Solar Power Forecast for Energy Management Systems in Smart Grid

Thailand-China Joint Public Seminar on Smart Grid and Renewable Energy Forecast

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CHULA ENGINEERING
Foundation toward Innovation

Outline

- Chula team and collaborators
- resources and facilities
- forecasting models
  - nowcasting
  - very short-term forecasting
  - short-term forecasting
- methods and implementation

Collaboration

Thailand-China Research Collaboration on Renewable Energy (Year 2/3)

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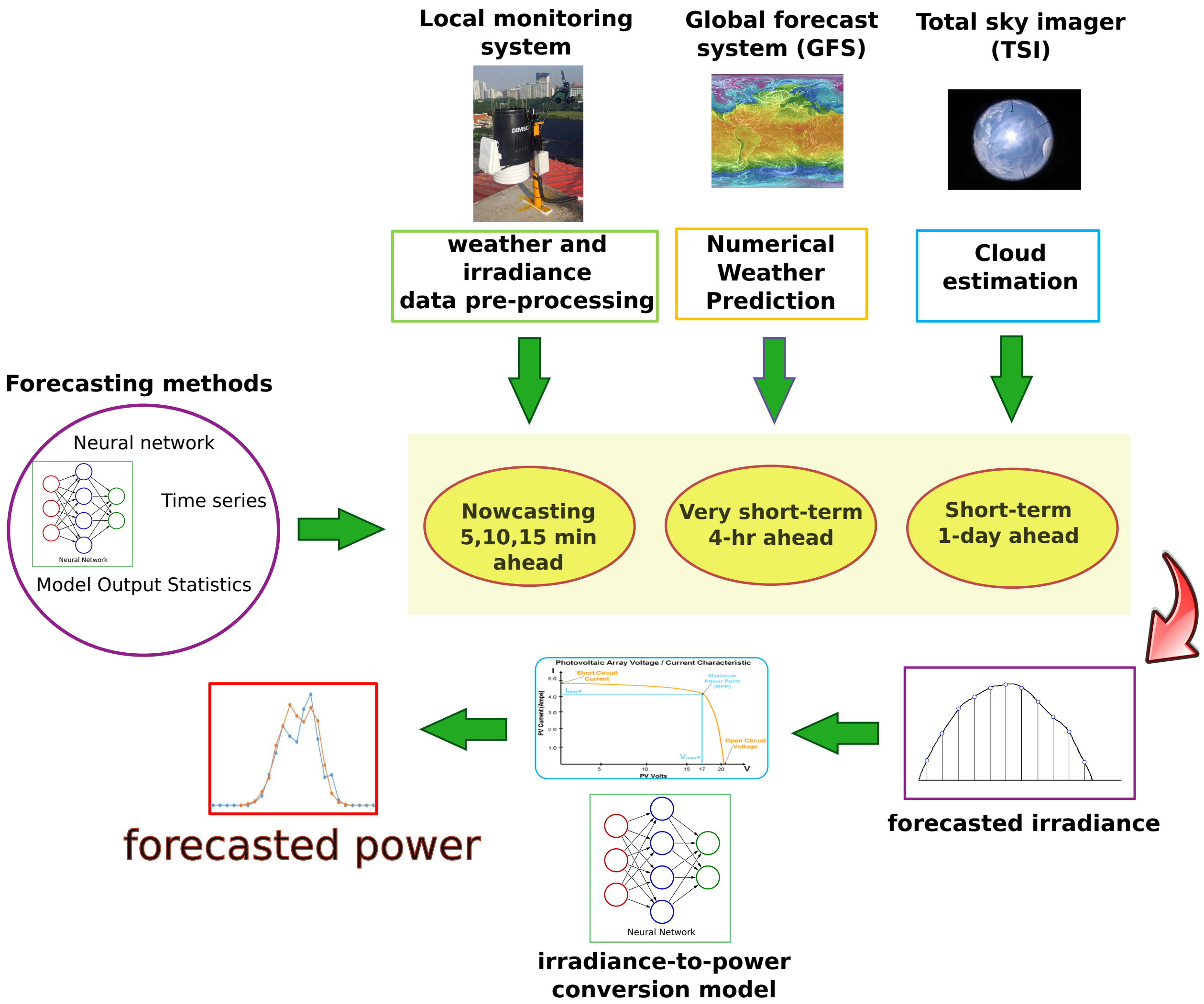
Project overview

we propose models for mainly **three** forecasting horizons

term	**horizon**	**time step (min)**	**applications**
nowcasting	5,10,15 min	5,10,15	frequency and voltage regulation
very short-term	4 hrs	30	scheduling, load following
short-term	24 hrs	60	planning

Project overview



Resources

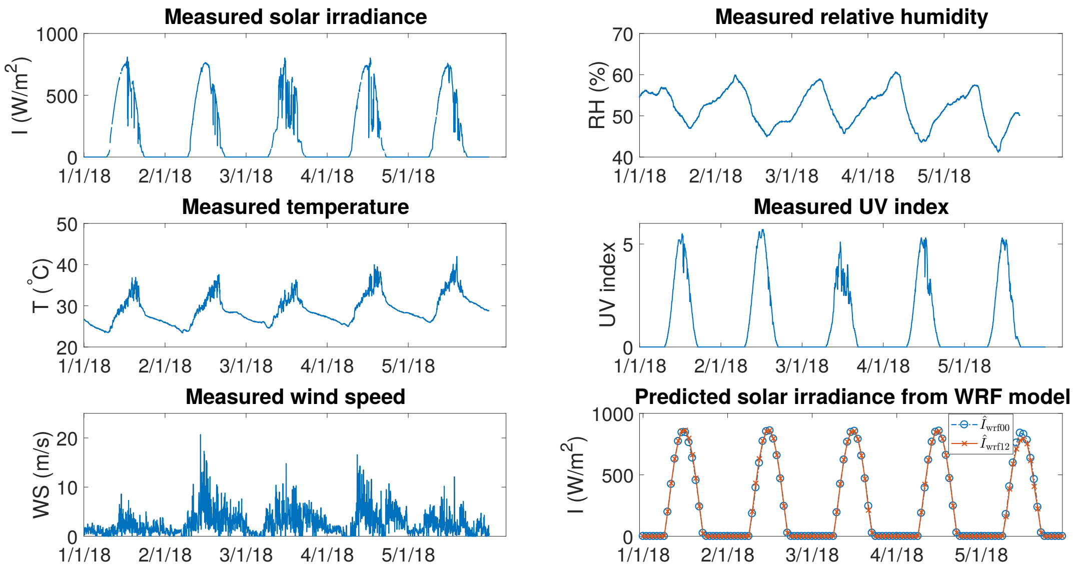
available equipment: rooftop PV system (8+15 kw) + pyrometer

