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TAKAGI-SUGENO ALGORITHM FOR GLOBAL SOLAR IRRADIATION USING AIR TEMPERATURE DATA

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Abstract

Air temperature is certainly the most measured surface meteorological parameter and accurate forecasting of air temperature is usually performed worldwide. This fact inspired the idea that a predicted value of air temperature may be used as input in solar radiation air temperature-based models, aiming to generate the reference solar radiation year or to forecast solar irradiation. Following this, a Takagi-Sugeno fuzzy model for estimating global solar irradiation via air temperature data is reported here. This is intended to be a simple and accurate tool for solar engineering use. Since air temperature-based models are sensitive to the origin locations, an approach for enlarging the area of application is presented. A critical assessment of the model performance against measured data is conducted, with overall results demonstrating a level of accuracy suitable for most practical applications.

Key words: air temperature, fuzzy logic, model performance, solar irradiation

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1. Introduction

In the near future, the weight of electricity generated by the solar-thermal and photovoltaic systems is expected to grow. Due to the fluctuating character of the solar resource and its dependence on non-deterministic weather patterns, a balanced operation of the power grid require accurate forecasting of the collectable solar energy (Lara-Fanego et al., 2011). Of great actuality are the various large scale biomass and biofuel programs (Ciubota-Rosie, 2008; Gavrilescu, 2008), which are in fact just another ways to collect and store the solar energy. Models for predicting agricultural productivity necessitate the knowledge of the solar radiation reference year. Since there is a very low spatial density of meteorological stations equipped for measuring solar radiation (Paulescu et al., 2010), a numerical method can be employed as a substitute for generating the reference year from available long-term measured meteorological data (Miguel and Bilbao, 2005). An outstanding introduction to solar radiation fundamentals and modeling techniques related to actual energy issues can be read in Sen (2008).

Although air temperature is an all-important meteorological parameter currently available everywhere around the world, it is rarely used in the estimation of solar radiation. Existing temperature-based models for solar irradiation can be separated into two groups. The models in the first group usually include daily extreme air temperature besides daily mean cloudiness (El-Metwally, 2004, Paulescu et al., 2011) or sunshine duration (Chandel et al., 2005). Embedding air temperature into the models is meant to increase the prediction quality, knowing from practical experience that prediction accuracy decays with increased cloudiness. The models in the second group (Donatelli and Bellocchi, 2001, Paulescu et al., 2006) generally calculate daily solar clearness index mainly by using the daily air temperature average and amplitude as inputs. Such

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models are of interest in sites where measurements related to the state of the sky (e.g. total cloud cover amount or relative sunshine) are not performed.

All the models discussed above are constructed in the frame of traditional statistical approach and their performance cannot be improved beyond it. Getting over this limit may be possible by employing the fuzzy sets theory (Zadeh, 1965), which basically replaces the Boolean logic with a multi-valued logic. While in various application s the fuzzy logic has been established as a usual method (Wang et al., 2007) it is still an emerging field in solar energy estimation. Some models developed inside fuzzy sets theory are summarized in the following. Gautman and Kaushika (2002) take into account the cloud cover by means of cloudiness, in a model for the estimation of the global solar radiation using fuzzy random variables. Gomez and Casanovas (2003) report a model to compute the solar irradiance on arbitrarily oriented surfaces based on fuzzy logic procedures. Sen (1998) and Sen et al. (2004) report fuzzy algorithms for estimating the solar irradiation from sunshine duration measurements. The authors' team reported in 2008 two fuzzy logic models: the first (Paulescu et al., 2008) employs fuzzy rules for evaluating the atmospheric transmittances linked to the main atmospheric attenuators. The second (Tulcan-Paulescu and Paulescu, 2008), also based on fuzzy logic, relates the global solar irradiation to the daily amplitude of air temperature.

