Improved generation of hourly solar irradiation artificial series using neural networks

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Objective

To present a new neural network approach for the generation of synthetic hourly irradiation series and compare the results to some classical methods used in the photo-voltaic field.

OUTLINE

- INTRODUCTION
- IRRADIATION SERIES
- GENERATION USING NN
- RESULTS & COMPARISONS
- CONCLUSIONS
- QUESTIONS & ANSWERS

INTRODUCTION. Problem

Problem

- To obtain solar irradiation data for any given location
- Measured historic sequences
  - Not available for most regions
  - Insufficient length

Purpose

- Analysis and design of photovoltaic (PV) converters
  - Hourly series required

INTRODUCTION. Solutions

❑ Classical Solutions

- ‘Universal’ Radiation models
  - First order autoregressive stochastic dissagregation methods
    - Hourly values generated from daily ones
    - Complex empirical expressions
    - Regression analysis
  - Problems
    - Computational requirements
    - Local dependencies
  - Reference Models
    - Aguiar & Collares (AC)
    - Graham & Hollands (GH)

IRRADIATION SERIES. Definitions

❑ Generated Data

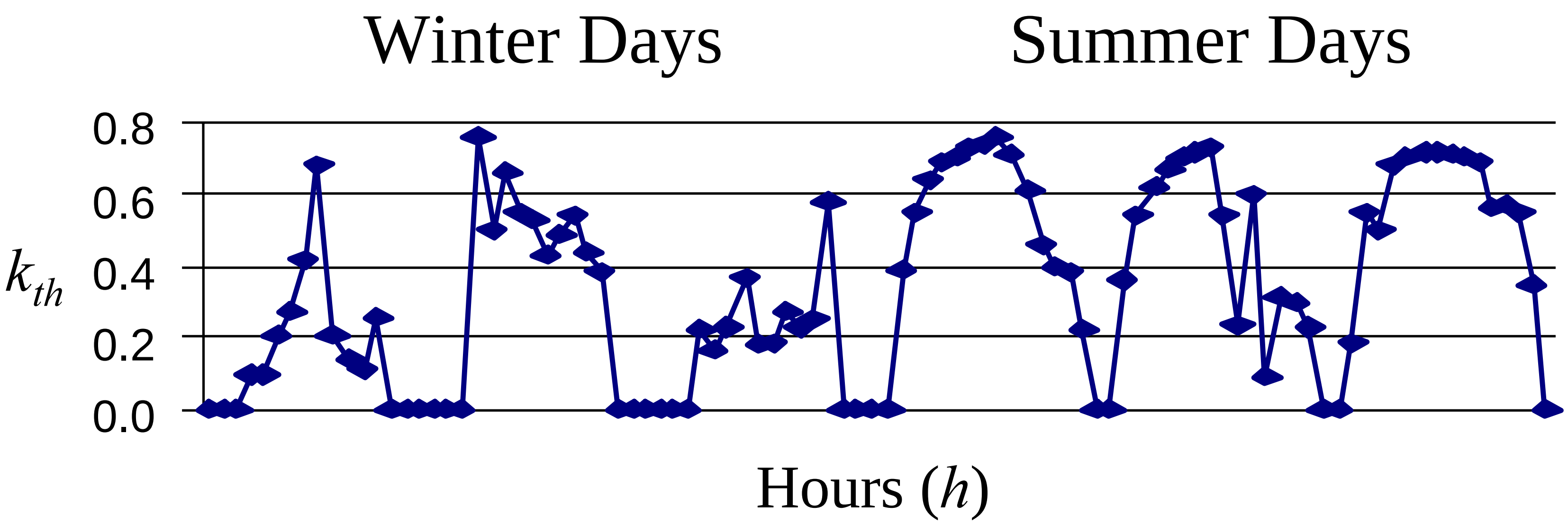
❍ Atmospheric Transmittance or Clarity Index

$$k_{th} = \frac{G_h}{B_h} \quad \in [0,1]$$

- k_{th} : Hourly Clarity Index during hour h
- G_h : Solar irradiation on a horizontal plane on the earth surface during hour h
- B_h : Extraatmospheric solar irradiation on a horizontal plane (deterministic: depends only on hour and latitude)

