Application of Fuzzy Logic to Forecast Hourly Solar Irradiation

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Presentation structure

- **Introduction to forecasting solar radiation and fuzzy sets theory**
- **Forecasting hourly global solar irradiation by fuzzy logic**
  - **Database**
  - **Models**
  - **Performance assessment**
  - **Conclusions**

Forecasting the solar radiation

- As the installed capacity of the photovoltaic plants and other solar energy conversion systems increases worldwide, accurate and high-resolution solar irradiance predictions are of vital importance for a balanced operation of the electric grid
- The density of meteorological stations that are equipped to observe solar radiation is very low. In this situation one can employ numerical methods as a suitable alternative to compensate for the scarcity of useful data.
- Most of the models for forecasting the solar radiation are based on traditional statistics.
- In the last years, models build *on fuzzy algorithms* have been developed (Boata and Gravila 2012).
- A fuzzy system consists of a chart between input (*premises*) and output (*conclusions*) represented by *IF - THEN* rules.
- There are two important classes of fuzzy models, categorized after the structure of the consequent part.
- The first class encloses *fuzzy logic models*, whereas the antecedent and the consequent parts are linguistic expressions.
- The second class includes *the Takagi-Sugeno fuzzy models* where the consequent part is a mathematical function while the antecedent part is also a linguistic expression.

•The fuzzy models form a new class, from which it is expected an improvement of prediction accuracy.

•Boata, R.St.; Gravila, P. Functional fuzzy approach for forecasting daily global solar irradiation. Atmos Res 2012, 112, 70-88.

Fuzzy logic model (FL)

- Fuzzy set:

$$A = \left\{ \left(x, m_A(x) \right) : x \in X \right\}$$

- A FL model consists of a collection of *r* rules:

  IF (*premises*) THEN (*conclusions*)

- Every premise or conclusion consists on expression as:

  (*variable*) IS (*attribute*)

- The weight m_C of a rule is computed in the so called inference step:

$$m_C = m_A \wedge m_B = \min\left(m_A(x), m_B(x) \right)$$

If several rules drive to the same conclusion than the individual confidence levels of the rules are combined by applying the fuzzy operator OR:

$$m_C = m_A \vee m_B = \max\left(m_A(x), m_B(x) \right)$$

Defuzzification is a decoding operation of the information enclosed into the results of the fuzzification and inference processes

The suitable output crisp value is extracted with the relation:

$$y_{crisp} = \frac{\sum_i c_i \int m_{y_i}(x)dx}{\sum_i \int m_{y_i}(x)dx}$$

where *i* is the total number of the active rules.

Forecasting hourly global solar irradiation by fuzzy logic

- This study is focused on forecasting of hourly global solar irradiation.
- Four new autoregressive-fuzzy models for forecasting clearness index, based on fuzzy sets theory, is presented.
- There are two arguments for this choice:
  - (i) The stochastic component of solar irradiance is isolated by means of clearness index and
  - (ii) Fuzzy logic is as an alternative to the binary logic, exhibits the flexibility to capture patterns from chaotic systems.
- The models are mainly differentiated by the number of the input variables and attributes
- The general structure of the models and their performance on measured data are discussed

Database

Data measured in Timisoara (Romania) during 2009 and 2010 are used to develop the fuzzy models. The data consists of global and diffuse solar irradiance.

Measurements are performed all day long at equal time intervals of 15 seconds. From these data, the time series of hourly clearness index values was calculated with:

$$k_t \equiv \frac{H}{H_{ext}}$$

where H and H_{ext} denote the hourly global solar irradiation at the ground and at the top of the atmosphere.

