CONTROL AND OPTIMIZATION IN SMART-GRIDS

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Course topics

- Session 1: Introduction to Power systems
  - Context and motivation
  - Power flow analysis
  - Economic dispatch
- **Session 2: Renewable sources**
  - **Stochastic models of variable sources**
  - **Dispatching random sources**
- Session 3: Energy dispatch
  - Risk-limiting dispatch
  - Matlab session

Course topics

- Session 4: Incentive-based demand response
  - Modeling demand
  - Peak time rebates
  - Contract design for demand response
- Session 5: Flexible loads
  - Modeling flexibility
  - Load dispatch
  - Case study: Electric vehicles
- Session 6: Micro-grids
  - Lean energy concept
  - Joint generation and load dispatch

Day-ahead Market

- Given a demand forecast D_k
- And a set of generators $G_1, G_2, G_3, \ldots, G_N$
- What is the <u>lowest cost</u> generation program that supplies the demand?

This is the economic dispatch problem!

Economic Dispatch

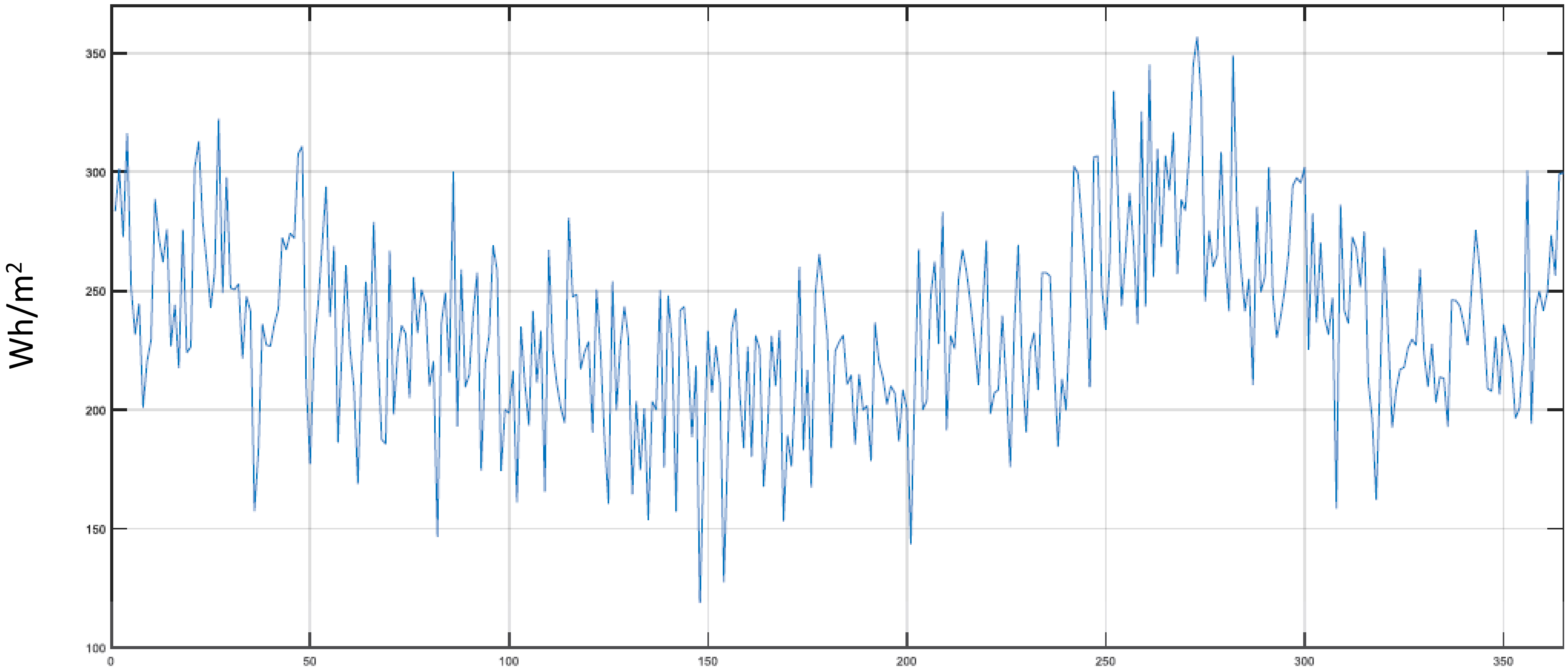
$$\min J = \sum_{k=1}^{K} \sum_{j=1}^{N} C(p_{jk})$$ *Sum of generation costs*

Subject to

$$\sum_{j=1}^{N} p_{jk} = D_k \qquad \forall k$$ Energy Balance

$$p_j{}^{min} \leq p_{jk} \leq p_j^{max}$$ Operational constraints

Renewable energies



Daily average of solar radiation for one year at Medina (Colombia)

Economic Dispatch

$$\min J = \sum_{k=1}^{K} \sum_{j=1}^{N} C(p_{jk})$$

Subject to

$$\sum_{j=1}^{N} p_{jk} = D_k \qquad \forall k$$

$$p_j^{\,min} \leq p_{jk} \leq p_j^{max}$$

- Can we use the same approach to dispatch renewable sources?
- Can we fix p_j ?

Give possible solutions…

Renewable energies

- Renewable power generation can be modeled as a stochastic process!

Stochastic Process

Unknown signals: Can be described by their statistical properties.

v(t,x,y,z) is an stochastic process:

- *Sequence of random variables*
- *Continuous ($v \in \mathbb{R}$) or discrete ($v \in S$)*

– How is it fully described in stochastic sense?

$$F_{(X(t_1),\dots,X(t_k))}(x_1, x_2, \dots, x_k) \rightarrow joint\ cdf$$

$$F_{(X(t_1),\dots,X(t_k))}(x_1, x_2, \dots, x_k) = \mathrm{P}[x(t_1) \le x_1, \dots]$$

Stochastic Process

Given:

$$F_{(X(t_1),\ldots,X(t_k))}(x_{1,}x_{2,\ldots},x_k) = joint\ cdf$$

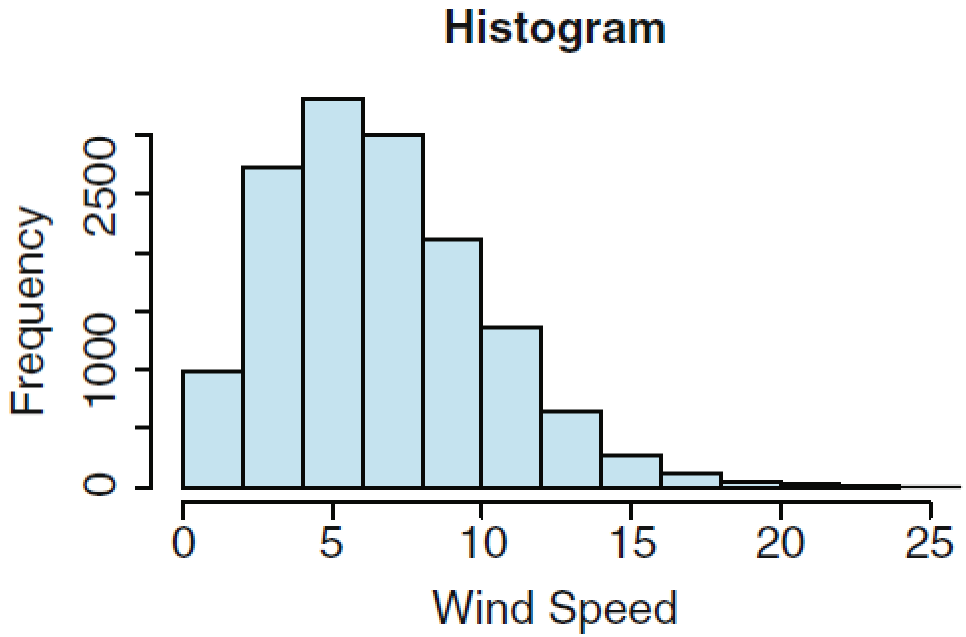
The probability density function (pdf) is:

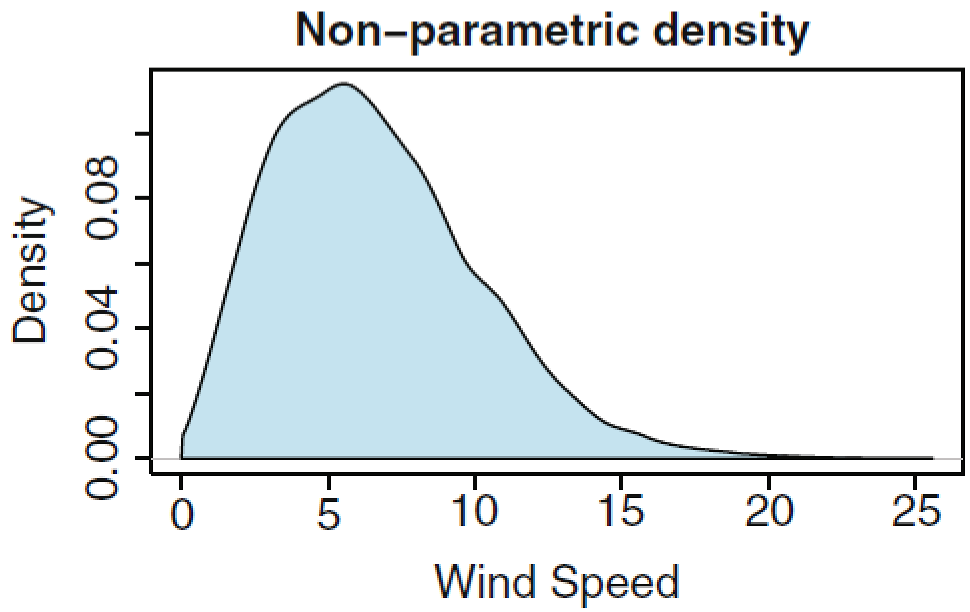
$$f_{(X(t_1),\ldots,X(t_k))}(x_{1,}x_{2,\ldots},x_k) = \frac{\partial^n F_{(X(t_1),\ldots,X(t_k))}(x_{1,}x_{2,\ldots},x_k)}{\partial x_1 x_{2\ldots} x_k}$$

–It is a highly complex representation

–The *pdf* is infinite dimensional, for any time k, for any space point,..

Stochastic Process





Descriptive *pdf* of wind speed in east-Denmark constructed from 1970-1979 data

Stochastic Process

Given:

$$f_{(X(t_1),\dots,X(t_k))}(x_{1,}x_{2,\dots},x_k) = \frac{\partial^n F_{(X(t_1),\dots,X(t_k))}(x_{1,}x_{2,\dots},x_k)}{\partial x_1 x_{2,\dots} x_k}$$

- First moments:

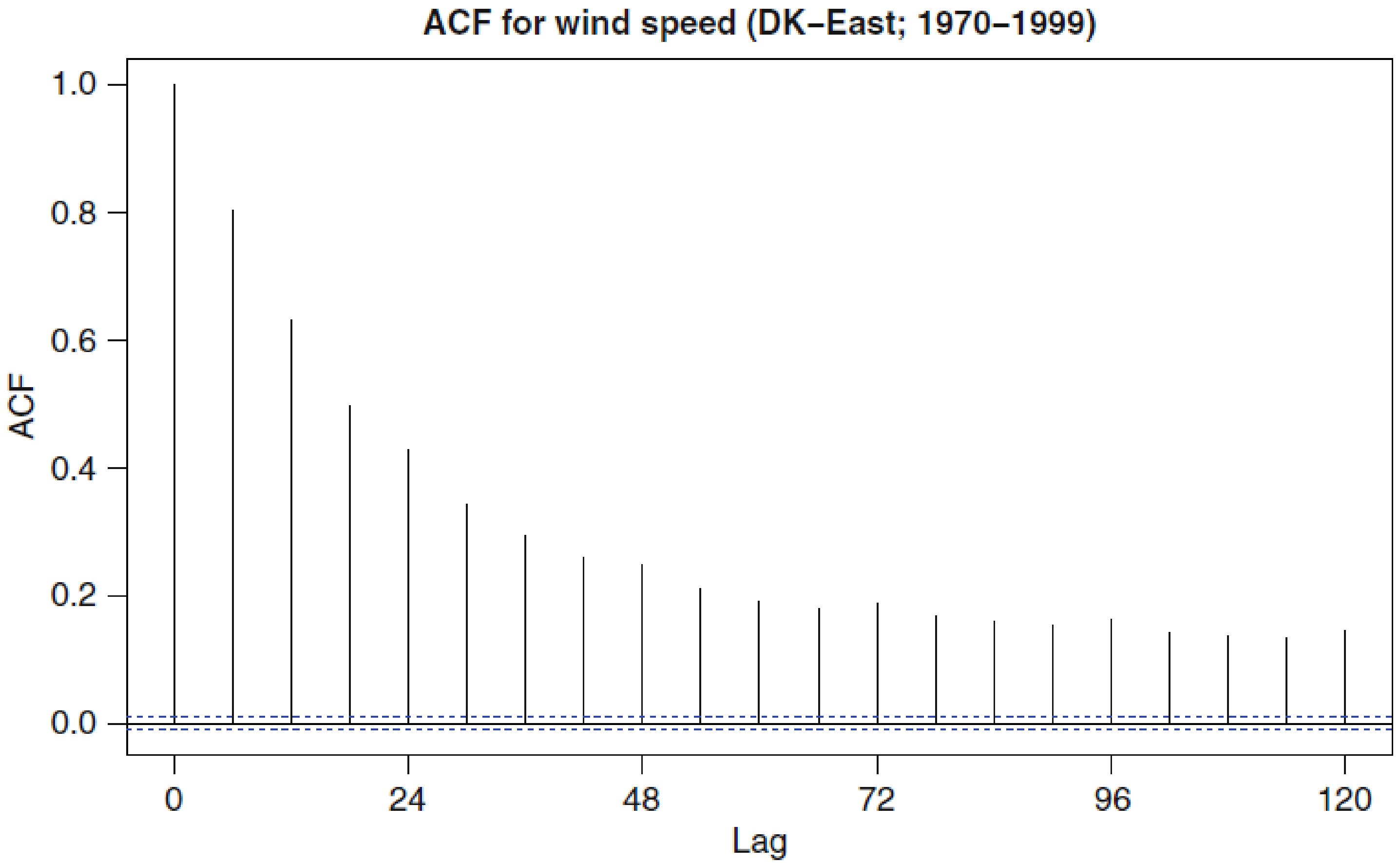
– Expected value

$$\mu_X(t_k) = E_X(t_k) = \int_{-\infty}^{\infty} x\, f_{X(t_k)}(x; t_k)dx$$

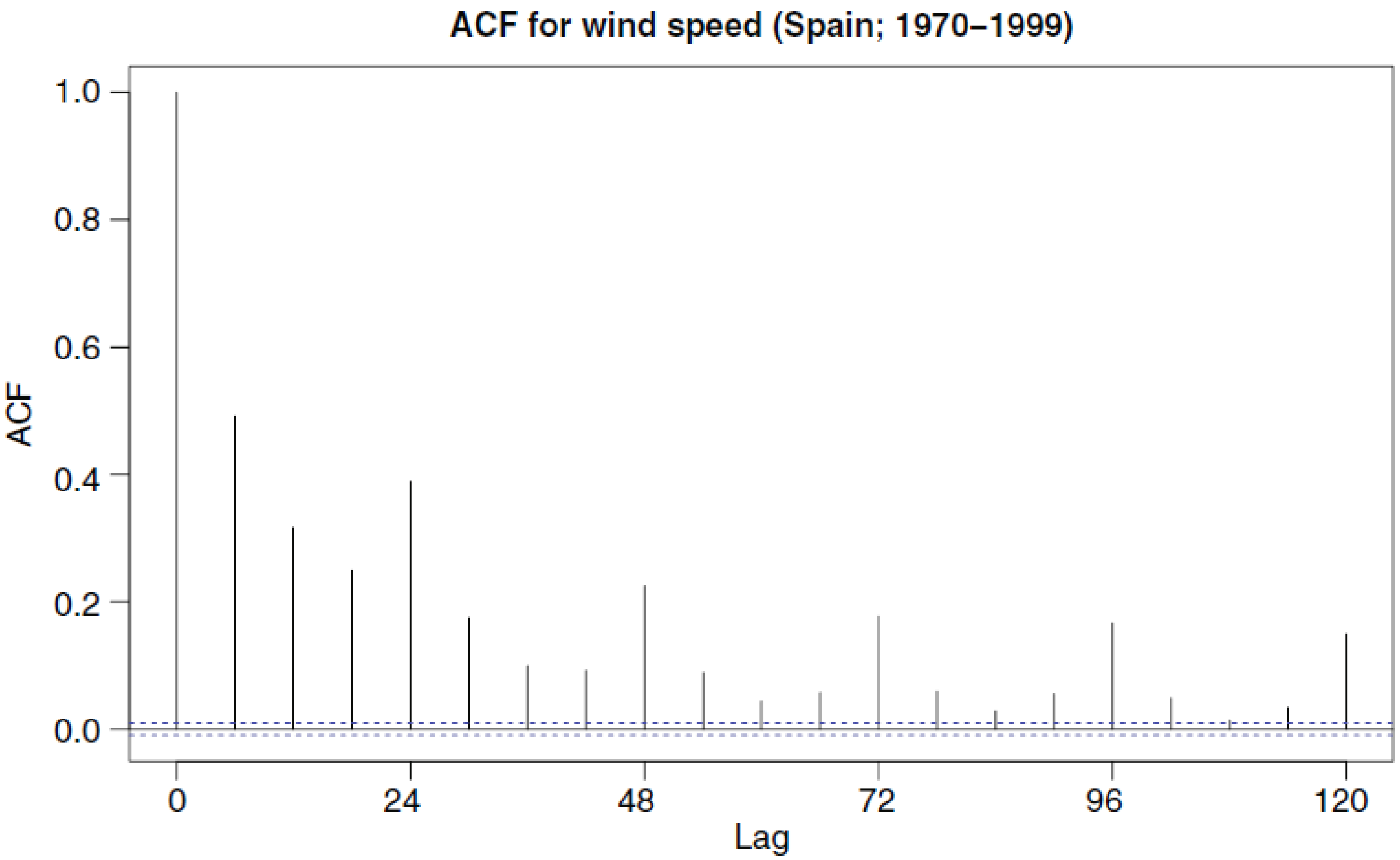
–Covariance

$$COV_{XX}(t_k, t_l) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x_k - E[x_k])(x_l - E[x_k])f_{(X(t_k),X(t_l))}(x_k, x_l; t_k, t_l)dx_k dx_l$$

