IOWA STATE UNIVERSITY
ECpE Department

Probabilistic Load and PV Generation Forecasting

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Outline

I – Probabilistic Load Forecasting

- Summary of Basic Ideas
- Designing A Scalable Forecaster
- Testing

II – Probabilistic PV Generation Forecasting

- Summary of Basic Ideas
- Designing A Scalable Forecaster
- Testing

Section I – Probabilistic Load Forecasting

- Summary of Basic Ideas
- Designing A Scalable Forecaster
- Testing

Load Forecasting - Basic Ideas

Summary:

- Core algorithm: Gaussian Process Regression (GPR)
- **Inputs**:

  $H_D(t)$: hour-of-the-day (1~24) $D_W(t)$: day-of-the-week (1~7)

  $D_Y(t)$: day-of-the-year (1~365) $M_Y(t)$: month-of-the-year (1~12)

  T(t): temperature with uncertainty P(t-1): load at time (t-1) (w/ and w/o uncertainty)
- **Outputs**: mean and standard deviation of the predicted load at time t, i.e., $\hat{P}(t)$
- Training dataset: 22 months
- Test dataset: 12 months
- Training stage:

  $\{\mathbf{X}(t), P(t)\} \rightarrow GPR^*$, where, $\mathbf{X}(t)=[H_D(t), D_W(t), D_Y(t), M_Y(t), T(t), P(t-1)]^T$
- Forecasting stage (Testing stage):

  $GPR^*(\mathbf{X}(t-1)) \rightarrow \hat{P}(t-1) \rightarrow \mathbf{X}(t) \rightarrow GPR^*(\mathbf{X}(t)) \rightarrow \hat{P}(t) \rightarrow \mathbf{X}(t+1) \rightarrow \ldots$

  For each time step, there are 15 Monte Carlo samples, i.e., 15 X(t)'s.
- Forecasting horizon: 24 hours (1 day)
- Forecasting resolution: 1-hour

Load Forecasting - A Scalable Forecaster

A Scalable Forecaster:

- Training one forecaster for ***each*** bus is time-consuming and inflexible.

  Question: How to develop a ***scalable*** forecaster that can adapt to buses with different customer numbers?

- **Proposed Solution**
  - Training Stage:

    Train a forecaster using the normalized load of a particular customer group.
  - Forecasting Stage:

    First, forecast the normalized loads, then, de-normalize the forecasted normalized loads.

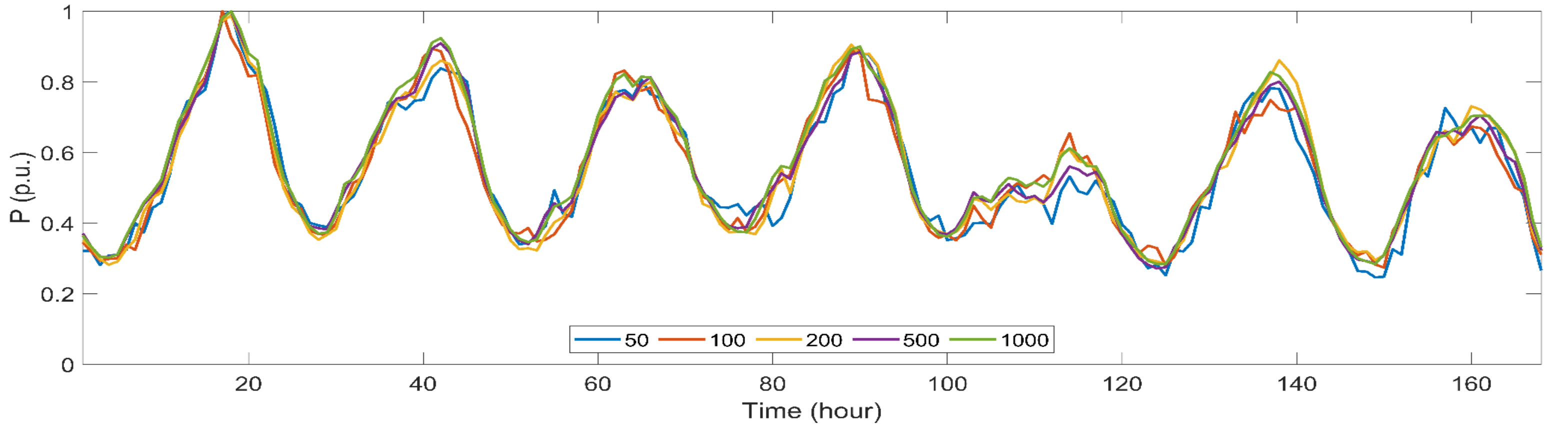
- **Two conditions** must be satisfied:
  - Load curve:

    Different customer groups must have similar normalized load curves.
  - Peak load:

