A NEW FUZZY MODELING FOR PREDICTING AIR TEMPERATURE IN YOGYAKARTA

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Abstract. *In fuzzy modeling, table lookup scheme (Wang's method) is a simple method that can be used to overcome the conflicting rule by determining each rule degree. The weakness of fuzzy model based on the method is that the fuzzy rules may not be complete so the fuzzy rules can not cover all values in the domain. Generalization of the Wang's method has been developed to construct completely fuzzy rules. This paper presents a new method for predicting air temperature in Yogyakarta combining Wang's method and generalized Wang's method.*

Keywords: *fuzzy model, fuzzy rules, Wang's method, generalized Wang's method, air temperature, predicting*

1. INTRODUCTION

Designing fuzzy rule base is one of some steps in fuzzy modeling. Fuzzy rule base is the heart of fuzzy model. In recently, fuzzy model was developed by some researchers. Wang [14] created fuzzy model based on table look up scheme, gradient descent training, recursive least squares and clustering methods. The weakness of the fuzzy model based on table look up scheme is that the fuzzy rule base may not be complete so the fuzzy rule cannot cover all values in the domain. Wu, et.al. [15] designed membership functions and fuzzy rules from training data using α-cut of fuzzy sets. In Wu and Chen's method, determining membership functions and fuzzy rules needs large computations. To reduce the complexity of computation, Yam [16] built a method to decrease fuzzy rules using singular value decomposition.

Yen, et. al. [17] developed fuzzy model by combining global and local learning to improve the interpretability. New form of fuzzy inference systems that is highly interpretable based on a judicious choice of membership function was presented by Bikdash [3]. Then, Herrera, et.al [7] constructed Takagi-Sugeno-Kang models having high interpretability using Taylor series approximation. Then, Pomares, et. al. [9] identified structure of fuzzy systems based on complete rules that can decide which input variables must be taken into account in the fuzzy system and how many membership functions are needed in every selected input variable. Abadi, et. al. [1] designed complete fuzzy rules using singular value decomposition. In this method, the prediction error of training data depended only on taking the number of singular values. To overcome the weakness of table look up scheme (Wang's method), Abadi, et. al. [2] designed generalized Wang's method.

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Fuzzy models have been applied to many fields such in economics, engineering, communications, medicine, climatology and meteorology, etc. Tatli, et.al. [13] constructed a new method for predicting the maximum daily temperature from time series. This method is used to design fuzzy base rule domain from the available daily maximum temperature records at Kandilli observatory in Istambul. Lee, et. al. [8] handled forecasting temperature based on two-factor high-order fuzzy time series. Furthermore, Chen, et.al. [4] designed temperature prediction using fuzzy time series based on relation matrix. Modeling average monthly temperature in Serang Banten using autoregressive model was done by Syamsuar [12]. Dong, et.al. [6] forecasted air temperature in Western Washington using regression model. Rodriguez-Lado, et.al. [10] applied multiple regression analysis and ordinary kriging to predict air temperature at Sao Paulo. ARMA model and Bayesian approach were used to modeling daily air temperature in Catalonia, Saez, et.al. [11]. Then, Chuanyam, et.al. [5] forecasted air temperature in the Southern Qilian mountain using linear regression.

In this paper, we will apply Wang method and generalized Wang's method to predict air temperature in Yogyakarta. The rest of this paper is organized as follows. In section 2, we briefly review the Wang's method to construct fuzzy model. In section 3, we generate fuzzy rules based on training data using generalized Wang's method. In section 4, we apply the proposed method to forecasting air temperature in Yogyakarta. We also compare the result of forecasting air temperature in Yogyakarta based on the generalized Wang's method and the Wang's method. Finally, some conclusions are discussed in section 5.

2. WANG'S METHOD FOR DESIGNING FUZZY RULES

In this section, we will introduce the Wang's method to construct fuzzy rules referred from Wang [14]. Suppose that we are given the following N input-output data: $(x_{1p}, x_{2p}, ..., x_{np}; y_p)$, $p = 1, 2, 3, ..., N$ where $x_{ip} \in [\alpha_i, \beta_i] \subset \mathbb{R}$ and $y_p \in [\alpha_y, \beta_y] \subset \mathbb{R}$, i = 1, 2, …, n. Designing fuzzy model using Wang's method is given by the following steps:

Step 1. Define fuzzy sets to cover the input and output domains.

For each space $[\alpha_i, \beta_i]$, i = 1, 2, …, n, define N_i fuzzy sets A_i^j, j = 1, 2, …, N_i which are complete in $[\alpha_i, \beta_i]$. Similarly, define N_y fuzzy sets B^j, j = 1, 2, …, N_y which are complete in $[\alpha_y, \beta_y]$.