The papers cited above emphasizes two items: (1) Various measures for the state of the sky can be constructed based on daily air temperature extremes; (2) Fuzzy algorithms may have the strength to find links among two apparently uncorrelated sets: solar radiation and air temperature. Starting from these facts, a simple but accurate model for estimating daily global solar irradiation, based on the Takagi-Sugeno fuzzy procedure, is reported in this paper. A short introduction in the Takagi-Sugeno approach is included in Appendix A. The entries in the model are restricted to daily air temperatures extremes. The specific goal of this study is the construction of a tool for engineers engaged in solar energy projects deployed in sites where solar irradiation measurements are not available. At least two applications are straight away. The first starts from the common observation that most of the meteorological stations maintain long term records of minimum and maximum of daily air temperature. By using as entry such long-term series of measurements, the model can be used for generating a solar reference year (Miguel and Bilbao, 2004). The second application starts from present day's progress in forecasting weather. Daily minimum and maximum air temperatures are weather surface parameters forecasted with increasing accuracy around the world. For example, MetOffice, the UK's National Weather Service, compares forecasts for both daily minimum and maximum temperatures to the actual values observed at 45 stations across the UK, and reports more than 80% of forecasts are accurate to within +/- 2°C (MetOffice 2012). Thus, this fuzzy model can be used to forecast daily collectable solar energy by using as entry predicted values of daily air temperature extremes.

2. Model description

Data measured during 1997-1999 at the meteorological station of Timisoara (45.46 N; 21.15º E; 85 m) have been used to build the fuzzy model. The daily amplitude of air temperature Δt has been chosen as input variable, because a lot of papers (some of them cited in the Introduction) have proven that solar irradiation can be computed with acceptable accuracy via air temperature amplitude. The Julian day j is the second input variable; it has been chosen to enhance the prediction quality in the cold season. The clearness index $k_t = H/H_{ext}$, as a descriptor for the stochastic part of solar irradiation, has been considered as output variable. H represents the daily global solar irradiation while H_{ext} represents the extraterrestrial solar irradiation.

Fig. 1 displays the time series plots of the input variable Δt and output variable k_t used to build the model. Each plot includes 1095 values. Visual inspection shows that the shape of k_t traces the variations of Δt. The distribution properties of both time series are summarized in Table 1, where the extreme values and the first four statistical moments are listed. From this table it can be seen that both series are nearly normal distributed, slightly platykurtic. The coefficients of variations of Δt and k_t are roughly identical, 40.4% and 41.11%, respectively, demonstrating that both series exhibit the same dispersion of the probability distribution.

In fuzzy sets theory the number of attributes of a variable depends on the application, i.e. it increases with growing input/output scattering. Because of a high scattering of k_t to Δt, several tests have been performed to find the appropriate number of membership functions. In the building stage of the model, *rmse* and *mbe* given by Eq. (5) and Eq. (6), respectively, have been calculated assuming various values for the number of attributes $n_{\Delta t}$ of air temperature amplitude. For instance: $n_{\Delta t} = 2$ leads to *rmse* = 0.339 and *mbe* = 0.122; $n_{\Delta t} = 4$ leads to *rmse* = 0.274 and *mbe* = -0.085 and $n_{\Delta t} = 8$ leads to *rmse* = 0.28 and *mbe* = 0.078. The results show a saturation of *rmse* for $n_{\Delta t} > 4$, fluctuating around 0.275. When the investigation has been extended on other sites, *rmse* saturates for values of $n_{\Delta t}$ near to 8. For instance, with data collected in Rome during 2000, for $n_{\Delta t} = 2$, 4 and 8 the following values of *rmse* were calculated: 0.204, 0.125 and 0.072, respectively. The same hierarchy has been also noted in most of the test locations (see Fig. 3). Based on overall results, daily air temperature amplitude has been characterized with eight attributes T_i, $i = 1\ldots8$.

Generally, the prediction uncertainty of solar radiation models is higher in winter when the sky is mostly cloudy than in summer when the sky is mostly clear. Santamouris et al. (1999) reported the same behavior of their fuzzy model. Assigning to the Julian day two attributes, the winter W and the summer S, enables setting specific rules for each season. Furthermore, the model will adapt better to the meteorological specificity of spring or autumn days, which can be either close to that of a winter day or to that of a summer day.

Fuzzy membership functions can take many forms but linear functions are often preferred, as this makes the subsequent calculations easier (Russell and Campbell, 1995). Triangular functions as shown in Fig. 2 are the simplest possible and have been selected. All the membership functions of the two input variables (Fig. 2) have been determined heuristically and then computationally optimized in order to provide the best fit of the outputs to the measured clearness index.