- Input variables:
  - *the clearness index measured at time t - 1*

    $$k_t^{t-1}$$

  - *the clearness index measured at time t – 2*

    $$k_t^{t-2}$$

  - *the clearness index measured at time t - 24*

    $$k_t^{t-24}$$

  - *hourly relative sunshine*

    $$\sigma$$

- Output variable:
  - *the clearness index for time t*

    $$k_t^{t}$$

Models description

- Model #1 has only one variable at the input $kt_{t\text{-}1}$ (measured at time t-1) characterized by 3 attributes.
- Model #2 extends the number of inputs increasing the order of auto-regressive terms to two, $kt_{t\text{-}1}$, $kt_{t\text{-}2}$. The variable $kt_{t\text{-}1}$ preserves the three attributes while the variable $kt_{t\text{-}2}$ is characterized by two attributes.
- The model #3 adds to model #1 an exogenous input, namely relative sunshine.
- The model #4 includes a seasonality term, $kt_{t\text{-}24}$ adjacent to $kt_{t\text{-}1}$.

Model #4 description

- Model #4 is a seasonal autoregressive fuzzy model with two input variables kt_{t-1}, kt_{t-24} and one output variable kt_t.
- The membership functions are specified in Fig. 1. The geometry of all membership functions was choosing triangular and always the peak of a triangle matches with the corresponding extremities of the adjacent membership functions.

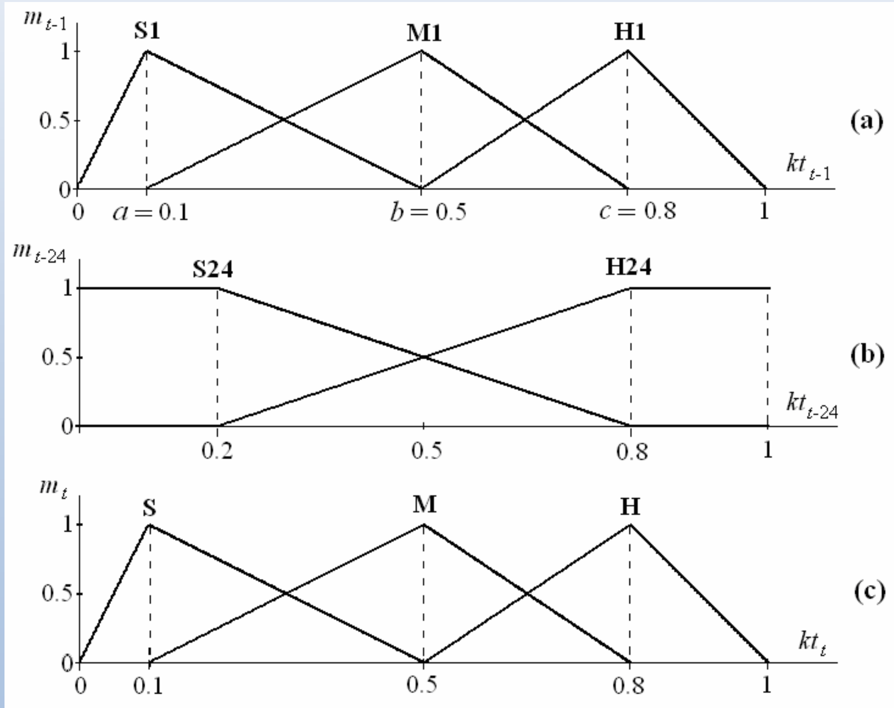

Figure 1. The membership functions of the variables: (a) kt_{t-1}; (b) kt_{t-24} and (c) kt_t

Model #4 description

- The membership functions of all variables, either *in* or *out*, reads:

$$m_{t-v} = \begin{cases} \max\left(0, \dfrac{kt_{t-v} - a_i}{b_i - a_i}\right) & \text{if} \quad kt_{t-v} < b_i \\ \max\left(0, 1 - \dfrac{kt_{t-v} - b_i}{c_i - b_i}\right) & otherwise \end{cases}$$

where v = 0, 1 or 24 specify the variable and the index i counts the attributes of a given variable. The parameters a_i, b_i and c_i have the meaning as is illustrated in Fig. 1a on the M1 attribute. The membership functions of the attributes S24 and H24 are saturated toward zero and infinite, respectively.

The mapping of the input to the output of the system, materialized in the rules-base, is listed in Table 1, as a matrix. The models #1, #2 and #3 have a similar structure with the model #4.

