

Subject	April 29, 2022
Notes	
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# Todo list

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- 1 Carbon Free Emissions Plan
- 2 Nationwide Trends
- 3 Current Statistics
- 4 Quantitative Data Analysis

Population of NYS 19.45 million as of 2019 [3]  
Population of NYC 8.149 million as of 2019 (cite census)

$$LCOE = \frac{\text{total annualized cost}}{\text{total annual energy output}}.$$

LCOE should be around 63/MWh for hydro, 32/MWh for land wind, 96/MWh for offshore-wind, 41/MWh for utility solar, 73/MWh for community distributed solar, 297/MWh based on 2019 NYISO numbers

## 5 Electricity Demand Forecast

## 6 Need

Amount of dispatchable need increases to 32,000 MW in 2040 under CLCPA assumptions

Load: Climate change and electrification results in increase in summer load

Electrification will transition NY from summer peaking to winter peaking Winter peak load under CLCPA will double Projected by 2040: 47KMW, winter peak over 57kMW

Need for dispatchable resources that perform on a multi-day period to maintain bulk power system reliability. No commercially available systems.

Increased need for transmission systems that accommodate more quantities of dispatchable energy.

We require the dispatchable resources to be fossil fuel free, and accommodate high ramping requirements as seen for sun and wind resources.

Reliability metrics: **transmission security** and **resource adequacy**.

Transmission security margins: **how robust the model is to distributional shift**

Loss of load expectation (days per year) (LOLE) Loss of load hours (hours per year) (LOLH)

Expected unserved energy (megawatt-hours per year)

### 6.1 Transmission

### 6.2 Inverter based resources

wehoiw

## 7 Accounting for uncertainty in project planning

Analysis of load, generation, demand, transmission

## 8 NN Architecture

Hyperparameter Tuning, 4 Linear layers with Dropout = 0.3 and ReLU activation

Batch size is 64, hidden dim is 64

## 9 New sources of generation

### 9.1 Wind

#### 9.1.1 Land

#### 9.1.2 Offshore

New offshore wind projects in pipeline:

**Empire Wind 1:** 816 MW, solicited 2018 [1]

**Empire Wind 2:** 1260 MW, solicited 2020 [1]

**Sunrise Wind:** 880 MW, solicited 2018 [1]

**Beacon Wind:** 1230 MW, solicited 2020 [1]

5 total projects totaling greater than 4300 MW, leading offshore generation pipeline in the nation

Official target goal for offshore wind generation is 9000 MW by 2035. [4]

Substation Locations: Astoria Substation, Gowanus Substation, Barrett Substation, Holbrook Substation, East Hampton Substation

Proposed Port Facilities: South Brooklyn Marine Terminal, Holbrook Substation, East Hampton Substation. [1]

All projects are currently in the data collection phase. [1]

NYSERDA offers contracts to purchase offshore renewable energy certificates (OREC) from offshore wind developers. NYSERDA sells these to load serving entities (LSEs) like utilities, which are required by law to purchase renewable energy credits. [? ]

### 9.1.3 Technology & Implementation

Advances in:

1. Materials
2. Engineering of turbine foundations
3. Turbine blade design

With respect to foundations: [9]

1. Monopiles - for depths up to 25m. Freestanding; cheap, easy to install and inexpensive to manufacture and transport. Used in 95% of installations worldwide.
2. Gravity - also for up to 25m, but used for less cohesive seabed compositions
3. Suction bucket - Can also be cost effective, but only for appropriate choice of seabed composition
4. Deepwater -
5. Tripod - 30m - 60m water depth
6. Jacket - > 50m water depth. Expensive and complex to install and manufacture; however, mature

### 9.1.4 Geography of the Long-Island Area

## 9.2 Solar

Official target: 10GW distributed solar by 2030 (cite NYSERDA)

Government sponsored incentives via tax credits, NYSun

## 9.3 Geothermal

# 10 Maintenance of mature technologies and infrastructure

## 10.1 Nuclear

# 11 Policy Changes

NYSERDA energy credits:

