**
- Concluding Remarks

Vector Autoregression (VAR)

- VAR is a **multi-variate stochastic process** used in modelling the **linear inter-dependencies** among time series

- Pioneered by Nobel laureate economist **Christopher A. Sims** for modelling macroeconomic dynamics



https://en.wikipedia.org/wiki/Christopher_A._Sims

Vector Autoregression

- In a VAR model, all variables are modelled in the same way
- The **state evolution of every variable** is affected by:
  - ✓ Its own lagged values (number of lags is the *order* of the model)
  - ✓ Lagged values of other variables
  - ✓ Constant intercept and random error term

- Example: Two-variable VAR with order 1:

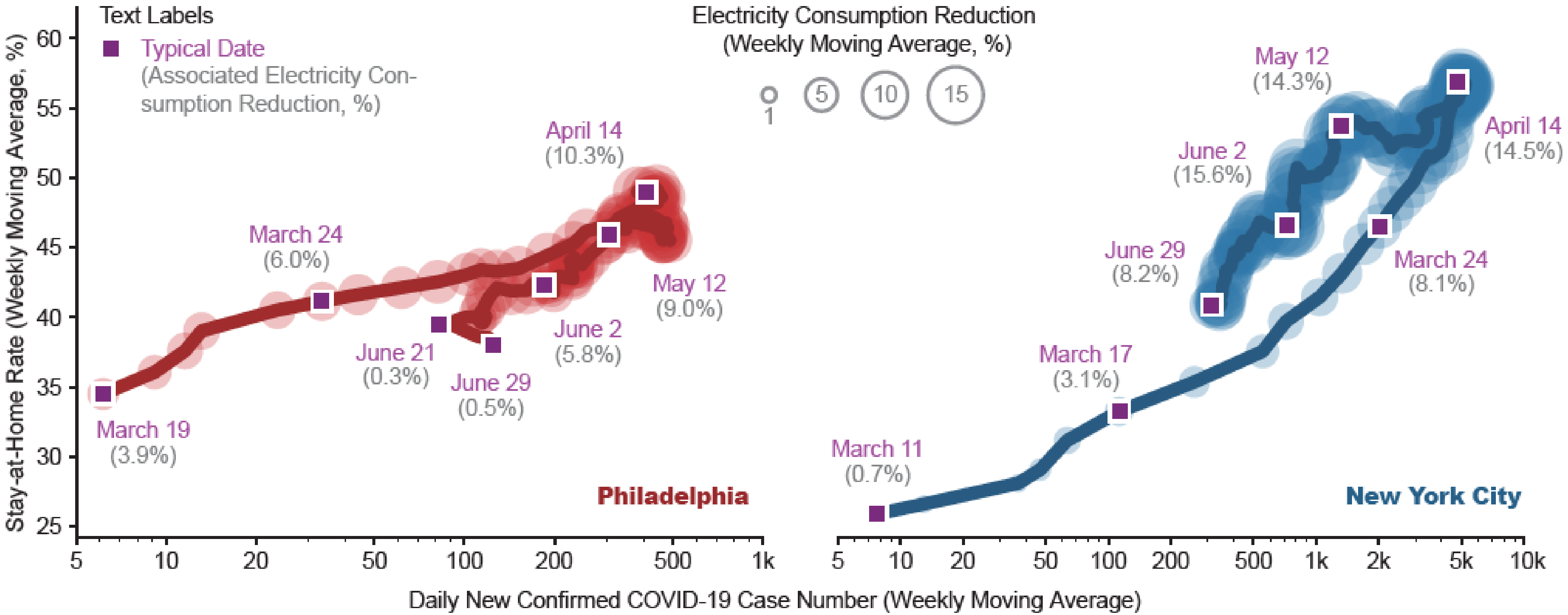
$$\underset{\text{Next state}}{\begin{bmatrix} x_{1,t+1} \\ x_{1,t+1} \end{bmatrix}} = \overset{\text{Intercept}}{\begin{bmatrix} c_1 \\ c_2 \end{bmatrix}} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \underset{\text{State}}{\begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix}} + \overset{\text{Error}}{\begin{bmatrix} e_{1,t+1} \\ e_{2,t+1} \end{bmatrix}}$$

Vector Autoregression

- Determining a VAR model of order P requires the computation of:
  - ✓ Coefficient matrices $[A_{t-1}, A_{t-2}, \ldots, A_{t-p}]$ for each lagged state
  - ✓ Constant intercept matrix C
- Usually formulated as an **overdetermined system identification** problem and is solved using **Ordinary Least-Square (OLS)**
- Training data are selected from March to May to capture the dynamics during the COVID-19 outbreak

