Deep Learning for Scenario Generation and Scenario Reduction in Short-Term Power System Operations

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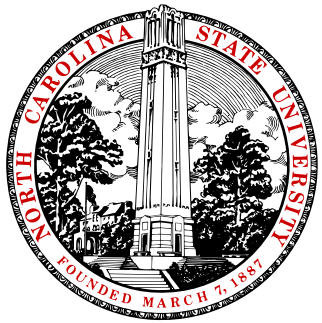


IEEE PES Big Data & Analytics Tutorial Series

February 26, 2021

Outline

Decision Making Under Uncertainty

- A two-stage stochastic programming approach

$$\begin{aligned} \underset{\boldsymbol{x}}{\text{minimize}} \quad & \boldsymbol{c}^T\boldsymbol{x} + \mathrm{E}_\omega[Q(\boldsymbol{x},\omega)] \\ \text{subject to} \quad & \boldsymbol{A}\boldsymbol{x} = \boldsymbol{b} \\ & \boldsymbol{x} \in \boldsymbol{X} \end{aligned}$$

where $Q(\boldsymbol{x},\omega)$ is the optimal value of the second-stage problem

$$\begin{aligned} \underset{\boldsymbol{y}}{\text{minimize}} \quad & \boldsymbol{q}(\omega)^T\boldsymbol{y} \\ \text{subject to} \quad & \boldsymbol{T}(\omega)\boldsymbol{x} + \boldsymbol{W}(\omega)\boldsymbol{y} = \boldsymbol{h}(\omega) \\ & \boldsymbol{y} \in \boldsymbol{Y} \end{aligned}$$

- In the first stage, the here-and-now decisions $\boldsymbol{x}$ are made
- Then the random outcome ω is realized
- In the second stage, the wait-and-see decisions (also known as recourse actions) $\boldsymbol{y}$ are made, which depend on both $\boldsymbol{x}$ and the realization of ω

Decision Making Under Uncertainty

- An equivalent form of the two-stage stochastic programming problem

$$
\begin{aligned}
\underset{\boldsymbol{x}, \boldsymbol{y}(\omega), \forall \omega}{\text{minimize}} \quad & \boldsymbol{c}^T \boldsymbol{x} + \mathrm{E}_\omega [\boldsymbol{q}(\omega)^T \boldsymbol{y}(\omega)] \\
\text{subject to} \quad & \boldsymbol{A}\boldsymbol{x} = \boldsymbol{b} \\
& \boldsymbol{T}(\omega)\boldsymbol{x} + \boldsymbol{W}(\omega)\boldsymbol{y}(\omega) = \boldsymbol{h}(\omega), \ \forall \omega \\
& \boldsymbol{x} \in \boldsymbol{X} \\
& \boldsymbol{y}(\omega) \in \boldsymbol{Y}, \ \forall \omega
\end{aligned}
$$

- A deterministic form when the sample space is finite ($\pi(\omega)$: probability of ω)

$$
\begin{aligned}
\underset{\boldsymbol{x}, \boldsymbol{y}(\omega), \forall \omega}{\text{minimize}} \quad & \boldsymbol{c}^T \boldsymbol{x} + \textstyle\sum_\omega \pi(\omega) \boldsymbol{q}(\omega)^T \boldsymbol{y}(\omega) \\
\text{subject to} \quad & \boldsymbol{A}\boldsymbol{x} = \boldsymbol{b} \\
& \boldsymbol{T}(\omega)\boldsymbol{x} + \boldsymbol{W}(\omega)\boldsymbol{y}(\omega) = \boldsymbol{h}(\omega), \ \forall \omega \\
& \boldsymbol{x} \in \boldsymbol{X} \\
& \boldsymbol{y}(\omega) \in \boldsymbol{Y}, \ \forall \omega
\end{aligned}
$$

Short-Term Power System Operations

- Net-zero carbon emissions by 2050: increasing penetration of renewable generation
- Intermittent and non-dispatchable nature of renewable generation such as wind: challenges in renewable energy integration
- New operating paradigms for unit commitment and economic dispatch: from a deterministic approach to a stochastic programming approach

A stochastic day-ahead scheduling problem

minimize	commitment cost + expected dispatch cost
subject to	power balance constraints
	transmission constraints
	generating unit constraints

- Commitment cost: start-up cost, no-load cost, etc.
- Dispatch cost: generation cost, load shedding penalty, etc.
- Generating unit constraints: generation capacity constraints, ramping constraints, minimum up-time/down-time constraints, etc.

Scenarios in Stochastic Programming

- What is the randomness in the stochastic day-ahead scheduling problem?
- Random outcome ω: wind power generation (or its forecast error) on the next day
- Stochastic process $\boldsymbol{\xi}(\omega)$: mapping ω to a real-valued vector indexed by time

$$\boldsymbol{\xi}(\omega) = (\xi_1(\omega), \ldots, \xi_{24}(\omega))$$

- It is hard to characterize or find the multivariate probability distribution of $\boldsymbol{\xi}$
- Even if the true distribution is known, the resulting stochastic programming problem may not be computationally tractable: some discretization is needed

Approximating a stochastic process by scenarios

- A scenario is a single realization of the stochastic process

$$\boldsymbol{s} = (s_1, \ldots, s_{24})$$

- We typically assume equally likely scenarios

$$\pi(\boldsymbol{s}) = 1/|\boldsymbol{S}|, \ \forall \boldsymbol{s} \in \boldsymbol{S}$$

Scenarios of Wind Power Generation

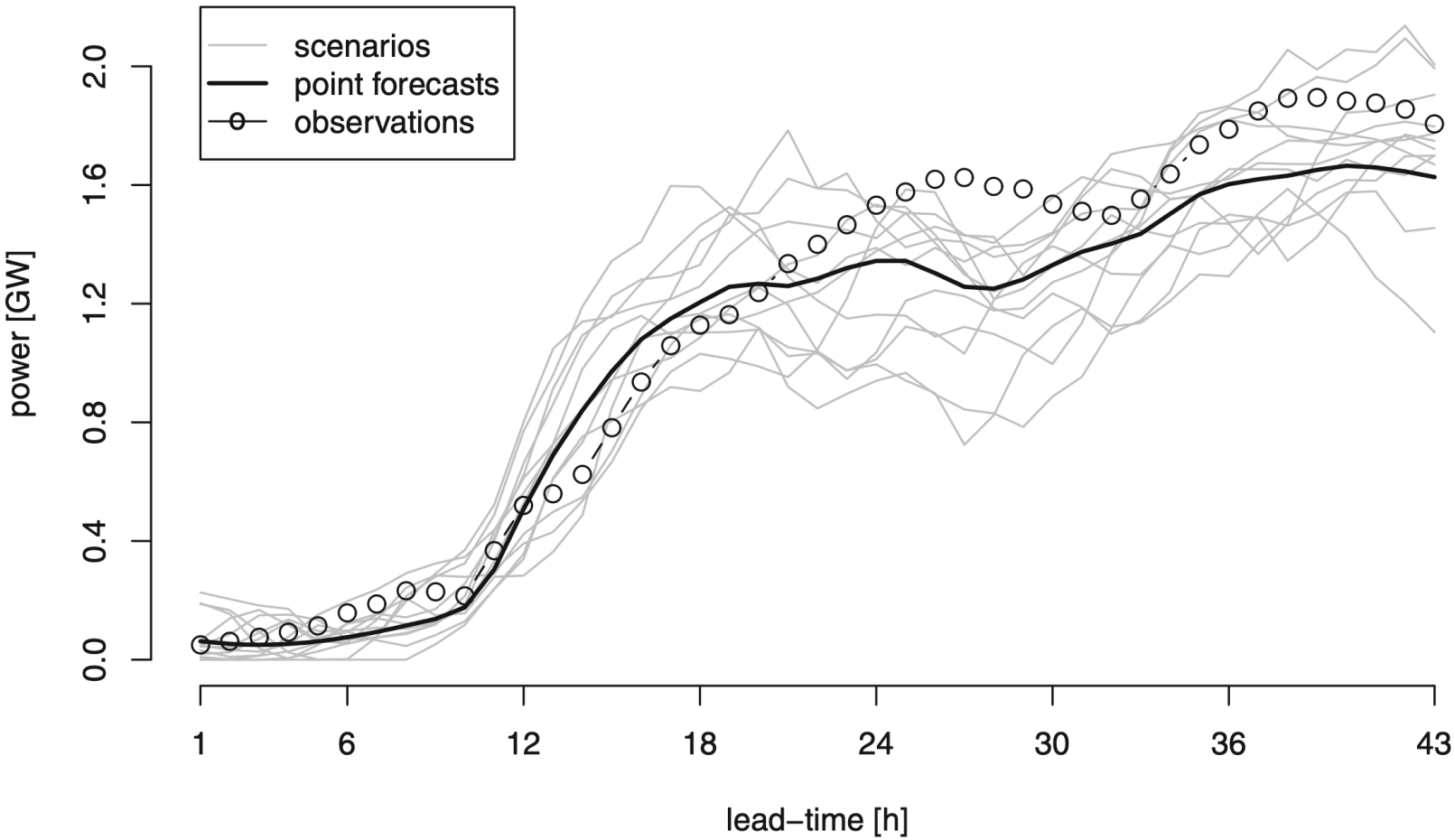


Figure: Scenarios (12 time trajectories) of wind power generation issued on 4th April 2007 at 00:00 UTC for the whole onshore capacity of Western Denmark (Source: [Morales et al. 2014])