1. Tier 1 (new renewables)
2. Tier 2 (maintenance resources)
3. Tier 2 (competitive program)
4. Tier 4 (NYC renewable energy)

## 11.1 Pricing Changes

## 11.2 Economic viability

Need Fair distribution of costs between ISOs and RTOs. [9]

Renewable Portfolio Standards

Aggressive federal support amenable to policy decision to focus on offshore wind – allows ISOs to reach LCOE levels for offshore installation costs similar to those seen in the UK, given the tax subsidies [9]

# 12 Viability (outside of financial)

## 12.1 Resource constraints

## 12.2 Trend constraints

## 12.3 Location constraints

# 13 Background

The last two decades have brought marked improvements in energy efficient systems and infrastructure on a global scale. The penetration profile of electricity generation sources has seen a nationwide trend towards renewable and "clean" energy source – offshore wind, nuclear, biofuels, and geothermal – and a complementary shift away from traditional fossil fuels.

The NYISO region is uniquely characterized by the speed at which it has adopted – and integrated – new technologies and developed infrastructure. It remains the only coal free region in the US, and leads the nation in installed capacity of several renewable sources – most notably offshore wind [1] . With five offshore wind projects in active development, New York is touted as the nation's "hub" for offshore wind, projecting to deliver approximately 4300 MW from these facilities alone, with goals to extend that to 9000 MW by 2040 . Quite remarkably, New York consumes less total energy per capita than all but two states, and .

While the NYISO has released a comprehensive plan towards 70% renewable energy by 2030, and 100% carbon-free electricity by 2040, there are several areas which remain unexploited. Our work aims to assess these areas of untapped potential and improvements in policy that can be leveraged to accelerate progress towards a more ambitious goal – how the NYISO region can be *fossil fuel free* by 2030. In particular, we We also provide a robust, quantitative analysis of projected energy demand and projected generation requirements needed to sustain this trend towards 100% carbon-free electricity in the next eight years.

check citation

citation

a little more here on adoption of other technologies (brief)?

cite main suggestions

## 13.1 Statewide Energy Profile

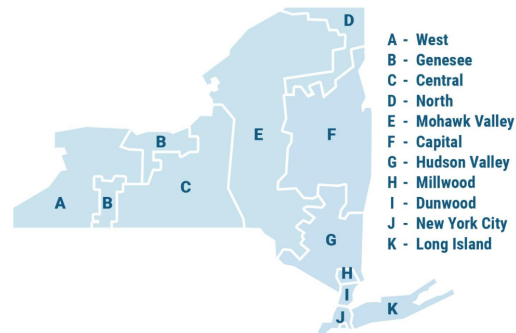


Figure 1: Zoning of NYISO.

New York has consistently met nearly 90% of energy requirements through nuclear, hydropower and natural gas alone. In 2020, New York accounted for nearly 11% of U.S. hydroelectricity generation, and was the third largest producer of hydroelectricity in the nation [2]. Renewable resources were responsible for nearly 60% of electricity generation alone that same year. Figure 1 shows the profile of electricity generation distributed across different sources as of March 2022. The

