# Energy Efficiency

Managing power supply and demand

# Assignments

Brightspace discussion question:

“What do you think is the biggest contributor to your own energy consumption and are there ways you could reduce it?”

Due Friday by 5pm.

First programming assignment:

Climate data visualization

Due Fri Feb 3 by midnight.

# Climate change in the news

# Climate change in the news

TEXAS OBSERVER

SINCE 1954

ENVIRONMENT

## SAN ANTONIO TO END USE OF COAL WITHIN FIVE YEARS

But CPS Energy's decision to switch to Natural Gas highlights the potential and peril of cities' clean energy transition.

by DELGER ERDENESANAA
JANUARY 26, 2023, 12:40 PM, CST

In 2010, San Antonio's electric utility added a new coal-fired generator to its J. K. Spruce power plant.

But the facility struggled financially to compete with fracked gas, solar, and wind energy.

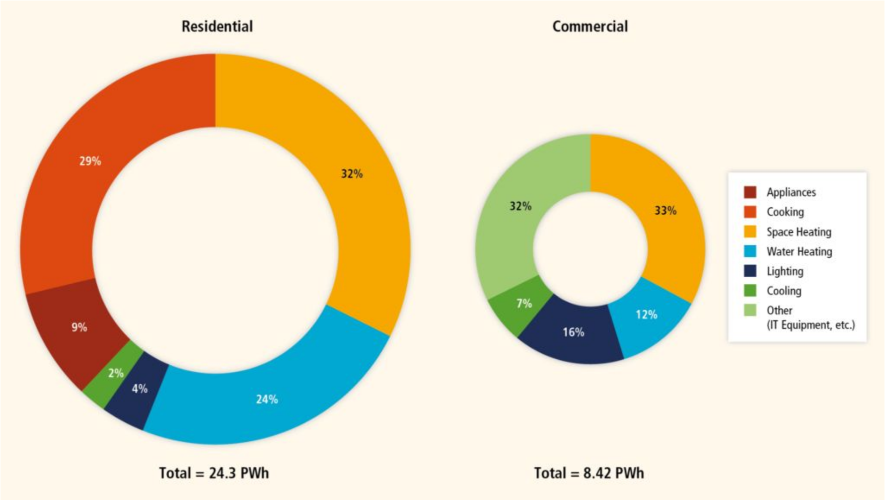
Community members were against heavy pollution generated by burning coal.

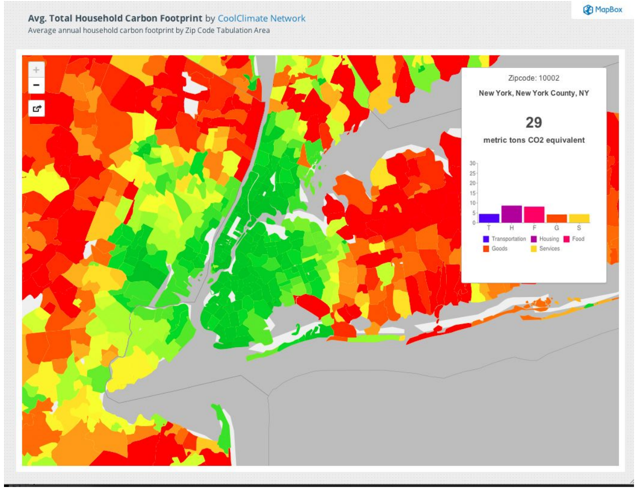
This week, board members of CPS Energy voted to stop using coal at the power plant.

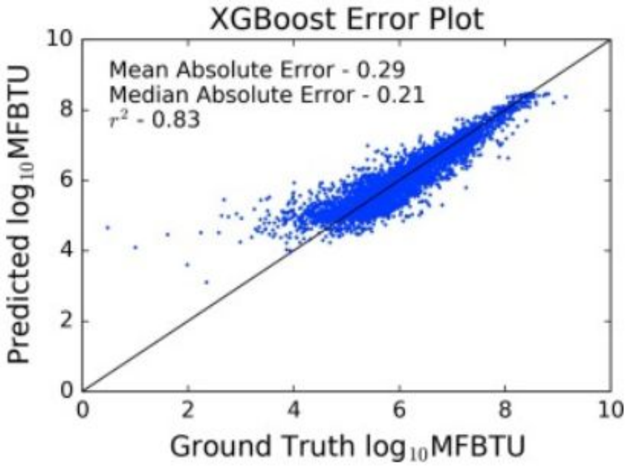
Board members elected to retrofit Spruce's newer unit to run on gas, as part of an overall plan to diversify the utility's energy mix.

"This victory has been a long time coming," said Emma Pabst, a campaigner with the Sierra Club's Lone Star Chapter. But she and others criticized the move toward gas as shortsighted. "It's just not the bold action we need to see on climate."

# Recap

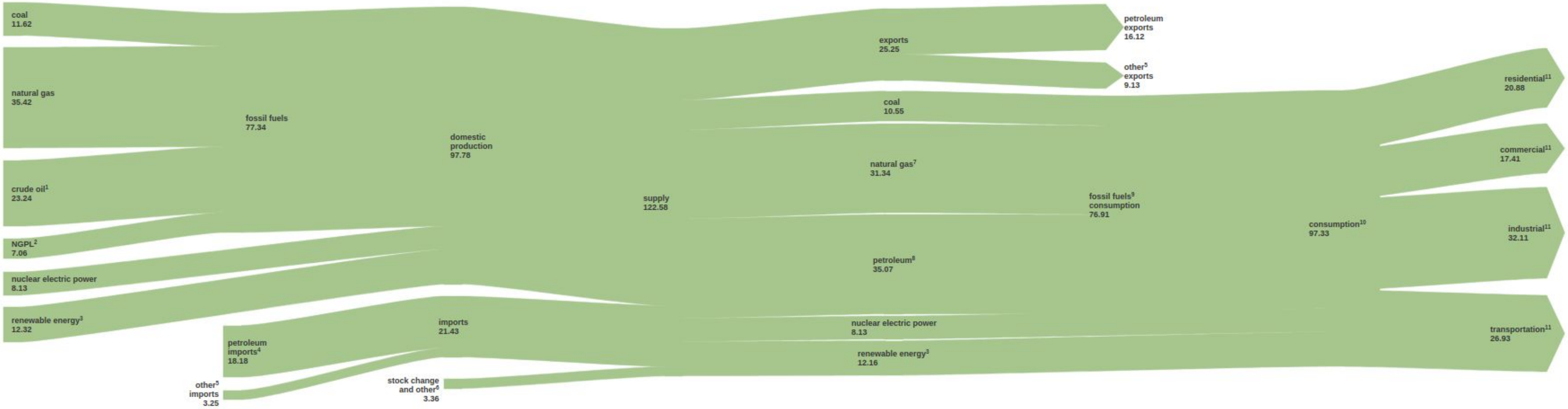

Residential
Commercial
29%
32%
9%
2%
4%
24%
32%
33%
7%
16%
12%
Appliances
Cooking
Space Heating
Water Heating
Lighting
Cooling
Other
(IT Equipment, etc.)
Total = 24.3 PWh
Total = 8.42 PWh


Avg. Total Household Carbon Footprint by CoolClimate Network
Average annual household carbon footprint by Zip Code Tabulation Area
MapBox
Zipcode: 10002
New York, New York County, NY
29
metric tons CO2 equivalent
Transportation
Housing
Food
Goods
Services


XGBoost Error Plot
Mean Absolute Error - 0.29
Median Absolute Error - 0.21
$r^2$ - 0.83
Predicted $\log_{10}$MFBTU
Ground Truth $\log_{10}$MFBTU
0
2
4
6
8
10