Scenario Generation

- Scenarios can be viewed as a type of forecasts
- Solving the stochastic programming problem: sample average approximation (SAA)

$$\mathrm{E}_{\boldsymbol{\xi}}[Q(\boldsymbol{x}, \boldsymbol{\xi})] \approx \frac{1}{|\boldsymbol{S}|} \sum_{\boldsymbol{s} \in \boldsymbol{S}} Q(\boldsymbol{x}, \boldsymbol{s})$$

- The SAA method has desirable asymptotic properties
- To yield high quality decisions, we need to build a high quality scenario set
- Scenario generation: given historical time series data, generate a number of representative sample paths into the future

Traditional approach

- Use historical data to fit a statistical model (such as ARIMA)
- Then generate random samples from the statistical model (Monte Carlo sampling)

- However, tractable statistical models with simplified assumptions may not well capture the underlying temporal dynamics

Scenario Generation

Non-parametric methods

- Radial basis function network [Sideratos et al. 2012]
- Fuzzy prediction interval [Sáez et al. 2015]
- Regular vine copula [Wang et al. 2018]
- Sparse Bayesian learning, kernel density estimation [Lin et al. 2019]
- Infinite Markov switching autoregressive [Xie et al. 2019]

- However, those supervised models require extensive domain knowledge for feature selection, and are difficult to tune and implement
- Most of the methods utilize information at multiple sites to improve the accuracy: they may not be applicable when only a single time series is in consideration
- Unsupervised models are preferred: generative adversarial networks (GANs) [Goodfellow et al. 2014] and many variants of GANs, including the sequence generative adversarial network (SeqGAN) [Yu et al. 2017]
- We will adapt the SeqGAN for scenario generation of hourly wind power generation (or its forecast error) on the next day

Scenario Reduction

- Good discrete approximations often require the generation of a large number of scenarios, which may render the underlying optimization problem intractable, especially in the presence of integer variables (such as unit commitment decisions)
- To regain tractability, we need to trim down the number of scenarios while deteriorating the accuracy of the approximation as little as possible
- Scenario reduction: given a large scenario set, generate a small scenario set that is representative of the original one
- Scenario reduction can be viewed as a time series clustering task
- Like common clustering algorithms, the generated scenarios do not necessarily belong to the original scenario set

Traditional approach

- Define a measure (such as the Euclidean distance) to quantify the similarity or the distance between two scenario sets
- Solve an optimization problem (which is generally nonconvex) to maximize the measure

Scenario Reduction

Measure based methods

- Fortet–Mourier probability metrics [Heitsch and Römisch 2009]
- Space and moment distance [Li et al. 2016]
- Radial basis kernel function [Wang et al. 2017]
- Nested distance [Beltrán et al. 2017]
- Probability metrics and correlations [Hu and Li 2019]

- However, those measure based methods depend on a predefined measure, which may deteriorate the generalization capability
- It is difficult to describe all the patterns in the large scenario sets, since the number of scenarios is reduced dramatically
- Time series clustering methods are preferred: smoothed formulation of dynamic time warping (DTW) [Cuturi and Blondel 2017], and mixture of autoencoders [Dizaji et al. 2017, Chazan et al. 2019]
- We will integrate a mixture of autoencoders with fuzzy clustering for scenario reduction of forecast errors of hourly wind power generation on the next day

Outline

Fully Connected Neural Network

- The deep in deep learning: successive layers of increasingly meaningful representations, which are learned jointly via neural networks
- Fully connected neural network (FNN): every neuron (unit) in each layer is connected to every neuron in the next layer
- Universal approximation theorems imply that neural networks can represent a wide variety of interesting functions when given appropriate weights

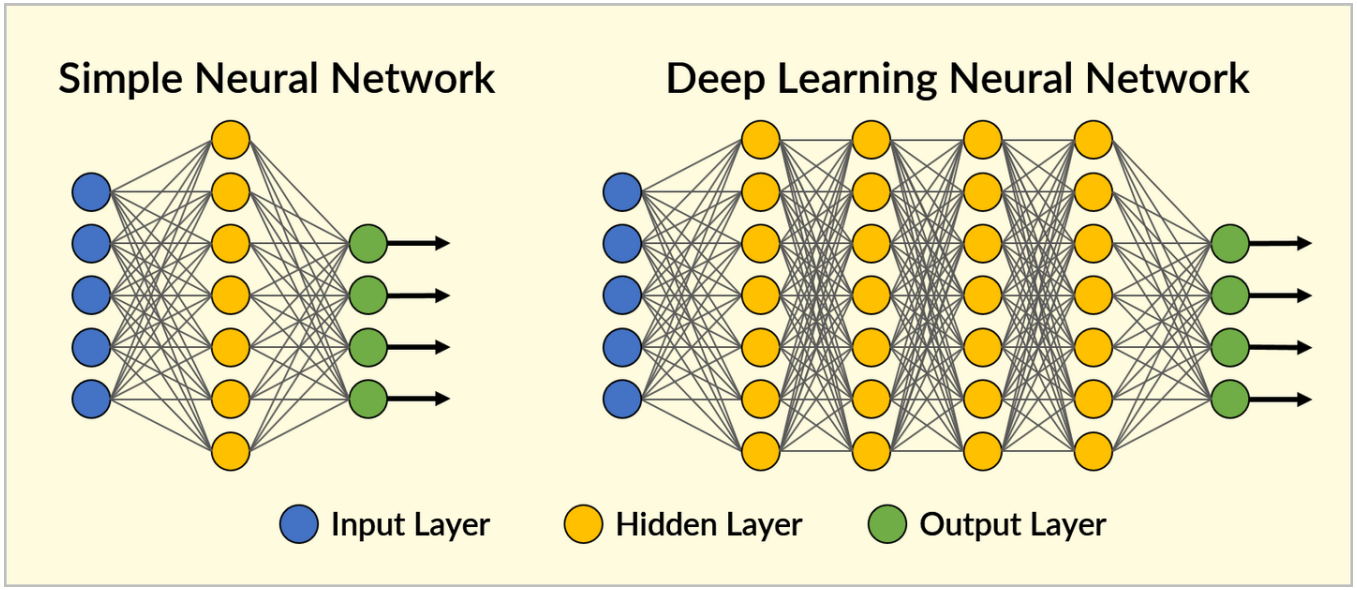


Figure: Simple and deep FNNs (Source: Internet)

Convolutional Neural Network

- Convolutional neural network (CNN): learn translation-invariant patterns and spatial hierarchies of patterns
- The convolution operation extracts patches from its input feature map and applies the same transformation to all of these patches, producing an output feature map
- Filters (in the depth axis) encode specific aspects of the input data
- The max-pooling operation downsamples feature maps
- Finally, we need the fully connected layers to learn the global patterns

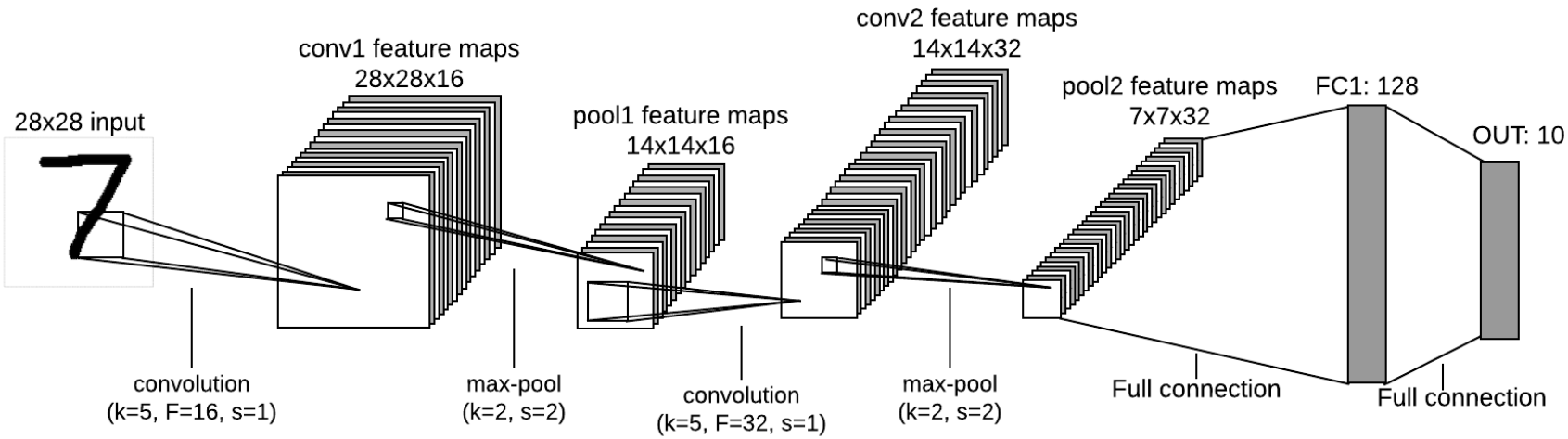


Figure: CNN for handwritten digit classification (Source: Internet)

Recurrent Neural Network

- FNNs and CNNs have no memory: they are called feedforward networks
- Recurrent neural network (RNN): process sequences by iterating through the sequence elements and maintaining a state containing information relative to what it has seen so far
- In theory, the simple RNN is able to retain information about inputs seen many time steps before
- In practice, such long-term dependencies are impossible to learn, due to the vanishing gradient problem