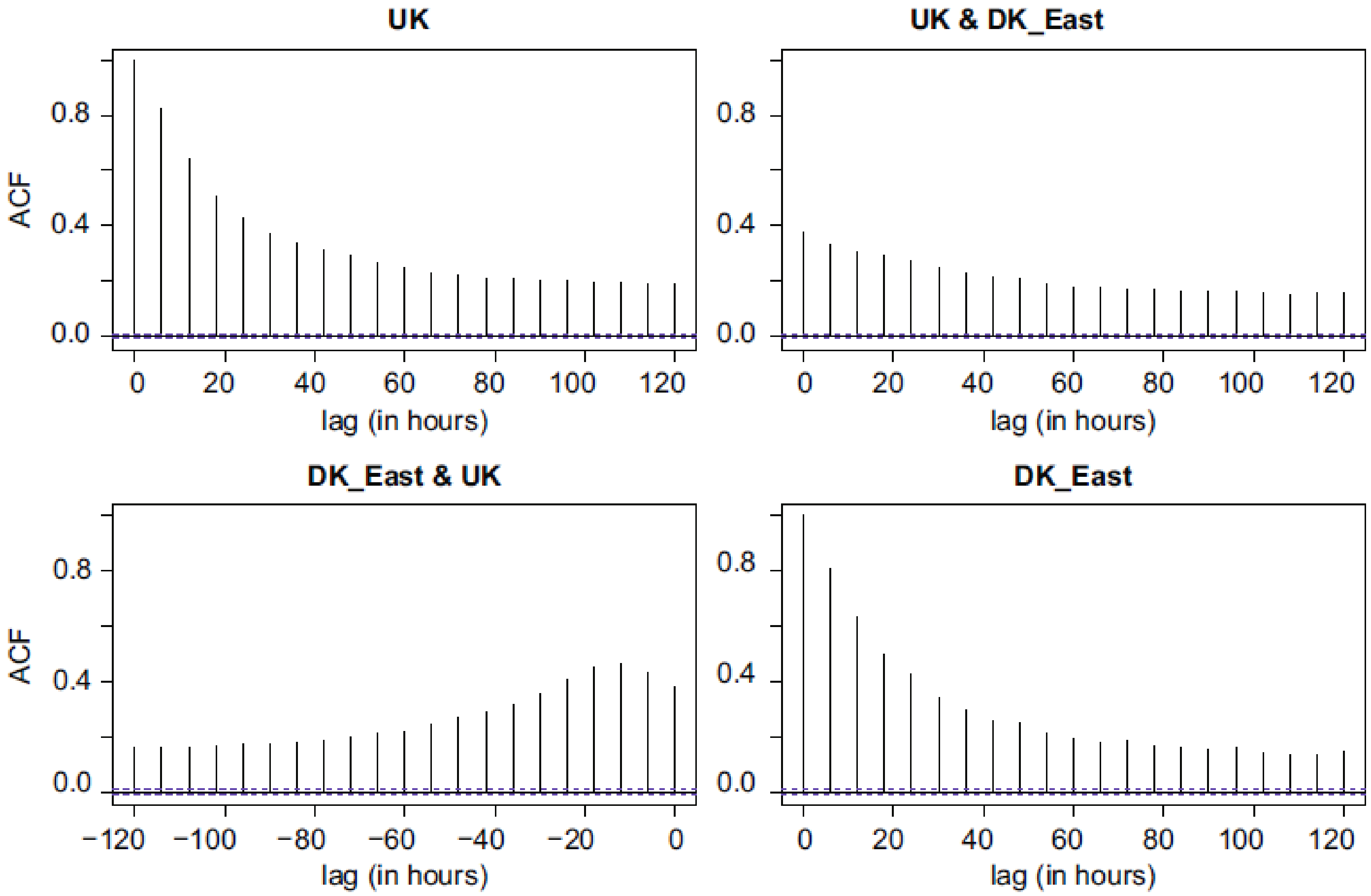
Stochastic Process



Stochastic Process



Stochastic Process



Quantiles

- Given a probability α, what is the value of the random variable y such that:

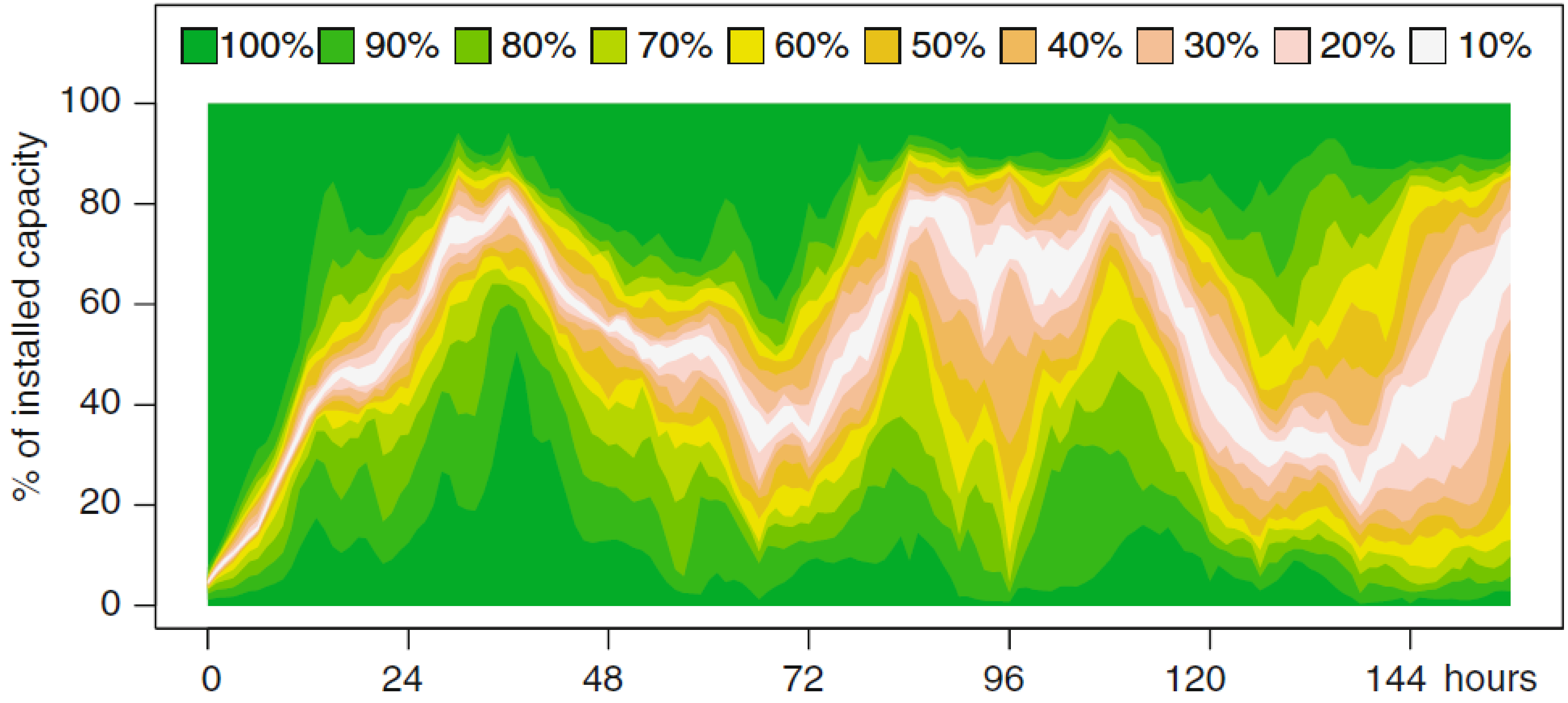
$$P[Y<y]= \alpha$$

That is:

$$q(\alpha)=F^{-1}(\alpha)$$

F is an (strictly) increasing function of y.

Quantiles



Forecast of wind generation expressed as quantiles [1]

Bayesian Estimation

How to obtain an optimal generation forecast from a probabilistic description of the renewable source?