The resulted linear equations for the input membership functions are (Eqs. 1-3):

$$m_i(\Delta t) = \begin{cases} \max\left(0, \dfrac{\Delta t - a_{1,i}}{a_{3,i} - a_{1,i}}\right) & \text{if } \Delta t < b_{3,i} \\ \max\left(0, 1 - \dfrac{\Delta t - a_{3,i}}{a_{2,i} - a_{3,i}}\right) & \text{otherwise} \end{cases}, i = 1..8 \quad (1)$$

$$m_W(j) = \begin{cases} \max\left(0, 1 - \dfrac{j - f_1}{c_1 - f_1}, \dfrac{j - f_3}{c_3 - f_3}\right) & \text{if } f_1 < j < c_3 \\ 1 & \text{otherwise} \end{cases} \quad (2)$$

$$m_S(j) = \begin{cases} max\left(0, \dfrac{j - d_2}{f_2 - d_2}\right) & if\ j < f_2 \\ 1 & otherwise \\ max\left(0, 1 - \dfrac{j - f_3}{d_3 - f_3}\right) & if\ j < f_3 \end{cases} \quad (3)$$

where the coefficients $a_{1,i}$, $a_{2,i}$ and $a_{3,i}$, $i = 1 \ldots 8$, in Eq. (1) are listed in Table 2.

The coefficients of Eq. (2-3) are: $d_2 = f_1 = 45$, $c_1 = f_2 = 120$, $f_3 = 240$ and $c_3 = 320$. The output set has been partitioned in eight subsets K_i. The coefficients of the output functions y_i, $i = 1 \ldots 8$, ($x_1 \equiv \Delta t$ and $x_2 \equiv j$ in Eq. (A1) from Appendix) have been calculated using a bivariate least square regression procedure and they are also listed in Table 3. For the fitting process of y_i coefficients, every subset K_i has been set up assuming a threshold of 0.5 for all input membership functions, i.e. $k_t \in K_i$ IF $m_i(\Delta t) > 0.5 \wedge m(j) > 0.5$. In the testing stage, in the few very warm days with large temperature amplitude, over unitary values ($y_8 > 1$) were noted. In order to avoid such unphysical values, y_8 has been limited to 0.8, which is a reasonable threshold of the clearness index in temperate climate.

The mapping of the input to the output of the fuzzy system is presented in Table 4 as a matrix. Since the daily amplitude of air temperature is a parameter influenced in a complex manner by the local meteo-climate, the model is sensitive to its origin location. It has been found that an improvement of the model accuracy can be achieved by a very simple linear mapping of the domain of the air temperature amplitude from the actual site into the similar domain of the origin location. Mathematically, the correction is expressed as (Eq. 4):

$$\Delta t_{in} = \Delta t^0_{\min} + \left(\Delta t - \Delta t_{\min}\right)\frac{\Delta t^0_{\max} - \Delta t^0_{\min}}{\Delta t_{\max} - \Delta t_{\min}} \quad (4)$$

where Δt_{in} is the algorithm input and Δt, Δt_{max} and Δt_{min} are, respectively, daily, the yearly maximum and minimum air temperature amplitude in the current location. The superscript 0 refers to the origin location, Timisoara. Measurements during 1997 - 1999 (this interval has been used to build the fuzzy model) indicate $\Delta t^0_{\max} - \Delta t^0_{\min} = 21.78°\text{C}$ and $\Delta t^0_{\min} = 1.0°\text{C}$, respectively.

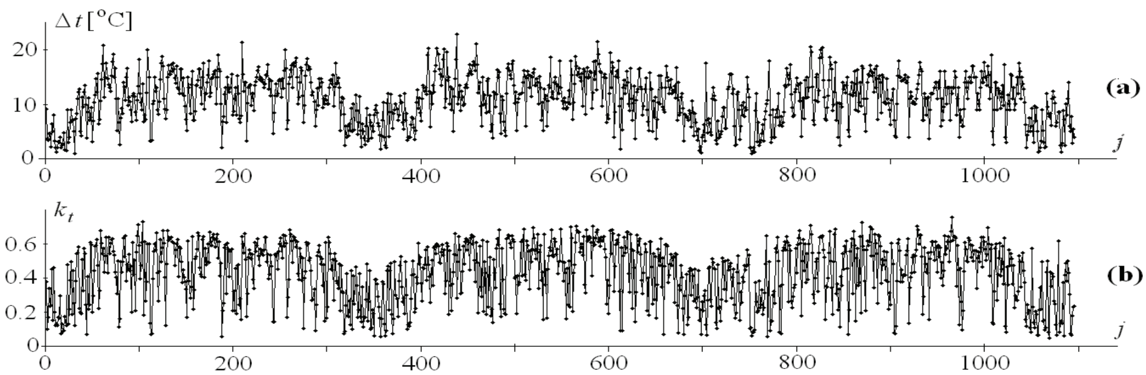

Fig. 1. Time series plot of (a) daily air temperature amplitude Δt and (b) daily clearness index k_t. Data measured during 1997-1999 at the station Timisoara (Romania) have been used