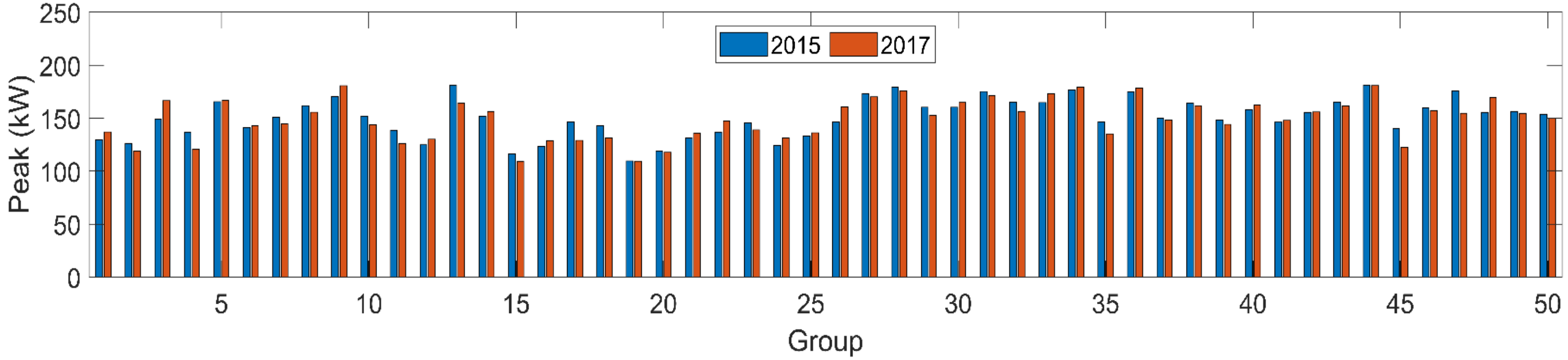
    For a particular customer group, the peak loads in different years should be similar. This is because when predicting a future load at time t, the load at time (t-1) should be normalized using the yearly peak load, which might not occur and needs to be approximated as the peak load in a historical year.

Load Forecasting - A Scalable Forecaster

➢ **Condition 1: Different customer groups have similar normalized load curves.**



➢ **Condition 2: For a particular customer group, different years have similar peak loads.**



Customer number in each group = 50, totally 50 groups (max(AE/P)=12.78%, mean(AE/P)=4.6%)

The two conditions are satisfied!

Load Forecasting - A Scalable Forecaster

A Scalable Forecaster (Three Steps):

Training:

Dependent variable $P_{nrm}(t) = \frac{P(t)}{P_{peak}}, \quad t = 2, \dots, N.$

Independent variables
$$\left\{ \begin{array}{l} P_{nrm}(t-1) = \frac{P(t-1)}{P_{peak}}, \quad t = 2, \dots, N. \\ T(t) \\ H_d(t), D_w(t), D_y(t), M_y(t) \end{array} \right.$$

=> GPR^*

Trained model

Forecasting:

Independent variables
$$\left\{ \begin{array}{l} P_{nrm}(t'-1) = \frac{P(t'-1)}{P_{hist,peak}}, \quad t' = 2, \dots, N'. \\ \hat{T}(t') \\ H_d(t'), D_w(t'), D_y(t'), M_y(t') \end{array} \right.$$

Trained model GPR^*

=> $\hat{P}_{nrm}(t')$

Forecasted normalized load

Note that: $P_{hist,peak} = \max\big(P(t)\big), t = 1, \dots, N'.$

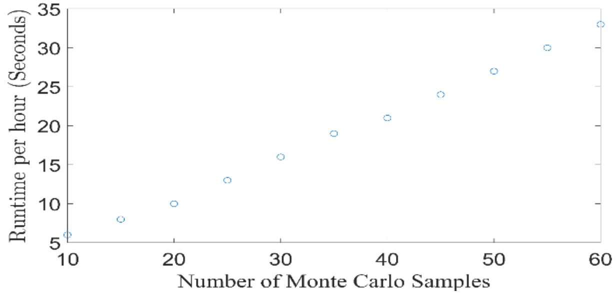
"De-normalizing":

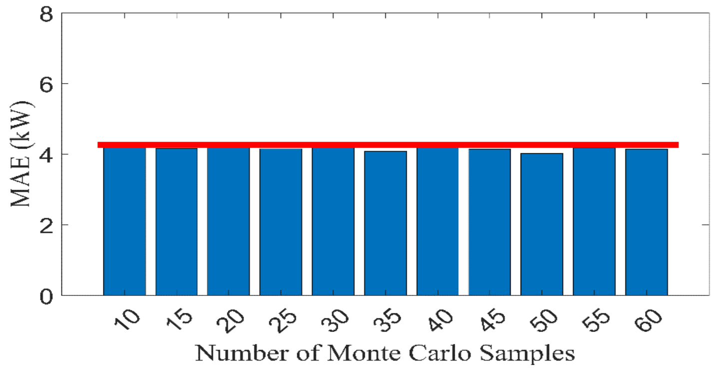
Forecasted nominal load $\hat{P}(t') = \hat{P}_{nrm}(t') * P_{hist,peak}$