Bayesian Estimation

- The unknown is NOT a parameter
- There is INFORMATION in the form of observed realizations of random variables
- Both the unknown and the observed information are described as random variables
- The unknown and the observed R.V. are Correlated.
- Estimation criteria:

–Minimize Bayesian Risk

–Minimize Mean Squared Error

Mean Squared Error

- Given an estimate X' of X (random variable), it is defined:
- Estimation error:

$$X = X - X'$$

- Mean squared error (Expected cost)

$$\mathbf{J} = E[\,X^T X\,] = E[\,(X-X')^T(X-X')\,]$$

MSE estimate: Minimize the mean squared error

- *We want to select an estimate* X' *such that* **J** *is minimized, using all the available information*.

Mean Squared Error

- SITUATION 1:

The unique available information is :

$f_X(x)$, *pdf* of X

What is the optimal MSE estimate of X?

- **J** = $E[X^T X] = E[(X-X')^T(X-X')]$

Mean Squared Error

- SITUATION 1:

The unique available information is :

$f_X(x)$, *pdf* of X

What is the optimal MSE estimate of X?

- $\mathbf{J} = E[X^T X] = E[(X-X')^T(X-X')]$

Answer:

X'=E[X]

What is the variance of this estimate?

Mean Squared Error

- SITUATION 2:

We are given the realization of another random variable Z, jointly distributed with the unknown X.

$f_{XZ}(x,z)$, *joint pdf* of X and Z

What is the optimal MSE estimate of X?

- **J** = $E[X^T X] = E[(X-X')^T(X-X')]$

Mean Squared Error

- SITUATION 2:

We are given the realization of another random variable Z, jointly distributed with the unknown X.

f_{XZ} *(x,z), joint pdf* of X and Z

What is the optimal MSE estimate of X?

- **J** = $E[X^T X] = E[(X-X')^T(X-X')]$

Answer:

$X'=E[X/Z]$

The optimal Bayesian estimate is the conditional mean!!

Mean Squared Error

- The conditional pdf can be expressed as:

$$f\,[X \mid Z] = \frac{f(Z \mid X)\, f(Z)}{f(X)}$$

- And the conditional mean is obtained as:

$$E[X/Z] = \int \mathrm{x}\;\; f_{X/Z}(x/z)\;\; dx$$

Mean Squared Error

A property of any MMSE estimator is that for any function *g(Z)* of the observed R.V. it holds that:

$$E[g(Z)\,(X - E[X \mid Z])^T = 0$$

Then:

$$E[\ ||X-E[X|Z]|| \leq E[\ ||X-g(Z)||\ ]$$

Renewable generation forecast

- Point forecast:
  - For the economic dispatch we are interested in the energy produced by a point source y at a future time *t+k*, given observations up to present time t.
  - The optimal point estimate is the conditional mean:

$$\hat{y}(t+k|t) = E[Y(t+k)|\Omega(t)]$$

  - Where $\Omega(t)$ is the information set at time t.

Renewable generation forecast

$\Omega(t)$ contains all data and knowledge of the process up to time t.

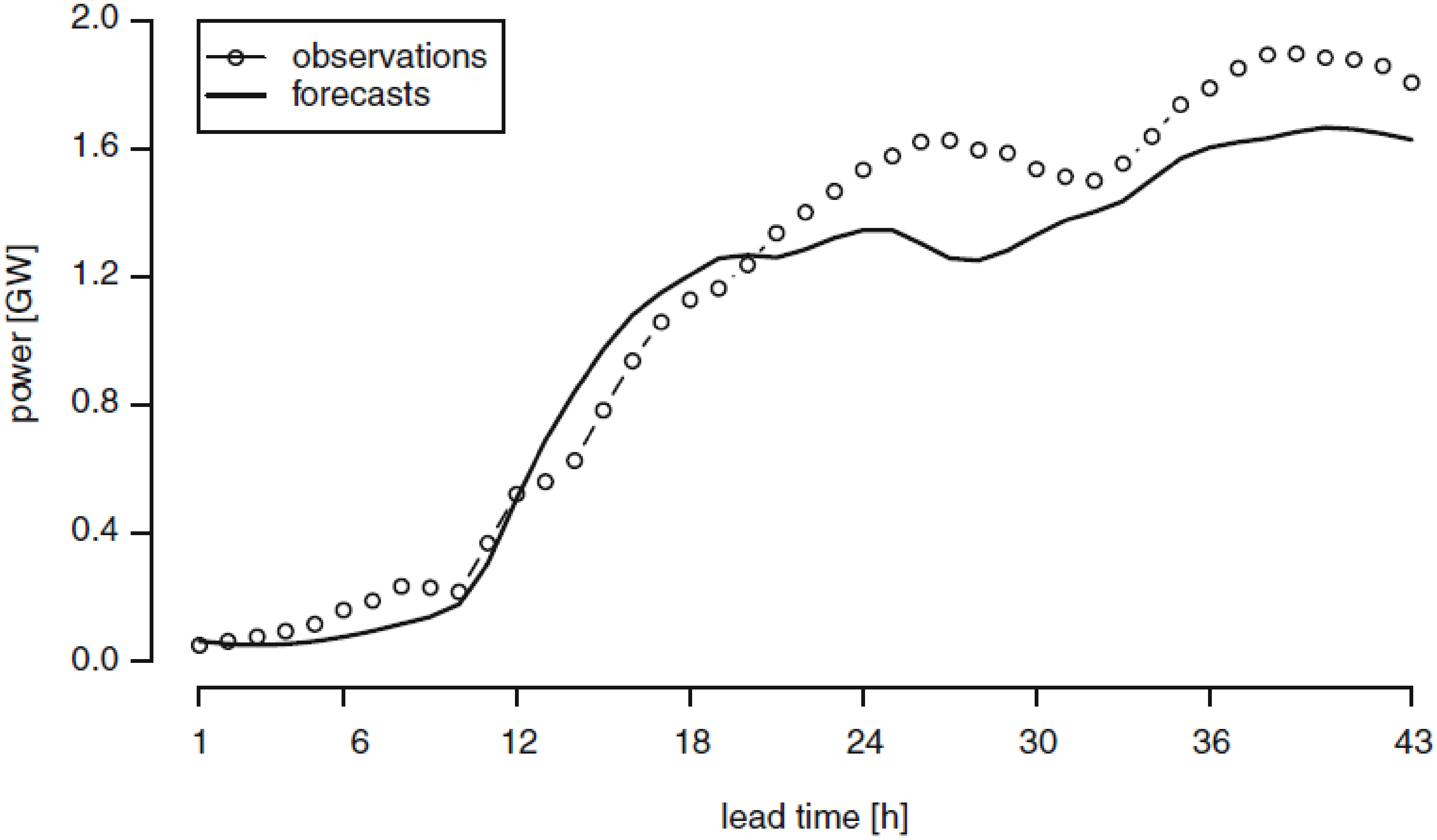
For example:

- Variable realization for previous intervals: $y(t), y(t-1), y(t-N)$
- Correlated variables realizations (weather, generation at close locations,…)
- Note that , for a known joint pdf

$$\hat{y}(t+k|t) = E[Y(t+k)|\Omega(t)]$$

Is a function of $\Omega(t)$

Renewable generation forecast



Point estimate and observations of wind generation in western Denmark, 4th April 2007.

Renewable generation forecast

Point estimates DO NOT give information on uncertainty levels!