Table 1. Extreme values and the first four statistical moments of the time series: (a) daily air temperature amplitude Δt and (b) daily clearness index k_t. Data measured during 1997-1999 at the station Timisoara (Romania) have been used

	Min	*Max*	*Mean*	*Variance*	*Skewness*	*Kurtosis*
Δt [°C]	1	22.78	10.946	19.602	-0.222	-0.671
k_t	0.049	0.756	0.428	0.031	-0.468	-0.942

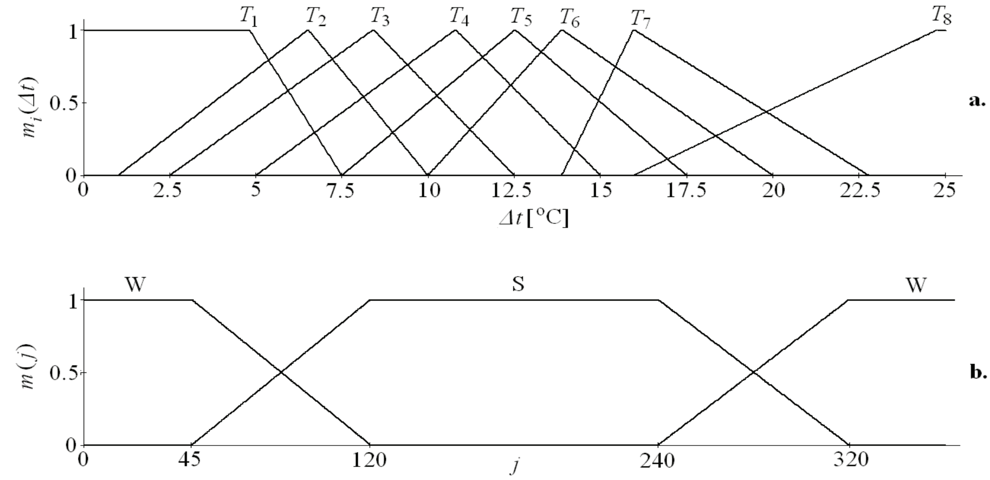

Fig. 2. The membership functions of the input variables attributes: (a) Daily air temperature amplitude (Eq.1) and (b) Julian day (Eqs. 2-3). T_i i = 1,..,8 denote attributes of Δt, while W and S denote the attributes of j

Table 2. Coefficients $a_{1,i}$, $a_{2,i}$ and $a_{3,i}$ of the membership functions associated to the Δt attributes (Eq. 1)

i	1	2	3	4	5	6	7	8
$a_{1,i}$	0	1	2.5	5	7.5	10	13.9	16
$a_{2,i}$	7.5	10	12.5	15	17.5	20	22.78	-
$a_{3,i}$	4.81	6.52	8.41	10.79	12.52	13.87	15.96	24.78

Table 3. Coefficients b_1, b_2 and b_3 of the output functions y_i (Eq. A1)

i	1	2	3	4	5	6	7	8
b_1	0.0830	0.0594	0.0468	0.0128	0.0862	0.4321	0.5616	0
b_2	0.0268	0.0246	0.0369	0.0425	0.0317	0.0089	$6.4 \cdot 10^{-4}$	0.0405
b_3	$2.61 \cdot 10^{-5}$	$8.3 \cdot 10^{-4}$	$-6.16 \cdot 10^{-5}$	$-5.0 \cdot 10^{-5}$	$5.21 \cdot 10^{-5}$	$2.41 \cdot 10^{-5}$	$2.5 \cdot 10^{-4}$	$6.4 \cdot 10^{-4}$

Table 4. Matrix of the system rules-base. Each rule is a fuzzy implication in the Eq. (A2) sense

The rules-base		Δt							
		T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8
j	**S**	y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8
	W	y_1	y_3	y_4	y_5	y_5	y_5	y_6	y_7

4. Assessment of the model accuracy

The model performance has been assessed against data recorded during 2000 and 1998 at eleven European stations located between 40°N and 50°N (Fig. 3). The measured data come from two online databases: daily maximum and minimum air temperature dataset from NCDC (2011) and for daily solar irradiation dataset from WRDC (2011). The model accuracy is assessed using two statistical indicators: the root mean square error (*rmse*) and the mean bias error (*mbe*) which are defined as (Eqs. 5-6):

$$rmse = \left[n \cdot \sum_{i=1}^{n} \left(F_i - y_i \right)^2 \right]^{1/2} \Big/ \sum_{i=1}^{n} y_i \qquad (5)$$

$$mbe = \sum_{i=1}^{n} \left(F_i - y_i \right) \Big/ \sum_{i=1}^{n} y_i \qquad (6)$$

where y_i and F_i are i-th measured and computed quantities, respectively, while n is the number of measurements taken into account.