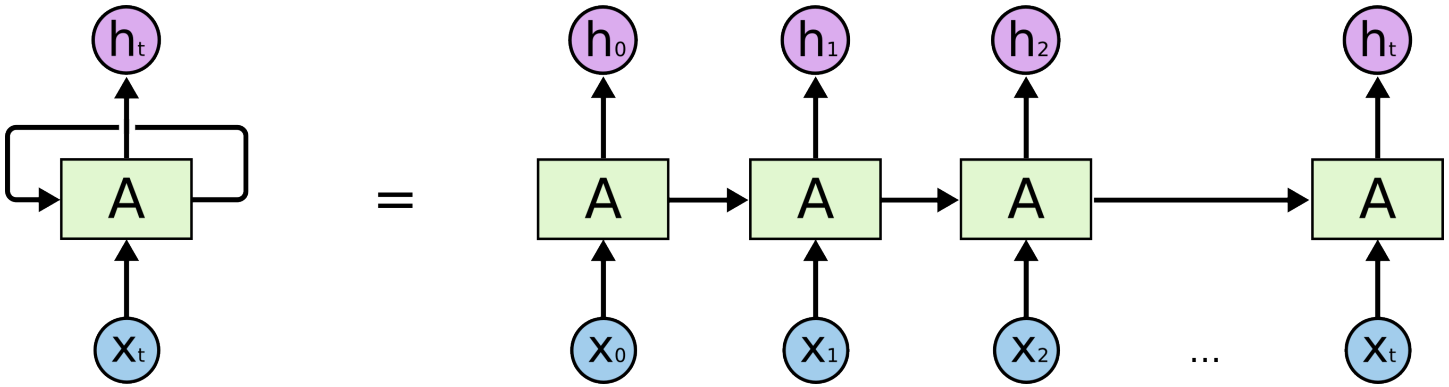


Figure: Simple RNN (`https://colah.github.io/posts/2015-08-Understanding-LSTMs/`)

Long Short-Term Memory

- Long short-term memory (LSTM): a special kind of RNNs that are explicitly designed to remember information for long periods of time
- Four interacting neural network layers (instead of one) in the repeating module
- Forget gate: what information to throw away from the cell state
- Input gate: what new information to store in the cell state
- Output gate: what information to output (and going to be the next hidden state)

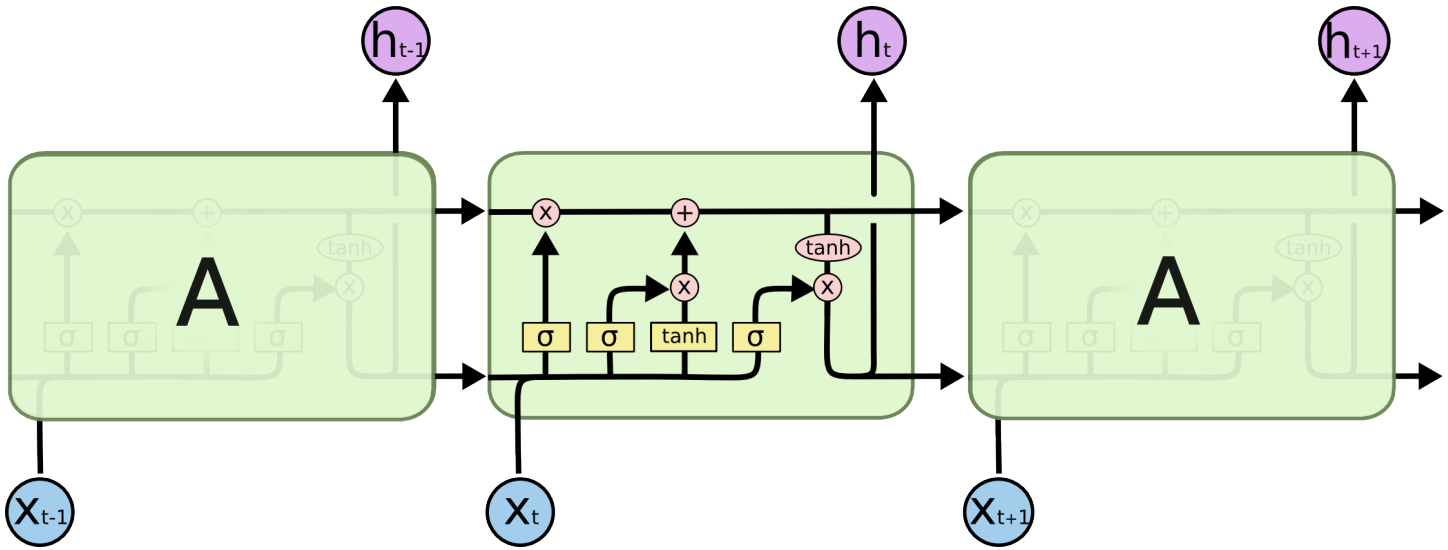


Figure: LSTM (`https://colah.github.io/posts/2015-08-Understanding-LSTMs/`)

Generative Adversarial Network

- Generative adversarial network (GAN): a generative model in which a generator network completes against an adversary, the discriminator network
- Generator: directly produce samples
- Discriminator: attempt to distinguish between samples drawn from the training data and samples drawn from the generator
- Learning in a GAN can be formulated as a zero-sum game: at convergence, the generator's samples are indistinguishable from real data

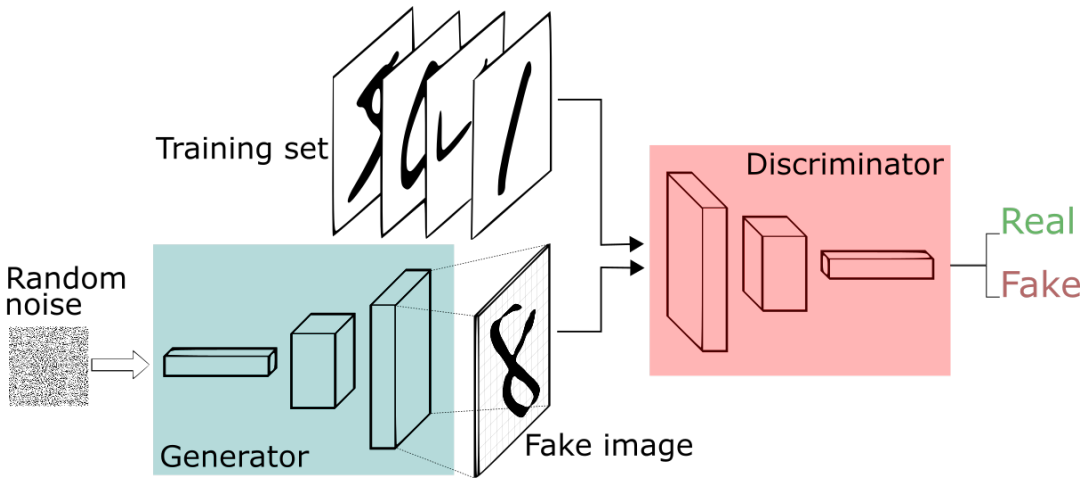


Figure: GAN (`https://sthalles.github.io/intro-to-gans/`)

Autoencoder

- Autoencoder: a neural network that is trained to attempt to copy its input to its output
- Hidden layer $\boldsymbol{h}$: describes a code (latent representation) used to represent the input
- Encoder $\boldsymbol{h} = \sigma(\boldsymbol{x})$: maps the input into the code
- Decoder $\boldsymbol{x}' = \sigma'(\boldsymbol{h})$: maps the code to a reconstruction of the input
- $\sigma'(\sigma(\boldsymbol{x})) = \boldsymbol{x}$ is not useful: autoencoders are restricted to copy only approximately
- We are interested in $\boldsymbol{h}$ (instead of $\boldsymbol{x}'$) taking on useful properties

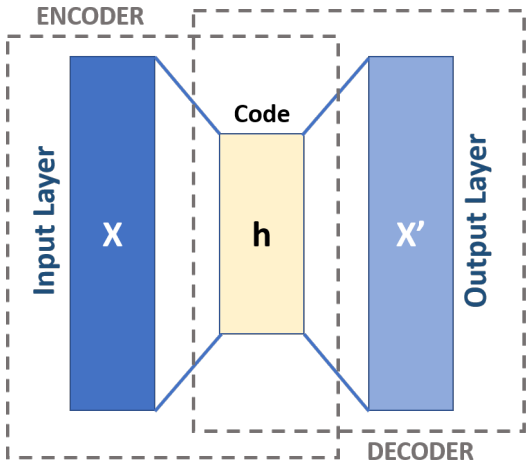


Figure: Autoencoder (`https://en.wikipedia.org/wiki/Autoencoder`)