Trace of Load Reduction and COVID 19 Confirmed Cases

- The traces show strong correlation between severity of COVID-19 outbreak, complete stay-at-home population and electricity consumption

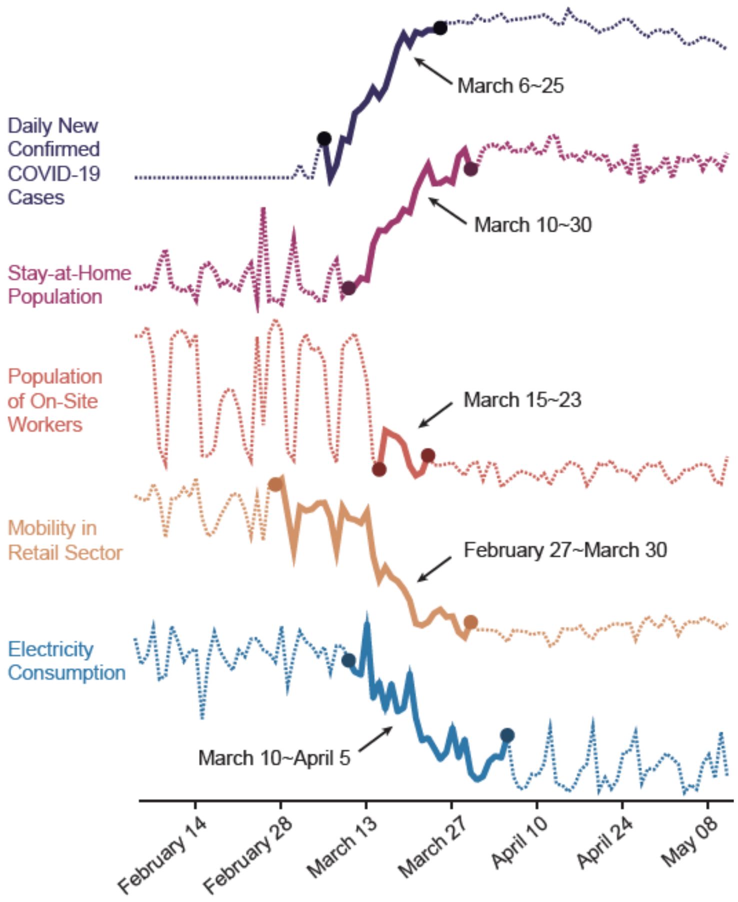


Possible Indicators of Consumption

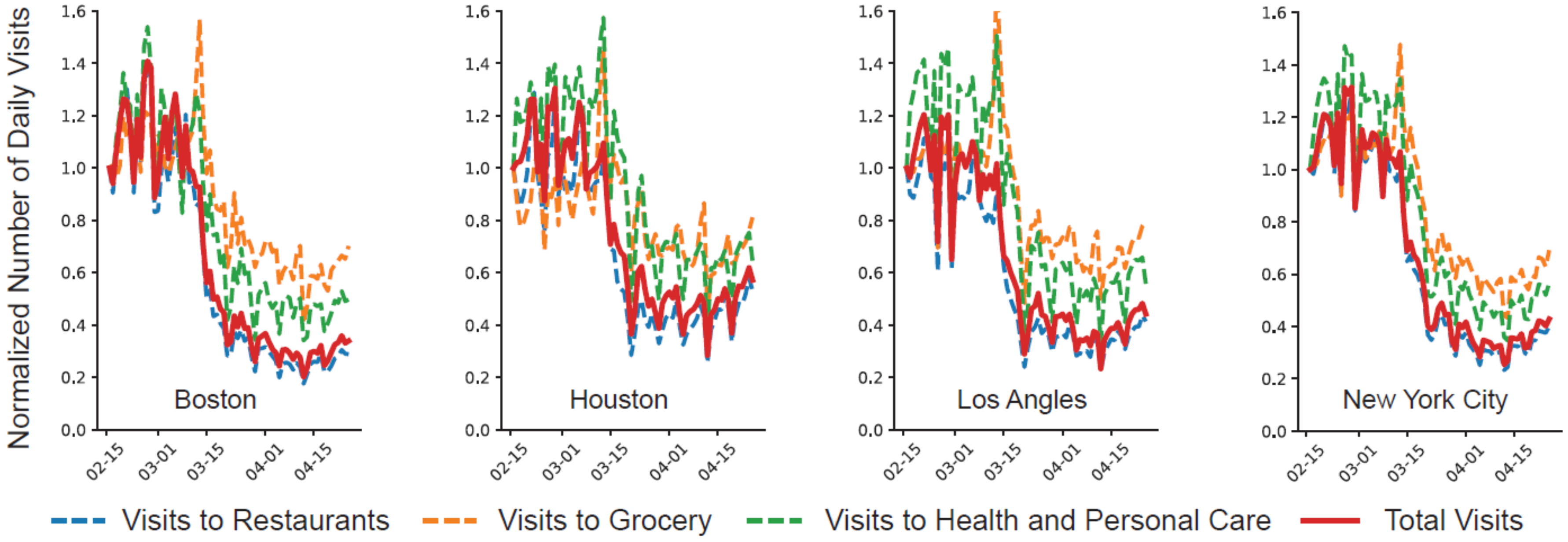
- Varying time-scale response of social distancing from top-down v.s. bottom-up