Statistical indicators of the model accuracy calculated with Eqs. (5-6) are posted in Table 5 and show that the estimation accuracy is reasonable and compares well with the precision achieved using classical correlations. For example, *rmse* and *mbe* for monthly mean daily global solar irradiation ranging between 0.037…0.260 and -0.22…0.091, respectively, have been found in Paulescu and Schlett (2004) after the verification of five traditional solar models with cloudiness (*rmse* between 0.05 and

0.026) and sunshine duration (*rmse* between 0.037 and 0.138) at input for the Romanian climate. In addition, results from Table 5 emphasize the ability of the fuzzy model to trace the specific air temperature regime in a given year. This is visible at the station of Budapest, where *rmse* is 0.080 in 2000 and 0.076 in 2002, for a different thermal regime Δt_{max}- Δt_{min}, 19.3ºC in 2000 and 16.9ºC in 2002.

Fig. 4 presents the fuzzy model estimations tracking the measurements at stations Budapesta with suitable accuracy. It shows the ability of the model to estimate the solar irradiation even in more cloudy or overcast days, both during the summer and the winter.

5. Conclusions

Constructed in an innovative manner inside fuzzy logic theory, a temperature-based model for global solar irradiation is reported. To address the issue that air temperature–based models are sensitive to origin, a simplified adaptive algorithm has been established. A critical assessment of the model accuracy has been conducted against data from European stations located between 40° and 50° N. Based on overall results it can be concluded that the model exhibits an acceptable level of accuracy, comparable with traditional models.

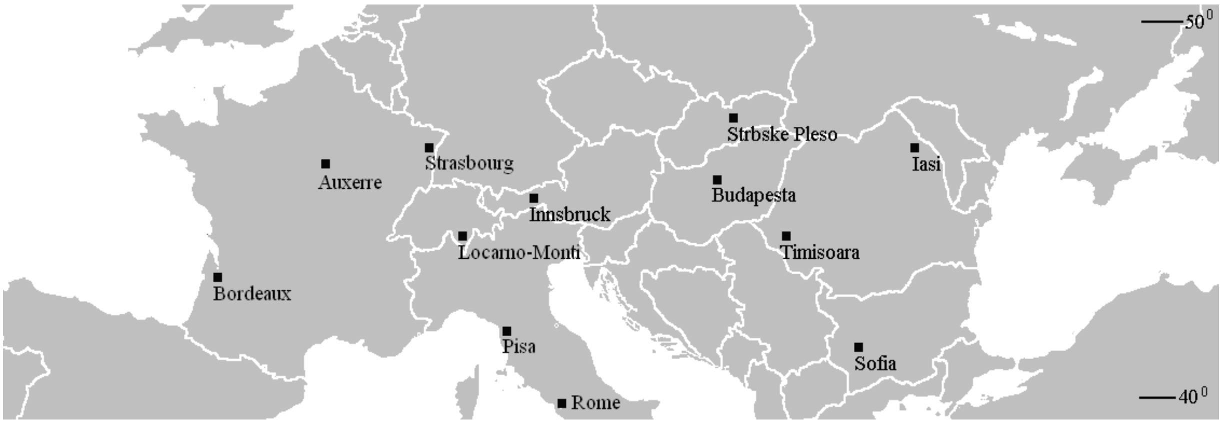

Fig. 3. Map showing the test locations

Table 5. The relative root mean square deviation (*rmse*) and the relative mean bias error (*mbe*) of the monthly mean of daily solar irradiation estimation