Outline

Sequence Generative Adversarial Network

Issues when applying GAN to generating sequences

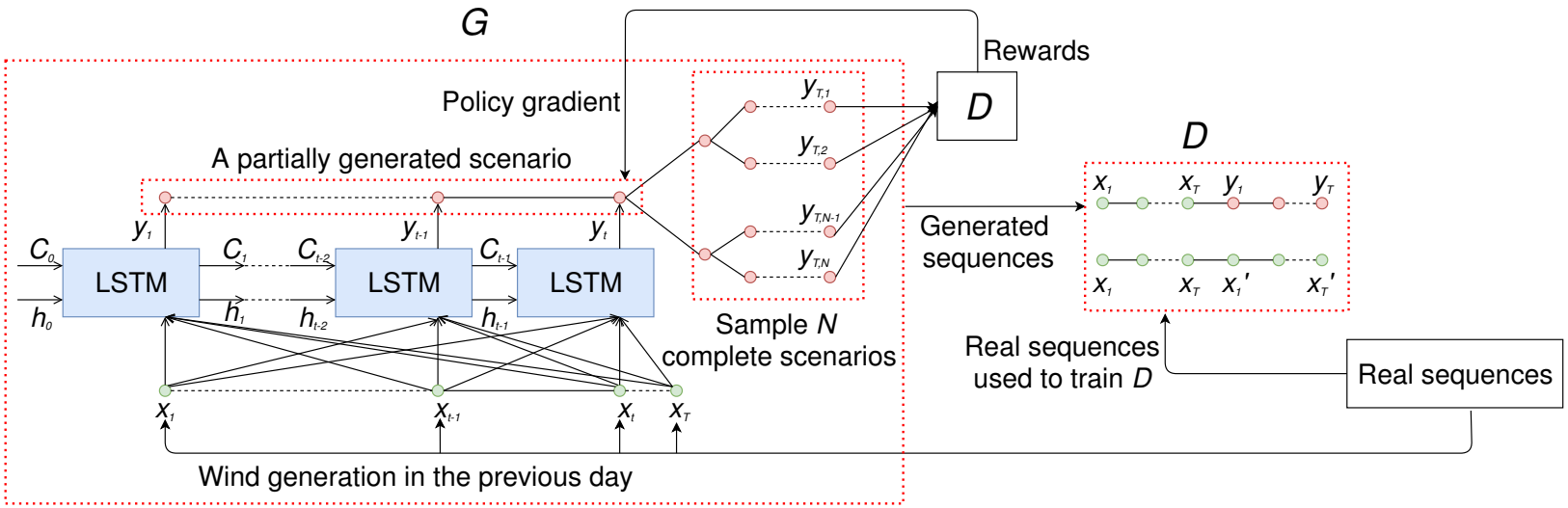
- First, GAN is designed for generating real-valued, continuous data but has difficulties in directly generating sequences of discrete tokens (such as texts)
- Second, GAN can only give the score for an entire sequence: for a partially generated sequence, it is non-trivial to balance its current score and its future score

- The first issue is minor: wind power generation (or its forecast error) is continuous; but discretization may still be preferred for convenience
- The second is critical: some values may be abnormal while the overall sequence has a good score, which may lead to unreasonable unit commitment decisions

Sequence Generative Adversarial Network (SeqGAN)

- Consider the sequence generation procedure as a sequential decision making process, solved by reinforcement learning: the state is the generated tokens so far and the action is the next token to be generated
- Regard the generative model as a stochastic parameterized policy: employ Monte Carlo search to approximate the state-action value for evaluating policy gradient

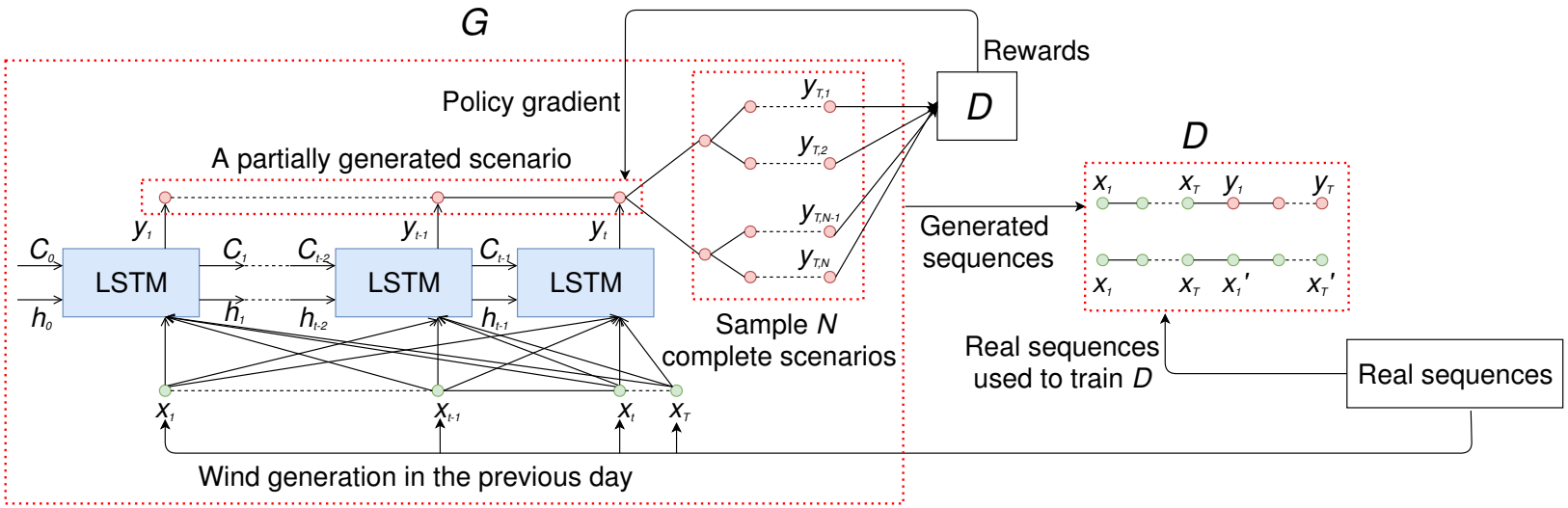
Sequence Generative Adversarial Network



- Input of the generator: 24 hourly wind power generations in the previous day
- Output of the generator: for each hour, softmax is used to obtain the discrete distribution of wind power generation (which can then be sampled for scenarios)
- The generator maximizes the reward to go from the beginning (state in t: $s_t = y_{1:t-1} = (y_1, \ldots, y_{t-1})$, action in t: y_t)

$$\max_{\theta} \; J(\theta) = \sum_{y_1} G_\theta(y_1|s_1) Q_{D_\phi}^{G_\theta}(s_1, y_1)$$

Sequence Generative Adversarial Network



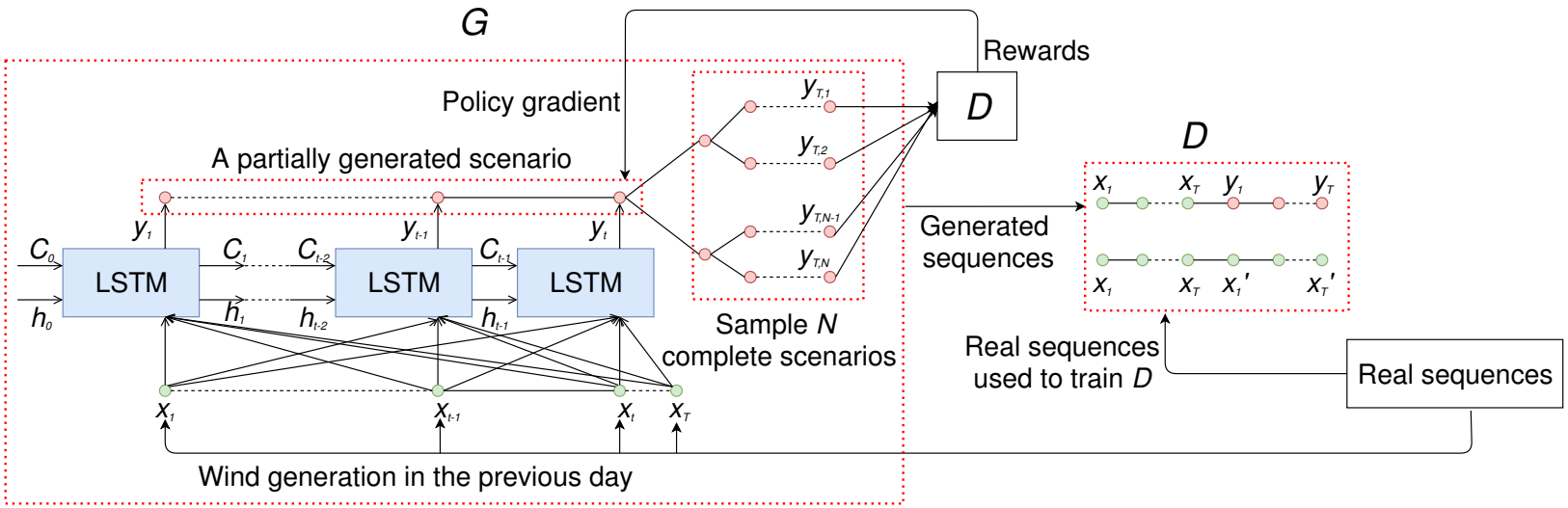
- An unbiased estimation for policy gradient (via which the generator is trained)

$$\nabla_\theta J(\theta) \approx \sum_{t=1}^{T} \mathrm{E}_{y_t \sim G_\theta(y_t|y_{1:t-1})}[(\nabla_\theta \log G_\theta(y_t|y_{1:t-1}))Q_{D_\phi}^{G_\theta}(y_{1:t-1}, y_t)]$$

- The discriminator minimizes the cross-entropy loss

$$\min_\phi -\mathrm{E}_{y\sim p_{\text{data}}}[\log D_\phi(y)] - \mathrm{E}_{y\sim G_\theta}[\log(1 - D_\phi(y))]$$

Sequence Generative Adversarial Network



- The discriminator only provides a reward value $D_\phi(y)$ (probability of being real) for a finished sequence y
- How to evaluate the state-action value function for each t?