Load Forecasting - Testing

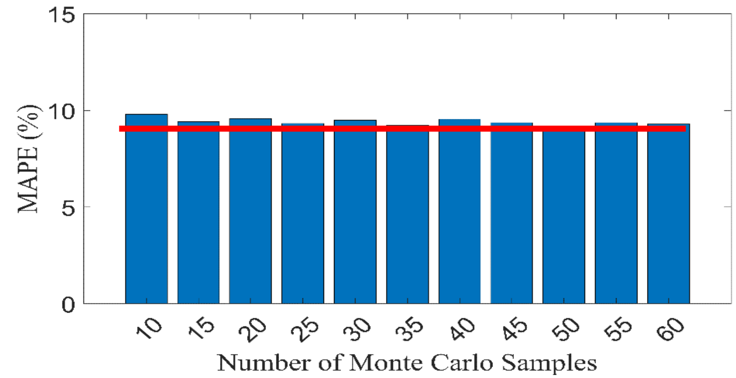
Reducing the Runtime:

Runtime is almost proportional to the number of Monte Carlo samples.

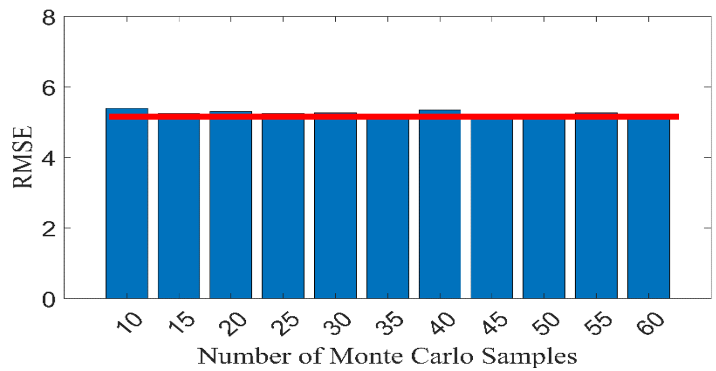




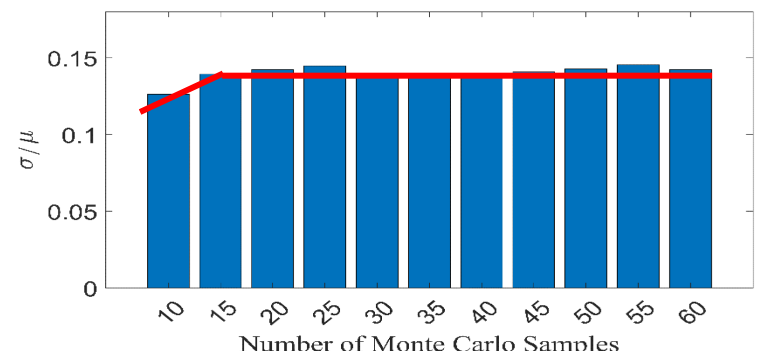
MAE (kW)



MAPE (%)