change to ref

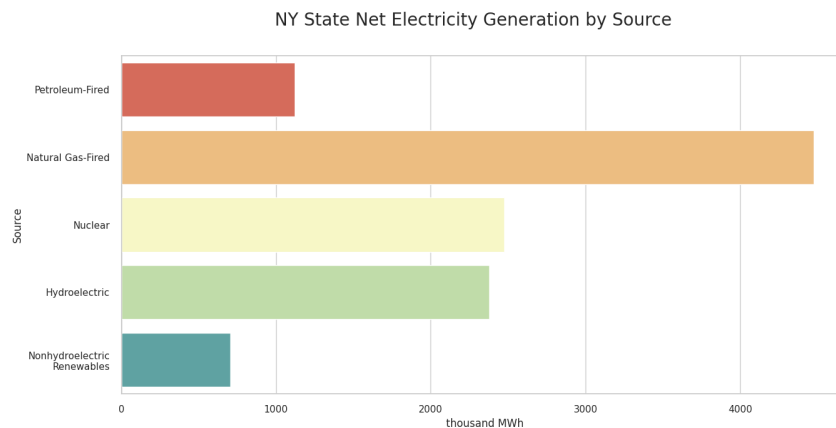


Figure 2

In recent years, the distribution has undergone a marked shift away from nuclear. Indian Point, responsible for nearly 25% of the state's electricity generation [8], of carbon free electricity, permanently shut down by April 2021. With a capacity factor of nearly 90%, facility delivered reliable base load electricity across the state, and its closure produced a void of approximately 2000MW of nuclear generating capacity. Since then, the share of the state's power from gas-fired generators has increased, jumping nearly 6% since the closure of its last unit (Indian Point Unit 3) in 2021. . With regards to the cost of electricity, average retail price is the 8th highest in the nation as of 2022, fluctuating between 20 and 22 cents per kWh.

double check statistics

### 13.1.1 Imports

For zones A-E receive hydro imports from the Quebec region, and the Tier 4 NYC project is responsible for serving downstate (zones F-K) load.

## 13.2 Current Plans

According to the Zero Emissions Electric grid in NY by 2040 study, New York is on track to meeting 70% of electricity generation from renewables by 2030. Interestingly, zones A-E, serving all of upstate new york, are on track to having 100% of emissions completely carbon free. . The key bottleneck is in Zones F-K, which serve downstate and is projected to meet 80% of its load with zero emissions resources by 2030. .

cite NY-SERDA

cite NY-SERDA

Figure 3

## 14 Transmission

### 14.1 Technology

### 14.2 Policy

#### 14.2.1 NYSUN

1. NYSun PV

#### 14.2.2 Tax Credits and Subsidies

1. Solar Energy System Equipment Credits
2. OREC for offshore wind solicitatoin
- 3.

## 15 Infrastructure

### 15.1 Control

Recent innovations in in statistical modeling, in particular data-driven optimization and machine learning, have severely overhauled the standard procedures and conventional lines of thinking for management of electricity on the grid. Interest in smart-buildings and online optimization techniques for realtime energy usage has exploded [13], [7], [11], especially with the advent of reinforcement learning and robust model predictive control [5], [12]. . Closely related are the capacity to accurately monitor systems and detect real-time faults. According to Bloomberg New Energy finance, U.S. utilities invested approximately \$3.4 billion in smart grid technologies at the distribution level, and since 2008, \$31.6 billion on the same, a much higher rate than initial forecasts. Smart grids promise to introduce several benefits on the control level, including increased efficiency and monitoring in transmission, voltage optimization in distribution system technologies, advanced metering infrastructure, and easier accessibility to energy usage data for individual consumers. [? ].

more RL citations

According to a 2010 NIST report, the challenges to adoption of smart grid technology can be roughly categorized into three needs that must be fulfilled: 1) smart infrastructure, 2) smart management systems, and 3) smart protection [10]. Furthermore, investment and development in each of these areas must be considered carefully on the transmission and distribution level. We argue that the current state of optimization and control technologies, as well as the unique geographical load profile of the New York region, is amenable to seeing this vision to its fruition, outlined in the next four sections.

## 15.2 Smart infrastructure

Although NYSERDA has invested in approximately \$65 million in awards to support the development of a statewide smart grid, we claim this investment must be increased, particularly in supporting incremental and experimental changes on the distribution level. The primary focus should not be on construction of new buildings that conveniently support this technology, but accelerated "retrofitting" of existing buildings with smart meters, monitoring tools and residential interfaces for local clusters. Furthermore, funds have been mostly divested in feasibility studies and research projects, which advance progress on breaking through the technical bottleneck, but we argue that the two main barriers to adoption at the present is the lack of regulatory framework and low public awareness and engagement. Previous barriers to entry, such as the lack of open standards, cybersecurity and data privacy concerns, and shortage of experts with relevant technical skills, have been significantly addressed within the last 5 years, due to the explosion in interest in machine learning and distributed systems and resultant efforts to enact regulations on data privacy and AI fairness .