# U.S. energy flow, 2021

quadrillion Btu

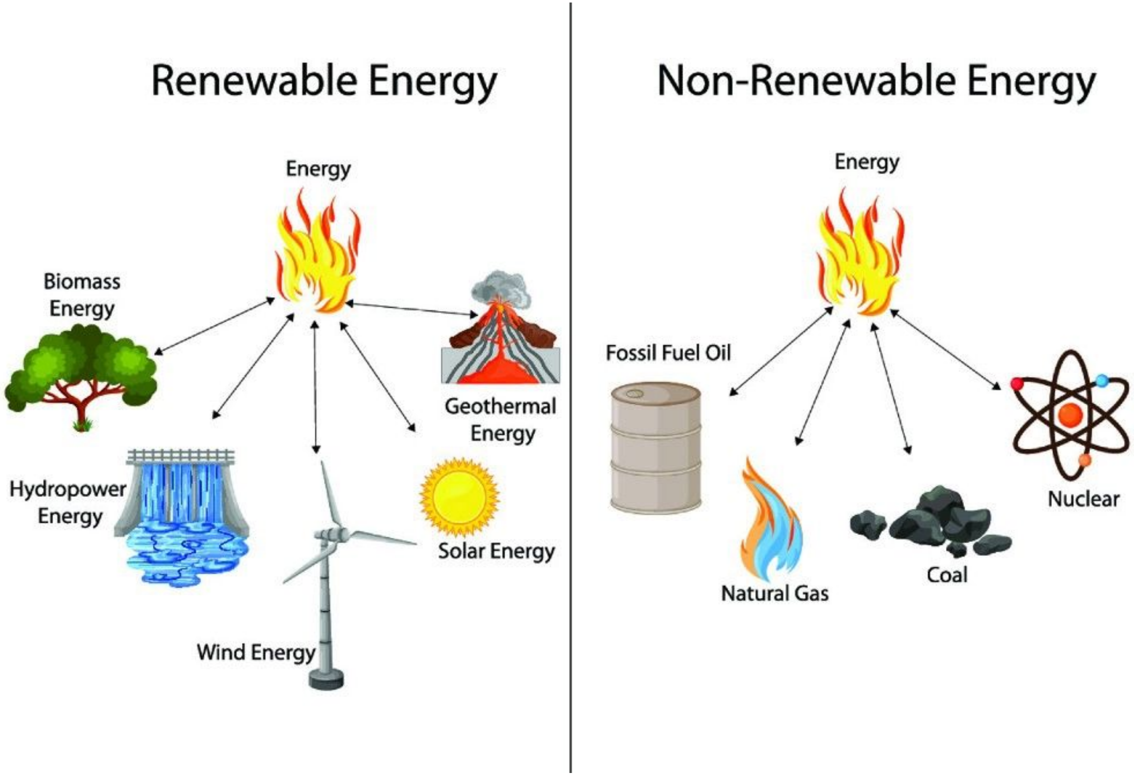


# Where does electricity come from?

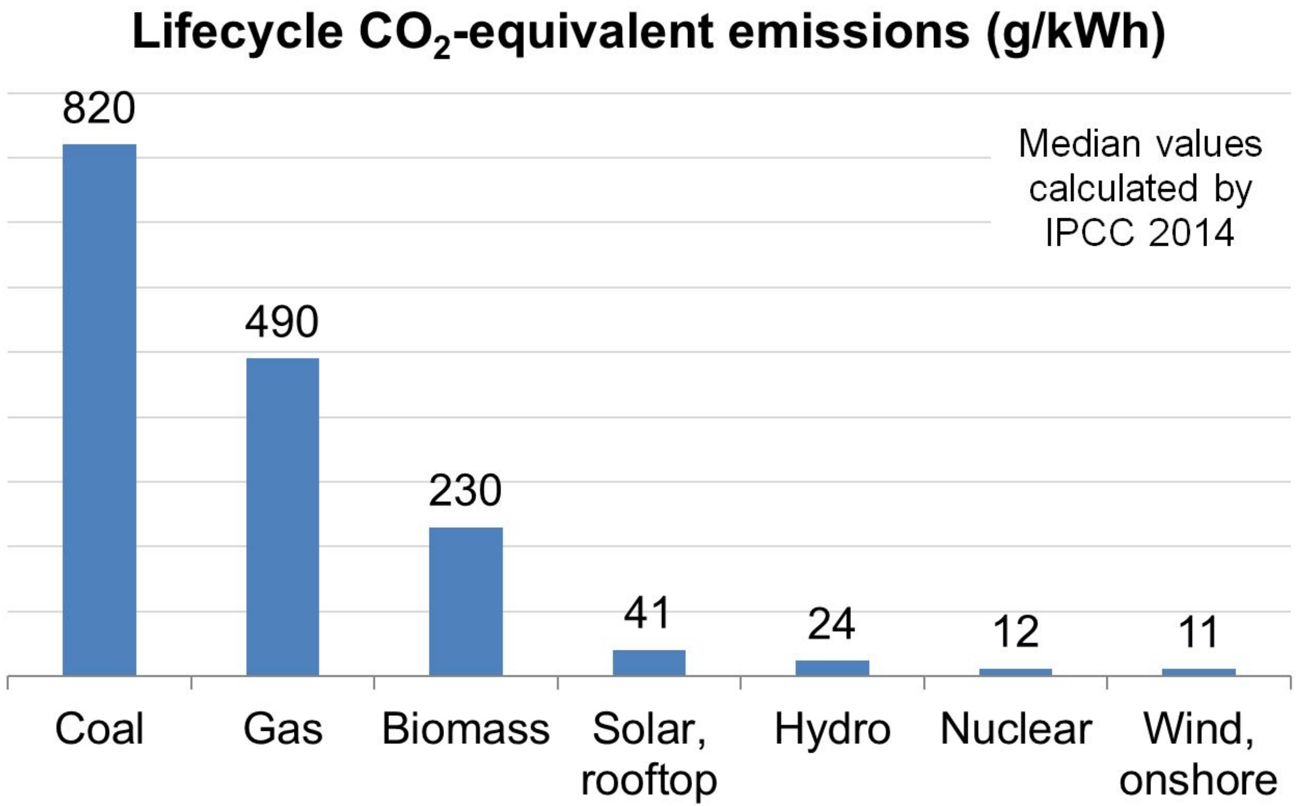
Renewable energy relies on sources that can be regenerated by existing natural forces.

Non-renewable energy relies on limited resources.

(Non)renewability does not determine if a source is GHG-emitting.



# GHGs from different energy sources




Direct emissions come from the generation of power itself.

Indirect emissions come from the production and maintenance of power plants.

# Labels

"Green" is not a well-specified term.

People debate if nuclear is green, and natural gas advocates have lobbied to label it as green.

## Ohio Gov. Declares Natural Gas 'Green Energy.' It Doesn't Work Like That.

A fossil fuel is a fossil fuel.

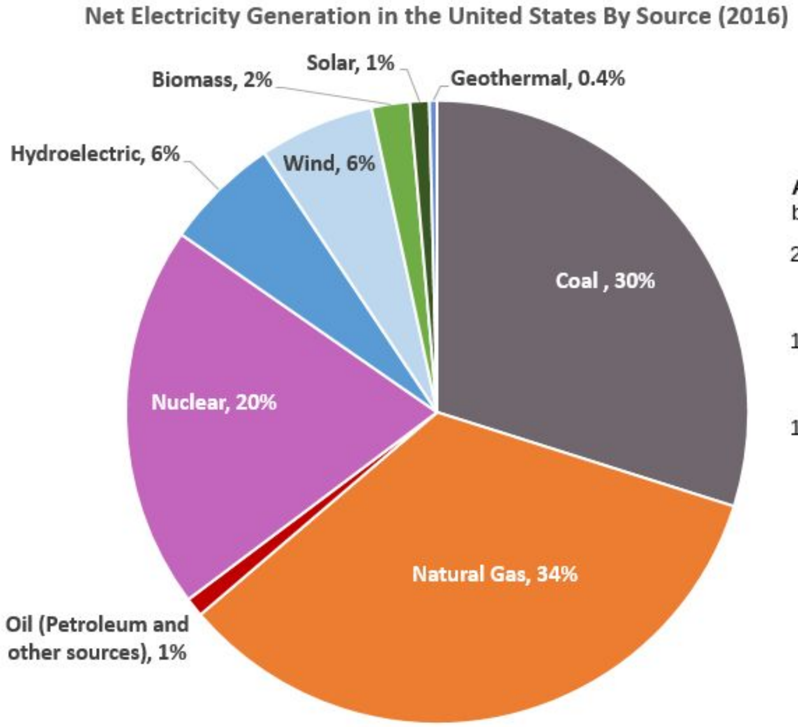
BY TIM NEWCOMB PUBLISHED: JAN 10, 2023

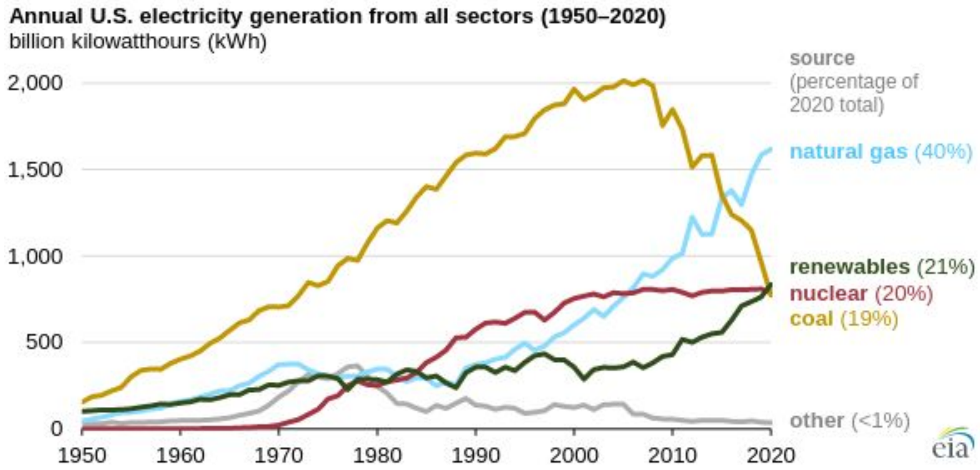
Tanaonte // Getty Images

- A new Ohio bill that calls natural gas a "green energy" opens state lands to oil and gas drilling.
- Natural gas is defined as a fossil fuel, albeit cleaner than some counterparts.
- Environment protectors say the new bill threatens Ohio state land to additional drilling.