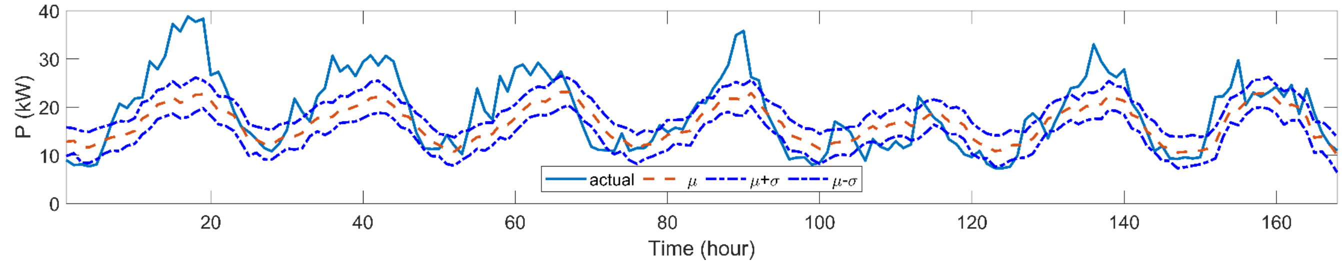
RMSE



σ/μ

Load Forecasting - Testing

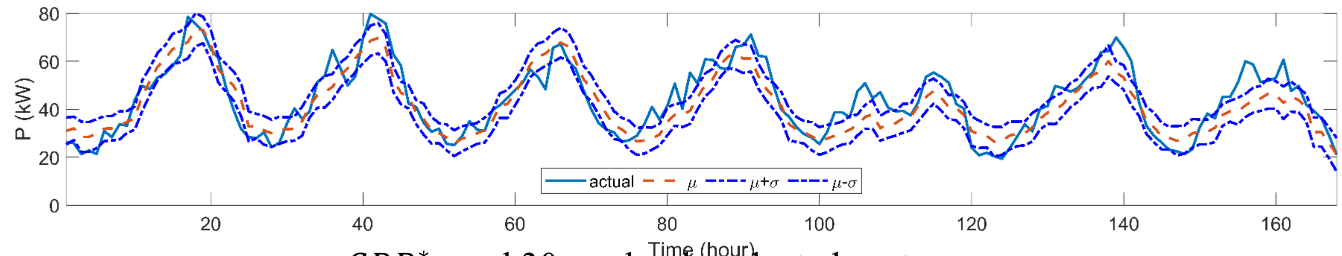
Real and Forecasted Load Curves:



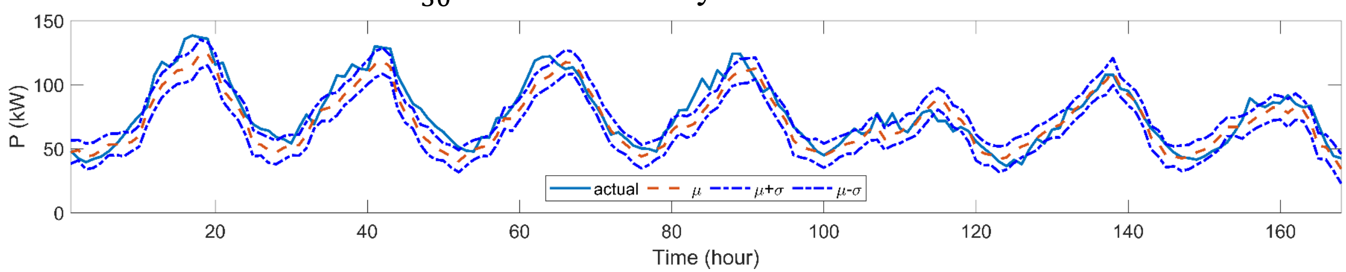
GPR_{10}^{*} and 10 randomly selected customers

Customer # for training

Customer # for forecasting



GPR_{30}^{*} and 30 randomly selected customers



GPR_{50}^{*} and 50 randomly selected customers

Summary: More customers result in smoother load curves.

Load Forecasting - Testing

Forecasting Error Metrics:

Customer # for training

Customer # for forecasting

	10	15	20	25	30	35	40
GPR^*_{10}	3.1	3.1	4.1	7.5	6.0	7.4	8.6
GPR^*_{15}	4.2	2.9	2.8	4.9	8.2	5.1	5.8
GPR^*_{20}	3.1	2.6	3.7	7.5	5.2	5.9	6.9
GPR^*_{25}	3.6	2.6	3.2	6.4	4.3	4.9	5.8
GPR^*_{30}	3.8	2.7	2.9	5.9	4.2	4.9	5.7
GPR^*_{35}	4.0	2.8	2.8	5.5	3.9	4.6	5.3
GPR^*_{40}	4.3	2.9	2.7	5.1	3.8	4.5	5.2

MAE (kW)

MAPE decreases as customer # increases.

	10	15	20	25	30	35	40
GPR^*_{10}	32.0	15.0	11.8	16.1	11.9	12.6	13.0
GPR^*_{15}	41.2	16.1	9.3	11.1	16.6	10.2	10.3
GPR^*_{20}	29.4	12.4	11.7	17.3	11.2	10.7	11.1
GPR^*_{25}	33.5	13.0	10.0	15.0	9.5	9.3	9.6
GPR^*_{30}	36.5	14.3	9.4	13.8	9.4	9.7	9.8
GPR^*_{35}	38.0	14.8	9.3	12.8	8.8	9.0	9.0
GPR^*_{40}	40.0	15.3	9.0	12.0	8.6	8.9	9.0

MAPE (%)

	10	15	20	25	30	35	40
GPR^*_{10}	13	17	32	91	62	94	129
GPR^*_{15}	23	12	13	37	97	36	49
GPR^*_{20}	14	11	21	73	40	54	77
GPR^*_{25}	18	11	16	55	29	38	53
GPR^*_{30}	20	11	14	49	28	37	49
GPR^*_{35}	22	12	13	42	25	32	43
GPR^*_{40}	25	13	12	37	24	32	41

MSE

	10	15	20	25	30	35	40
GPR^*_{10}	0.18	0.18	0.18	0.18	0.18	0.18	0.18
GPR^*_{15}	0.16	0.16	0.16	0.16	0.16	0.16	0.16
GPR^*_{20}	0.15	0.15	0.15	0.15	0.15	0.15	0.15
GPR^*_{25}	0.14	0.14	0.14	0.14	0.14	0.14	0.14
GPR^*_{30}	0.14	0.14	0.14	0.14	0.14	0.14	0.14
GPR^*_{35}	0.14	0.14	0.14	0.14	0.14	0.14	0.14
GPR^*_{40}	0.13	0.13	0.13	0.13	0.13	0.13	0.13