IRRADIATION SERIES. Example

Example of Hourly Clarity Index in three winter days and in three summer days



GENERATION USING NN. Fundamentals

Time Series Prediction Using a MLP

$$\hat{s}_{n+1} = G(s_{n-p+1}, \ldots, s_n) \cong MLP(s_{n-p+1}, \ldots, s_n)$$

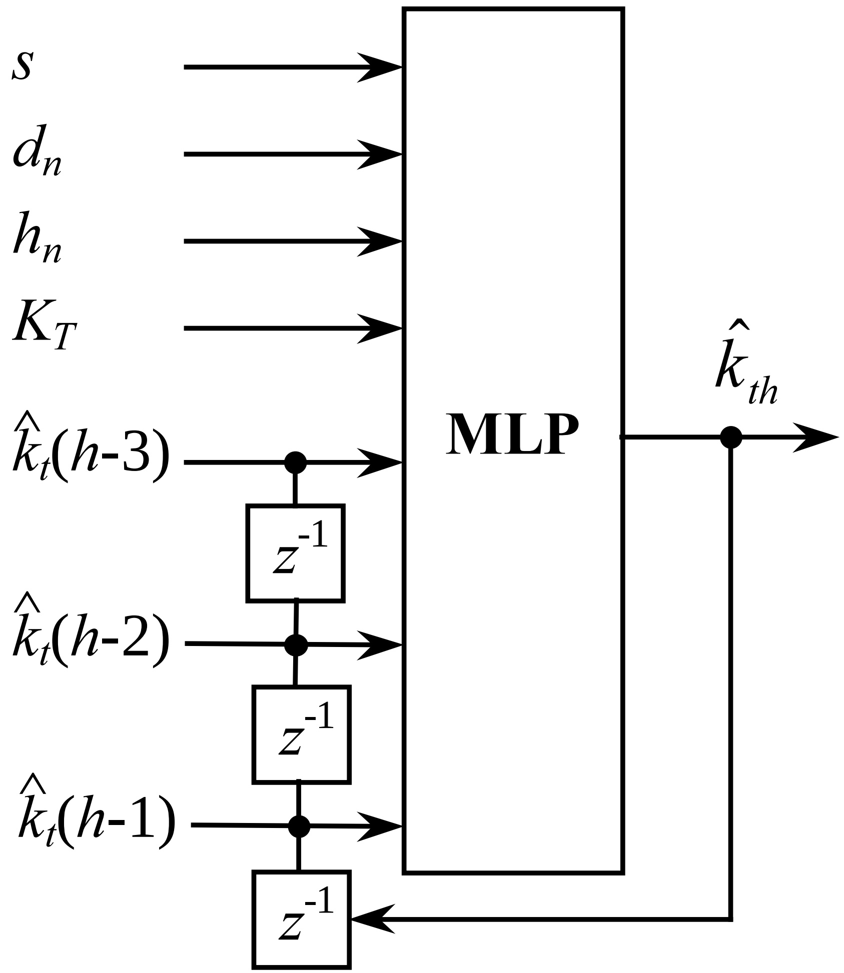
Training a MLP with a representative set $\{s_n\}$ will find the desired relationship, approximating the time series function G

- Supervised training
- Feedback architecture
- Prediction by network evolution

GENERATION USING NN. Method

- **Step by step inclusion of available info**
  - No explicit knowledge of relationships among information sources
- **Experiments data from Madrid**
  - 9 years (8 for training + 1 for testing results)
  - 16 values/day
- **Training**
  - Backprop momentum with random presentations + second order
  - Day-by-day prediction

GENERATION USING NN. MLP Architecture



- Inputs
  - s : sunrise/sunset
  - d_n: day number
  - h_n: hour number
  - K_T: daily clarity index
- Topology
  - 7x15x1 fully connected
  - feedthrough (input s)

GENERATION USING NN. Advantages

Main Advantages

- Generality
  - Reduced knowledge of the problem to be considered
  - Simple framework with general applicability
- Reproductiveness
  - The method may be applied to any given place
- Universality
  - If NN trained with enough data from different places

RESULTS

❑ Quality measure used

$$MRV = \frac{\sum_h (k_{th} - \widehat{k}_{th})^2}{\sum_h (k_{th} - \bar{k}_t)^2}$$

❑ Results

- After 40 epochs
  - MRV(9th year) = 0.1022
  - MRV(years 1-8) = 0.1026
- Emulates *deterministic* component of the series
- Lacks *random* rippling