Table 1. Matrix of the system rule base of the model #4.

		kt_{t-1}		
		S1	M1	H1
kt_{t-24}	S24	S	S	M
	H24	M	H	H

There are 6 rules, the each rule (A_1 = S24, A_2 = H24, B_1 = S1, B_2 = M1, B_3 = H1, C_1 = s, C_2 = M, C_3 = H; i = 1,2; j = 1,2,3; k = 1,2,3;) reads:

$$\text{IF } k_t^{t-24} \text{ IS } A_i \text{ AND } k_t^{t-1} \text{ IS } B_j \text{ THEN } k_t^t \text{ IS } C_k$$

Models performance assessment

- The models performance has been assessed with three statistical indicators: relative root mean squared error (*rRMSE*), relative mean bias error (*rMBE*) and relative mean absolute error (*rMAE*).

- *Fitting period*. Table 2 shows the models ability to fit the data.

  Only forecasts for the daylight time were considered.

  The model #4 is the best fit to the data, with an improvement in *rRMSE* over persistence of 25.2%. The persistence model assumes that the conditions at the time of the forecast will not change.

  The ability of the fuzzy model to trace the measured time series is well illustrated in Fig. 2, where the measured and the forecasted *kt* series with model #4 in 10 days (16 to 25 June 2009) are plotted.

  The DNS series was also modeled by a seasonal autoregressive integrated moving average sARIMA model , as the first competitor. The model ARIMA(1,0,1)×(1,0,1)24 was identified as the best, with *rRMSE* = 0.254 and *rMBE* = -0.021.

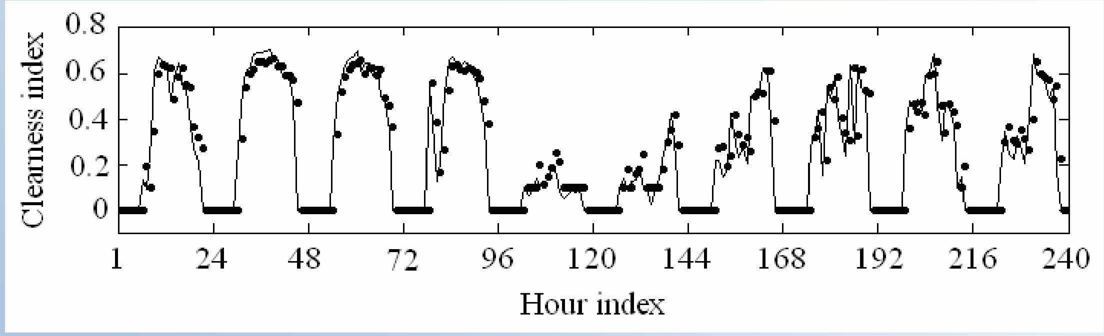

Figure 2. Measured and forecasted clearness index with model #4 in ten days of the fitting period (16 to 25 June 2009).

Models performance assessment

•*Testing period*. All the models were tested against data measured in 2010. Only the model parameters are re-estimated when it is applied to another location.

The models performance in the testing period is also presented in Table 2. The model #4 registered the best performance with *rRMSE* = 0.283. The improvement in *rRMSE* over persistence is of 24.3%. A smaller improvement in *rRMSE* of only 4% is found compared to sARIMA model.

Table 2. Statistical indicators of the models accuracy in the fitting period.