with sensors of: wind speed, wind direction, temperature, relative humidity, UV index, irradiance, power of solar cells

Available data of CU location

measurements: sampling period (mostly) is 3 mins

1. solar data:
   - solar irradiance
   - solar power
2. weather data:
   - temperature
   - relative humidity
   - wind speed
   - wind direction
   - UV index

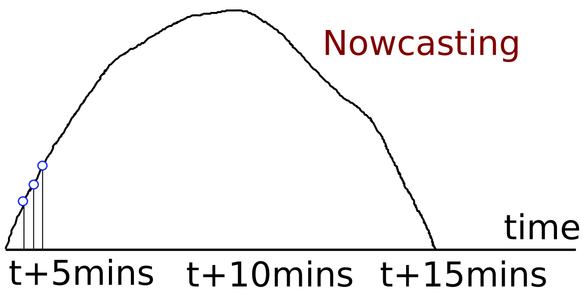


prediction: running on a PC: Intel Xeon E3-1225 3.3GHz, Ram 8GB, HDD 1TB

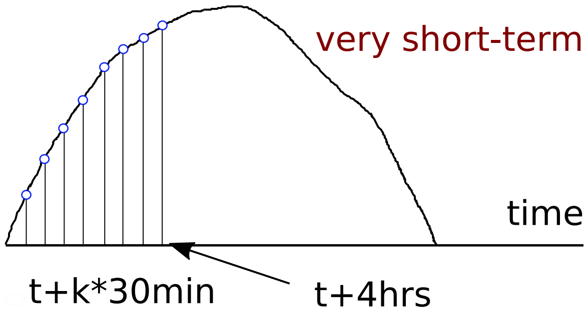
- hourly forecasted WRF of weather and solar irradiance (on grid 3×3 km^2)

Forecasting methods

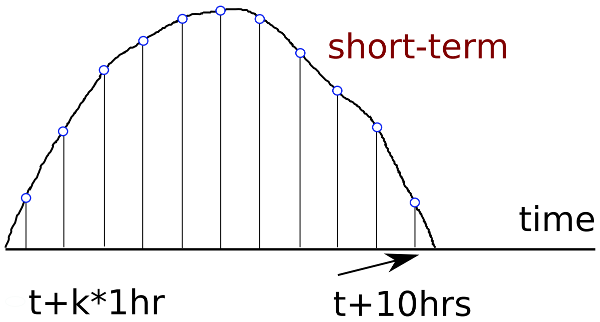
method: forecast solar power from solar irradiance (main input)