Station	***Latitude (deg)***	***Longitude (deg)***	***Altitude (m)***	***Year***	***rmse***	***mbe***
Rome (IT)	41°78'N	12°55'E	105	1998	0.114	-0.079
				2000	0.072	0.003
Sofia (BG)	42°39'N	23°23'E	586	2000	0.092	-0.044
Pisa (IT)	43°68'N	10°38'E	6	1998	0.105	-0.084
Bordeaux (FR)	44°50'N	0°42'W	49	1998	0.126	-0.110
				2000	0.062	-0.021
Locarno-Monti (CH)	46°10'N	8°47'E	366	2000	0.083	-0.032
Iasi (RO)	47°10'N	27°36'E	90	2000	0.175	-0.149
Innsbruck (A)	47°15'N	11°21'N	579	2000	0.067	-0.057
Budapesta (H)	47°26'N	19°11'E	138	2000	0.080	-0.056
				2002	0.076	0.055
Auxerre (FR)	47°48'N	3°33'E	207	2000	0.062	-0.047
Strasbourg (FR)	48°33'N	7°38'E	153	1998	0.107	0.070
				2000	0.055	-0.034
Strbske Pleso (SK)	49°07'N	20°04'E	1387	2000	0.110	0.064

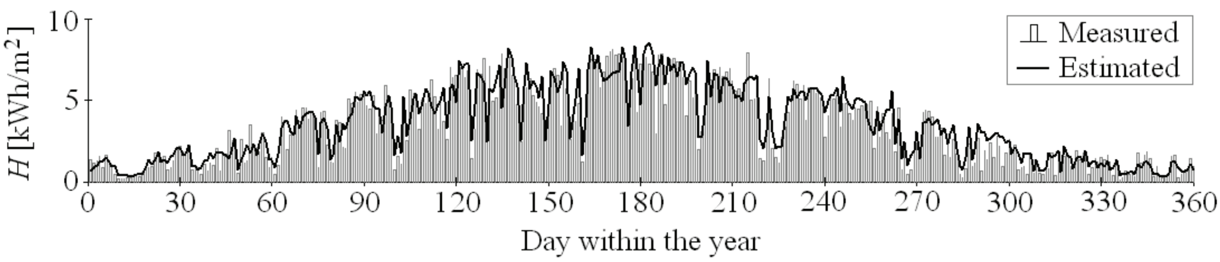

Fig. 4. Measured and estimated daily global solar irradiation H in the year 2002 at the station of Budapest

The great advantage of the model presented here is it's using at input only the daily air temperature extremes, widely accessible for worldwide locations. Thus, even in sites where direct measurements of solar irradiation is not available, two major applications become possible: (1) Forecasting daily collectable solar energy by using as entry predicted values of daily air temperature extremes which are accurately performed around the world and (2) Generating of the reference solar year by using as entry long-term measurements of daily air temperature extremes at input.

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Appendix A: Takagi-Sugeno fuzzy models

The Takagi-Sugeno fuzzy models (Takagi and Sugeno, 1985) form a special class of the fuzzy systems. While the premises and the map from the input to the output of the system resembles the fuzzy logic system (for an intuitive introduction see Sec. 2 from Paulescu et al., 2008), the output membership attributes are replaced with mathematical functions. Thus, each rule, expressed as a sentence "IF *premises* THEN *conclusion*", drives to a crisp conclusion calculated as a linear combination of the input variables (Eq. A1):

$$y(x_1, x_2, ..., x_n) = b_0 + \sum_{i=1}^{n} b_i x_i \tag{A1}$$

where x_1, x_2,…, x_n stand for the n input variables. In this paper we have considered a model with $n = 2$. In this case, the TS model consists of a collection of r rules, each expressed by Eq. (A2):

$$\mathrm{IF} x_1 \mathrm{IS} A \mathrm{AND} x_2 \mathrm{IS} B \mathrm{THEN} y_i = a_{1,i} + a_{2,i} x_1 + a_{3,i} x_2 \qquad i = 1..r \tag{A2}$$

where A and B are attributes of the input variables x_1 and x_2, respectively.

The weight m_k of the #k rule is computed by intersecting the individual premises, $m_k = \min(m_A, m_B)$, where m_A and m_B are the membership functions associated to the attributes A and B, respectively. If p rules drive to the same conclusion y_i, then the individual weights are combined by applying the fuzzy reunion, $m_i = \max(m_1, m_2, ..., m_p)$. The suitable output crisp value is simply calculated by taking the weighted average outputs y_i, i = 1, 2,..., q, where q is the total number of active rules (Eq. A3):

$$y_c = \sum_{i=1}^{q} m_i y_i \Big/ \sum_{i=1}^{q} m_i \tag{A3}$$

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