Step 2. Generate one rule from one input-output pair.

For each input-output pair $(x_{1p}, x_{2p}, ..., x_{np}; y_p)$, determine the membership value of x_{ip}, i = 1, 2, …, n in fuzzy sets A_i^j, j = 1, 2, …, N_i and membership value of y_p in fuzzy sets B^j, j = 1, 2, …, N_y. Then, for each input variable x_{ip}, i = 1, 2, …, n, determine the fuzzy set in which x_{ip} has the largest membership value. In other word, determine A_i^{j*} such that $\mu_{A_i^{j*}}(x_{ip}) \geq \mu_{A_i^j}(x_{ip})$, $j = 1, 2, ..., N_i$. Similarly, determine B^{l*} such that $\mu_{B^{l*}}(y_p) \geq \mu_{B^l}(y_p)$, $l = 1, 2, ..., N_y$. Finally, we have fuzzy IF-THEN rule in form:

$$\text{IF } x_1 \text{ is } A_1^{j*} \text{ and } x_2 \text{ is } A_2^{j*} \text{ and ... and } x_n \text{ is } A_n^{j*}, \text{THEN } y \text{ is } B^{l*} \qquad (1)$$

Step 3. Compute degree of each rule designed in step 2.

From Step 2, one rule is generated by one input-output pair. If the number of input-output data is large, then it is possible that there are the conflicting rules. Two rules become conflicting rules if the rules have same IF parts but different THEN parts. To resolve this problem, we assign a degree to each rule designed in Step 2. The degree of rule is defined as follows: suppose the rules (1) is constructed by the input-output pair $(x_{1p}, x_{2p}, ..., x_{np}; y_p)$, then its degree is defined as

$$D(rule) = \prod_{i=1}^{n} \mu_{A_i^{j^*}}(x_{ip}) \mu_{B^{l^*}}(y_p)$$

Step 4. Construct the fuzzy rule base.

The rule base consists of the following three sets of rules: (1) The rules designed in Step 2 that do not conflict with any other rules; (2) The rule from a conflicting group that has the maximum degree; (3) Linguistic rules from human experts.

Step 5. Construct fuzzy model using the fuzzy rule base.

We can use any fuzzifier, inference engine and defuzzifier and combine with the fuzzy rule base to design fuzzy model.

If the number of training data is N and the number of all possible combinations of the fuzzy sets defined for the input variables is $\prod_{i=1}^{n} N_i$, then the number of fuzzy rules generated by Wang's method may be much less than both N and $\prod_{i=1}^{n} N_i$. Then, the fuzzy rule base generated by this method may not be complete so that the fuzzy rules can not cover all values in the input spaces. To overcome this weakness, we will design the fuzzy rules covering all values in input spaces in the following section.

3. CONSTRUCTING FUZZY RULES USING GENERALIZED WANG'S METHOD

In this section, constructing fuzzy rules refer to Abadi, et.al. [2]. Given the following N input-output data: $(x_{1p}, x_{2p}, ..., x_{np}; y_p)$, $p = 1, 2, 3, ..., N$ where $x_{ip} \in [\alpha_i, \beta_i] \subset \mathbb{R}$ and $y_p \in [\alpha_y, \beta_y] \subset \mathbb{R}$, i = 1, 2, …, n. A method to generate complete fuzzy rules is given by the following steps:

Step 1. Define fuzzy sets to cover the input and output spaces.

For each space $[\alpha_i, \beta_i]$, i = 1, 2, …, n, define N_i fuzzy sets A_i^j, j = 1, 2, …, N_i which are complete and normal in $[\alpha_i, \beta_i]$. Similarly, define N_y fuzzy sets B^j, j = 1, 2, …, N_y which are complete and normal in $[\alpha_y, \beta_y]$.

Step 2. Determine all possible antecedents of fuzzy rule candidates.

Based on the Step 1, there are $\prod_{i=1}^{n} N_i$ antecedents of fuzzy rule candidates. The antecedent has form: x_1 is $A_1^{j_1}$ and x_2 is $A_2^{j_2}$ and ... and x_n is $A_n^{j_n}$ simplified by $A_1^{j_1}$ and $A_2^{j_2}$ and ... and $A_n^{j_n}$ For example, if we have two input and we define two fuzzy sets A_1, A_2 for first input space and C_1, C_2 for second input space, then all possible antecedents of fuzzy rule candidates are A_1 and C_1; A_1 and C_2; A_2 and C_1; A_2 and C_2.

Step 3. Determine consequence of each fuzzy rule candidate.