[cite source](#)

## 15.3 Smart management systems

## 15.4 Smart protection

Increasing standardization of mass data collection systems in the private and public sector have led to rising concerns of privacy and equity with respect to smart systems. As mentioned before, however, efforts to introduce data privacy regulations in legislation, like the New York Privacy Act, and to foster public awareness and competence, have grown significantly over the last 10 years. .

[cite source](#)

### 15.4.1 Microgrids

Several research institutes, including NREL, Berkeley Lab, Sandia National Laboratory, and the EPRI, have developed robust microgrid simulation software capable of multiobjective optimization and a systems engineering approach to modeling complex electrical and thermal energy demand requirements, both with respect to dynamics and economic feasibility. [6]. Furthermore, the emergence of DC technologies and proliferation of IoT devices will help smart grid systems scale naturally with existing infrastructure [6].

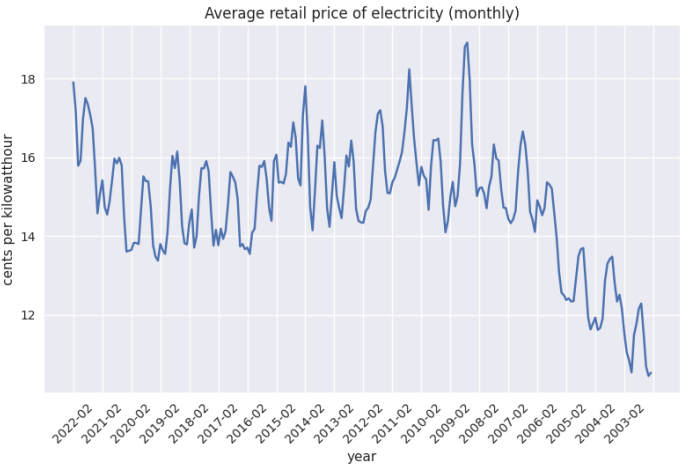
## 15.5 Power Inverters

### 15.5.1 Other things to possibly include

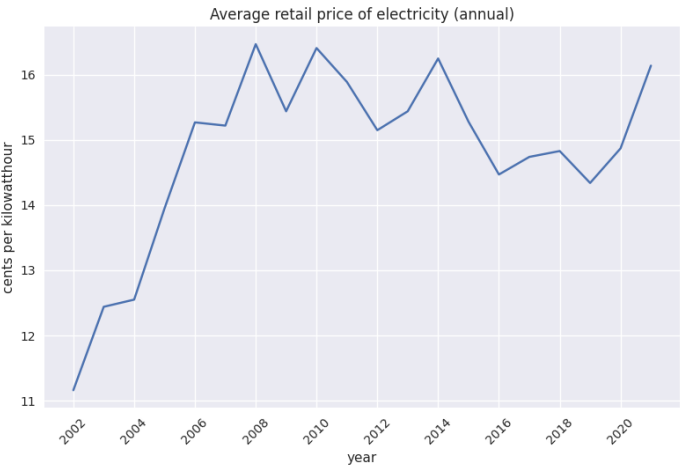
1. statistics on estimated impact of smart grids on energy efficiency and usage
2. statistics on number of IoT devices per household in New York
3. statistics to support increased interest in ML applications
4. statistics on why efforts should revolve around retrofitting

## 16 Quantitative Analysis

We first sought to characterize the energy load, demand, transmission and generation profiles on annual and monthly timescales, as well as obtain projected estimates until 2030. Figures of total energy consumption, generation, and average retail price for electricity generation are shown below.