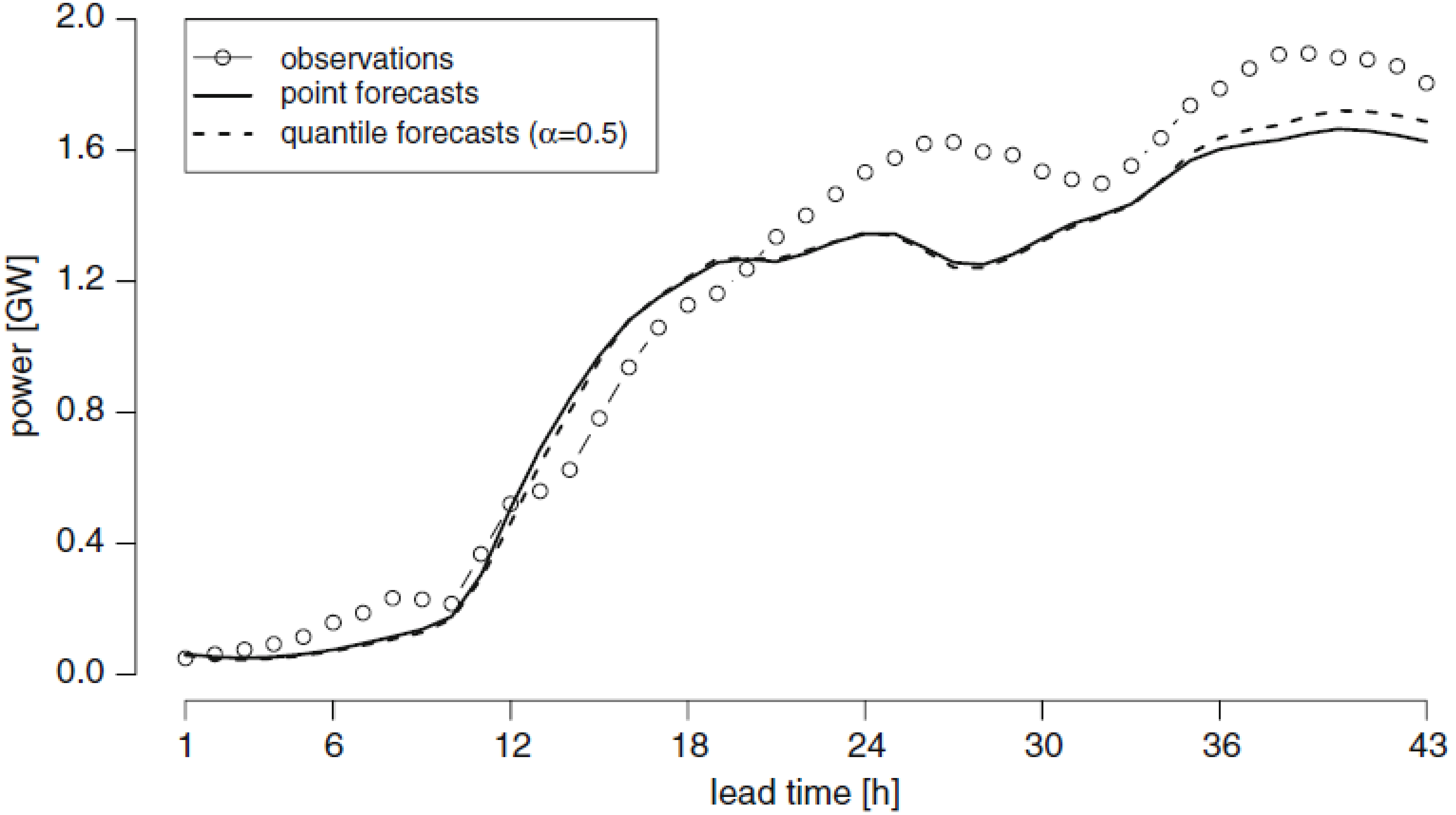
Better instruments can be derived:

- **Quantile forecasts:** $\hat{q}(t+k, \alpha)$

is the R.V. value such that:

$$P[\, Y(t+k) \leq \hat{q}(t+k, \alpha) \mid \Omega(t) \,] = \alpha$$

Renewable generation forecast



0.5 quantile estimate and observations of wind generation in western Denmark, 4th April 2007.

Renewable generation forecast

- **Prediction intervals:** A prediction interval is a range of possible outcomes for the variable Y(t+k,β), given the present information *Ω(t)*, for a level of probability (1- β):

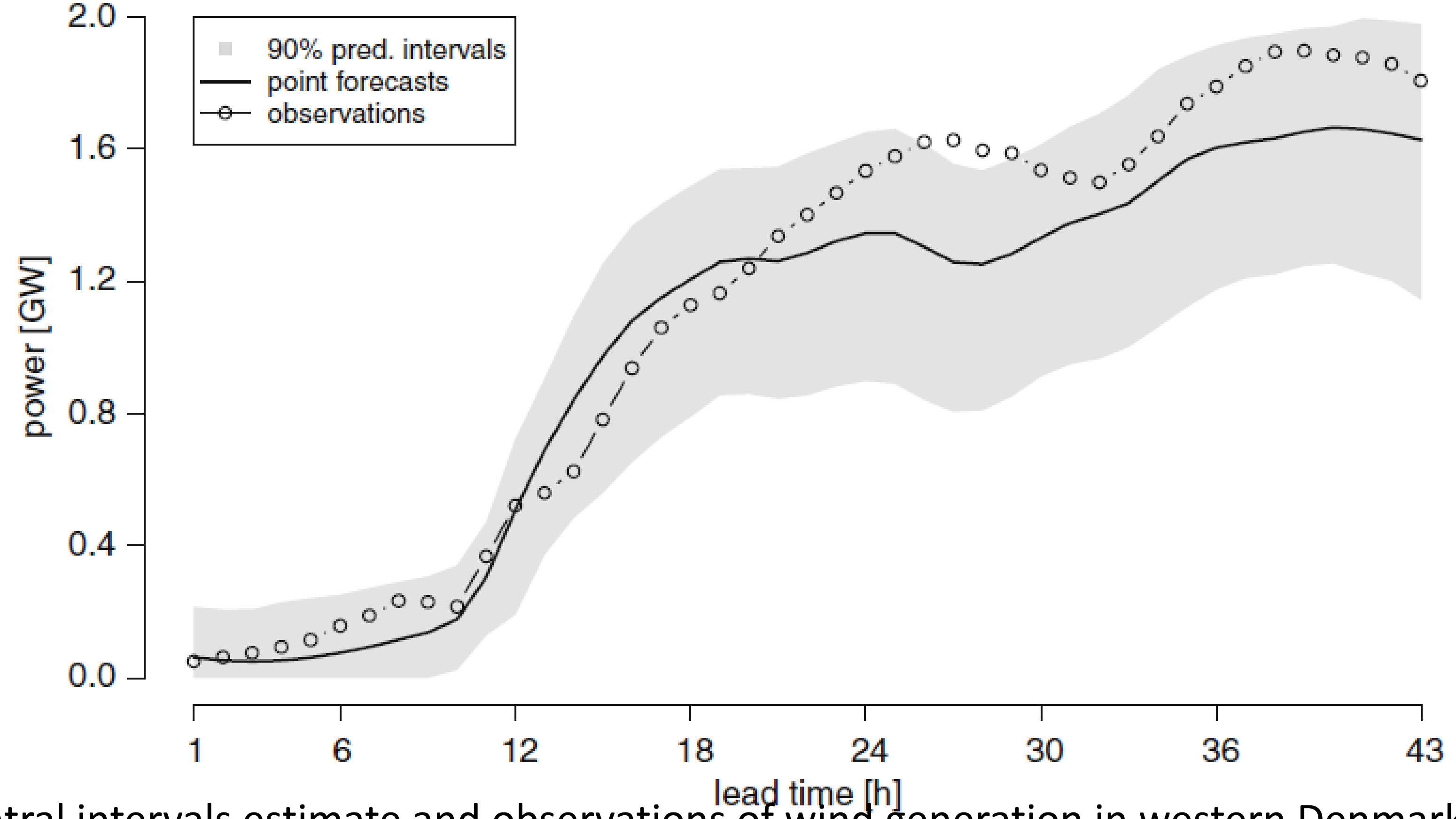
$$P[\, Y(t+k) \in I\hat{}(t+k,\, \beta) \mid \Omega(t) \,] = 1-\beta$$

- where

$$I\hat{}(t+k,\, \alpha) = [q\hat{}(t+k,\, \alpha_{min});\, q\hat{}(t+k,\, \alpha_{max})]$$

- *Note that the intervals are not unique for a given provability level.*
- *Central intervals are usually employed (centered on the median).*

Renewable generation forecast



10% central intervals estimate and observations of wind generation in western Denmark, 4th April 2007.

Renewable generation forecast

Scenario approach:

- A pdf can be represented by samples of the random variable.

Being Y a random process, a realization (sample) is a sequence:

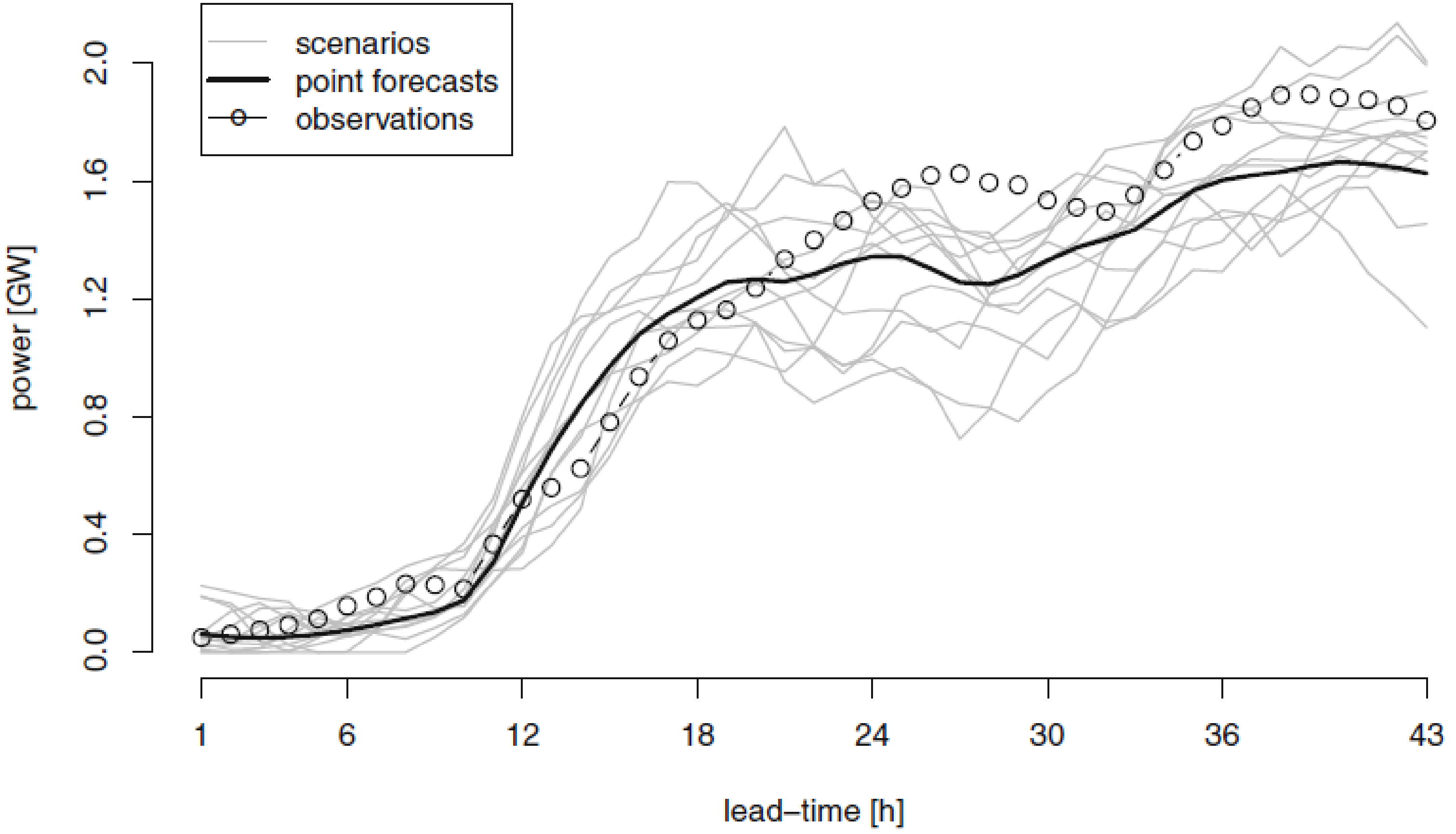
$$Y\hat{}(t,j)=[y(t+1,j), y(t+2,j), \ldots, y(t+k,j)],$$

where

$y(t+i,j)$ is a sample of the pdf $f(y(t+i)\,|\,\Omega(t))$

- As the number j of samples grows, the scenarios are a precise representation of the pdf.
- This approach is useful very in stochastic programming (more on this later)

Renewable generation forecast



Observations and 12 scenarios of wind generation in western Denmark, 4th April 2007.

Case study

Solar radiation estimation

- Isolated migro-grid
- Solar panels are the only energy source
- Next day generation is required to plan energy management:
  - Battery charging scheduling
  - Interruptible services
  - Unserved load
- Limited computational resources

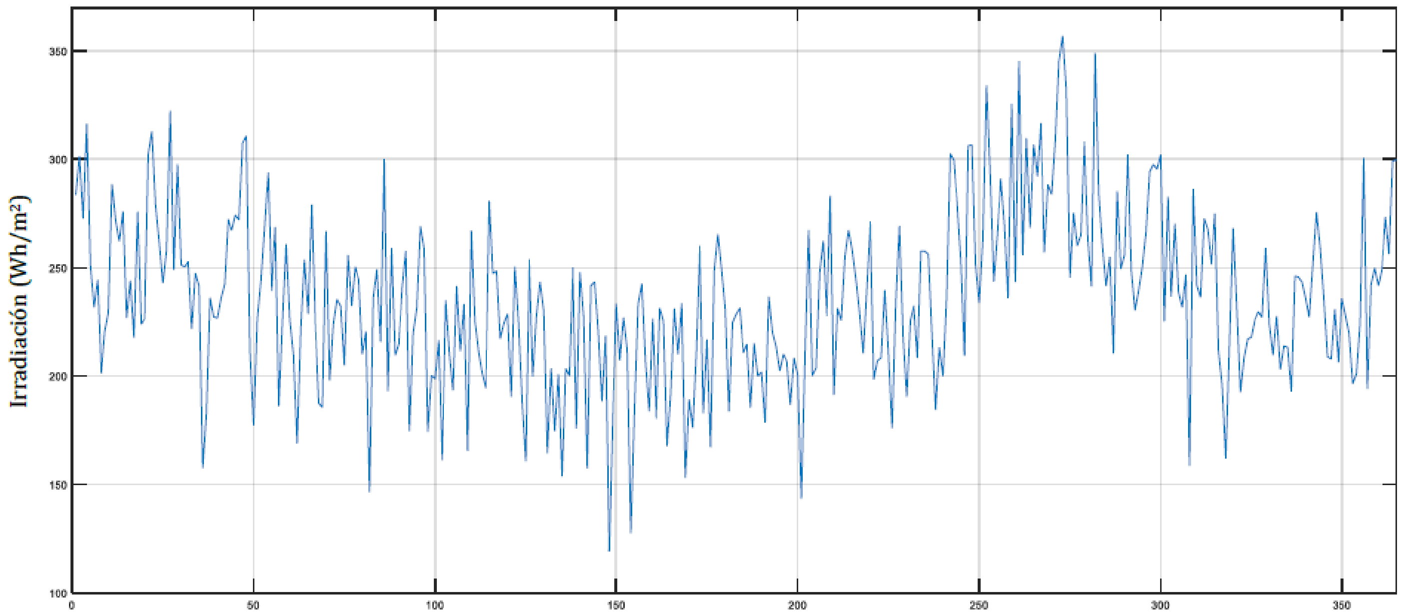
Case Study

Available data:

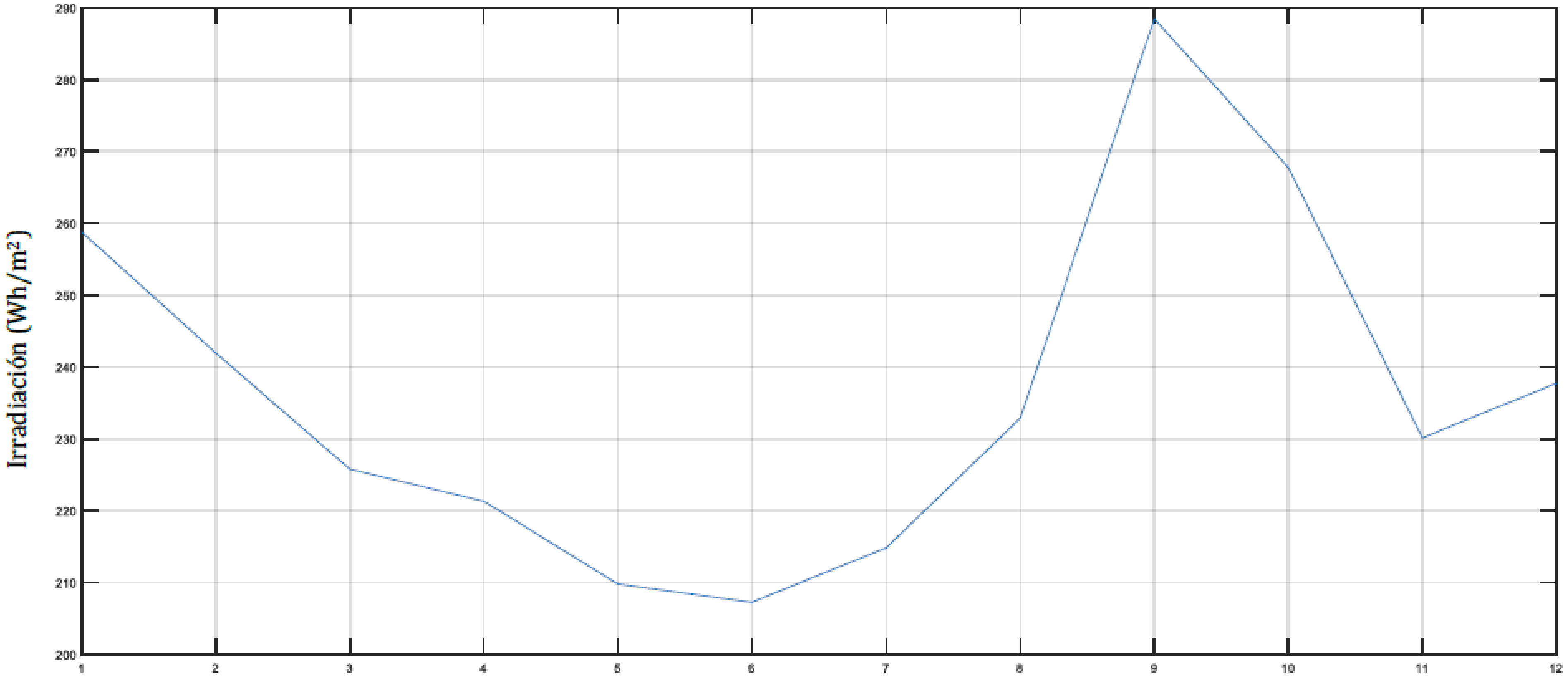
- Solar irradiation (insolation) in Wh/m^2.
- Hourly measurements between June 2008 and December 2014.