COMPARISONS. Trend component

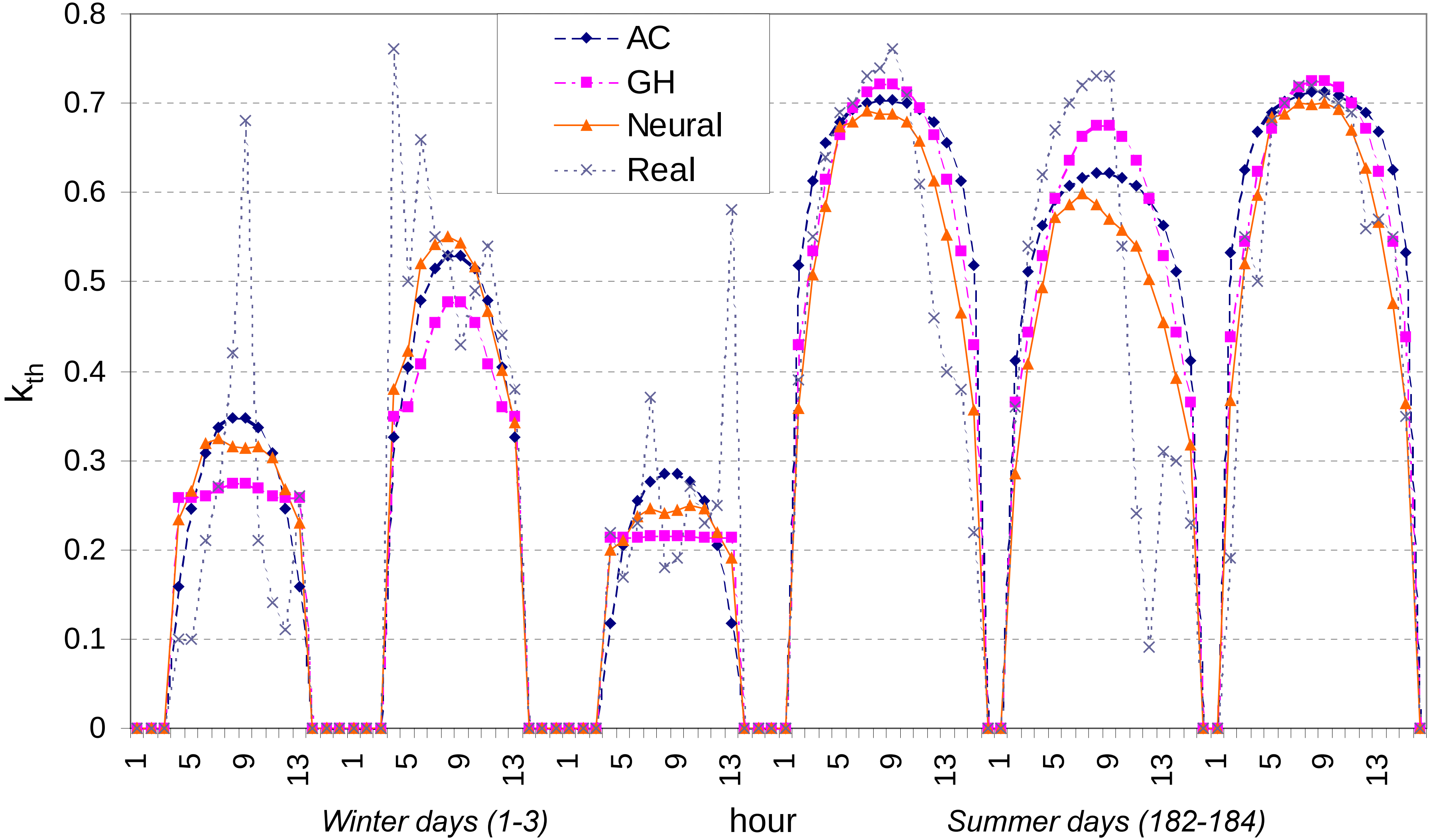
Method	*MRV* *Training Years*	*Test Year*	*Training/ Regression time (s)*
MLP (40 epochs)	*0.1026*	*0.1022*	*790*
MLP (2 epochs)	*0.1204*	*0.1198*	*45*
GH (Original parameters)	*0.1523*	*0.1607*	*-*
GH (Madrid regressions)	*0.1281*	*0.1253*	*1030*
AC (Original parameters)	*0.1524*	*0.1597*	*-*
AC (Madrid regressions)	*0.1484*	*0.1512*	*1100*