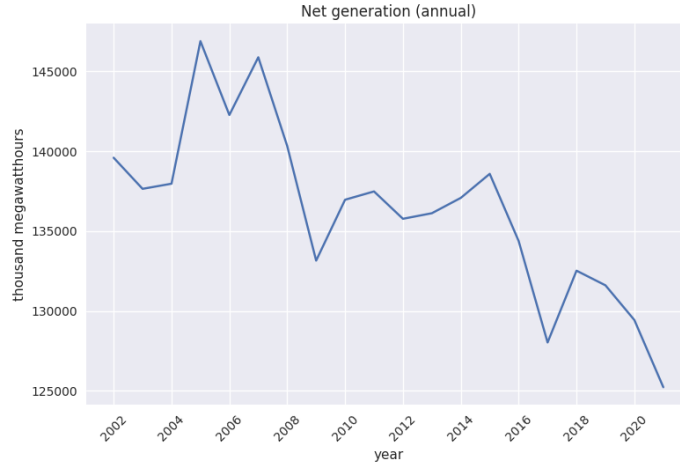


(a)

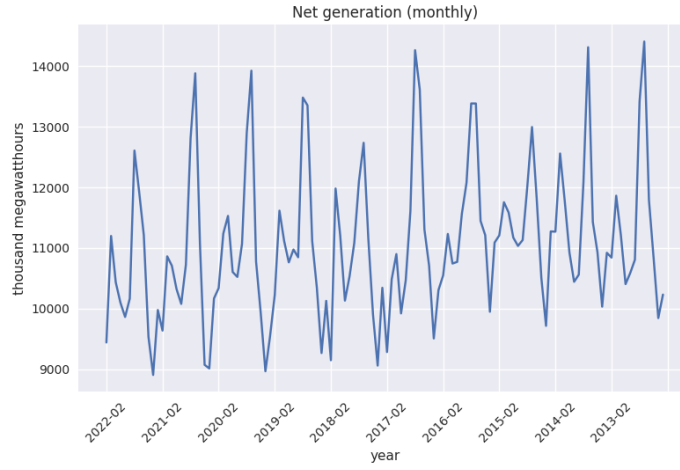


(b)





(a)



(b)

### 16.0.1 ARIMA

ARIMA, or AutoRegressive Integrated Moving Average, is a commonly used method for time series analysis. Due to the seasonal and diurnal nature of electricity demand, we implemented a seasonal ARIMA model. Formally, ARIMA is described by the equations

$$y_t^* = \Delta^d y_t \quad (1)$$

$$y_t^* = \mu + \underbrace{\sum_{i=1}^p \phi_i y_{t-i}^*}_{\text{AR}} + \underbrace{\sum_{i=1}^q \theta_i \epsilon_{t-i}}_{\text{MA}} + \epsilon_t \quad (2)$$

where  $\mu$  denotes the mean.

A seasonal arima model is of the form

$$\text{ARIMA}(p, q) \times (P, Q)_s. \quad (3)$$

where

### 16.0.2 LSTM

We additionally generated yearly predictions using a Long Short Term Memory RNN model, given that neural function approximation is more expressive and tends to lead to less generalization error than statistical regression techniques. Formally, an LSTM unit is described by the equations

$$f_t = \sigma_g (W_f x_t + U_f c_{t-1} + b_f) \quad (4)$$

$$i_t = \sigma_g (W_i x_t + U_i c_{t-1} + b_i) \quad (5)$$

$$o_t = \sigma_g (W_o x_t + U_o c_{t-1} + b_o) \quad (6)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c (W_c x_t + b_c) \quad (7)$$

$$h_t = o_t \circ \sigma_h (c_t) \quad (8)$$

where  $i$  denotes the input,  $h$  denotes the output of the hidden layer,  $o$  denotes the output of the output layer, and  $c$  and  $f$  are .