ANN with
cloud detection



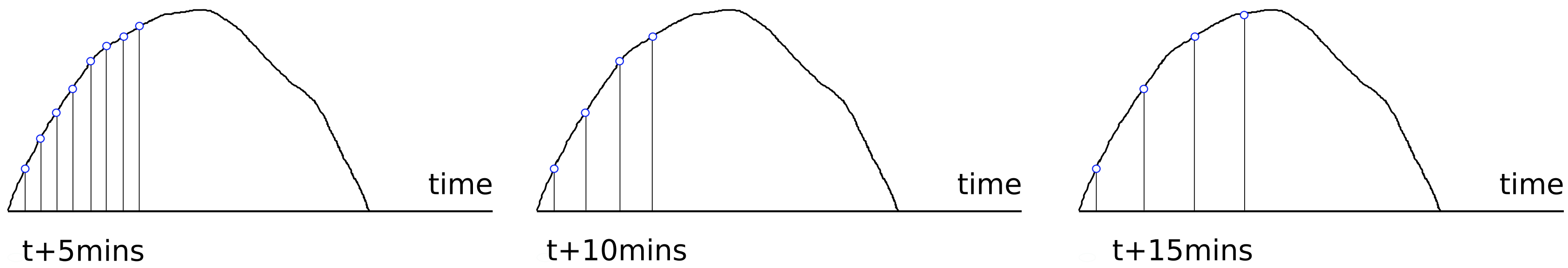
ANN

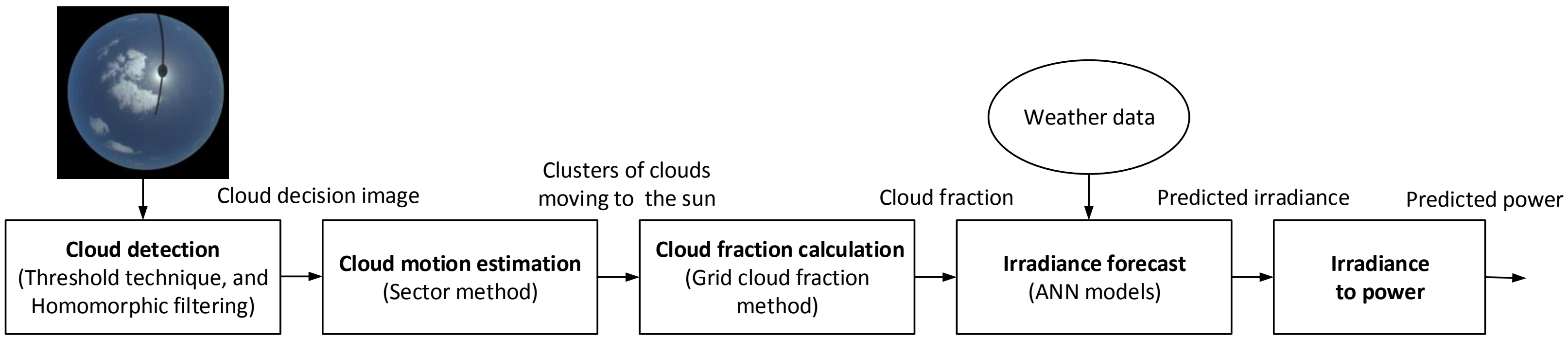


NWP and bias correction
using regression models

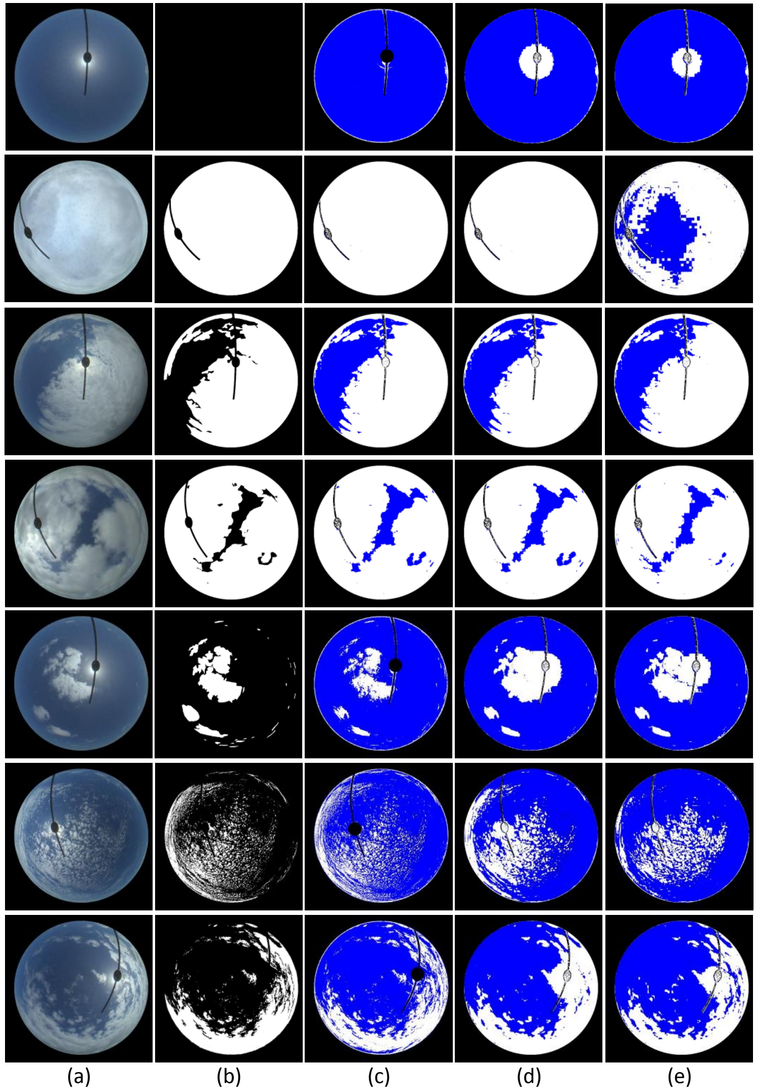
goal: provide 3 models with forecast horizon of 5,10,15 mins

forecasting time: t moves in one minute





data: weather, irradiance and cloud images from UC Sandiego, USA



method: homomorphic filtering to reduce brightness around the sun

row 1: clear sky
row 2-4: overcast
row 5-6: partly cloudy

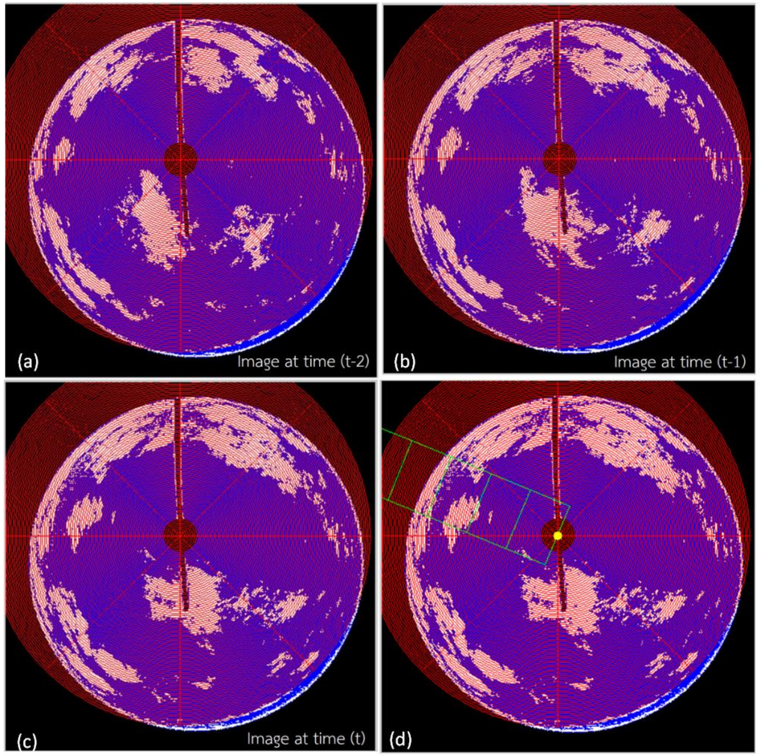
(a) sky image

(b) ground truth image

(c) proposed method

(d) thresholding NBRR method

(e) thresholding RBD method



use sector method to detect which cloud section is moving toward the sun

(a) image at time $t-2$

(b) image at time $t-1$

(c) image at time t

(d) constructing the grid (100x150 pixel) in the direction of cloud motion

calculate the cloud fraction on the grid of cloud moving toward the sun

$$\text{cloud fraction} = \frac{\text{total cloud pixels}}{\text{total cloud pixels} + \text{total sky pixels}}$$

apply ANN to forecast solar irradiance using 10 inputs:

- cloud information at grids of interest
  - cloud fraction at time t
  - rate of change of cloud fraction at time t
- irradiance measurements: (0,5,10,15 min lags)
  - $I(t)$
  - $I(t-5)$
  - $I(t-10)$
  - $I(t-15)$
- weather data at time t
  - surface/ambient temperatures
  - wind speed, wind direction
  - relative humidity

forecasting results are reported on the periods of

- 11:00 to 14:30
- 10:00 to 11:00 and 14:30 to 16:00
- 9:00 to 10:00 and 16:00 to 17:00

as the number of cloud grids are different in those periods

three sets of inputs for ANN are considered

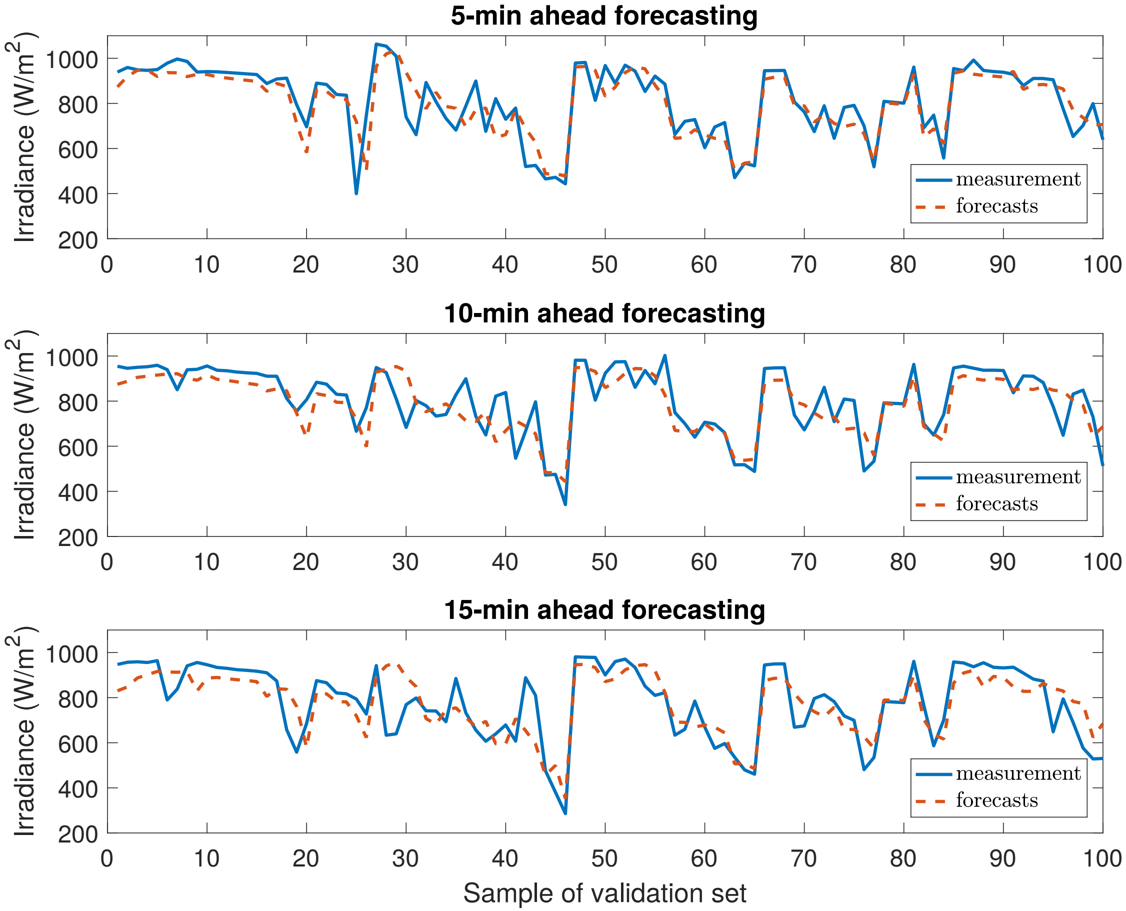
- irradiance measurements only
- irradiance and cloud information
- transformed variables (from ten) by PCA

only data of partly cloudy days were trained in ANN

RMSE of irradiance forecasts (averaged over all time periods)