$$Q_{D_\phi}^{G_\theta}(y_{1:t-1}, y_t) = \begin{cases} (1/N)\sum_{n=1}^{N} D_\phi(y_{1:t}, y_{t+1:T}^n), & t < T \\ D_\phi(y_{1:T}), & t = T \end{cases}$$

where $y_{t+1:T}^1, \ldots, y_{t+1:T}^N$ are sampled by Monte Carlo given $y_{1:t}$ and G_θ

Outline

Generated Scenarios of Forecast Errors

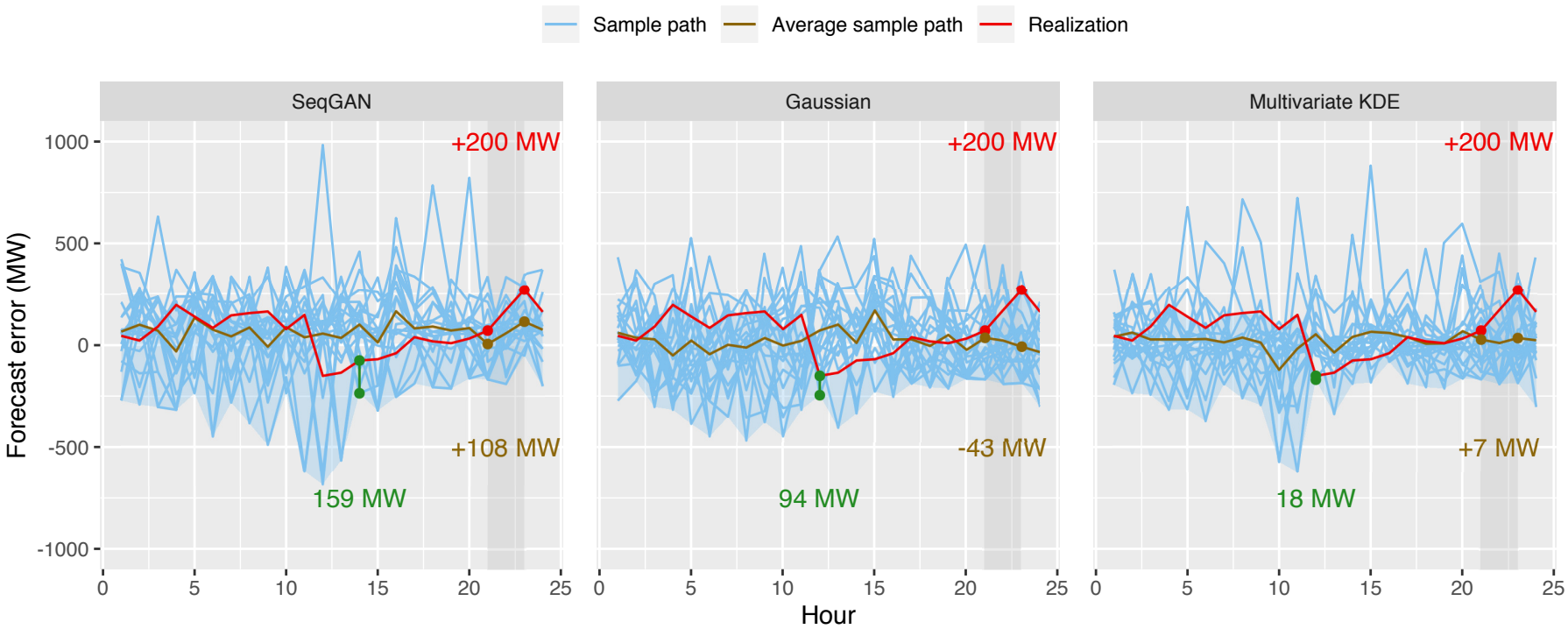


Figure: 20 scenarios of forecast errors for April 29, 2019, based on the BPA data

- The least safe margin for SeqGAN is larger: more robust decisions
- SeqGAN follows the fast ramping events better

Generated Scenarios of Wind Power Generation

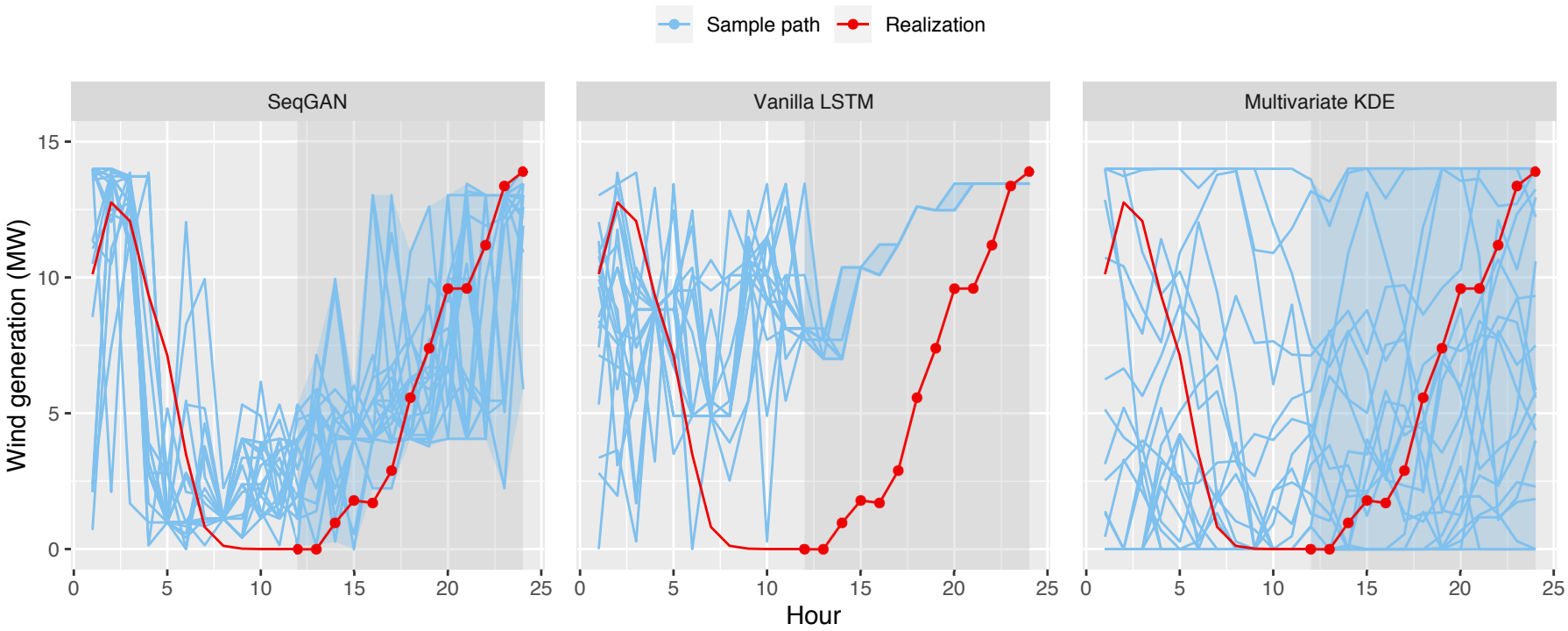


Figure: 20 scenarios of wind power generation for December 25, 2012, based on the NREL data

- SeqGAN generates more diverse scenarios which lead to more robust decisions
- SeqGAN captures the patterns better (not too diverse to be useful)

Assessment of Generated Scenarios of Forecast Errors

- Skill score: measure of accuracy of forecasts such as scenarios
- All the skills scores introduced here are negatively oriented (the lower the better)
- N generated scenarios

$$\boldsymbol{s}^{(i)} = (s_1^{(i)}, \ldots, s_{24}^{(i)}),\ i = 1, \ldots, N$$

- Observation

$$\boldsymbol{z} = (z_1, \ldots, z_{24})$$

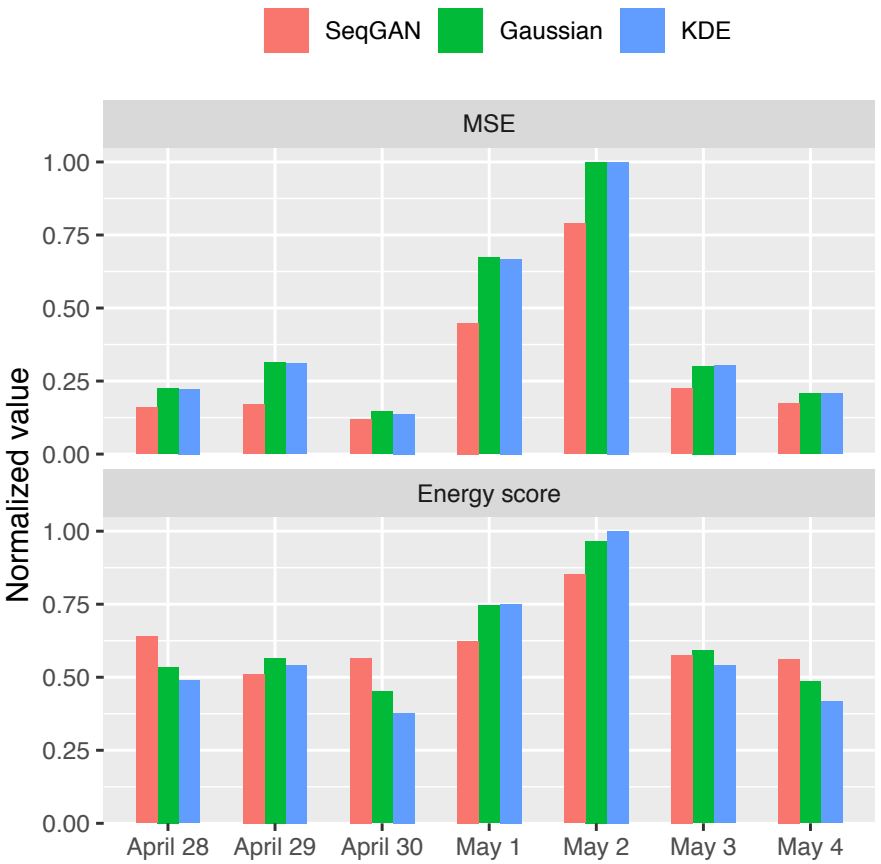
- Mean squared error (MSE)

$$\frac{1}{24}\sum_{t=1}^{24}\left(\frac{1}{N}\sum_{i=1}^{N} s_t^{(i)} - z_t\right)^2$$