popular mechanics

# Where does electricity come from in the US?

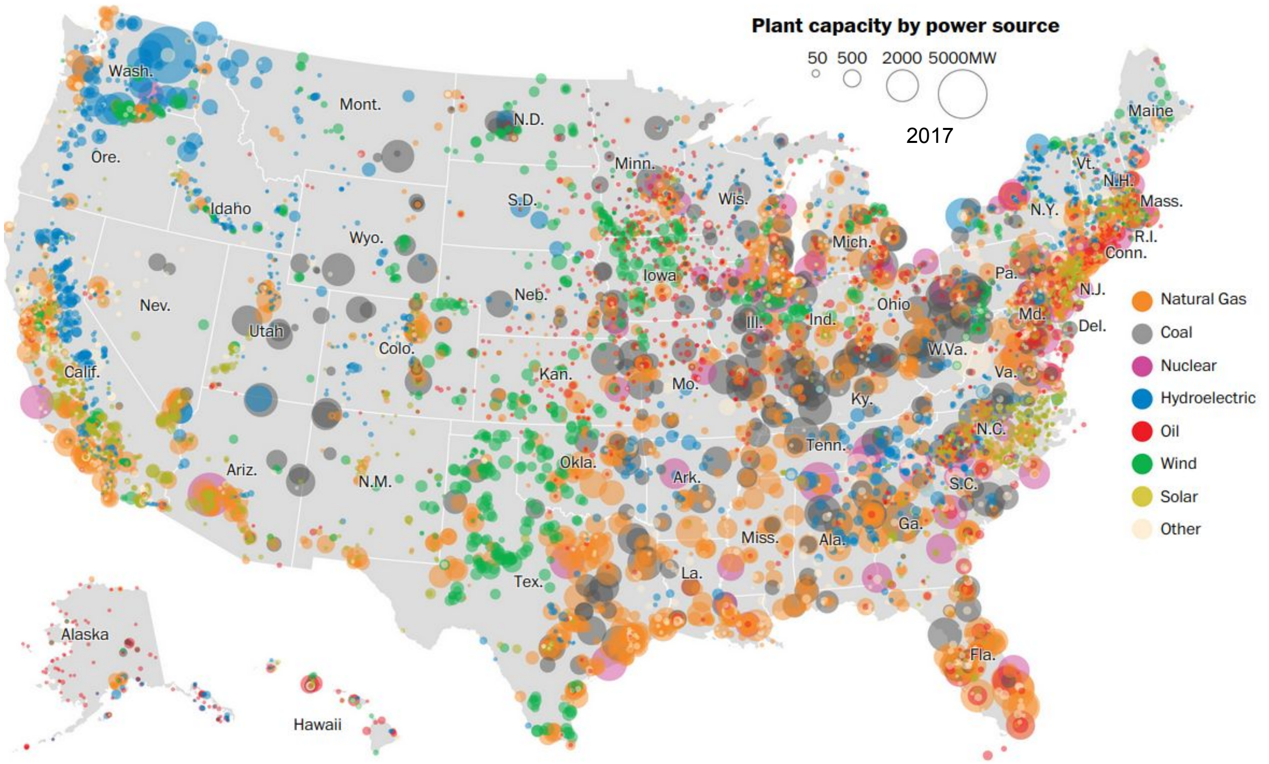



EPA

EIA

# Where does electricity come from in the US?




https://www.washingtonpost.com/graphics/national/power-plants/

Natural gas has expanded due to fracking.

Coal is more popular in the East.

Nuclear has a high power:space ratio, but is used unevenly across states.

Hydroelectric requires the right environmental factors.

Oil is only the leading source in Hawaii

Wind is best in the plain states.

Solar is predominant in Southwest and certain Eastern states.

# Where does electricity come from globally?

Global energy consumption, 2000 to 2021

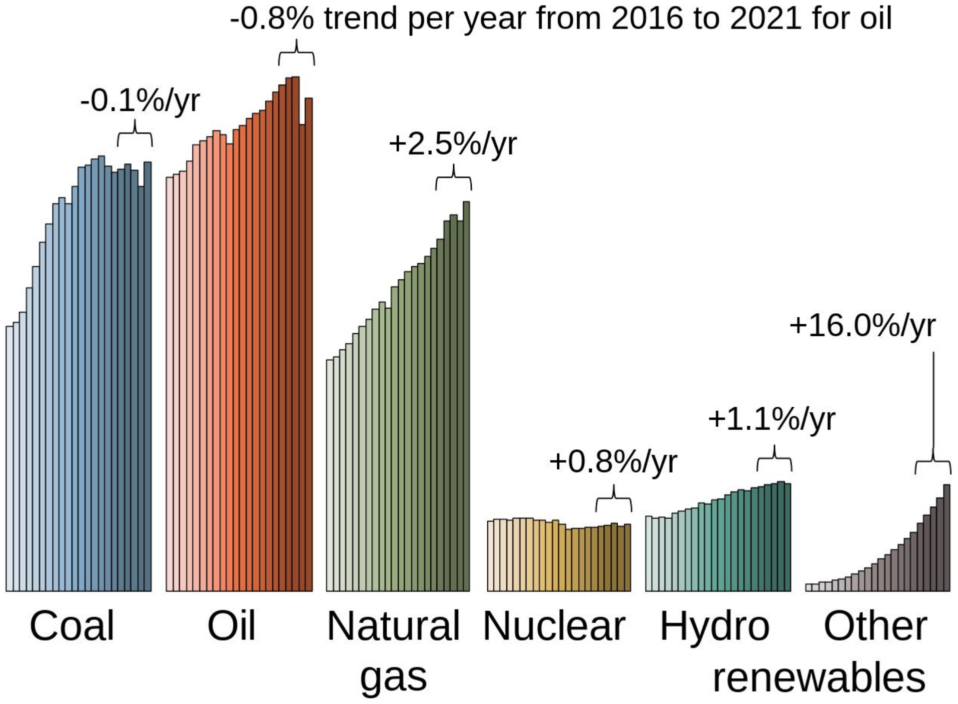
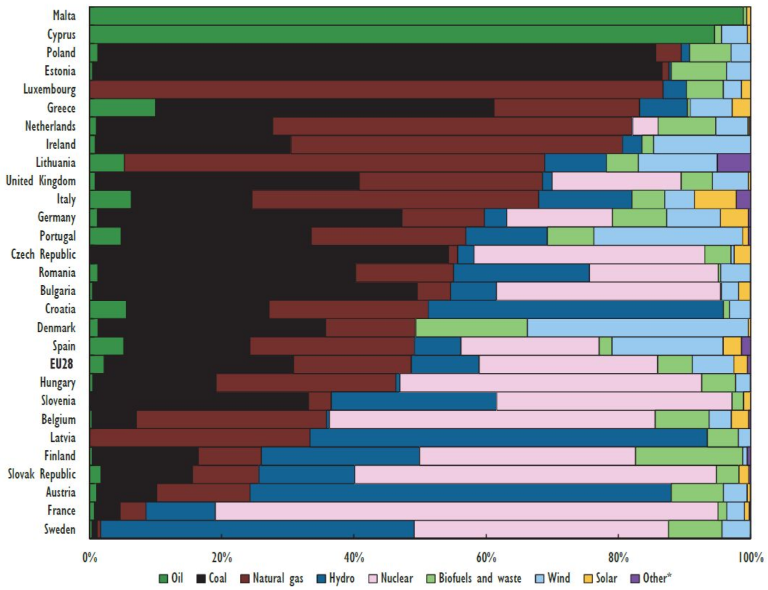



**Figure 5.2** Electricity generation in the European Union by country and source, 2012




* *Other* includes geothermal, peat and ambient heat production.

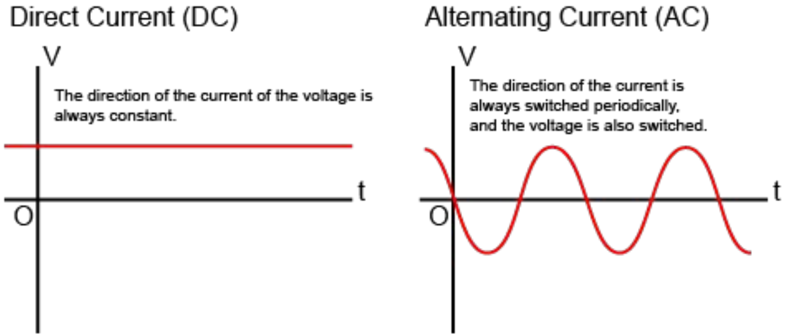
Sources: IEA (2014a), *Energy Balances of OECD Countries*, OECD/IEA, Paris; IEA (2014c), *Energy Statistics of Non-OECD Countries*, OECD/IEA, Paris.

# How does the power grid work?

https://www.wsj.com/video/how-does-the-us-power-grid-work/1671AA83-D0D2-4C75-913C-B381341159F4.html

# Grid Balancing

Supply needs to equal demand on a second-by-second basis. Errors of 1% in the frequency of generated AC currents can cause problems