- Very strong inertia can be observed in the load reduction. The load changes in 2-3 days are mainly due to its own trend. Often 1-2 weeks later, other factors gradually make a more evident impact.

- Slight rebounds of on-site workers and retail mobility around the end of April coincided with the re-opening policies



Shutdown Patterns in the USA



- Normalized number of daily visits to three selected POI categories:
  - ✓ Restaurants, grocery and health/personal care
  - ✓ The number shows the relative value compared to Feb.15, 2020 (Saturday)

Variables Selection

- The following variables are selected as input candidates for the VAR model:

  ✓ Logarithm of load Reduction in MW

  ✓ Logarithm of New Daily Confirmed Case

  ✓ Stay-at-Home Population
    - Number of devices that stay at home **completely**

  ✓ Median Home Dwell Time Percentage
    - Median of the sampled population

  ✓ Population of Full/Part-time On-site Workers

  ✓ Mobility in Retail Sector
    - Logarithm of the number of visitors to retail POIs

VAR Input Verification

- The variables selected for the VAR model are pre-verified using statistical tests:

- **Augmented Dicket-Fuller (ADF) Test:**
  - ✓ The stationarity of *detrended* time-series is a prerequisite for VAR calibration.
  - ✓ ADF is a unit root test to examine the stationarity of a time-series variable.
  - ✓ Test result is indicated by the value of Akaike Information Criterion (AIC).

- **Cointegration Test:**
  - ✓ The input timeseries should not have long-term correlation.
  - ✓ Such correlation is indicated by the presence of cointegration.

Stock, J. H. & Watson, M. W. Vector Autoregressions. *J. Econ. Perspectives* 15, 101–115 (2001).

Restricted VAR

- Motivation – **Granger Causality Wald Test**
  - ✓ A probabilistic method to estimate casual relationships among random variable represented as time-series.
  - ✓ Intuition: Events in the *future* cannot affect the *past.*
  - ✓ Causality can be *statistically tested* by examining the present value of one timeseries and lagged values of another time-series.

- The VAR model should NOT have counter-logical causal relationships
  - ✓ It makes no sense that load reduction is "causing" new COVID-19 cases.
  - ✓ These relationships need to be eliminated from the VAR model.
  - ✓ Hence we use **Restricted** VAR to impose constraints such that the corresponding entries in the coefficient matrices are **equal to zero**.

Stock, J. H. & Watson, M. W. Vector Autoregressions. *J. Econ. Perspectives* 15, 101–115 (2001).

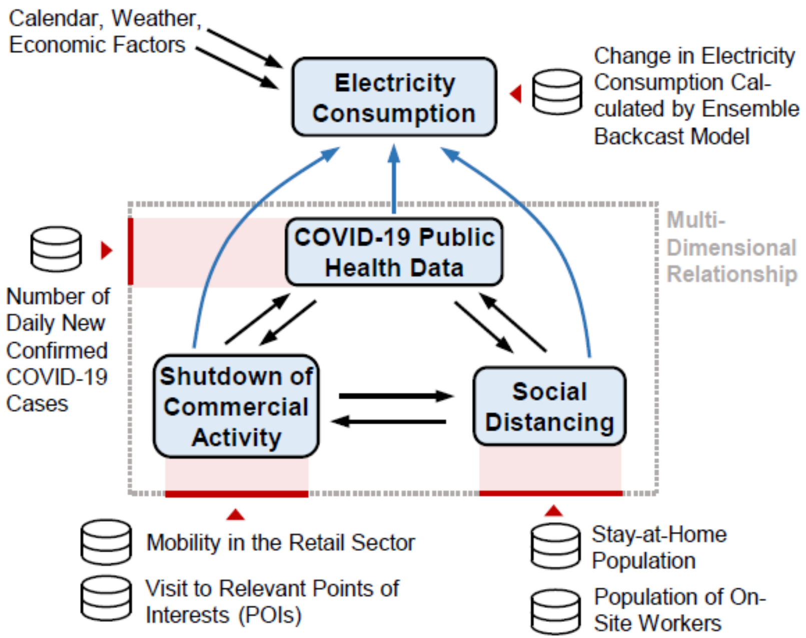
Restricted VAR Verification

- The validity of Restricted VAR model is verified from four perspectives
- **Unit Root Test for Model Stationarity**
  - ✓ The model also needs to be stationary.
  - ✓ A commonly used technique is ADF test.