Required estimates:

- Insolation for the next 12 hours (day)



Case Study



Monthly average of insolation for the complete data set.

Case study

Linear auto-regressive models:

- AR:

$$y(t) = \alpha_0 + \alpha_1 y(t-1) + \alpha_2 y(t-2) + \dots + \alpha_p y(t-p) + \varepsilon(t)$$

- *ARMA:*

$$y(t) = \alpha_0 + \alpha_1 y(t-1) + \alpha_2 y(t-2) + \dots + \alpha_p y(t-p) + \varepsilon(t) + \vartheta_1 \varepsilon(t-1) + \vartheta_2 \varepsilon(t-2) + \dots + \vartheta_q \varepsilon(t-q)$$

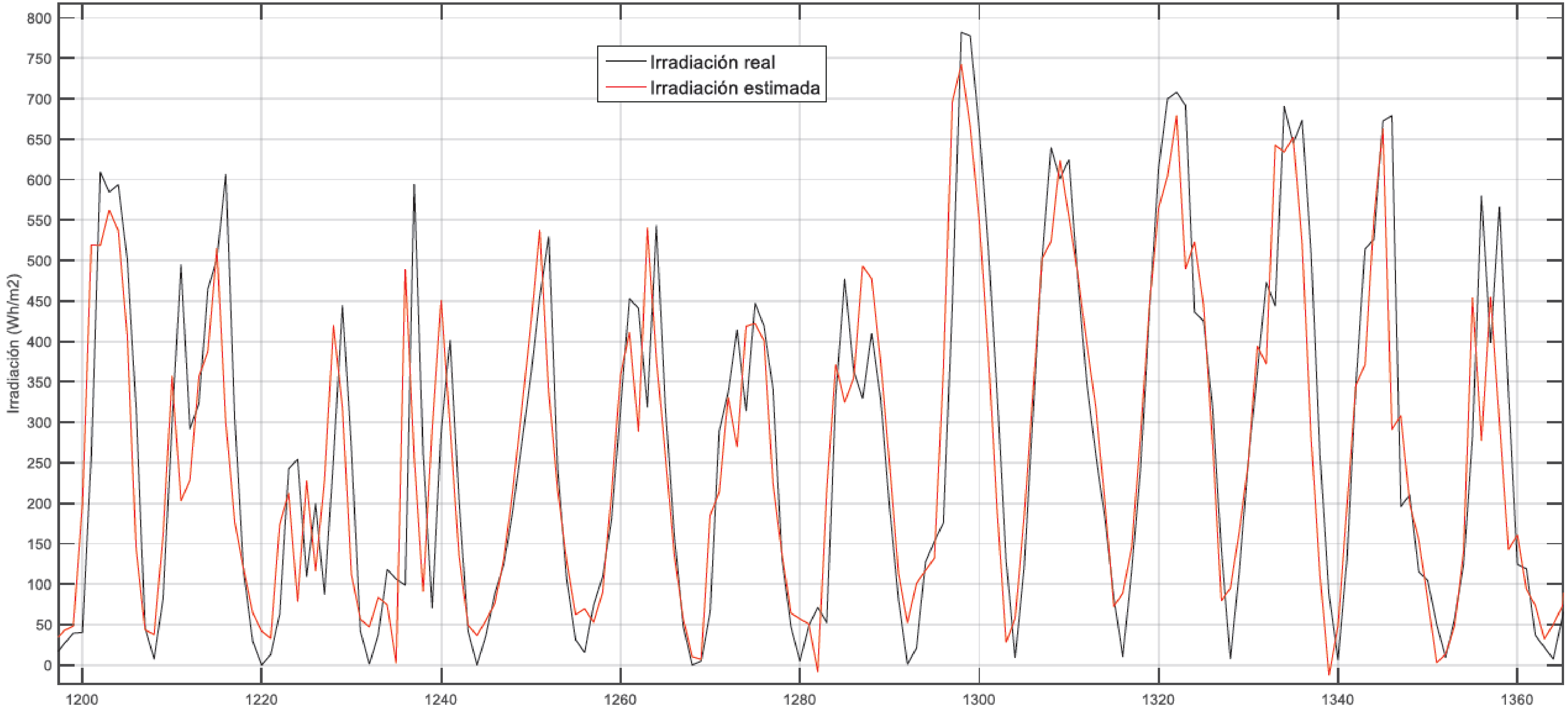
- *$\varepsilon(t)$ is assumed as white noise.*

Case study

Data preprocessing:

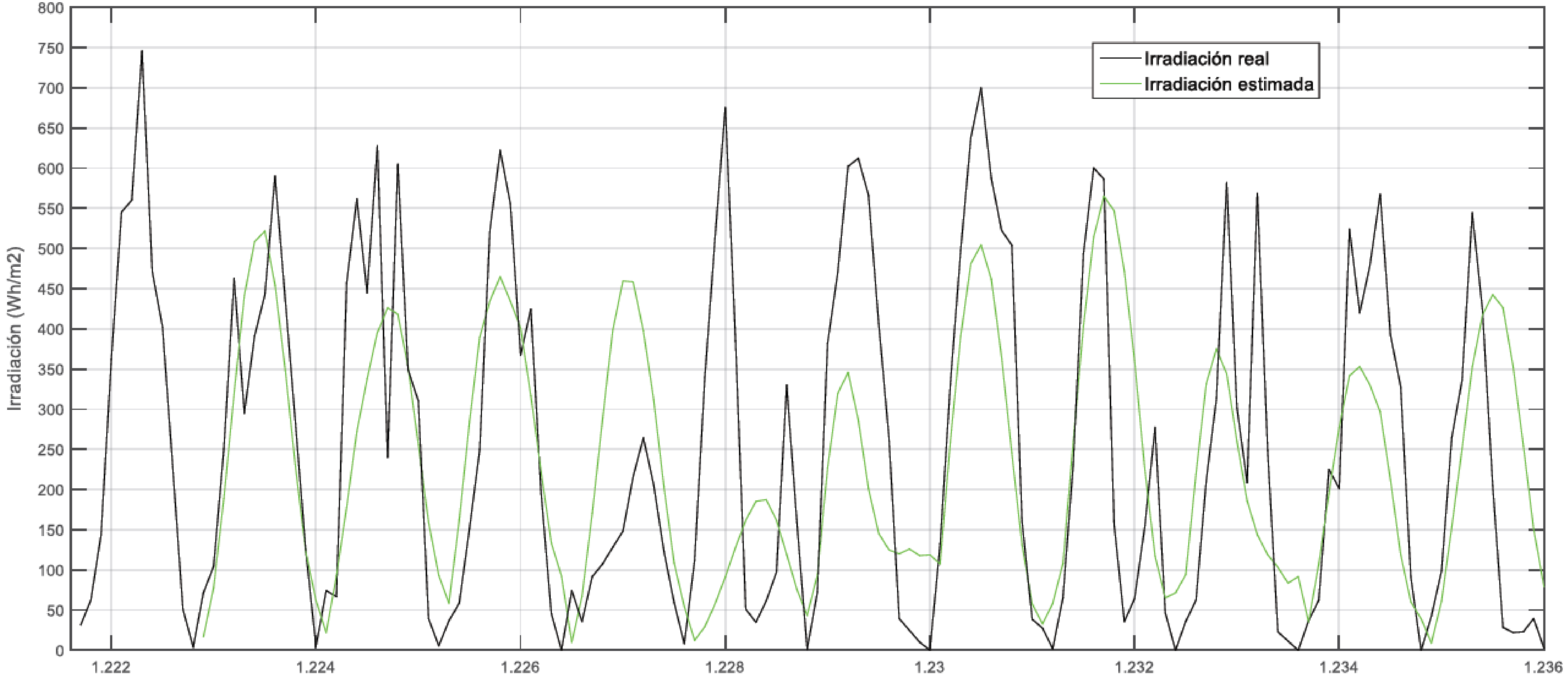
- Eliminate outliers
- Fill missing data
- Select estimation set (70% of available data)
- Adjust data to solve least squares problem
- Estimate coefficients θ_i and α_i.

Case Study



One hour ahead forecast, AR model, p=12, FIT=44%.