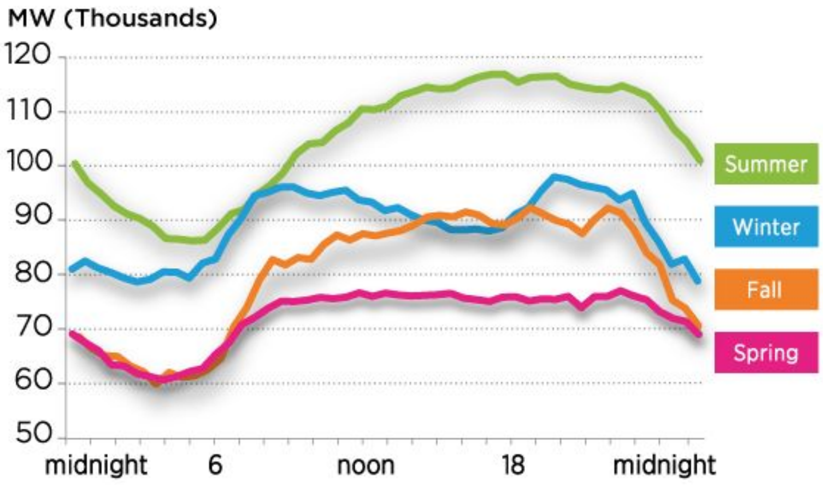



Demand > Supply --> Blackouts

Supply > Demand -->  Damage from excess voltage

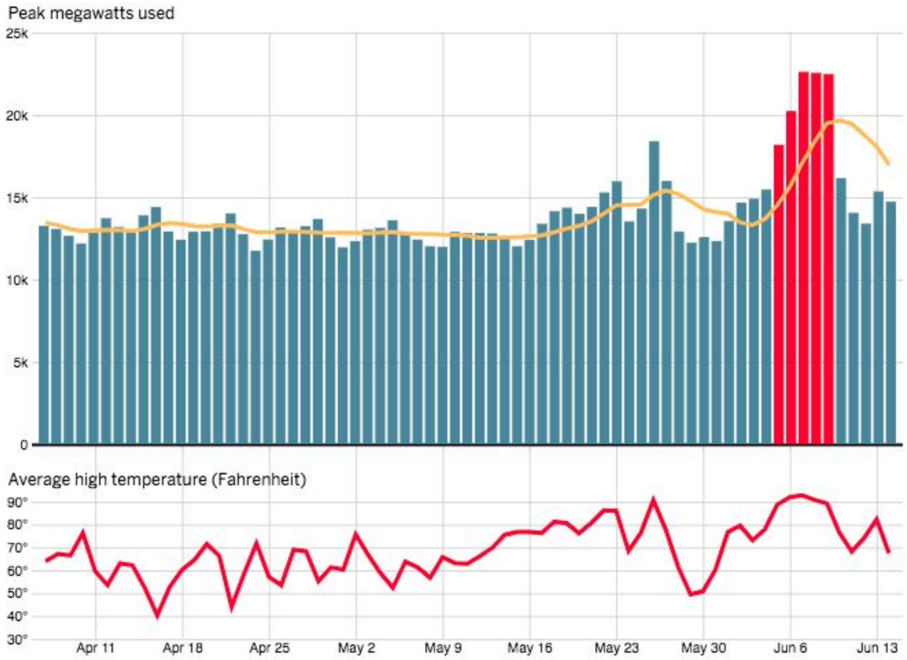
# Impacts on demand

# Impacts on demand




Predictable seasonal and daily trends

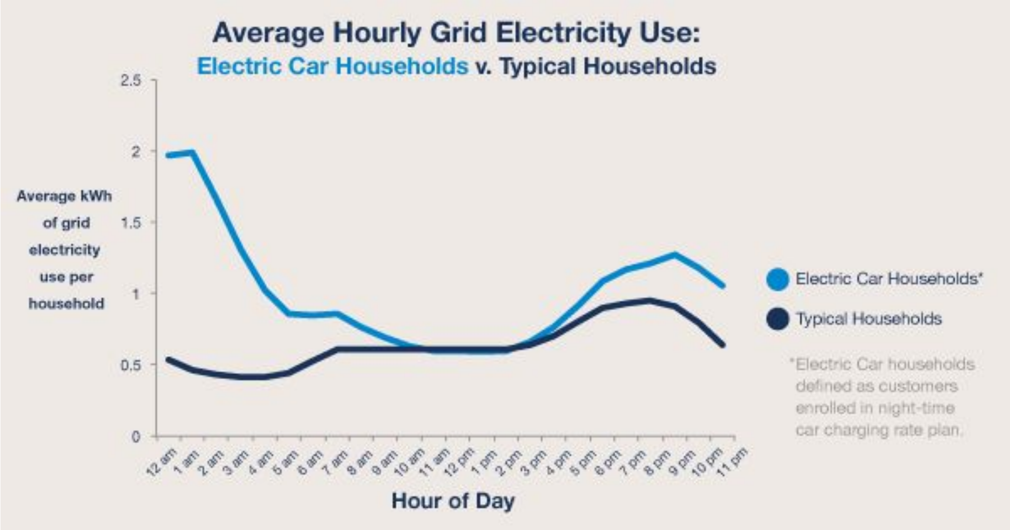
# Impacts on demand




Boston Globe

Extreme weather events

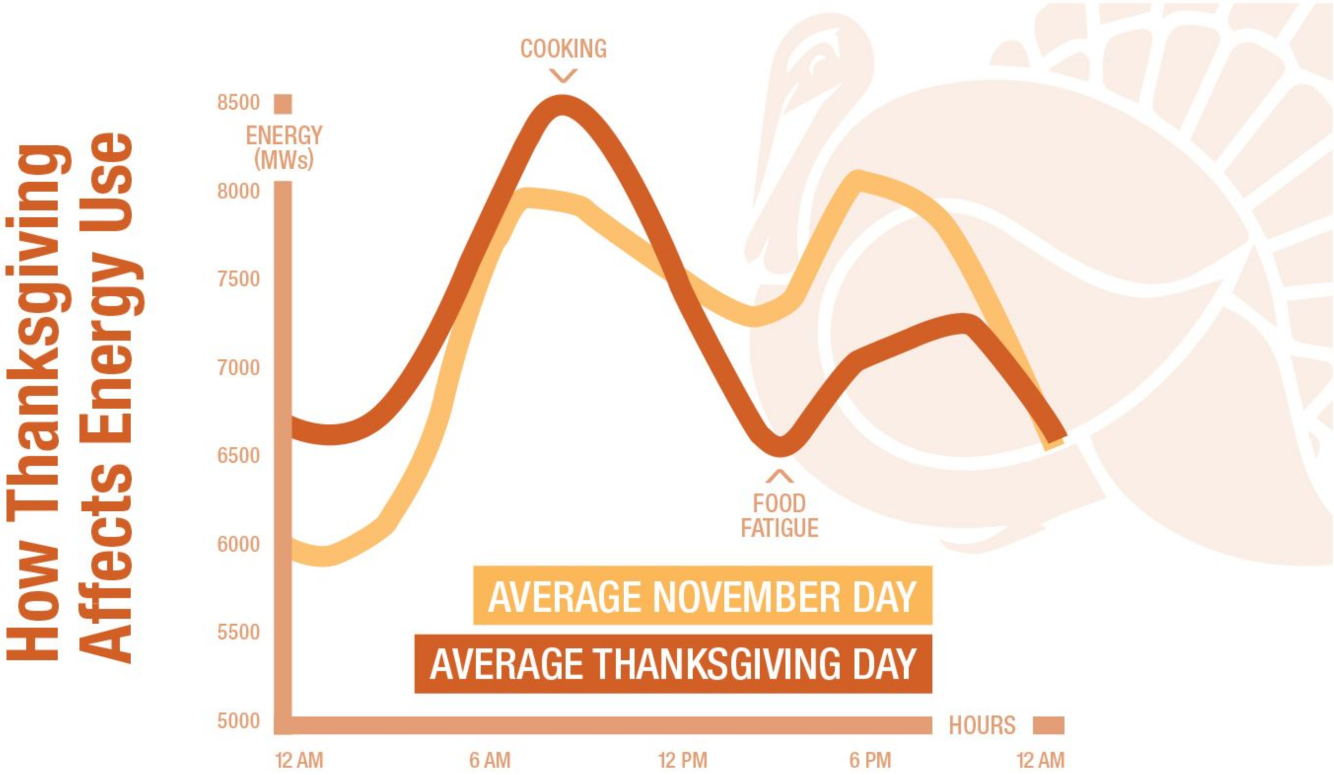
# Impacts on demand




Increased electrification of devices.