Trend values tabulated for AC & GH

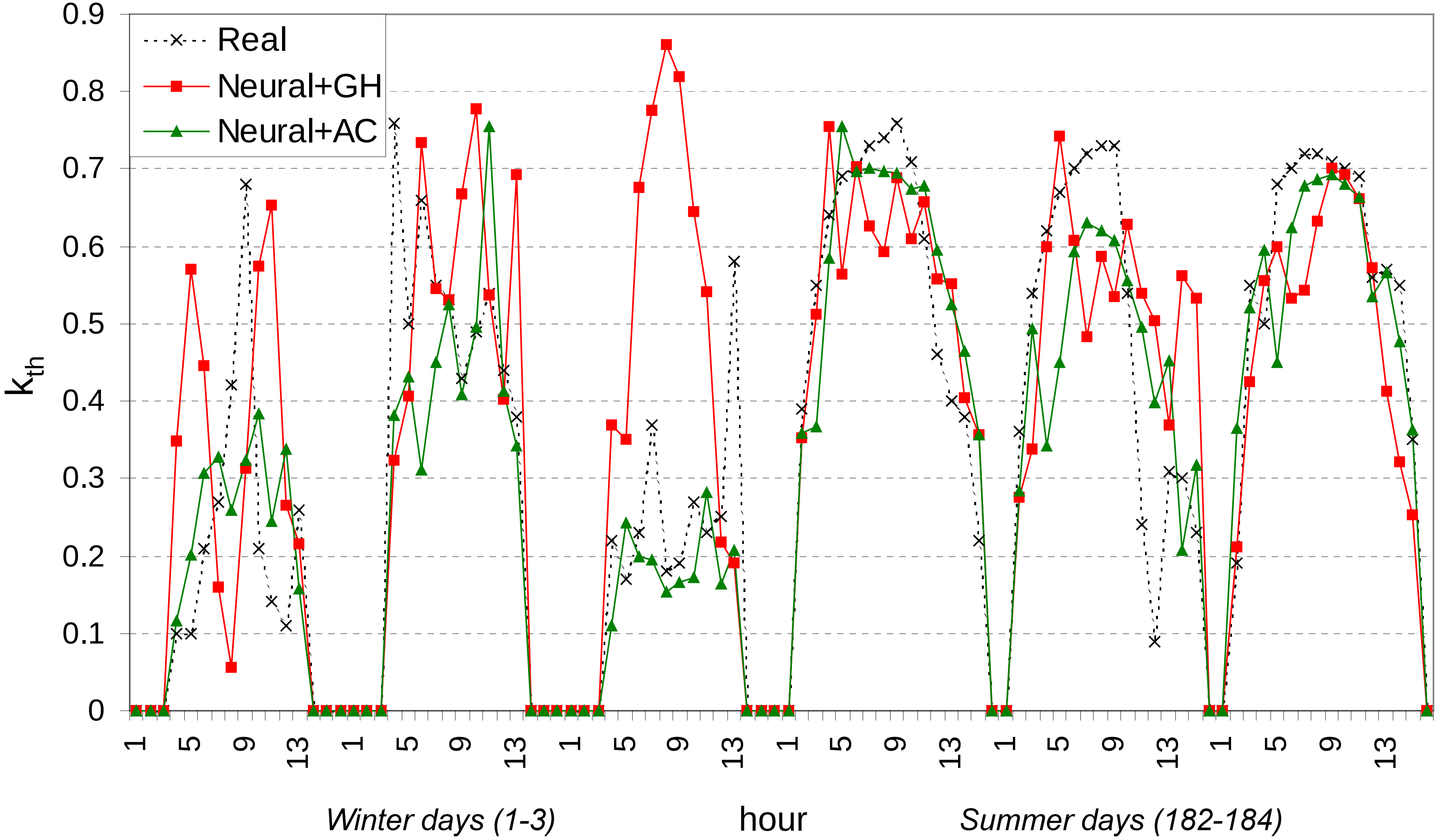
$k_t = k_{tm} + \alpha$ $\quad$ k_{tm} : trend component

α : random component

COMPARISONS. Trend component



COMPARISONS. Rippling added



CONCLUSIONS

- Generic NN based methodology for the generation of time series following the average tendency of hourly clearness index series $\{k_{th}\}$
  - Little knowledge of relationships between variables
  - Does not assume an *a priori* model
- Outperforms classical methods
  - Lower error
  - Less time to optimize generation for a given location
  - More generic (to be tested)

CONCLUSIONS. Further work

- Testing generality of the developed method
- Generation of the stochastic component
  - Similar framework used for variance prediction
- Extension to other time scales.
  - Day scale (K_T)
  - Minute scale
    - No theoretical framework or model available

QUESTIONS & ANSWERS