- Energy score

$$\frac{1}{24}\sum_{t=1}^{24}\left(\frac{1}{N}\sum_{i=1}^{N}|z_t - s_t^{(i)}| - \frac{1}{2N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}|s_t^{(i)} - s_t^{(j)}|\right)$$

Assessment of Generated Scenarios of Forecast Errors



- SeqGAN achieves the best MSE
- SeqGAN achieves a better energy score when the uncertainty is high

Assessment of Generated Scenarios of Wind Power Generation

- For wind power generation, we are more interested in event-based measures
- Brier score: measure the deviation of the generated scenarios from the observation with respect to capturing the predefined events (such as large ramping events)

$$\frac{1}{24}\sum_{t=1}^{24}\left(\frac{1}{N}\sum_{i=1}^{N} f_t(\boldsymbol{s}^{(i)}) - f_t(\boldsymbol{z})\right)^2$$

where $f_t(\boldsymbol{s})$ indicates whether the predefined event occurs in hour t in $\boldsymbol{s}$

Event	SeqGAN	LSTM	KDE
10% up in 1 hour	**0.2148**	0.2500	0.2240
20% up in 2 hours	**0.1866**	0.2167	0.1960
10% down in 1 hour	**0.1745**	0.1930	0.2151
20% down in 2 hours	**0.1617**	0.2178	0.1917

Table: The Brier scores for 1 peak week of 1 site in the NREL data

Assessment of Generated Scenarios of Wind Power Generation

- Variogram score of order p

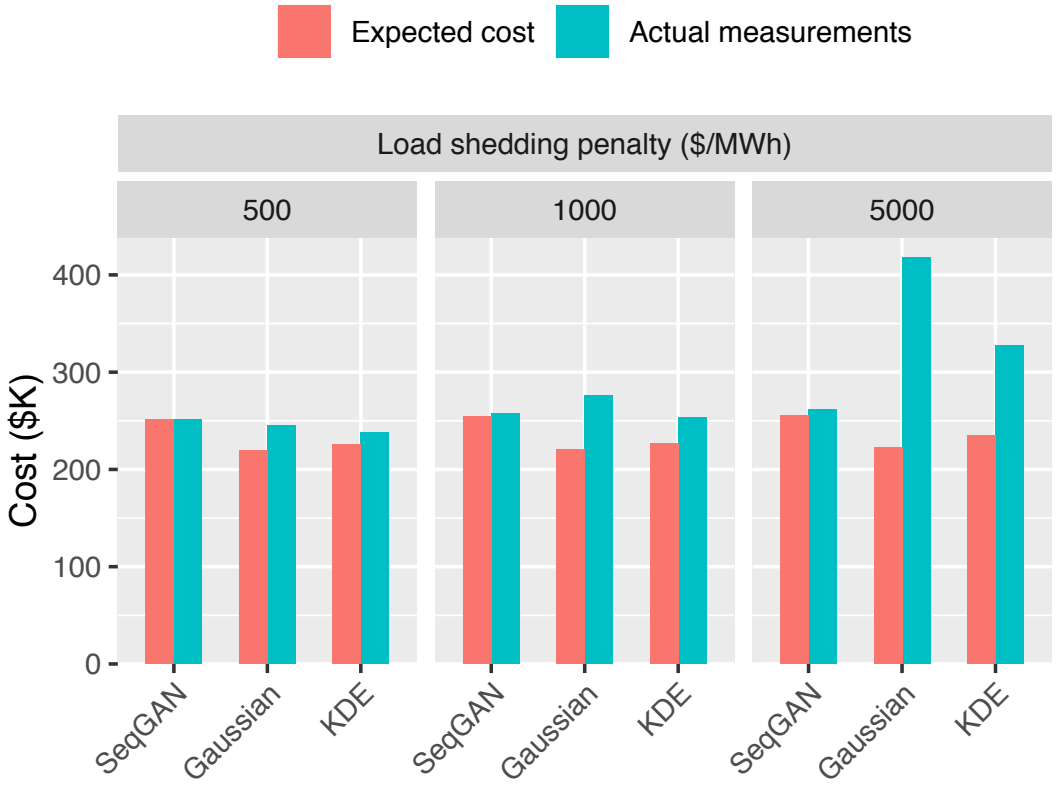
$$\sum_{t_1=1}^{24}\sum_{t_2=1}^{24}\left(|z_{t_1}-z_{t_2}|^p-\frac{1}{N}\sum_{i=1}^{N}|s_{t_1}^{(i)}-s_{t_2}^{(i)}|^p\right)^2$$

	$p=1$			$p=2$		
Case	SeqGAN	LSTM	KDE	SeqGAN	LSTM	KDE
1a	**0.505**	0.553	0.530	**0.497**	0.584	0.546
1b	**0.346**	0.350	0.388	**0.278**	0.287	0.306
2a	**0.530**	0.572	0.626	**0.448**	0.461	0.491
2b	**0.506**	0.588	0.554	**0.421**	0.538	0.457
3a	**0.462**	0.574	0.513	**0.346**	0.439	0.381
3b	**0.349**	0.389	0.432	**0.324**	0.363	0.424

Table: The Variogram scores for 1 peak and 1 off-peak week of 3 sites in the NREL data

Case Study on a Modified IEEE 24-Bus System

- Day-ahead scheduling: two-stage stochastic mixed-integer linear programming
- For each algorithm, we generate 100 scenarios, and evaluate the expected cost
- We also evaluate the realized cost which depends on the actual observation
- The scenario set generated by SeqGAN is the most representative



Outline

Scenario Reduction

- Problem statement: given N scenarios (with equal probabilities)

$$\boldsymbol{s}^{(i)} = (s_1^{(i)}, \ldots, s_{24}^{(i)}),\ i = 1, \ldots, N$$

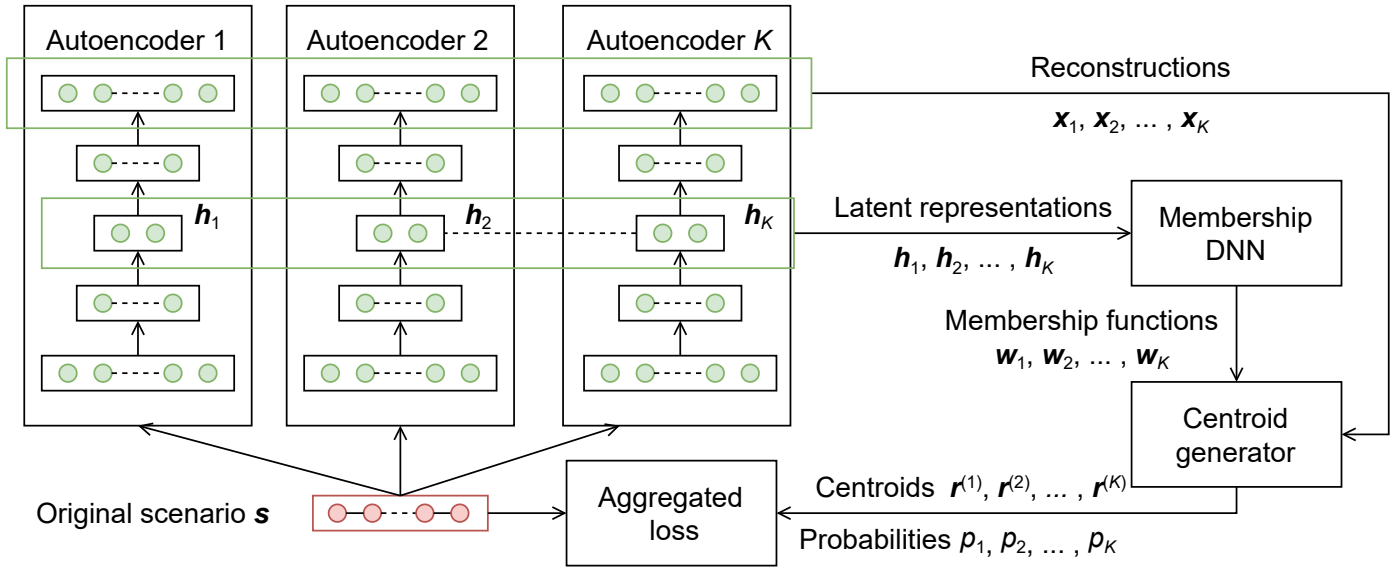
generate K ($K \ll N$) scenarios and assign probability p_k for each k

$$\boldsymbol{r}^{(k)} = (r_1^{(k)}, \ldots, r_{24}^{(k)}),\ k = 1, \ldots, K$$

Mixed Autoencoder Based Fuzzy Clustering (MAFC)