World Economic Forum

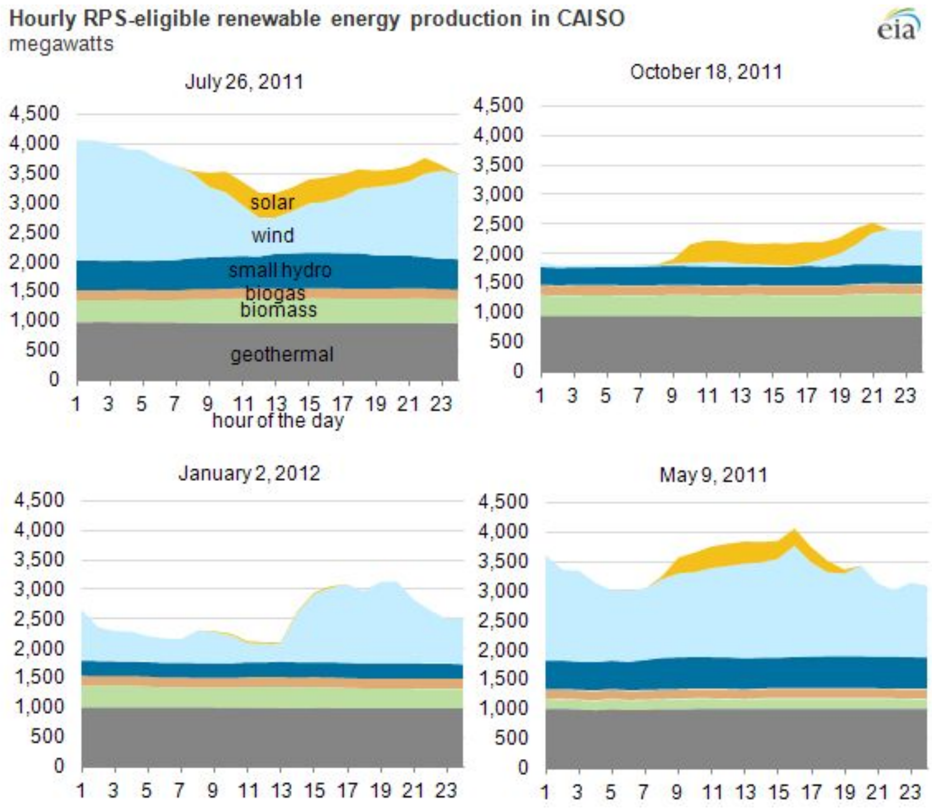
# Major cultural events




bpa

# Impacts on supply

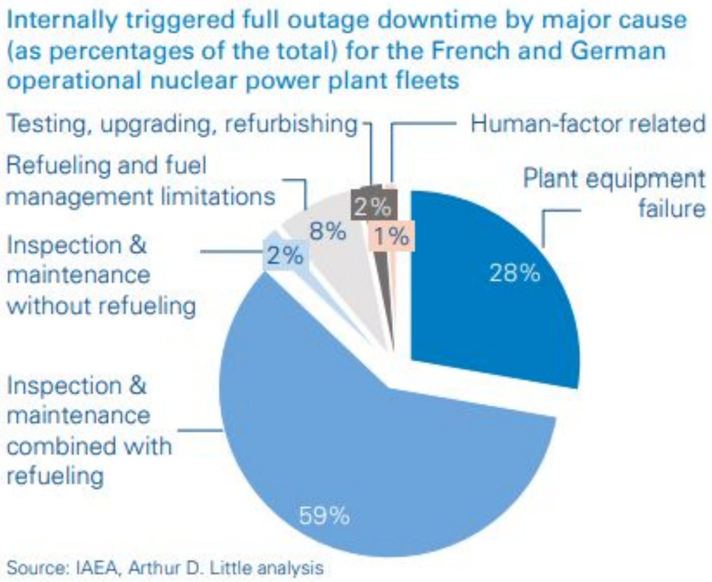
# Impacts on supply

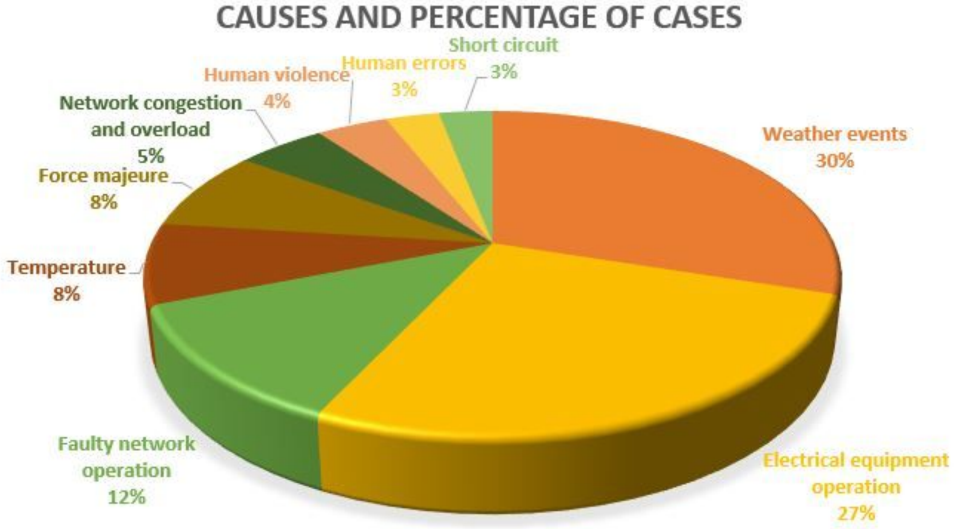



Variability of renewables

# Impacts on supply

Power plant planned maintenance and unexpected failures




Hydroelectric

# Impacts on supply

## Major political events

***Ukraine Nuclear Plant Pulled Off Line After Shelling Kindles Blaze***

A fire caused by shelling forced the staff of Europe's largest nuclear plant to disconnect from the nation's power grid, showing that risks remained at the plant despite the presence of U.N. experts.

Give this article

**War in Ukraine: Russia says it may cut gas supplies if oil ban goes ahead**

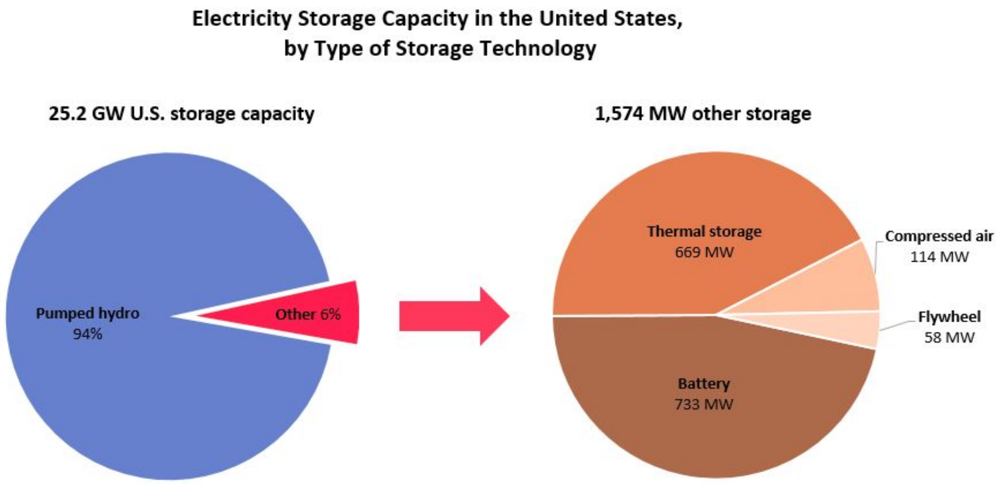
8 March 2022 · Comments

Russia-Ukraine war


The Nord Stream 1 gas pipeline was inaugurated just over a decade ago

# Power storage

- **Pumped hydroelectric.** Electricity is used to pump water up to a reservoir. When water is released from the reservoir, it flows down through a turbine to generate electricity.
- **Compressed air.** Electricity is used to compress air at up to 1,000 pounds per square inch and store it, often in underground caverns. When electricity demand is high, the pressurized air is released to generate electricity through an expansion turbine generator.
- **Flywheels.** Electricity is used to accelerate a flywheel (a type of rotor) through which the energy is conserved as kinetic rotational energy. When the energy is needed, the spinning force of the flywheel is used to turn a generator. Some flywheels use magnetic bearings, operate in a vacuum to reduce drag, and can attain rotational speeds up to 60,000 revolutions per minute.
- **Batteries.** Similar to common rechargeable batteries, very large batteries can store electricity until it is needed. These systems can use lithium ion, lead acid, lithium iron or other battery technologies.
- **Thermal energy storage.** Electricity can be used to produce thermal energy, which can be stored until it is needed. For example, electricity can be used to produce chilled water or ice during times of low demand and later used for cooling during periods of peak electricity consumption.




EPA

# Power Storage

Forms of storing power are too large, too slow, and/or too costly to fully solve the grid balancing problem.

CLIMATE CHANGE

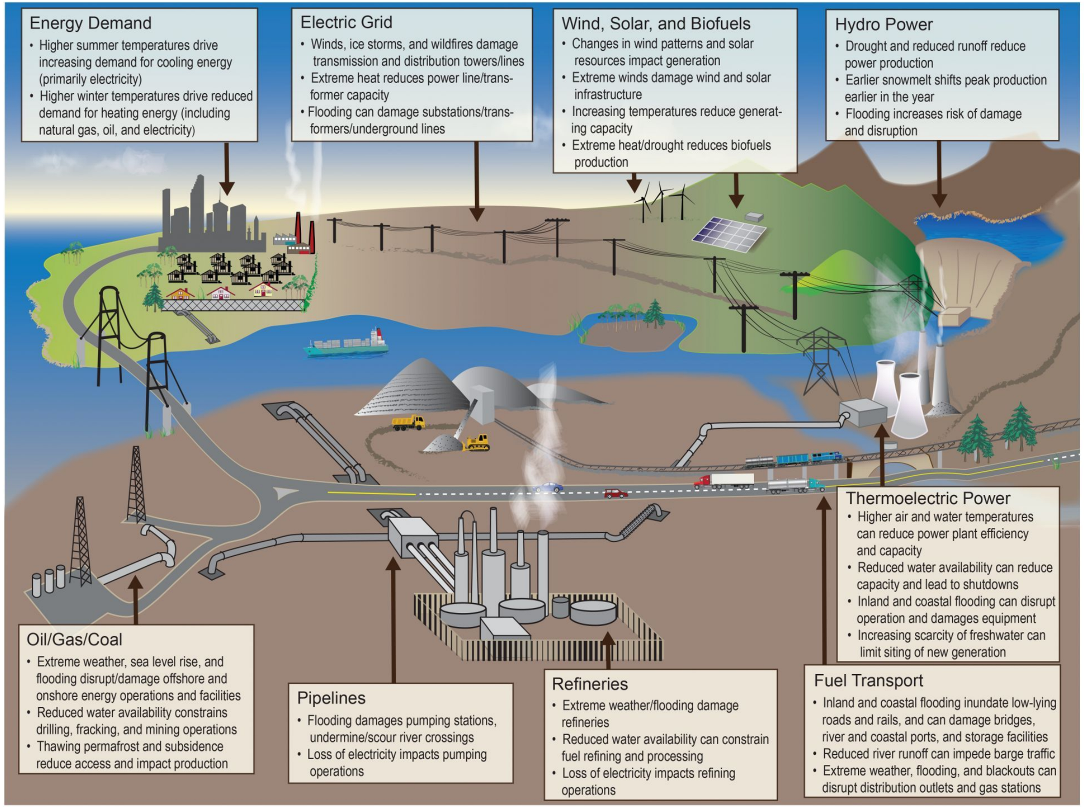
## The $2.5 trillion reason we can’t rely on batteries to clean up the grid

Fluctuating solar and wind power require lots of energy storage, and lithium-ion batteries seem like the obvious choice—but they are far too expensive to play a major role.

By James Temple

July 27, 2018

# How climate change will impact power



# Opportunities for ML

# Methods for predicting demand

ELSEVIER

Advances in Applied Energy
Volume 2, 26 May 2021, 100025

## Predicting city-scale daily electricity consumption using data-driven models

Wang, Zhe, Hong, Tianzhen, Li, Han, Mary Ann Piette

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https://doi.org/10.1016/j.adapen.2021.100025  Get rights and content



### Highlights

- We studied how city electricity use is influenced by weather and COVID-19 pandemic.
- Seven data-driven models were applied and evaluated for data of three cities.
- Gradient boosting tree model delivers the most accurate prediction with CVRMSE of 4%–6%.
- 1 °C increase of ambient temperature drives up the three cities electricity usage by around 5%.
- COVID-19 curtailment reduced city-scale electricity usage by 2%–12%.

## Electric vehicle charging demand forecasting using deep learning model

**Zhiyan Yi, Xiaoyue Cathy Liu, Ran Wei, Xi Chen & Jiangpeng Dai**

**To cite this article:** Zhiyan Yi, Xiaoyue Cathy Liu, Ran Wei, Xi Chen & Jiangpeng Dai (2022) Electric vehicle charging demand forecasting using deep learning model, Journal of Intelligent Transportation Systems, 26:6, 690-703, DOI: 10.1080/15472450.2021.1966627

**To link to this article:** https://doi.org/10.1080/15472450.2021.1966627

**ABSTRACT**
Greenhouse gas (GHG) emission and excessive fuel consumption have become a pressing issue nowadays. Particularly, $CO_2$ emissions from transportation account for approximately one-quarter of global emissions since 2016. Electric vehicle (EV) is considered an appealing option to address the aforementioned concerns. However, with the growing EV market, issues such as insufficient charging infrastructure to support such ever-increasing demand emerge as well. Effectively forecasting the commercial EV charging demand ensures the reliability and robustness of grid utility in the short term and helps with investment planning and resource allocation for charging infrastructures in the long run. To this end, this article presents a time-series forecasting of the monthly commercial EV charging demand using a deep learning approach-Sequence to Sequence (Seq2Seq). The proposed model is validated by real-world datasets from the State of Utah and the City of Los Angeles. Two prediction targets, namely one-step ahead prediction and multi-step ahead prediction, are tested. Further, the model is benchmarked and compared against other time series and machine learning models. Experiments show that both Seq2seq and long short-term memory (LSTM) generate satisfactory prediction performance for one-step prediction. However, when performing the multi-step prediction, Seq2Seq significantly outperforms other models in terms of various performance metrics, indicating the model's strong capability for sequential data predictions.