Model	*Fitting period*			*Testing period*		
	rMBE	*rMAE*	*rRMSE*	*rMBE*	*rMAE*	*rRMSE*
#1	0.023	0.202	0.278	0.029	0.235	0.318
#2	0.023	0.202	0.278	0.029	0.234	0.318
#3	0.022	0.202	0.277	0.027	0.234	0.316
#4	0.013	0.182	0.243	0.033	0.213	0.283
ARIMA(1,0,1)×(1,0,1)24	-0.021	0.184	0.254	-0.018	0.219	0.295
Persistence	-0.060	0.221	0.325	-0.048	0.255	0.374

•The ultimate goal of this work is the forecasting of hourly solar irradiation. Reikard (2009) reported a comparison of different models (including ARIMA, UCM - unobserved components model, NN – neural networks and hybrid models) for forecasting mean hourly solar irradiance at different horizons of time, against data measured at six stations. The results were assessed in terms of mean absolute percentage errors (*MAPE*). For one hour forecast horizon, *MAPE* reported in Reikard (2009), falls between 19.6% and 75.4%. Comparing the forecasted solar irradiation time series generated by the model #4 with measurements we found *MAPE* = 29.4% in the fitting period and *MAPE* = 37.0% in the testing period. Therefore, our results are in good agreement with the results from Reikard (2009).

•Reikard, G. Predicting solar radition at high resolution: A comparison of time series forecasts. *Sol Energy* **2009**, *83*, 342-349.

Models performance assessment

When the fuzzy models were tested monthly, the models accuracy was better in summer months than in winter months. As example, monthly statistical indicators of accuracy for model #4 are presented in Table 3. It can be seen that *rRMSE* decreases from 32.4% in January to 19.6% in August and increases again to 41.6% in December, which indicates a seasonal dependence of the model accuracy. This is in accord with the results reported in Paulescu et al. (2013), which demonstrated that the accuracy of the autoregressive models for sunshine number is primarily linked to the stability of the state of the sky, which, however, depends on the season.

Month	*Clearness index*			*Solar irradiation*		
	rMBE	*rMAE*	*rRMSE*	*rMBE*	*rMAE*	*rRMSE*
January	0.089	0.2461	0.334	0.062	0.230	0.324
February	0.071	0.2357	0.304	0.069	0.227	0.296
March	0.007	0.2234	0.292	-0.001	0.212	0.291
April	0.011	0.2114	0.285	-0.010	0.202	0.313
May	0.058	0.2488	0.334	0.034	0.229	0.337
June	0.025	0.1963	0.257	0.010	0.170	0.244
July	0.036	0.1874	0.244	0.015	0.161	0.233
August	-0.009	0.1613	0.212	-0.019	0.141	0.196
September	0.022	0.2042	0.270	0.007	0.189	0.267
October	-0.009	0.255	0.334	0.002	0.253	0.368
November	0.094	0.2119	0.278	0.058	0.177	0.240
December	0.189	0.3228	0.424	0.175	0.311	0.416

Table 3. Statistical indicators of accuracy of the model #4 in each month of the year 2010.

•Paulescu, M.; Badescu, V.; Brabec, M. Tools for PV plant operators: Nowcasting of passing clouds. Energy 2013, 54, 104-12.

Conclusions

- In this paper four auto-regressive fuzzy models for forecasting hourly global solar irradiation are assessed. Being a measure of the stochastic component of solar irradiation, the hourly clearness index is the effective forecasted quantity. A seasonal fuzzy model which includes two auto-regressive terms of order 1 and 24 was found as the most performing. The proposed model exploits a very simple rules-base matrix. Since the data series used to build the model can be considered coming from an arbitrary environment, the procedure is general and it can be applied in any place where hourly global solar irradiation is currently measured, only a re-estimation of the parameters being necessary. The detailed presentation of the model is intended to help the potential users to devise an appropriate fuzzy model for their own requirements.
- The comparison with the traditional ARIMA model shows that the fuzzy logic approach is a competitive alternative for accurate forecasting short-term solar irradiation. Allowing intermediate values between the two binary options 0 and 1, the fuzzy sets theory can provide mathematics with the ability to capture uncertainties associated with natural phenomena. Thus, fuzzy logic may be regarded as an extension of the binary logic, which is successful in many applications, like computer science, but may lack the flexibility needed in other applications, like solar irradiation forecasting.
- Further efforts will be devoted to the integration of some meteorological parameters in the fuzzy algorithm (related to the state of the sky, atmospheric pressure), aiming to increase the model accuracy.

Acknowledgments

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Thank you for your attention!