- First, several deep autoencoders map time series to latent representations
- The deep hypothesis spaces in the autoencoders provide high generalization capability and capture the complex temporal dynamics
- Second, those latent representations are fed into a membership DNN, which outputs the degree to which each scenario belongs to each cluster
- Third, based on the membership degrees, fuzzy time series clustering is employed to evaluate the centroids
- Compared with hard clustering, fuzzy clustering is better at preserving the patterns in the original scenario set

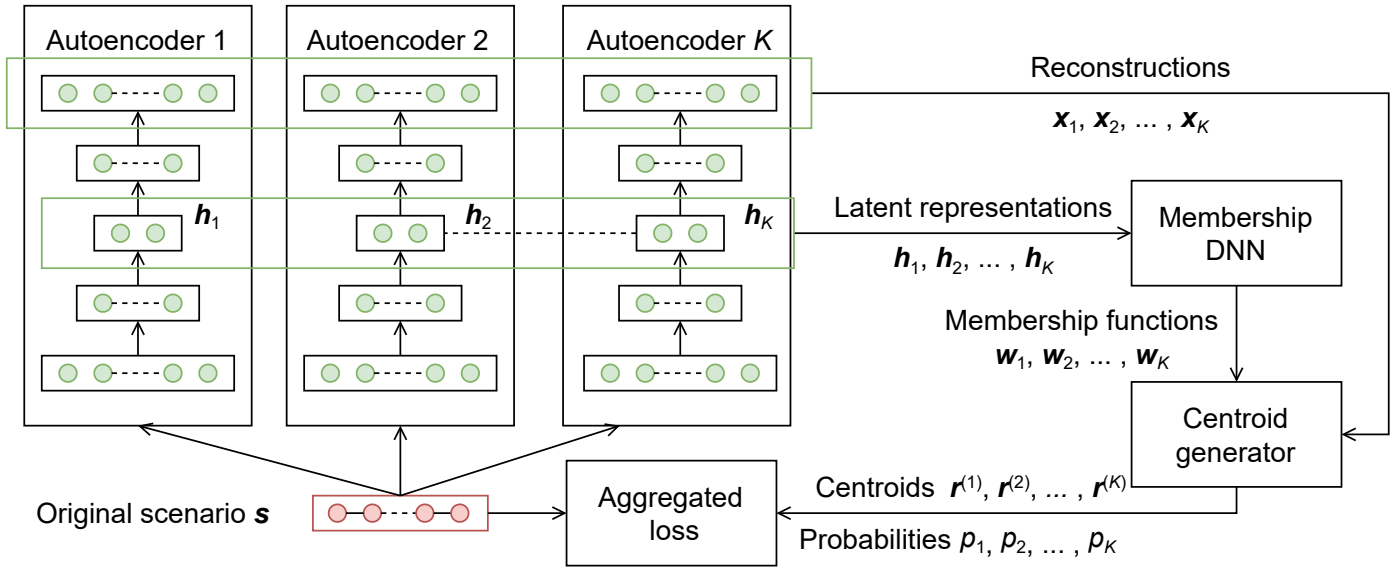
Mixed Autoencoder Based Fuzzy Clustering



- K autoencoders: extract the latent representations $\boldsymbol{h}_1^{(i)}, \ldots, \boldsymbol{h}_K^{(i)}$ of each $\boldsymbol{s}^{(i)}$
- $z_k^{(i)}$: output of the membership DNN before the last activation function (softmax)
- Membership degree $w_k^{(i)}$: the degree to which $\boldsymbol{s}^{(i)}$ belongs to cluster k

$$w_k^{(i)} = \frac{e^{z_k^{(i)}}}{\sum_{l=1}^{K} e^{z_l^{(i)}}}$$

Mixed Autoencoder Based Fuzzy Clustering

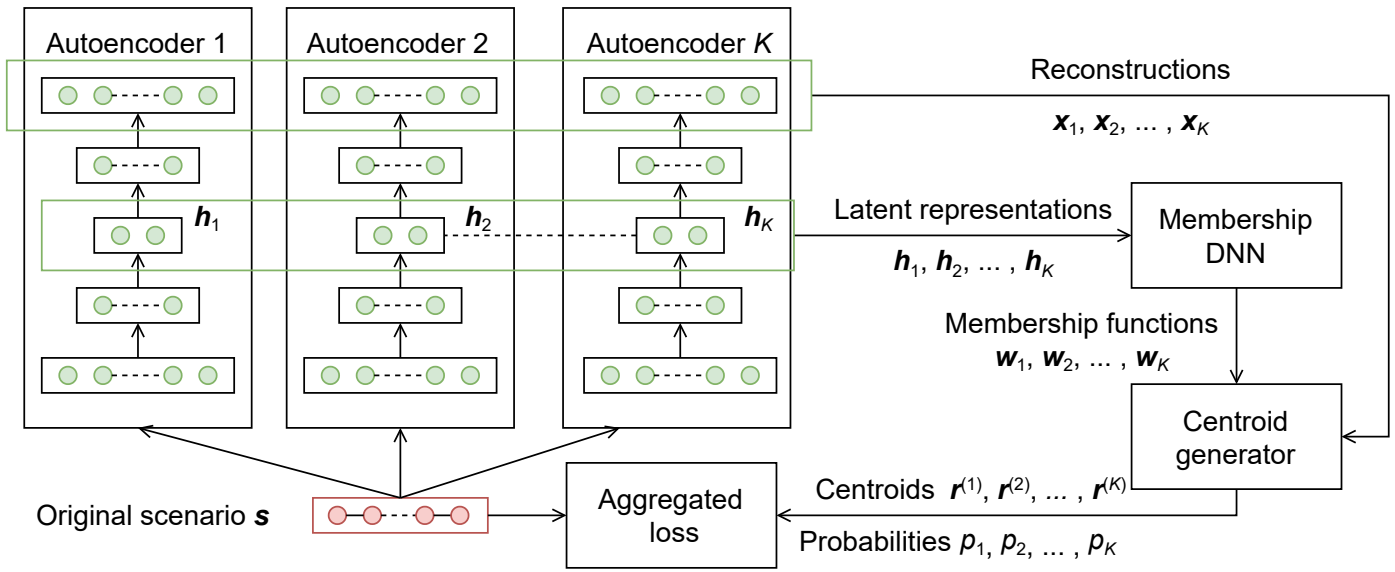


- $\boldsymbol{x}_1^{(i)}, \ldots, \boldsymbol{x}_K^{(i)}$: reconstructions of $\boldsymbol{s}^{(i)}$
- Centroids under fuzzy clustering

$$\boldsymbol{r}^{(k)} = \frac{\sum_{i=1}^{N} (w_k^{(i)})^m \boldsymbol{x}_k^{(i)}}{\sum_{i=1}^{N} (w_k^{(i)})^m}$$

where the hyperparameter m controls the level of fuzziness (the higher the fuzzier)

Mixed Autoencoder Based Fuzzy Clustering



- Assign probability p_k to each cluster k

$$p_k = \frac{1}{N} \sum_{i=1}^{N} w_k^{(i)}$$

- Loss function augmented by sample-wise entropy

$$L = \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} p_k \| \boldsymbol{s}^{(i)} - \boldsymbol{c}^{(k)} \|^2 - \alpha \sum_{i=1}^{N} \sum_{k=1}^{K} (w_k^{(i)})^m \log(w_k^{(i)})$$

Outline

Setup

- Bonneville Power Administration (BPA): capacity of 4,450 MW
- Elia (Belgian grid operator): capacity of 3,667 MW
- Both data sets have day-ahead forecasts so that we can focus on forecast errors
- For each data set, we fit a kernel density estimation model, and then sample 2,000 scenarios as the original scenario set
- For each original scenario set, the task is to produce reduced scenario sets with 10 and 20 scenarios, respectively

Benchmark algorithms

- Simultaneous backward reduction (SBR)
- k-Shape
- Global alignment kernel (GAK)
- Smoothed formulation of dynamic time warping (SoftDTW)
- k-means
- Principal component analysis (PCA) with k-means
- Mixed autoencoders with DNN (MAFC without fuzzy clustering)

Assessment of Scenario Reduction

- Cosine distance

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} p_k \left(1 - \frac{\boldsymbol{s}^{(i)} \cdot \boldsymbol{r}^{(k)}}{\|\boldsymbol{s}^{(i)}\|\|\boldsymbol{r}^{(k)}\|}\right)$$