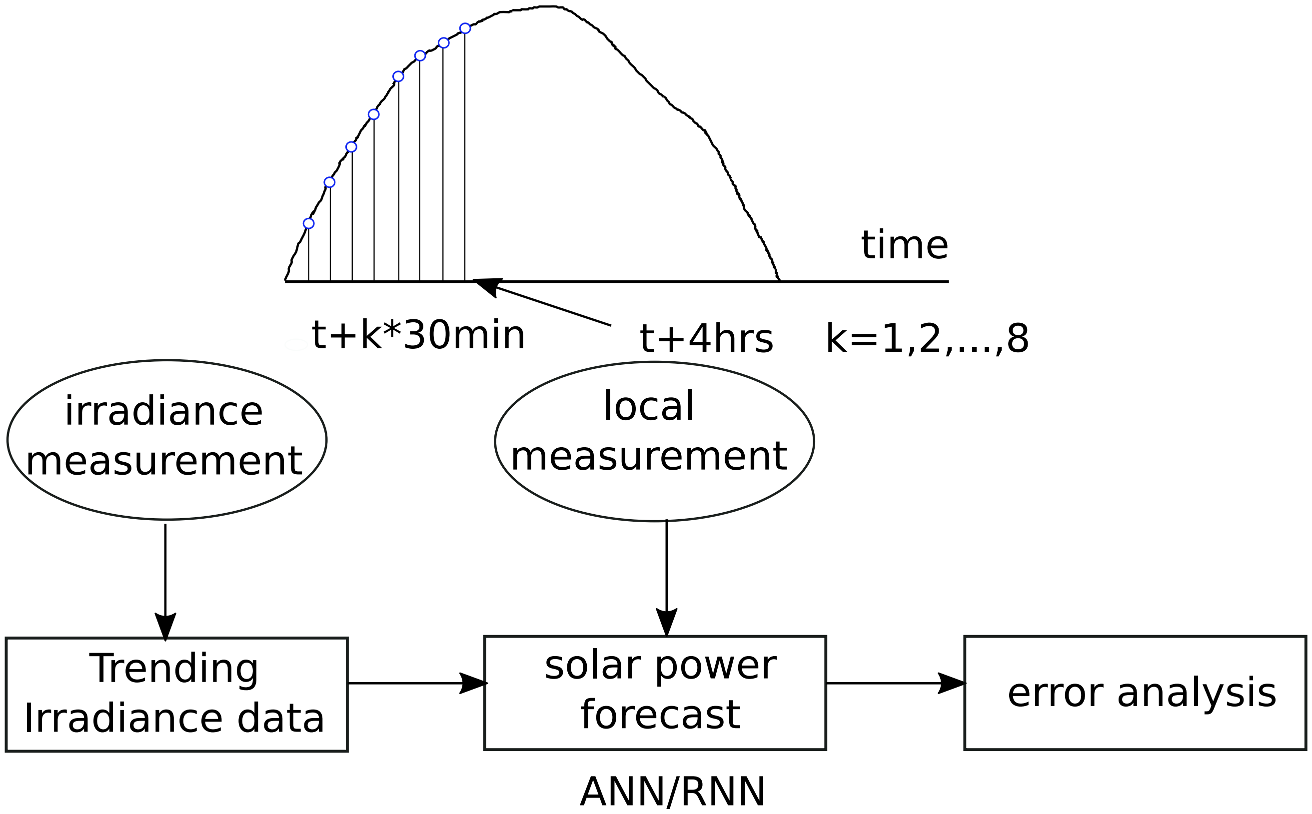
sets of inputs	5-min model	10-min model	15-min model
irradiance measurements only	72.51	88.27	93.40
irradiance and cloud information	72.40	87.53	92.08
transformed inputs by PCA	72.10	86.65	**89.30**

- gradually decreased errors in 10-min and 15-min models when using cloud example of forecasts from models using PCA inputs



data are validated and plotted from partly cloudy days only goal: provide solar power forecasts of 30-min time step with horizon of 4 hours

forecasting time: t moves every 30 mins



data: weather, irradiance, solar power from solar farm in Mae Hong Son goal: select relevant inputs for recurrent neural network

- local measurement: at current date (d) and time (t)
  - irradiance $I(t)$
  - temperature $\mathrm{T}(t)$
  - solar power $P(t)$
- estimates of *one-day-lagged* solar irradiance at future times

$$\hat{I}(t), \hat{I}(t+30), \ldots, \hat{I}(t+240) \qquad t \text{ is in minute}$$

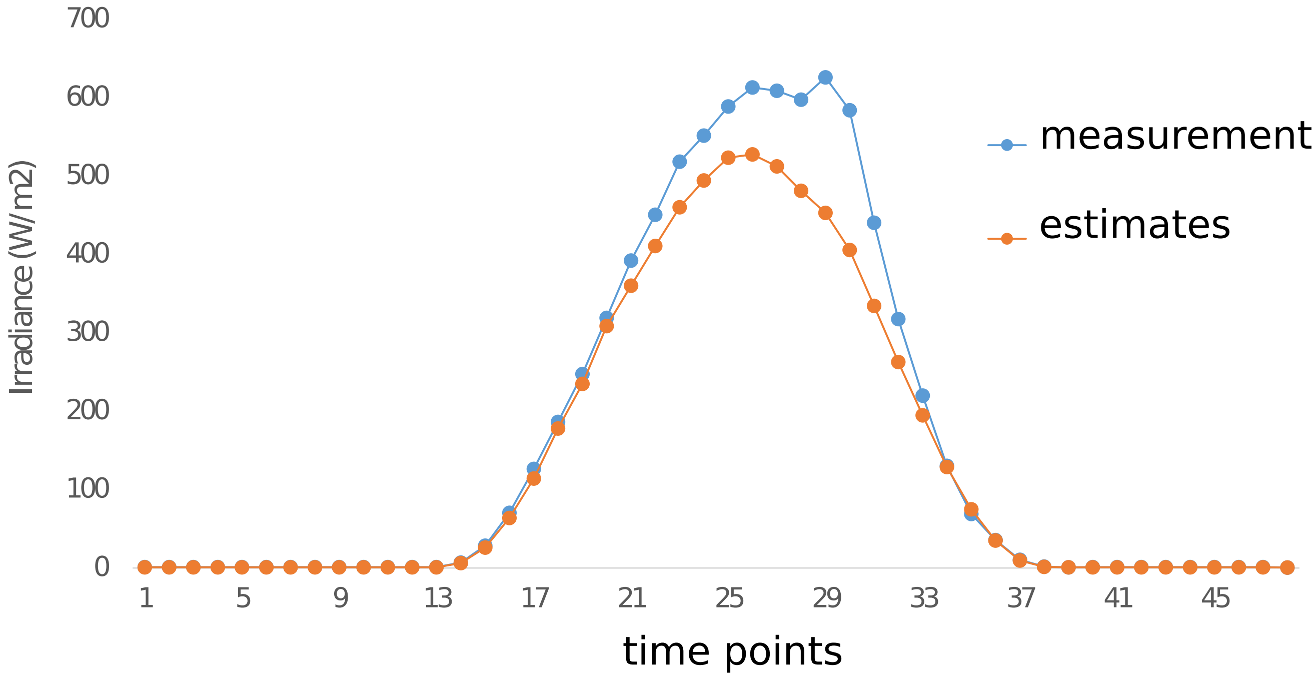
RNN target: solar power at current date and future times