complete

### 16.0.3 Support Vector Regression

Primal Formulation:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{\ell} (\xi_i + \xi_i^*) \\ \text{subject to} \quad & y_i - \langle w, x_i \rangle - b \leq \epsilon + \xi_i, \\ & \langle w, x_i \rangle + b - y_i \leq \epsilon + \xi_i^*, \\ & \xi_i, \xi_i^* \geq 0 \end{aligned} \quad (9)$$

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{\ell} (\xi_i + \xi_i^*) \\ \text{subject to} \quad & \begin{cases} y_i - \langle w, x_i \rangle - b \leq \epsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{aligned}$$

Figure 6

Dual Formulation:

$$\begin{aligned} \text{maximize} \quad & \begin{cases} -\frac{1}{2} \sum_{i,j=1}^{\ell} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) \langle x_i, x_j \rangle \\ -\epsilon \sum_{i=1}^{\ell} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{\ell} y_i (\alpha_i - \alpha_i^*) \end{cases} \\ \text{subject to} \quad & \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) = 0 \text{ and } \alpha_i, \alpha_i^* \in [0, C] \end{aligned}$$

Figure 7

The results of the analysis is presented in figure [? ]

#### 16.0.4 Comparisons to Existing Models

### 17 Limitations

1. Lack of quantitative analysis on the impact of increased investment to smart grids - mention that doing an SSI M and a reachability matrix is out of the scope of this class
- 2.

### References

- [1] New York's Offshore Wind Projects.
- [2] Story of Our Grid.
- [3] U.S. Census Bureau QuickFacts: New York.
- [4] U.S. Energy Information Administration - EIA - Independent Statistics and Analysis.
- [5] Wei-Han Chen and Fengqi You. Efficient Greenhouse Temperature Control with Data-Driven Robust Model Predictive. In *2020 American Control Conference (ACC)*, pages 1986–1991, Denver, CO, USA, July 2020. IEEE.
- [6] Wei Feng, Ming Jin, Xu Liu, Yi Bao, Chris Marnay, Cheng Yao, and Jiancheng Yu. A review of microgrid development in the United States – A decade of progress on policies, demonstrations, controls, and software tools. *Applied Energy*, 228:1656–1668, October 2018.
- [7] Muhammad Hilal Khan, Azzam Ul Asar, Nasim Ullah, Fahad R. Albogamy, and Muhammad Kashif Rafique. Modeling and Optimization of Smart Building Energy Management System Considering Both Electrical and Thermal Load. *Energies*, 15(2):574, January 2022.
- [8] Patrick McGeehan. Indian Point Is Shutting Down. That Means More Fossil Fuel. *The New York Times*, April 2021.
- [9] Daniel Mitchell, Jamie Blanche, Sam Harper, Theodore Lim, Ranjeetkumar Gupta, Osama Zaki, Wenshuo Tang, Valentin Robu, Simon Watson, and David Flynn. A review: Challenges and opportunities for artificial intelligence and robotics in the offshore wind sector. *Energy and AI*, 8:100146, May 2022.
- [10] Jesús Jaime Moreno Escobar, Oswaldo Morales Matamoros, Ricardo Tejeida Padilla, Ixchel Lina Reyes, and Hugo Quintana Espinosa. A Comprehensive Review on Smart Grids: Challenges and Opportunities. *Sensors*, 21(21):6978, October 2021.
- [11] David Sembroiz, Davide Careglio, Sergio Ricciardi, and Ugo Fiore. Planning and operational energy optimization solutions for smart buildings. *Information Sciences*, 476:439–452, February 2019.
- [12] Shiyu Yang, Man Pun Wan, Wanyu Chen, Bing Feng Ng, and Deqing Zhai. An adaptive robust model predictive control for indoor climate optimization and uncertainties handling in buildings. *Building and Environment*, 163:106326, October 2019.
- [13] Liang Yu, Shuqi Qin, Meng Zhang, Chao Shen, Tao Jiang, and Xiaohong Guan. A Review of Deep Reinforcement Learning for Smart Building Energy Management. *IEEE Internet of Things Journal*, 8(15):12046–12063, August 2021. arXiv: 2008.05074.