- While none is close to 0, MAFC achieves the best score

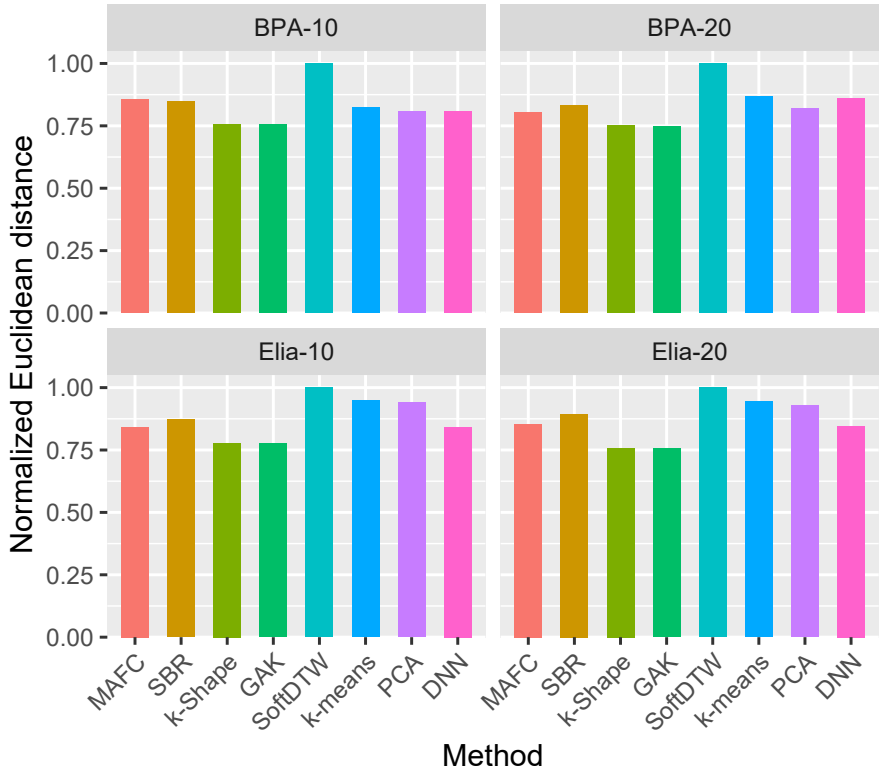
Method	BPA-10	BPA-20	Elia-10	Elia-20
MAFC	**0.885**	**0.888**	**0.896**	**0.896**
SBR	1.009	1.023	0.924	0.944
k-Shape	0.998	0.999	0.986	1.002
GAK	0.915	0.914	0.951	0.960
SoftDTW	0.981	0.986	0.959	0.974
k-means	0.944	0.962	0.962	0.966
PCA	0.935	0.942	0.942	0.954
DNN	0.905	0.896	0.928	0.914

Assessment of Scenario Reduction

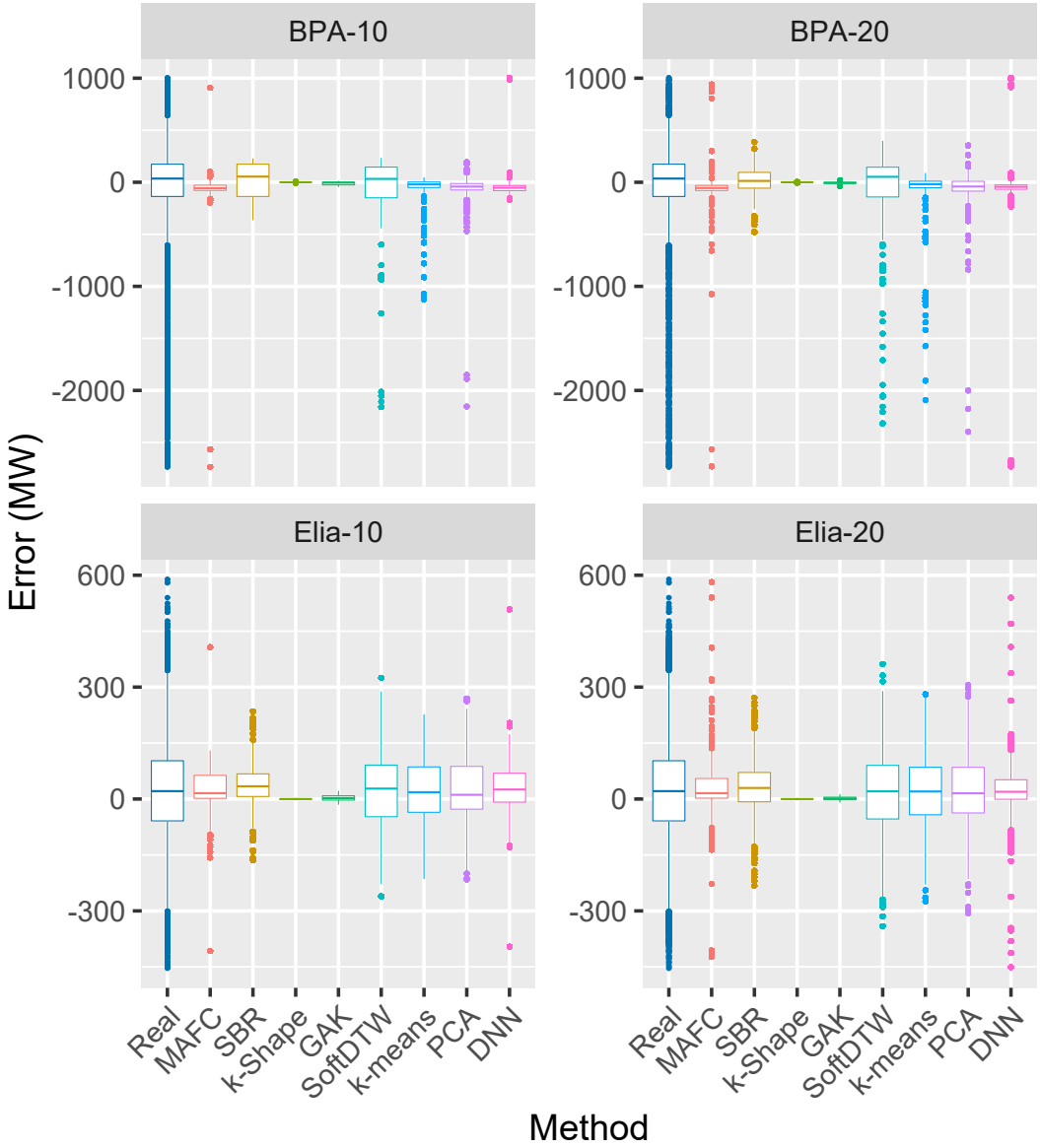
- Euclidean distance

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} p_k \left\| \boldsymbol{s}^{(i)} - \boldsymbol{r}^{(k)} \right\|^2$$

- MAFC achieves average scores, because this metric penalizes HILP scenarios

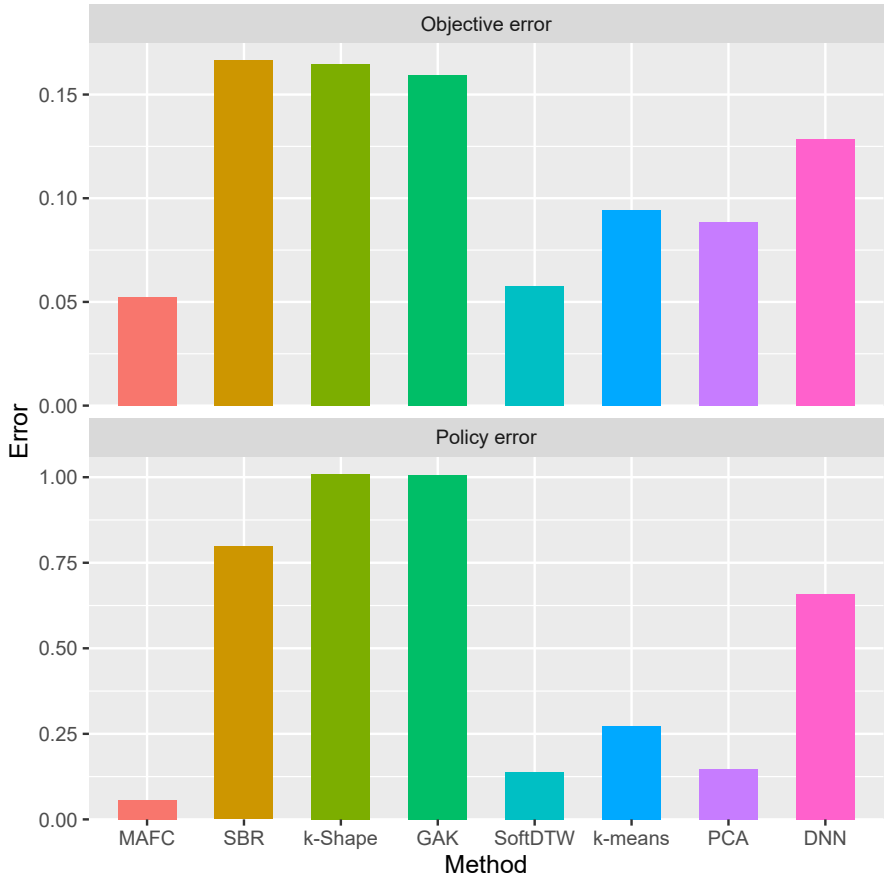


Assessment of Scenario Reduction



Case Study on a Modified IEEE 24-Bus System

- Objective error: difference between expected costs under $\boldsymbol{S}$ and under $\boldsymbol{R}$
- Policy error: obtain first-stage decisions under $\boldsymbol{S}$ and $\boldsymbol{R}$ respectively, and then evaluate the realized costs under $\boldsymbol{S}$ and calculate the difference



Outline

Conclusion

- Stochastic programming is a natural approach to short-term power system operations under high penetration of renewable generation
- To yield high quality decisions (such as day-ahead unit commitment decisions), we need to build high quality scenario sets that are representative of the underlying multivariate probability distributions
- We may also need to trim down the scenario set for the tractability of the optimization problem (which possibly involves integer variables)
- While scenario generation and scenario reduction have been extensively studied, generalization capability and feature engineering remain challenges
- In SeqGAN for scenario generation, the observation in the previous day (instead of a random noise) is used as the input, and the Monte Carlo method is employed to estimate the scores of partially generated sequences at each time step
- In MAFC for scenario reduction, a mixture of deep autoencoders map the original scenarios to latent representations which are fed into a membership deep neural network, and fuzzy clustering is employed to better preserve the patterns
- Both statistical metrics and test cases demonstrate the superior performance of the proposed deep learning approaches

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