# Methods for predicting supply

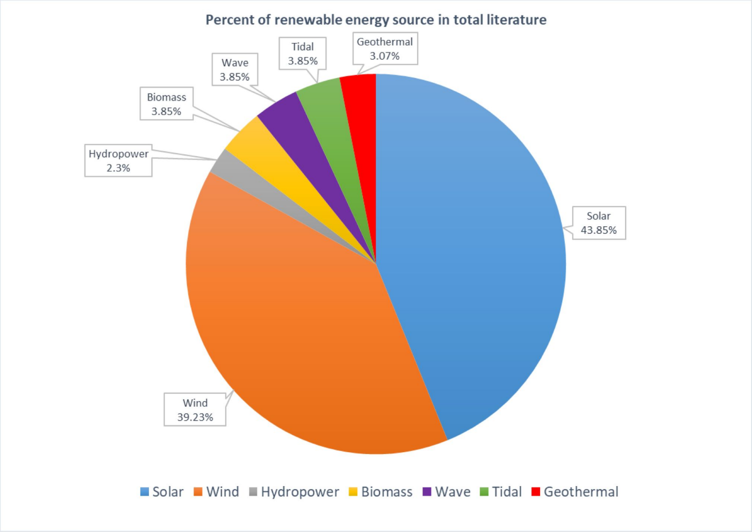
Open Access | Review

## A Survey of Machine Learning Models in Renewable Energy Predictions

by Jung-Pin Lai [1], Yu-Ming Chang [1,2], Chieh-Huang Chen [1] and Ping-Feng Pai [1,3,*]

1 PhD Program in Strategy and Development of Emerging Industries, National Chi Nan University, Nantou 54561, Taiwan
2 Department of Culinary Arts and Hotel Management, HungKuang University, Taichung 43302, Taiwan
3 Department of Information Management, National Chi Nan University, Nantou 54561, Taiwan
* Author to whom correspondence should be addressed.

*Appl. Sci.* **2020**, *10*(17), 5975; https://doi.org/10.3390/app10175975




| Sources of Energy | Models | Techniques |
|---|---|---|
| Wind | Artificial intelligence | Gaussian process regression(GPR), Support vector regression(SVR), Artificial neural networks(ANN) [16]; xGBoost regression, SVR, Random forest(RF) [18]; Least squares support vector machine(SVM) [19]; SVR, ANN, Gradient boosting(GB), RF [20]; RF [21]; GB trees [22]; Multi-layer perceptron(MLP) [24]; Deep neural network(DNN)-principal component analysis [25]; Feedforward ANN [26]; Efficient deep convolution neural network [27,34]; Linear regression, neural networks, SVR [28]; Convolutional neural networks(CNN) [29,37]; DNN [30,31]; Efficient deep CNN [32]; Stacked auto-encoders, back propagation [33]; Predictive deep CNN [35]; Improved radial basis function neural network-based model with an error feedback scheme [36]; ANN and genetic programming [38]; Long short-term memory(LSTM) [39,42]; Improved LSTM-enhanced forget-gate network [40]; LSTM-ANN [41]; Auto-LSTM [43]; Shared weight LSTM network [44]; Ensem-LSTM [45]; Instance-based transfer-GB decision trees [114]; Extreme learning machine(ELM) [115,116]; Empirical mode decomposition(EMD)-stacked auto-encoders-ELM [117]; Pattern sequence-based forecasting [118] |
| | Statistical | Physics-informed statistical [17] |
| | Hybrid | Adaptive neuro-fuzzy inference system, Particle swarm optimization(PSO), Genetic algorithm [23]; Improved dragonfly algorithm-SVM [46]; Deep belief network with genetic algorithms [47]; Type-2 fuzzy neural network-PSO [48]; Multi-objective ant Lion algorithm-Least squares SVM [49]; Complete ensemble EMD-multi-Objective grey wolf optimization-ELM [50]; Variational Mode decomposition(VMD)-Backtracking Search-regularized ELM [51]; Coral reefs optimization algorithm with substrate layer, ELM [52]; Stacked extreme-learning machine [53]; VMD-singular spectrum analysis-LSTM-ELM [54]; Ensemble EMD-deep Boltzmann machine [55]; ELM-Improved complementary ensemble EMD with Adaptive noise-Autoregressive integrated moving average(ARIMA) [56]; Bayesian model averaging and Ensemble learning [57]; Sparse Bayesian-based robust functional regression [58]; Kernel principal component analysis-Core vector regression-Competition over resource [59]; Wavelet packet decomposition-LSTM [60]; Empirical wavelet transformation, Recurrent neural network(RNN) [61] |
| Solar | Artificial intelligence | Gated recurrent units [64]; RF [65], SVR, RF [66]; RF [67]; RF, gradient boosted regression, extreme GB [68]; Linear regression, decision trees, SVM, ANN [69]; ANN, SVM, GB, RF [70]; ANN [71,72,73,74,75,119,120,121]; CNN [76]; DNN [77,78,79]; DNN, RNN, LSTM [80]; LSTM, auto-LSTM, gate recurrent unit(GRU), machine learning and statistical hybrid model [81]; LSTM [82,84,85]; LSTM, GRU [83]; Copula-base nonlinear quantile regression [88]; Multi-method [122]; Smart persistence [123]; *K*-nearest-neighbors, GB [124]; *K*-nearest-neighbors, SVM [125]; Angstrom-Prescott [126]; Multilayer feed-forward neural network [127]; Support vector classification [128]; GPR [129]; Regime-dependent ANN [130]; ELM [131]; Adaptive forward–backward greedy algorithm, leapForward, spikeslab, Cubist and bagEarthGCV [132]; Static and dynamic ensembles [133] |
| | Statistical | ARIMA [62,63] |
| | Hybrid | Wavelet decomposition-Hybrid [86]; Improve moth-flame optimization algorithm-SVM [87]; SVM-PSO [89]; Cluster-based approach, ANN, SVM [90]; SVM, Horizon, General [134]; ANN, Principle component analysis [135]; Auto regressive mobile average, MLP, Regression trees [136]; Ensemble EMD-least square SVR [137]; Least absolute shrinkage and Selection operator, LSTM [138]; RF, SVR, ARIMA, k-nearest neighbors [139]; Mycielski-Markov [140]; VMD-deep CNN [141]; PSO-ELM [142,143]; Multi-objective PSO [144]; Artificial bee colony-empirical models [145]; Gated recurrent unit and Attention mechanism [146] |
| Hydropower | Artificial intelligence | Bayesian linear regression [106] |
| | Hybrid | Grey wolf optimization-adaptive neuro-Fuzzy inference system [91]; Long-medium and short-term, Bayesian stochastic dynamic programming [107] |
| Biomass | Artificial intelligence | Linear regression, k-nearest neighbors' regression, SVM, Decision tree regression [93]; Gradient boosted regression trees [94]; Decision tree regression, MLP [95] |
| | Hybrid | SVM-Simulated annealing [96]; PSO-SVM [108] |
| Wave | Artificial intelligence | Fuzzy inference systems, ANN [109]; GPR [110]; Interval type-2 fuzzy inference system [111] |
| | Hybrid | Improved complete ensemble EMD-ELM [97]; Bayesian optimization-grouping genetic algorithm-ELM [98] |
| Tidal | Artificial intelligence | Wavelet-SVR [99] |
| | Hybrid | Wavelet and ANN, Fourier series based on least square method [100]; GPR-Bayesian [101]; Ensemble EMD-Least squares SVM [102]; Modified harmony search [103] |
| Geothermal | Artificial intelligence | LSTM [104]; Multiple regression-ANN [112]; RF [113] |

# Methods for measuring supply

## *"How clean is my electricity if I use it right now?"*

Now your customers can know. Our breakthrough, proprietary technology detects which power plants are powering your devices and when. Our solutions can empower any IoT device, from thermostats to electric vehicles, to automatically prioritize energy from cleaner generation sources.

Every time you use electricity, that instantly causes a single power plant to make a little more. But... which power plant? Usually, it's a fossil fuel plant like coal, which is why using energy creates pollution. Yet as renewable energy keeps growing, there are more and more moments today when using electricity instead only activates a clean power plant like wind or solar. That's creating a powerful new way to switch to cleaner energy: timing.

And thanks to the growing Internet of Things, today there are now over 20 billion devices worldwide that can effortlessly and automatically use electricity at particular times. So, if your company manufactures, owns, or operates a lot of IoT devices—anything from smart thermostats to electric vehicles to energy storage—you actually have the latent ability to effortlessly and automatically run on cleaner energy.

WattTime is a nonprofit founded to make it easy for manufacturers and operators of smart devices to go green this way without affecting their device performance, user comfort, or even cost. We've packaged this into a set of simple tools we call Automated Emissions Reduction, like real-time and forecast emissions data through our API. Now, one of the most powerful environmental actions a company can take comes with set-it-and-forget-it simplicity.