- **Ljung-Box Test and Durbin-Watson for Residual Autocorrelation**
  - ✓ Endogeneity of the residual may render the regression result invalid.
  - ✓ LB test - H_0: residual are i.i.d; H_a: residual have serial-correlation.
  - ✓ DW test - H_0: residual are serially uncorrelated; H_a: residual come from a 1st order auto-regression process.

Stock, J. H. & Watson, M. W. Vector Autoregressions. *J. Econ. Perspectives* 15, 101–115 (2001).

Restricted VAR

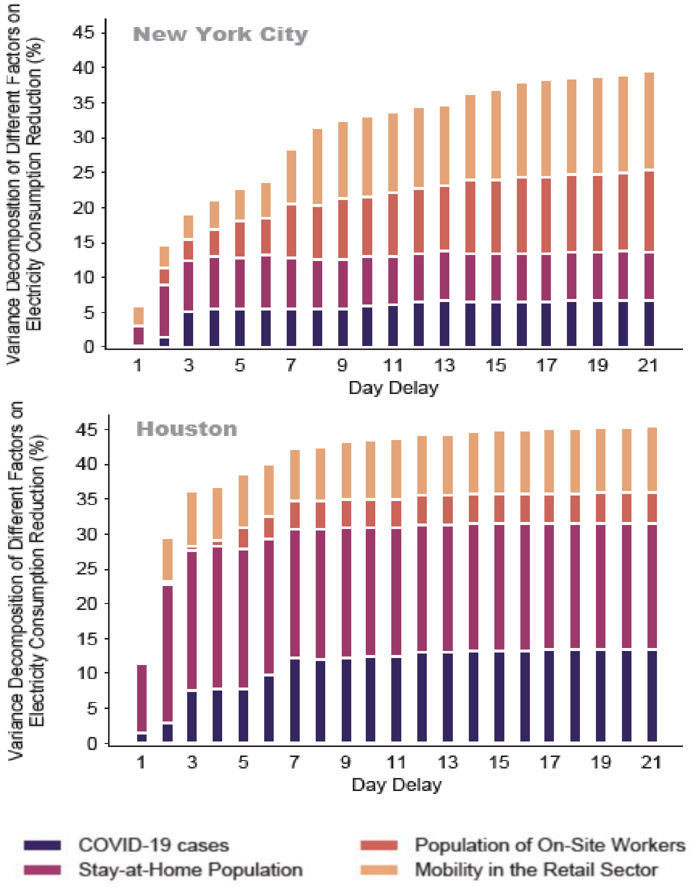


Some indicators:

- ✓ **Electricity Consumption**: Daily consumption (calculated using the ensemble backcast model)
- ✓ **COVID Cases**: daily new confirmed case number.
- ✓ **Social Distancing**: social distancing factors (completely stay-at-home and on-site worker population)
- ✓ **Shutdown**: Population mobility in the retail sector and number of visits to Point-of-Interests

The overall model is fine-tuned to fit the real-world data.