σ/μ

II – Probabilistic PV Generation Forecasting

- Summary of Basic Ideas
- Designing A Scalable Forecaster
- Testing

Generation Forecasting - Basic Ideas

Summary:

- Core algorithm: Gaussian Process Regression (GPR)
- **Inputs**:

  $H_D(t)$: hour-of-the-day (1~24) $D_Y(t)$: day-of-the-year (1~365)

  GHI(t): global horizontal irradiance with uncertainty
- **Outputs**: mean and standard deviation of PV generation at time t, i.e., $\widehat{G}(t)$
- Training dataset: 24 months
- Test dataset: 12 months
- Training stage:

  $\{\mathbf{X}(t), G(t)\} \rightarrow GPR^*$, where, $\mathbf{X}(t)=[H_D(t), D_Y(t), GHI(t)]^T$
- Forecasting stage (Testing stage):

  $GPR^*(\mathbf{X}(t)) \rightarrow \widehat{G}(t)$, $GPR^*(\mathbf{X}(t+1)) \rightarrow \widehat{G}(t+1)$, …

  For each time step, there are 15 Monte Carlo samples, i.e., 15 $\mathbf{X}(t)$'s.
- Forecasting horizon: 24 hours (1 day)
- Forecasting resolution: 1-hour

Similar to the load, a scalable PV generation forecaster is developed.

Generation Forecasting - A Scalable Fore.

A Scalable Forecaster:

- Training one forecaster for ***each*** bus is time-consuming and inflexible.

  Question: How to develop a ***scalable*** forecaster that can adapt to buses with different PV numbers?

- **Proposed Solution**
  - Training Stage:

    Train a forecaster using the normalized generation of a particular PV group.
  - Forecasting Stage:

    First, forecast the normalized generations, then, de-normalize the forecasted normalized generations.

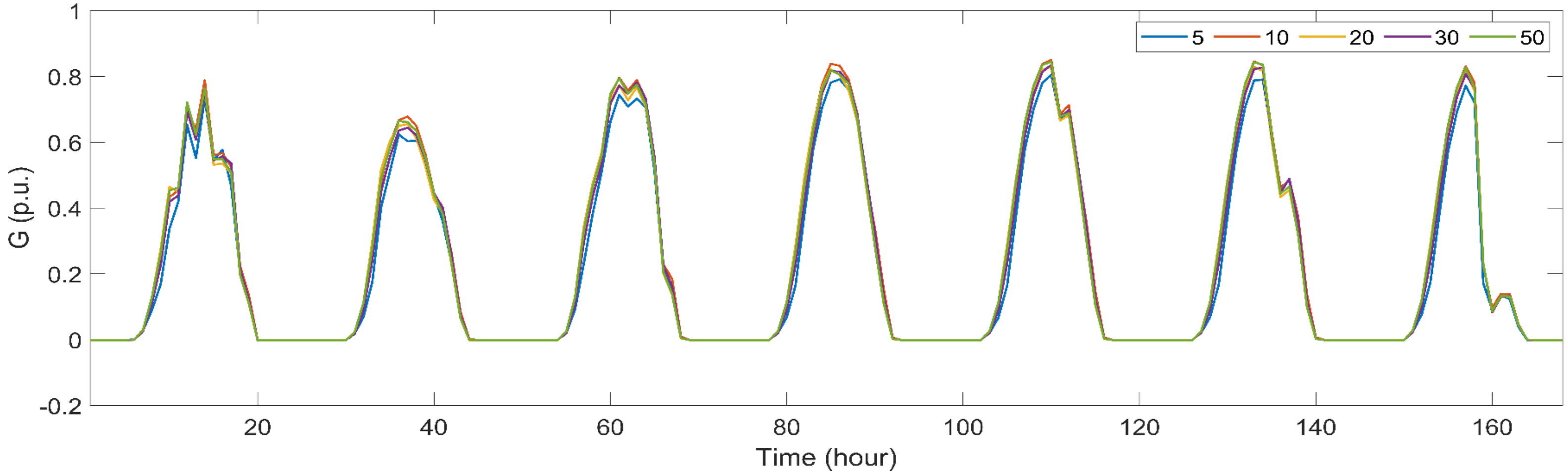
- **Two conditions** must be satisfied:
  - Generation curve:

    Different PV groups must have similar normalized generation curves.
  - Peak generation:

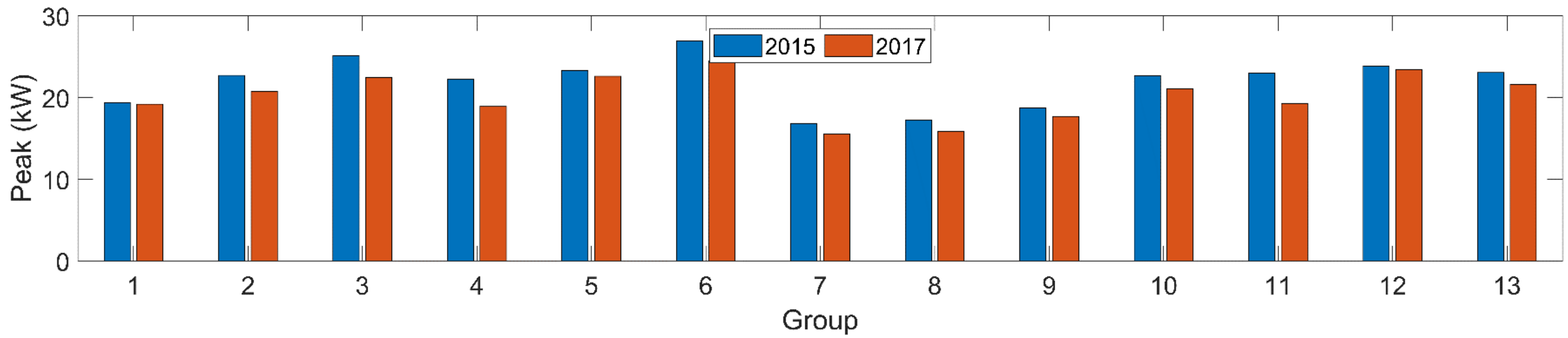
    For a particular PV group, the peak generations for different years should be similar. This is because when predicting a future normalized generation, the yearly peak generation is needed for normalization. The yearly peak generation might not occur, and should be estimated as a peak generation in a historical year.

Generation Forecasting - A Scalable Foreca

- Condition 1: Different PV groups have similar normalized generation curves.



- Condition 2: For a particular PV group, different years have similar peak generations.



PV number in each group = 5, totally 13 groups (max(AE/G)=16.2%, mean(AE/G)=7.6%)

The two conditions are satisfied!

Generation Forecasting - A Scalable Fore.

A Scalable Forecaster (Three Steps):

Training:

Dependent variable $G_{nrm}(t) = \frac{G(t)}{G_{peak}}, \quad t = 1, \ldots, N.$

Independent variables $\begin{cases} GHI(t) \\ H_d(t), D_y(t) \end{cases}$

=> GPR^* Trained model

Forecasting:

Independent variables $\begin{cases} \widehat{GHI}(t') \\ H_d(t'), D_y(t') \end{cases}$

Trained model GPR^*

=> $\hat{G}_{nrm}(t')$ Forecasted normalized generation

Note that: $G_{hist,peak} = \max\big(G(t)\big), t = 1, \ldots, N'.$

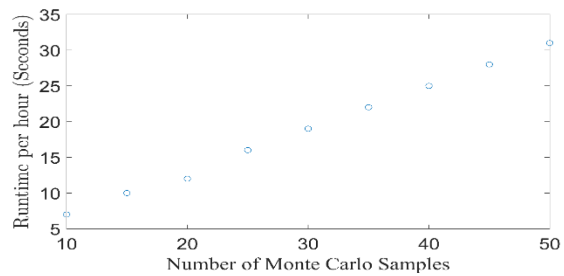
"De-normalizing":

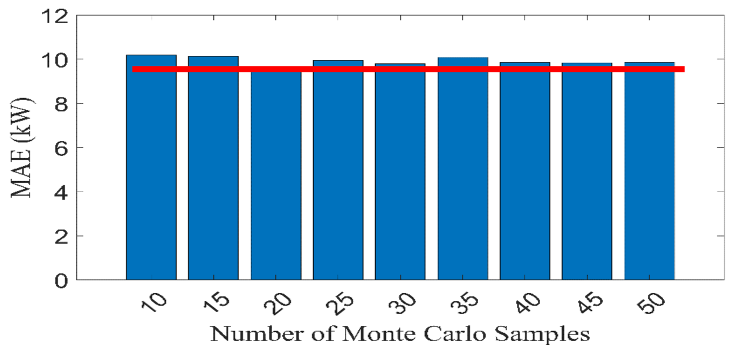
Forecasted nominal generation $\hat{G}(t') = \hat{G}_{nrm}(t') * G_{hist,peak}$

Generation Forecasting - Testing

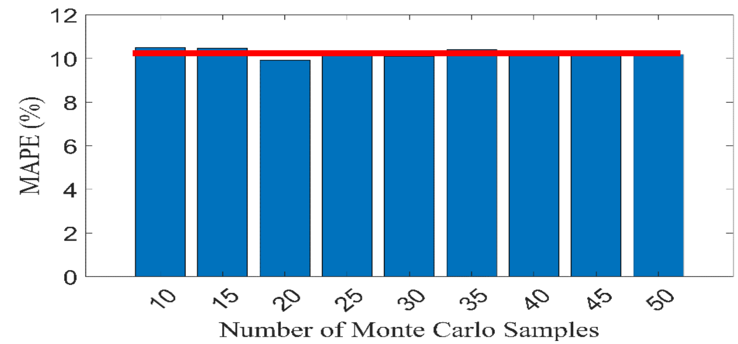
Reducing the Runtime:

Runtime is almost proportional to the number of Monte Carlo samples.