# Methods for power grid function

## Predicting failures:

# Machine Learning for the New York City Power Grid

Cynthia Rudin[†*], David Waltz[*], Roger N. Anderson[*], Albert Boulanger[*], Ansaf Salleb-Aouissi[*], Maggie Chow[‡], Haimonti Dutta[*], Philip Gross[*≀], Bert Huang[*], Steve Ierome[‡], Delfina Isaac[‡], Arthur Kressner[‡], Rebecca J. Passonneau[*], Axinia Radeva[*], Leon Wu[*]

**Abstract**—Power companies can benefit from the use of knowledge discovery methods and statistical machine learning for preventive maintenance. We introduce a general process for transforming historical electrical grid data into models that aim to predict the risk of failures for components and systems. These models can be used directly by power companies to assist with prioritization of maintenance and repair work. Specialized versions of this process are used to produce 1) feeder failure rankings, 2) cable, joint, terminator and transformer rankings, 3) feeder MTBF (Mean Time Between Failure) estimates and 4) manhole events vulnerability rankings. The process in its most general form can handle diverse, noisy, sources that are historical (static), semi-real-time, or real-time, incorporates state-of-the-art machine learning algorithms for prioritization (supervised ranking or MTBF), and includes an evaluation of results via cross-validation and blind test. Above and beyond the ranked lists and MTBF estimates are business management interfaces that allow the prediction capability to be integrated directly into corporate planning and decision support; such interfaces rely on several important properties of our general modeling approach: that machine learning features are meaningful to domain experts, that the processing of data is transparent, and that prediction results are accurate enough to support sound decision making. We discuss the challenges in working with historical electrical grid data that were not designed for predictive purposes. The "rawness" of these data contrasts with the accuracy of the statistical models that can be obtained from the process; these models are sufficiently accurate to assist in maintaining New York City's electrical grid.

**Index Terms**—applications of machine learning, electrical grid, smart grid, knowledge discovery, supervised ranking, computational sustainability, reliability

## Grid design:



# Guided Machine Learning for Power Grid Segmentation

**Publisher: IEEE**



A. Marot ; S. Tazi ; B. Donnot ; P. Panciatici **All Authors**





**Abstract:**
The segmentation of large scale power grids into zones is crucial for control room operators when managing the grid complexity near real time. In this paper we propose a new method in two steps which is able to automatically do this segmentation, while taking into account the real time context, in order to help them handle shifting dynamics. Our method relies on a "guided" machine learning approach. As a first step, we define and compute a task specific "Influence Graph" in a guided manner. We indeed simulate on a grid state chosen interventions, representative of our task of interest (managing active power flows in our case). For visualization and interpretation, we then build a higher representation of the grid relevant to this task by applying the graph community detection algorithm Infomap on this Influence Graph. To illustrate our method and demonstrate its practical interest, we apply it on commonly used systems, the IEEE-14 and IEEE-118. We show promising and original interpretable results, especially on the previously well studied RTS-96 system for grid segmentation. We eventually share initial investigation and results on a large-scale system, the French power grid, whose segmentation had a surprising resemblance with RTE's historical partitioning.

# Paper Deep Dive

## Machine Learning for AC Optimal Power Flow

Neel Guha [1] Zhecheng Wang [2] Matt Wytock [3] Arun Majumdar [2]

**Abstract**

We explore machine learning methods for AC Optimal Powerflow (ACOPF) - the task of optimizing power generation in a transmission network according while respecting physical and engineering constraints. We present two formulations of ACOPF as a machine learning problem: 1) an *end-to-end prediction* task where we directly predict the optimal generator settings, and 2) a *constraint prediction* task where we predict the set of active constraints in the optimal solution. We validate these approaches on two benchmark grids.

https://arxiv.org/pdf/1910.08842.pdf

# The problem of “optimal power flow”

The objective of OPF is to find a steady state operating point that ***minimizes the cost of electric power generation while satisfying operating constraints and meeting demand.***

How can you most efficiently balance the grid?

# The problem of “optimal power flow”

The objective of OPF is to find a steady state operating point that ***minimizes the cost of electric power generation while satisfying operating constraints and meeting demand.***

How can you most efficiently balance the grid?

| Formulation | Variables | Number of variables | Number of equations |
|---|---|---|---|
| BIM | $V_i = (v_i e^{j\delta_i})$<br>$S_g^G = (p_g^G + jq_g^G)$<br>$S_l^L = (p_l^L + jq_l^L)$ | $N + G + L$<br>$(2N + 2G + 2L)$ | $N$<br>$(2N)$ |
| BFM | $V_i = (v_i e^{j\delta_i})$<br>$S_g^G = (p_g^G + jq_g^G)$<br>$S_l^L = (p_l^L + jq_l^L)$<br>$I_{ij}^s = (i_{ij}^s e^{j\gamma_{ij}^s})$<br>$S_{ij} = (p_{ij} + jq_{ij})$<br>$S_{ji} = (p_{ji} + jq_{ji})$ | $N + G + L + 3E$<br>$(2N + 2G + 2L + 6E)$ | $N + 3E$<br>$(2N + 6E)$ |

This is a really hard computational problem that scales with the size of the grid!

# OPF is hard

“In addition to minimizing generator costs, solutions must adhere to physical laws governing power flow (i.e. Kirchhoff’s voltage law) and respect the engineering limits of the grid. As a result, ACOPF is computationally intractable under the demands of daily grid management. In order to account for rapid fluctuations in power demand and supply, grid operators must solve ACOPF over the entire grid (comprising of tens of thousands of nodes) every five minutes.”

Current mathematical solvers either fail to converge within this time frame or produce suboptimal solutions.

# OPF is important

“A 2012 report from the Federal Energy Regulatory Commission estimated that the inefficiencies induced by approximate-solution techniques may cost billions of dollars and release unnecessary emissions”

Variants of the OPF that include how much different sources of energy cost at different times can also save money.

# Brainstorm

What kind of data would you want to have to be able to approach this problem?

What kind of methods would you apply?

How would you measure success?

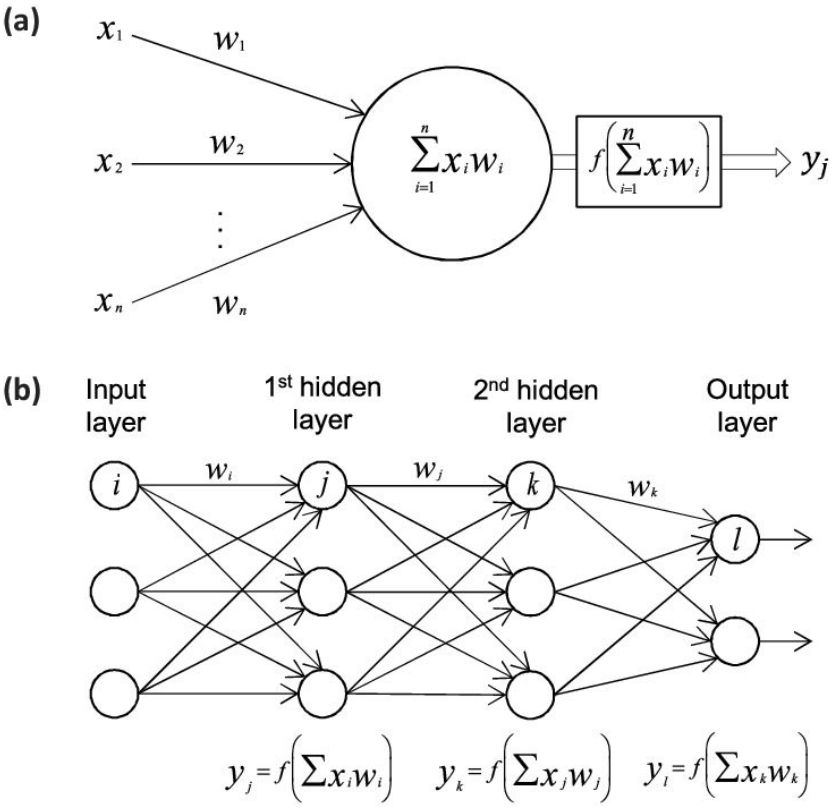
If successful, how could this system be useful?

# Approach

In this paper, we observe that it should be possible to learn a model that can predict an accurate solution over a fixed grid topology/constraint set. Intuitively, we expect some measure of consistency in the solution space - **similar load distributions should correspond to similar generator settings**.This suggests an underlying structure to the ACOPF problem, which a machine learning model can exploit.

**Neural networks** have demonstrated the ability to model extremely complicated non-convex functions, making them highly attractive for this setting. A model could be trained off-line on historic data and used in real-time to make predictions on an optimal power setting.

# Neural networks




"Train a model to directly predict the optimal generator setting for a given load distribution. This is challenging, as the model's output must be adherence with physical laws/engineering limits."