$$\hat{P}(t), \hat{P}(t+30), \ldots, \hat{P}(t+240) \qquad t \text{ is in minute}$$

goal: estimate *one-day-lagged* solar irradiance using past measurements

$$\hat{I}(d-1) = \beta I(d-1) + (1-\beta) I(d-2), \quad 0 < \beta < 1$$

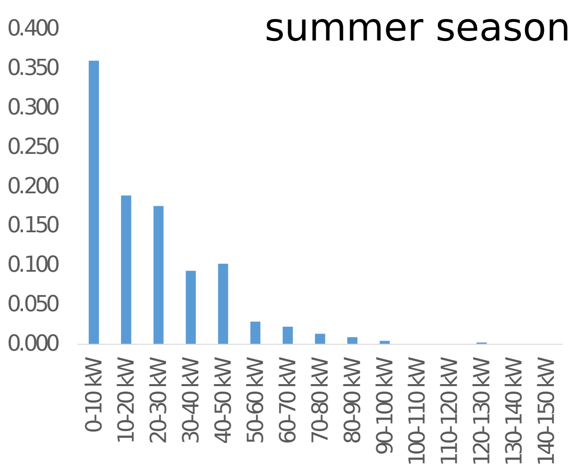
known as *exponential moving average*

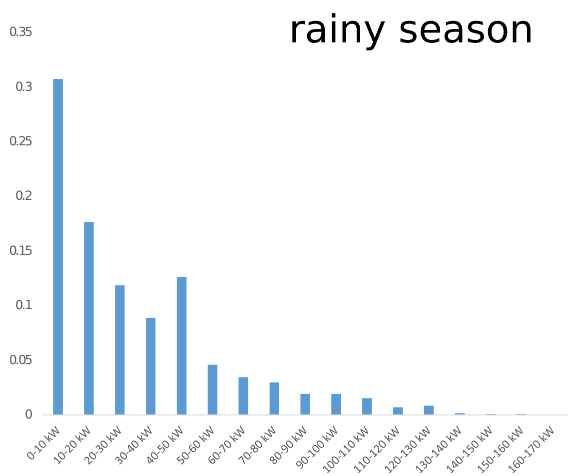


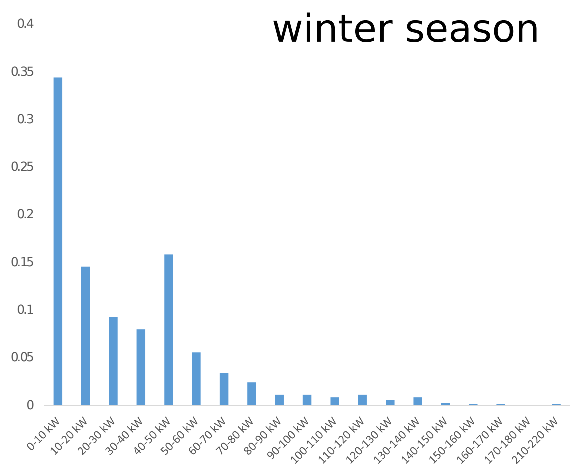
the estimates are evaluated at $t = 30, 60, \ldots, 240$ minutes (8 time points) forecasting result with install capacity 500 kW

time of forecast	1 hour	2 hours	3 hours	4 hours
mean of absolute error (kW)	19.5	22.4	23.5	24.5
max of absolute error (kW)	153.7	160.4	197.3	199.5

histogram of forecasted errors

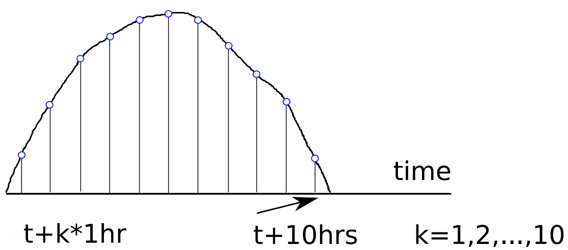


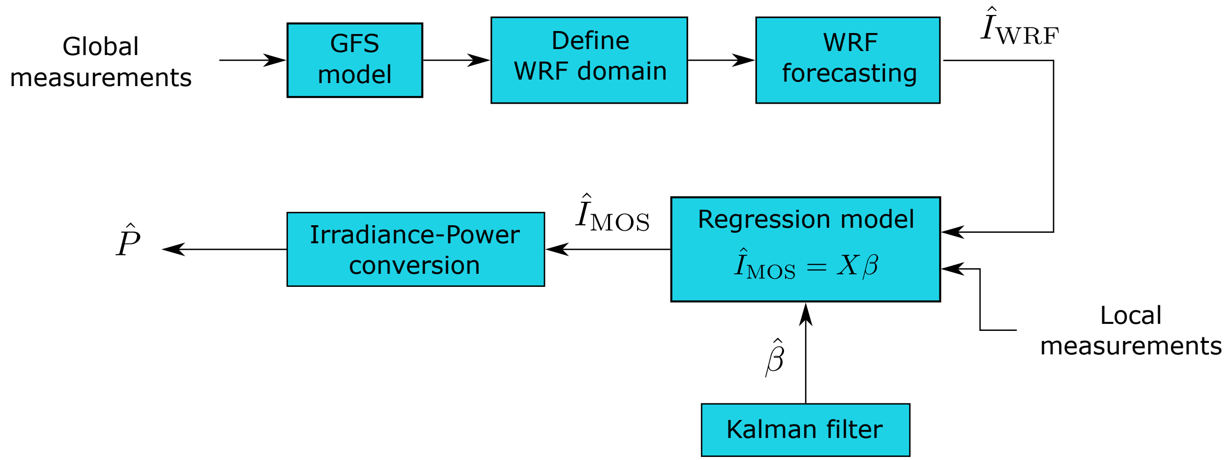




more diversion of forecasted errors in rainy and winter (as expected) goal: provide solar power forecasts of 1-hr time step with horizon of 10 hrs

forecasting time: t moves daily





data: WRF forecasts, weather and irradiance at Chulalongkorn university

MOS is a multiple linear regression (regress I on relevant variables)