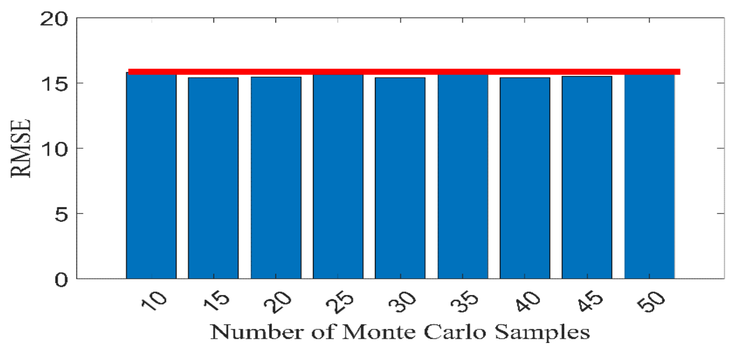




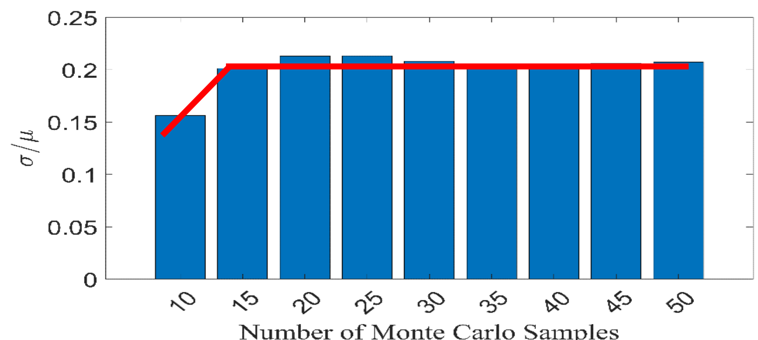
MAE (kW)



MAPE (%)



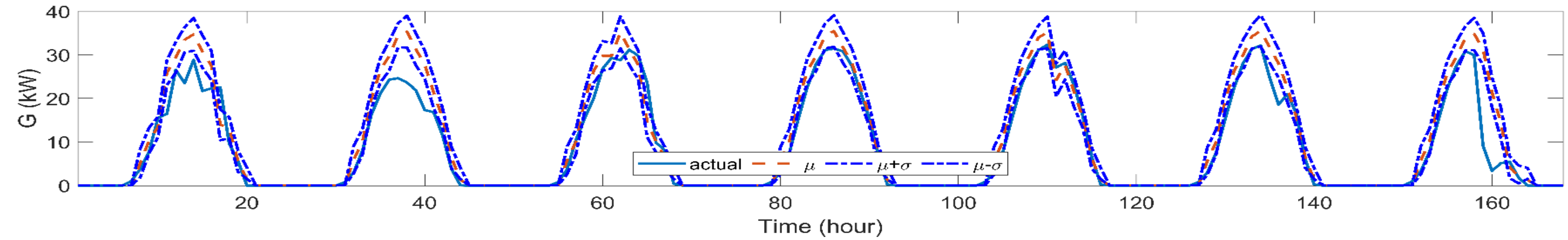
RMSE



σ/μ

Generation Forecasting - Testing

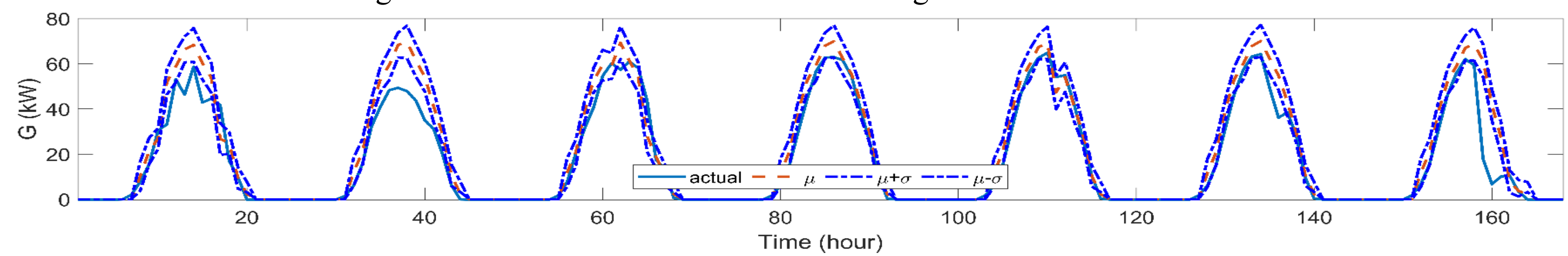
Real and Forecasted PV Generation Curves:



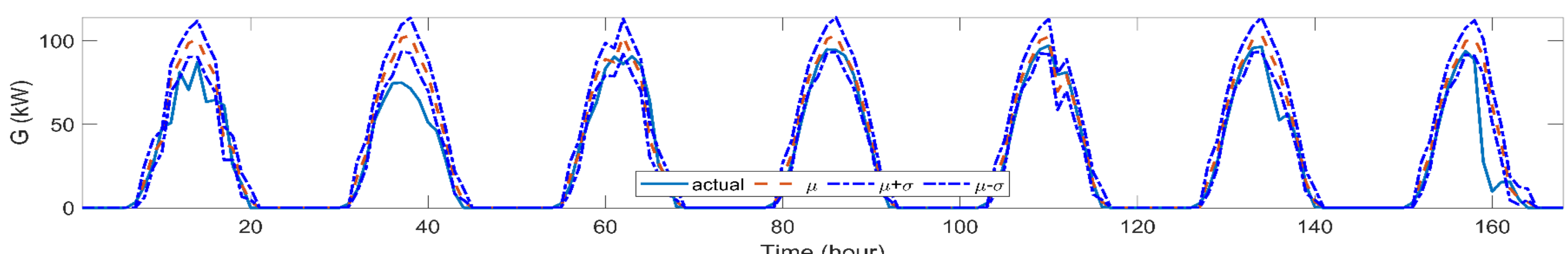
GPR_{10}^{*} and 10 randomly selected PVs

PV # for training

PV # for forecasting



GPR_{30}^{*} and 30 randomly selected PVs



GPR_{50}^{*} and 50 randomly selected PVs

Summary: Different PV groups show almost similar shapes.

Generation Forecasting - Testing

Forecasting Error Metrics:

PV # for training

PV # for forecasting

	10	15	20	25	30	35	40
GPR^*_{10}	4.1	6.2	8.3	9.2	11.0	13.2	15.0
GPR^*_{15}	3.9	5.6	7.5	8.2	9.8	11.8	13.4
GPR^*_{20}	4.2	6.0	8.0	8.8	10.5	12.7	14.4
GPR^*_{25}	4.1	6.1	8.1	9.0	10.7	12.9	14.7
GPR^*_{30}	4.3	6.1	8.2	8.9	10.7	12.9	14.5
GPR^*_{35}	4.4	6.3	8.4	9.2	11.0	13.3	15.0
GPR^*_{40}	4.3	6.2	8.3	9.1	10.9	13.2	14.9

MAE (kW)

MAPE does not change significantly as PV # increases.

	10	15	20	25	30	35	40
GPR^*_{10}	12.8	12.6	12.8	11.6	11.3	11.8	11.7
GPR^*_{15}	12.0	11.3	11.6	10.3	10.1	10.5	10.5
GPR^*_{20}	12.9	12.2	12.8	11.1	10.9	11.3	11.3
GPR^*_{25}	12.7	12.4	12.5	11.3	11.1	11.5	11.5
GPR^*_{30}	13.3	12.4	12.6	11.2	11.0	11.5	11.4
GPR^*_{35}	13.5	12.8	12.9	11.6	11.4	11.8	11.8
GPR^*_{40}	13.3	12.6	12.8	11.5	11.2	11.7	11.6

MAPE (%)

	10	15	20	25	30	35	40
GPR^*_{10}	34	78	133	183	268	374	493
GPR^*_{15}	30	70	118	162	239	333	438
GPR^*_{20}	32	74	127	172	252	353	461
GPR^*_{25}	33	77	130	178	262	366	481
GPR^*_{30}	33	74	128	171	251	353	457
GPR^*_{35}	34	78	133	179	262	369	480
GPR^*_{40}	34	77	131	177	259	364	474

MSE

	10	15	20	25	30	35	40
GPR^*_{10}	0.21	0.21	0.21	0.21	0.21	0.21	0.21
GPR^*_{15}	0.22	0.22	0.22	0.22	0.22	0.22	0.22
GPR^*_{20}	0.22	0.22	0.22	0.22	0.22	0.22	0.22
GPR^*_{25}	0.21	0.21	0.21	0.21	0.21	0.21	0.21
GPR^*_{30}	0.21	0.21	0.21	0.21	0.21	0.21	0.21
GPR^*_{35}	0.21	0.21	0.21	0.21	0.21	0.21	0.21
GPR^*_{40}	0.22	0.22	0.22	0.22	0.22	0.22	0.22

σ/μ

Thanks!

Q&A.