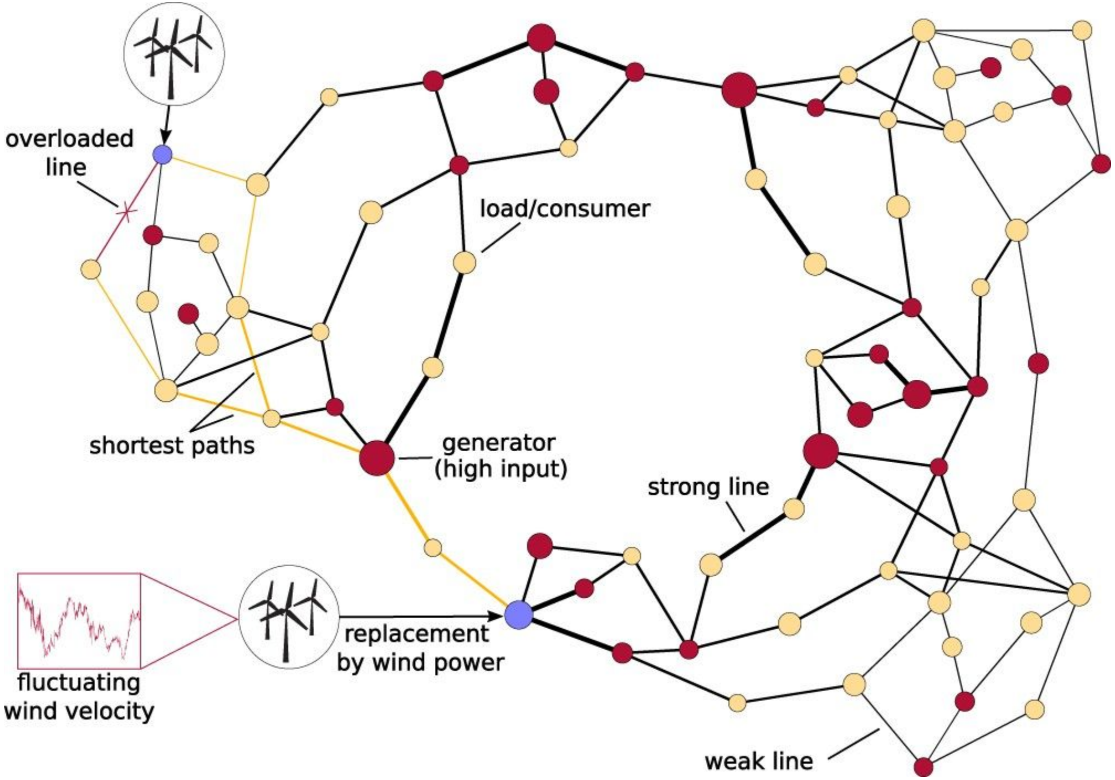
particular model. We examine a range of different architectures and training strategies. We performed a grid search considering models with 1-2 hidden layers, 128/256/512 hidden neurons, ReLU/Tanh activations. We also experimented with vanilla MSE loss, and a variant with linear penalties for constraint violations (described in Section 3.1). Each model was trained with Adam ($\mathrm{lr} = 0.001$) until loss convergence, for a maximum of 2000 epochs.

Vieira et al.

# Inputs and Outputs

### 3.1. End-to-end Prediction

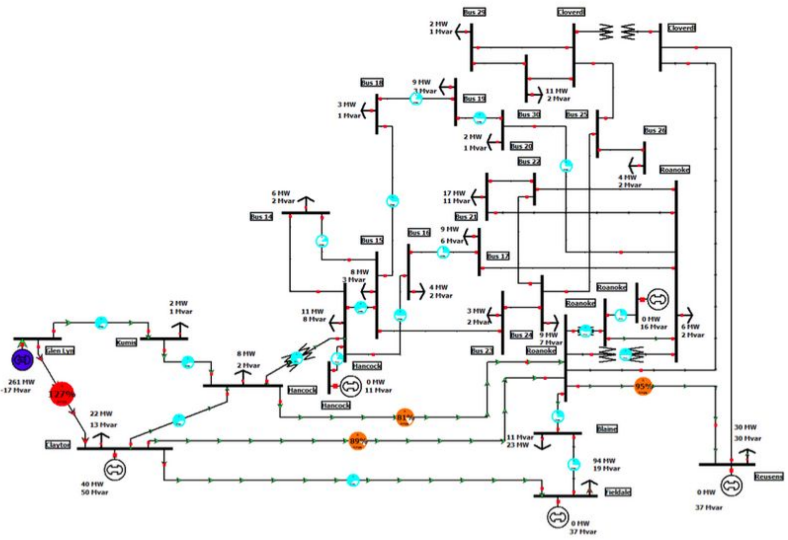
In this setting, we pose the AC OPF problem as a regression task, where we predict the grid control variables ($P_i^G$ and $V_i^G$) from the grid demand ($P_i^L$ and $Q_i^L$). These fix a set of equations with equal number of unknowns, which can be solved to identify the remaining state values for the grid. Formally, given a dataset of $n$ solved grids with load distributions $\mathbf{X} = \{[P_0^L, ..., P_{\mathbf{N}}^L, Q_0^L, ..., Q_{\mathbf{N}}^L]\}_{i=1}^n$ and corresponding optimal generator settings $\mathbf{Y} = \{[P_0^G, ..., P_{\mathbf{G}}^G, V_0^G, ..., V_{\mathbf{G}}^L]\}_{i=1}^n$, our goal is to learn $f_\theta : \mathcal{X} \rightarrow \mathcal{Y}$ which minimizes the mean-squared error between the optimal generator settings $\mathbf{Y}$ and the predicted generator settings $\tilde{Y}$. Solving for the remain-




Model will depend on specifics of grid structure.

# Datasets

IEEE provides simulated grid data based on real US grid properties.



We validated approaches for end-to-end prediction and constraint prediction on IEEE 30-bus [3] and 118-bus test cases[4]. These test cases include predetermined constraints.

### 4.1. Dataset Generation

The IEEE test cases include a pre-calculated load distribution (denoted as $x^*$. In order to construct a dataset for each case, we repeatedly sample candidate load distributions $x' \sim \text{Uniform}((1-\delta) \cdot x^*, (1+\delta) \cdot x^*)$, for some fixed $\delta$. We identify $y'$ by solving the OPF problem for $x'$ via Matpower (Zimmerman et al., 2011). In some cases, the solver fails to converge, suggesting that the sampled $x'$ has no solution given the grid constraints. In this case, we discard $x'$.

We generated 95000 solved grids for case118 and 812888 solved grids for case30 with $\delta = 0.1$ (a 10% perturbation to the IEEE base demand). Interestingly, we observe that while 100% of the samples generated for case118 were successfully solved, only 81.2% of the samples for case30 were successfully solved. For all prediction tasks, we used a 90/10 train-test split and report results on the test set.

# Evaluation

### 4.2. End to end prediction

We evaluate task performance along two metrics:

- **Legality Rate**: The proportion of predicted grids which satisfy all engineering and physical constraints. (Reliability)
- **Avg. Cost Deviation**: The average fractional difference between the cost of the predicted grid, and the cost of the true grid: $\frac{1}{n}\sum_i^n |1 - \frac{\text{pred cost}_i}{\text{true cost}_i}|$ over legal grids. (Optimality)

# Results

# Results

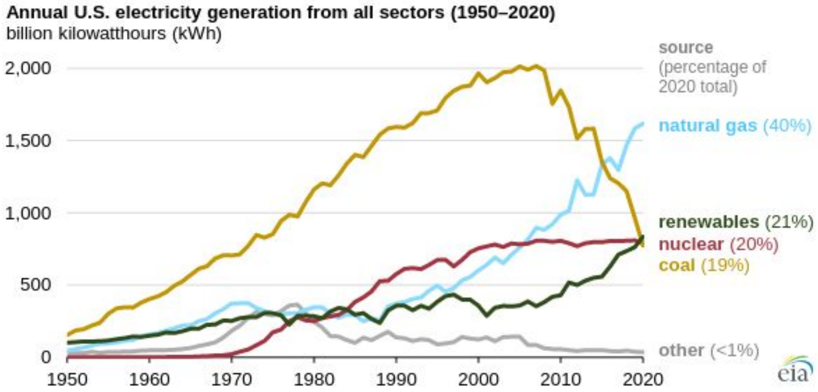
Table 1 reports the best performance for each grid type. For case30, the optimal model was a two layer neural network with tanh activations, and no loss penalty. For case118, the optimal model was a three layer network with 512 hidden neurons, ReLU activations, and a constraint loss penalty. Interestingly, we observe better performance on case118 than case30. Though we would intuitively expect task difficulty to scale with grid size, this result suggests that other factors could affect a model's generalization ability. In particular, smaller grids could be less stable, and thus more likely to produce a wide range of (less predictable) behavior under varying demand distributions. We also observe that the cost of the optimal model predictions were within 1% of the optimal cost.

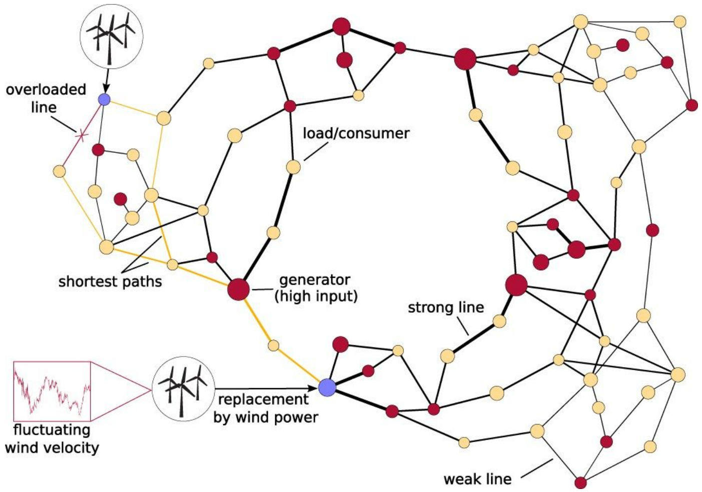
Not great! Not bad!

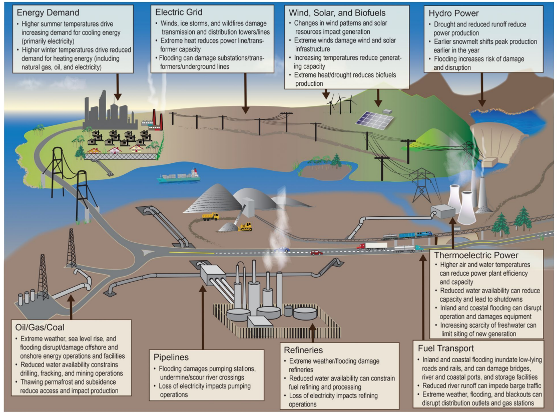
| Grid | Legality Rate | Avg. Cost Deviation |
|---|---|---|
| case30 | 0.51 | 0.002 |
| case118 | 0.70 | 0.002 |

*Table 1.* End-to-end prediction performance. Average cost deviation is only reported for legal grids.

# Summary

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**Machine Learning for AC Optimal Power Flow**

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Neel Guha [1] Zhecheng Wang [2] Matt Wytock [3] Arun Majumdar [2]