- **model 1:** 6 regressors

$$I(t) = \beta_1 \hat{I}_{\mathrm{wrf}}(t) + \beta_2 \widehat{\mathrm{RH}}_{\mathrm{wrf}}(t) + \beta_3 \hat{\mathrm{T}}_{\mathrm{wrf}}(t) + \beta_4 I_{\mathrm{clr}}(t) + \beta_5 \cos\theta(t) + \beta_6 \hat{k}_{\mathrm{wrf}}(t)$$

- **model 2:** 3 regressors

$$I(t) = \beta_1 \hat{I}_{\mathrm{wrf}}(t) + \beta_2 \widehat{\mathrm{RH}}_{\mathrm{wrf}}(t) + \beta_3 \hat{\mathrm{T}}_{\mathrm{wrf}}(t)$$

goal: use MOS to improve predicted I from *WRF forecasts and clear sky model*

(10-step prediction limits us from using local measurements as regressors)

MOS with varying regression coefficients

$$I(t) = \beta_1(t)x_1(t) + \beta_2(t)x_2(t) + \cdots + \beta_n(t)x_n(t)$$

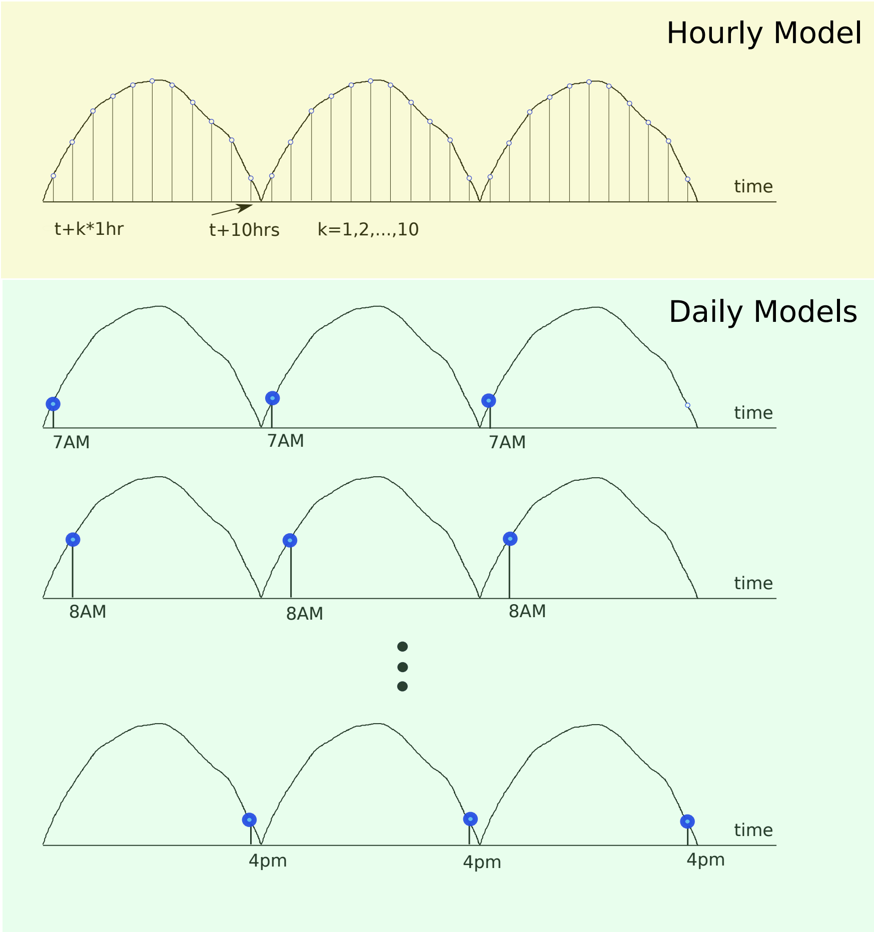
regression in state-space form:

$$\beta(t+1) = \beta(t) + w(t), \quad I(t) = \begin{bmatrix} x_1(t) & \cdots & x_n(t) \end{bmatrix} \beta(t) + v(t)$$

and use KF to estimate the state ($\hat{\beta}(t)$) and output ($\hat{I}(t)$)

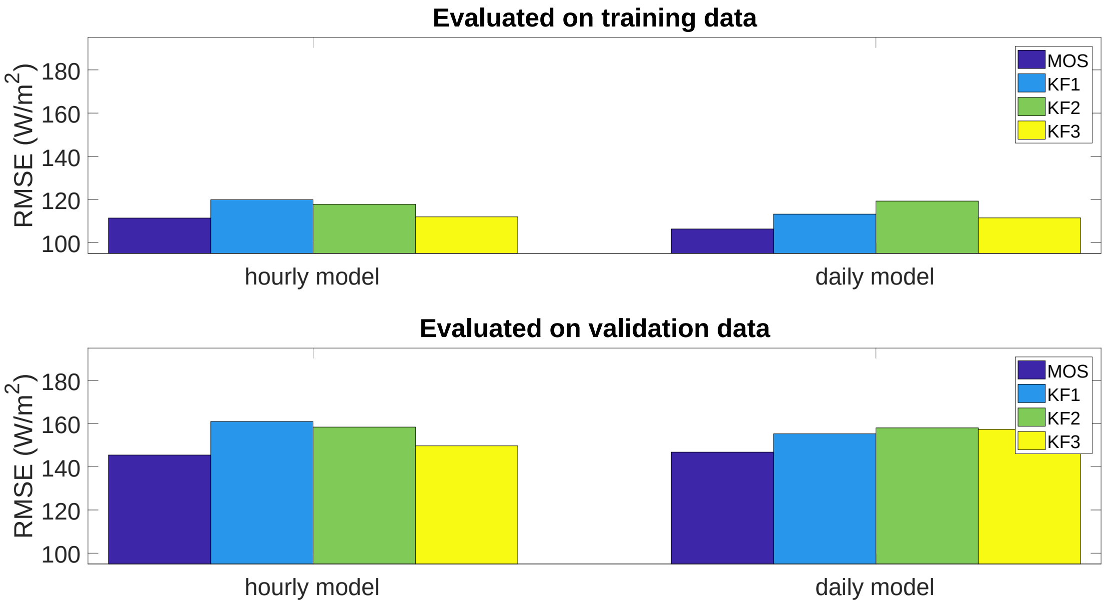
- assume random walk model on the regression coefficients
- process and measurement noise covariances are estimated from residual errors