Restricted VAR Results - FEVD

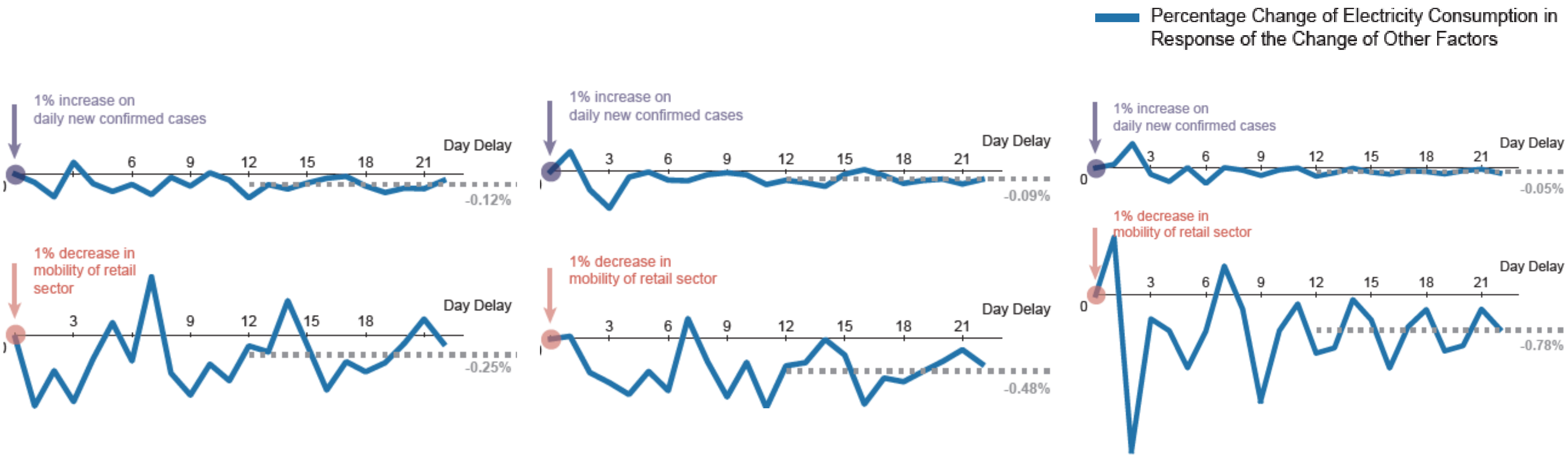


- Figures on the left show the ***variance decomposition (VD)*** of the load reduction rate for ***NYC*** and ***Houston***.

- The height of each color block indicates the proportion of variance contribution from the corresponding input variable

- Cities' results are diverse. Although ***NYC*** has similar proportion contributed by the other four variables as ***Houston***, ***Houston*** is more likely to be affected by the stay-at-home population. Additionally, ***Houston*** has a faster dynamic of the change of electricity consumption.

Restricted VAR Results – Impulse Response



- The impulse responses describe the dynamic evolution of the load reduction that would result from a unit shock (1%) in one of the influencing factors
- In NYC, 1% increase in daily new COVID-19 cases results in 0.25% load reduction in steady state, while 1% decrease in retail mobility in Houston results in 0.78% load reduction.
- The change in Houston load is **relatively more sensitive** to variation in commercial activity

Prediction Using Restricted VAR Model

- Once the parameters of the VAR model has been determined, it can be used to forecast an arbitrary number of periods into the future:
  - ✓ The first future state is **only dependent on past** P known measurements.
  - ✓ The predicted values can be used recursively to generate more predictions.

- However, unlike weather forecasts which is widely available days in advance, there is currently no reliable **forecast for Social Mobility data**
  - ✓ Appropriate models derived from factors including public policies may be developed.

- Forecast results from Restricted VAR model can be used in **evaluating the effect on electricity sector** for possible **lockdown and isolation policies** in the future for government decision making
  - ✓ A paper has already adopted this idea in load forecasting, see the reference below.

Y. Chen, W. Yang, and B. Zhang, "Using Mobility for Electrical Load Forecasting During the COVID-19 Pandemic", arXiv preprint arXiv: 2006.08826, 2020

Public Policy Support: A Predictive VAR Model

Calendar Data:
- Season
- Month/day/time

Weather Data:
- Temperature (squared/cubed)
- Humidity
- Precipitation
- Wind speed
- Solar irradiation intensity

Social Activity Data:
- Median stay-at-home time
- Complete stay-at-home rate
- Mobility in retail sector
- Number of on-site workers

Restricted VAR Model

Timeseries of hourly/daily load capacity

Outline

- COVID-19 as a Public Health Crisis: Timeline
- Short-run Impact on the U.S. Electricity Sector
- Cross-Domain Data-driven Analysis: Some Preliminary Insights
- What's Next? A Predictive Model
- Concluding Remarks

Concluding Remarks

- The overall electricity sector in the US is undergoing volatile changes.
  - ✓ The Northeastern region in particular.

- The change in electricity consumption is highly correlated with cross-domain factors including COVID-19 **confirmed cases**, degree of **social distancing** and level of **commercial activities**.

- Conventionally used indicators for load forecast, reliably and risk assessment could be augmented to include **cross-domain factors** during the process of re-opening the economy.

Our Research Progress and Future Work

- Correlation with socioeconomic activity data set (higher resolution)
- Policy evaluation and long-term change on the electricity consumption
- You are welcome to go through our data hub (https://github.com/tamu-engineering-research/COVID-EMDA), and your feedback is greatly appreciated!

Thank You!

Questions?

Thank You, and Stay Safe!

Le.xie@tamu.edu