Case Study



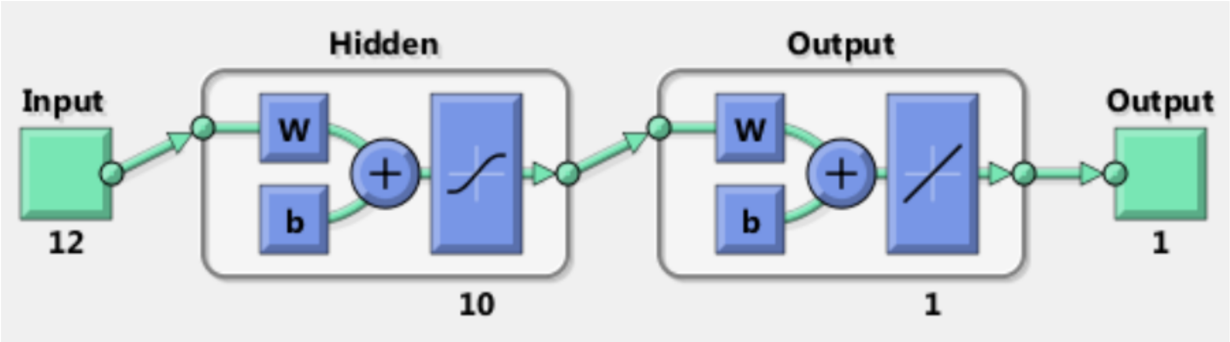
12 hours ahead forecast, AR model, p=12, FIT=24%.

Case Study

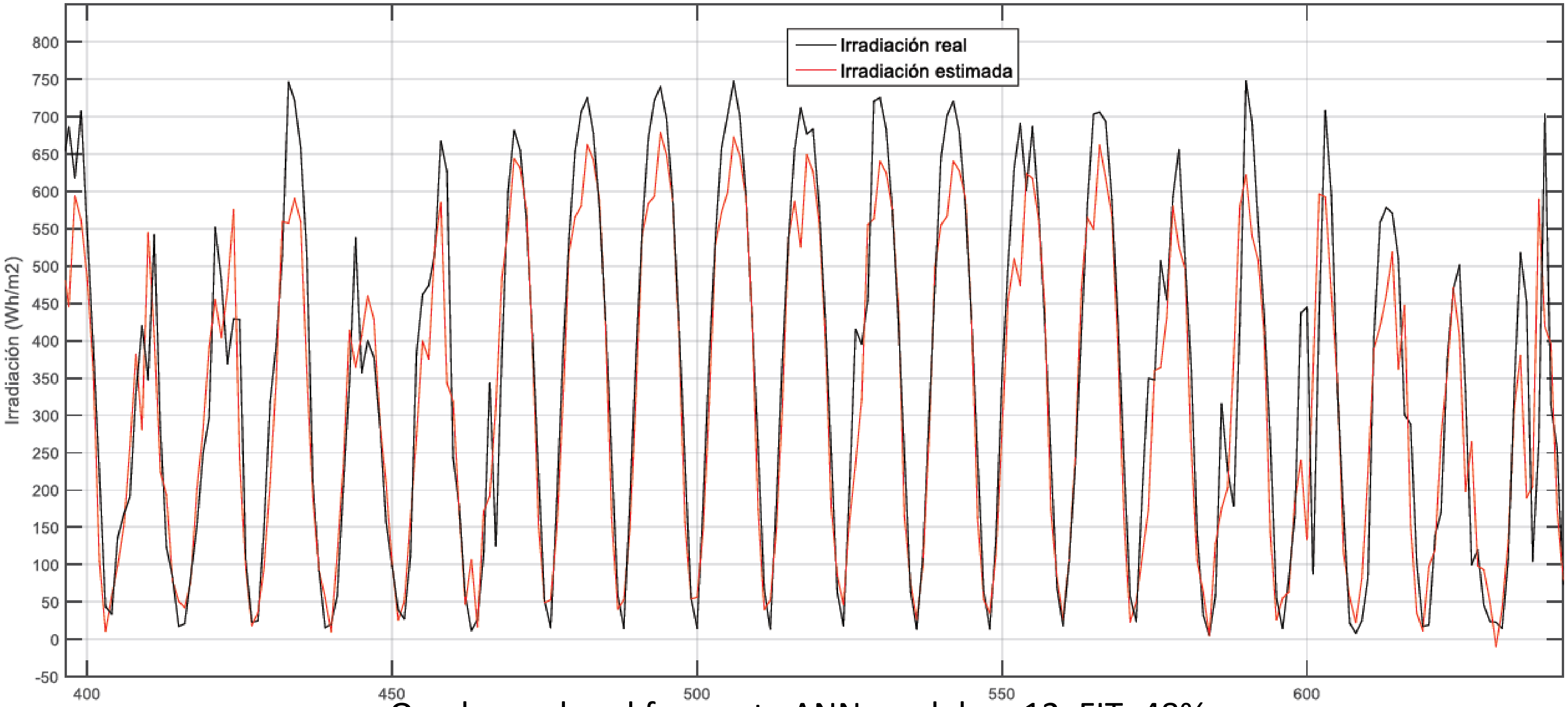
- Linear estimators are optimal for joint Gaussian distributions.
- In general, the conditional mean is a non-linear map, from available information to the optimal estimate.
- It can be approximated as a non-linear function from data:

$$\hat{y}(t) = \mathbf{G}(\, y(t-1), y(t-2), \ldots , y(t-p)\,)$$

- *ANN are universal approximators:*

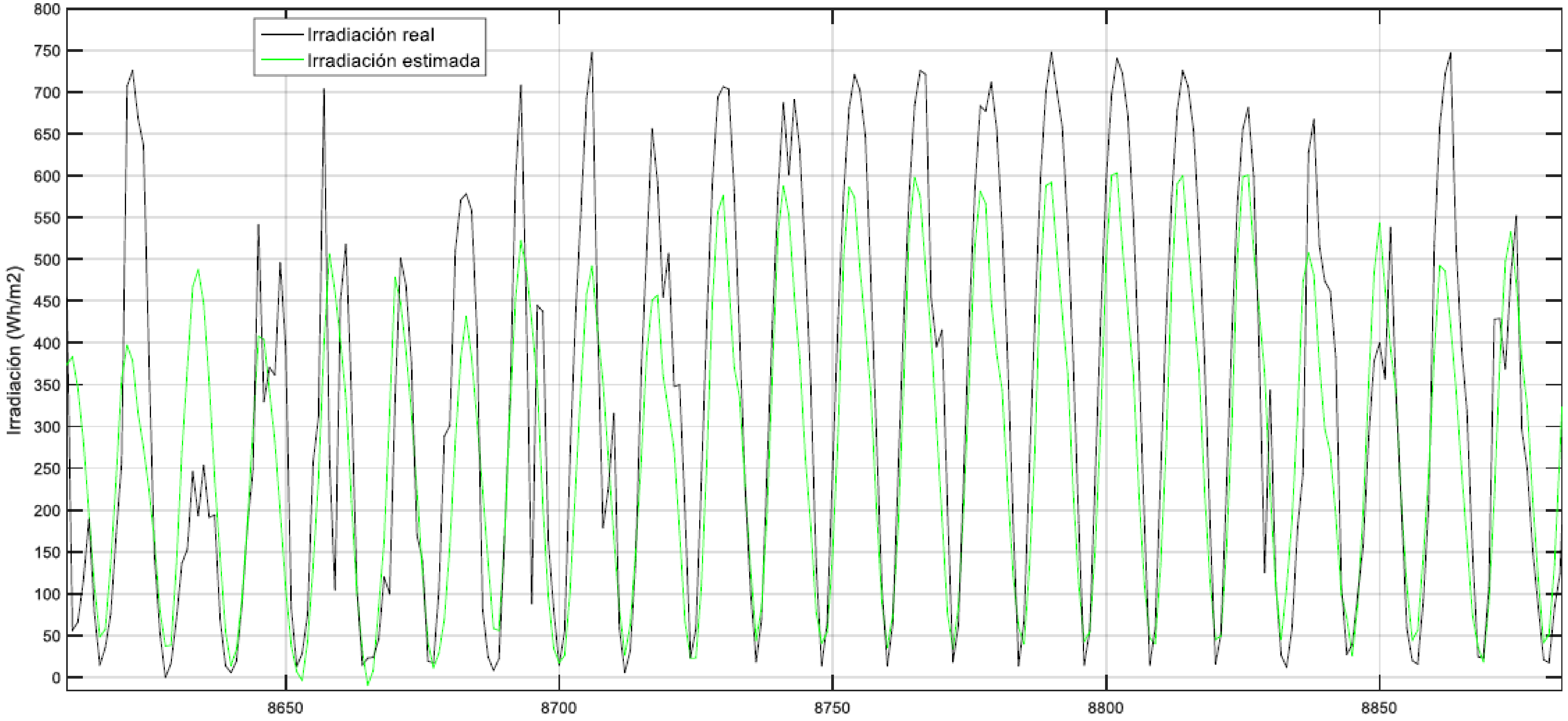


Case Study



One hour ahead forecast, ANN model, p=12, FIT=48%.

Case Study



12 hours ahead forecast, ANN model, p=12, FIT=32%.

Case Study

Model	Horizon	FIT (%)	RMSE (Wh/m^2)
AR	1	44	114
ANN	1	48	105
AR	12	24	162
ANN	12	32	144

Bibliography

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