both MOS and MOS+KF are implemented in two time scales



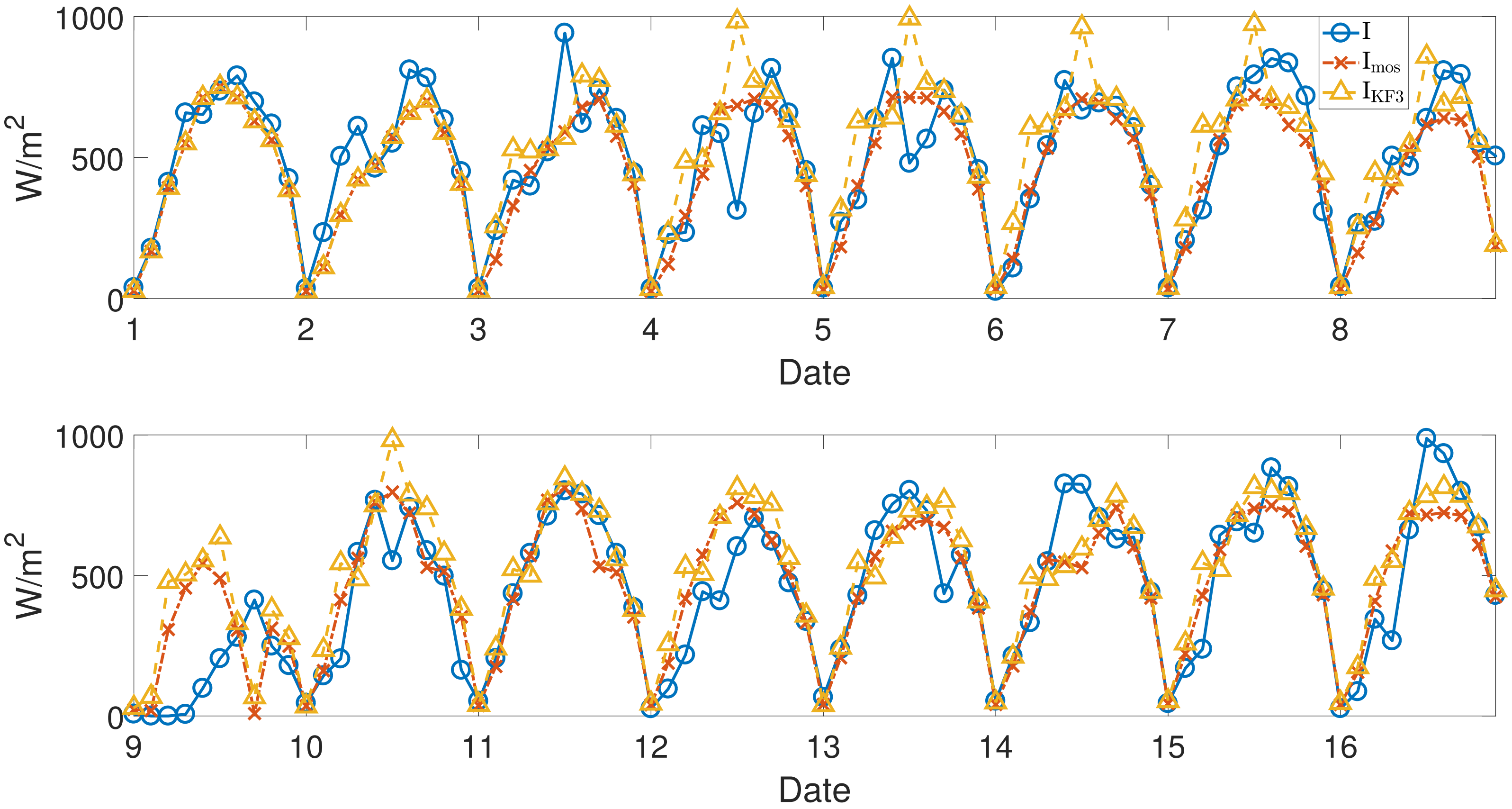
hourly: single model and t runs hourly
daily: 10 models and t runs daily

trade off between model complexity and number of available data comparison between MOS and MOS+KF models using 3 regressors



- performances of MOS and MOS+KF are unexpectedly very close
- no improvement of daily models on hourly model

example of forecasting result using hourly model during Mar 1-16, 2018



Summary as of May 7, 2018

- weather data: mostly available; some data require checking and cleaning
  - solar irradiance and solar power measurement are not always coherent
  - some samples of solar irradiance suddenly drop at noon on clear days
- WRF prediction: limited and need more time to acquire more samples since Dec 2017
- nowcasting: using cloud info as prior improves the forecasts over using weather and irradiance measurements but the improvement is not significant
- very short-term forecasting: RNN provides less forecasted errors than ANN
- short-term forecasting:
  - MOS+KF should outperform MOS when it is running over time
  - daily models should outperform hourly model as it can adapt to specific characteristic of solar irradiance at specific time
  - need more WRF forecasts to validate the comparisons among models

Acknowledgement

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