For each antecedent $A_1^{j_1}$ and $A_2^{j_2}$ and ... and $A_n^{j_n}$, the consequence of fuzzy rule is determined by degree of the rule $\mu_{A_1^{j_1}}(x_{1p}) \mu_{A_2^{j_2}}(x_{2p}) ... \mu_{A_n^{j_n}}(x_{np}) \mu_{B^j}(y_p)$ based on the training data. Choosing the consequence is done as follows: For any training data $(x_{1p}, x_{2p}, ..., x_{np}; y_p)$ and for any fuzzy set B^j, choose B^{j*} such that $\mu_{A_1^{j_1}}(x_{1p*})\mu_{A_2^{j_2}}(x_{2p*})...\mu_{A_n^{j_n}}(x_{np*})\mu_{B^{j*}}(y_{p*}) \geq \mu_{A_1^{j_1}}(x_{1p})\mu_{A_2^{j_2}}(x_{2p})...\mu_{A_n^{j_n}}(x_{np})\mu_{B^j}(y_p)$, for some $(x_{1p*}, x_{2p*}, ..., x_{np*}; y_{p*})$.

If there are at least two B^{j*} such that $\mu_{A_1^{j_1}}(x_{1p*})...\mu_{A_n^{j_n}}(x_{np*})\mu_{B^{j*}}(y_{p*}) \geq \mu_{A_1^{j_1}}(x_{1p})...\mu_{A_n^{j_n}}(x_{np})\mu_{B^j}(y_p)$, then choose one of some B^{j*}.

From this step, we have the fuzzy rule in form:

$$\text{IF } x_1 \text{ is } A_1^{j_1} \text{ and } x_2 \text{ is } A_2^{j_2} \text{ and ... and } x_n \text{ is } A_n^{j_n}, \text{ THEN } y \text{ is } B^{j*}$$

So if we continue this step for every antecedent, we get $\prod_{i=1}^{n} N_i$ complete fuzzy rules.

Step 4. Construct fuzzy rule base.

The $\prod_{i=1}^{n} N_i$ fuzzy rules designed by Step 3 are used to construct fuzzy rule base.

Step 5. Design fuzzy model using fuzzy rule base.

Fuzzy model is designed by combining the fuzzy rule base and any fuzzifier, inference engine, defuzzifier. For example, if we use singleton fuzzifier, product inference engine and center average defuzzifier, then the fuzzy model has form:

$$f(x_1, x_2, ..., x_n) = \frac{\sum_{j=1}^{M} b_j \prod_{i=1}^{n} \mu_{A_i^j}(x_i)}{\sum_{j=1}^{M} \prod_{i=1}^{n} \mu_{A_i^j}(x_i)} \qquad (2)$$

where M is the number of rules and b_j is center of fuzzy set B^j.

From Step 3, the set of fuzzy rules constructed by this method contains fuzzy rules designed by the Wang's method. Therefore the proposed method is generalization of the Wang's method.

4. FORECASTING AIR TEMPERATURE USING WANG'S METHOD AND GENERALIZED WANG'S METHOD

In this section, we apply the proposed method to forecast air temperature in Yogyakarta. The proposed method is implemented using Matlab 6.5.1. The data of air temperature (^0C), humidity (%) and cloud density (octa) are taken from September 2010 to December 20010 at BMKG Yogyakarta. The first 80 data are used to training and the rest data are used to testing. We construct fuzzy rules using table lookup scheme (Wang's method) and generalized Wang's method.

In this paper, we will predict air temperature based on air temperature, cloud density and humidity factors. The universes of discourse of air temperature, cloud density and humidity are defined as [23.5, 29], [1, 8], [70, 95] respectively. We define twelve fuzzy sets $A_1, A_2, ..., A_{12}$ on [23.5, 29], eight fuzzy sets $B_1, B_2, ..., B_8$ on [1, 8], six fuzzy sets $C_1, C_2, ..., C_6$ on [70, 95], with Gaussian membership functions. Fuzzy sets defined on universes of discourse can be seen at Figure 1.

First, we construct fuzzy rules using Wang's method. Fuzzy rules are generated by training data based on time series of air temperature only, air temperature and cloud density, air temperature and humidity. Second, we construct fuzzy rules using generalized Wang's method based on time series of air temperature only. Generalized Wang's method yields completely 144 fuzzy rules in form:

$$R^j: \text{“IF } x_{k-2} \text{ is } A_{i_1} \text{ and } x_{k-1} \text{ is } A_{i_2}\text{, THEN } x_k \text{ is } A^j\text{”}$$

where j = 1, 2, …, 144, $i_1, i_2 = 1, 2, ..., 12$ and $A^j \in \{A_1, A_2, ..., A_{12}\}$.

Then, resulted fuzzy rules based on time series of air temperature only, air temperature and cloud density, air temperature and humidity are shown in Table 1, Table 2, Table 3 respectively. The number of fuzzy rules based on those factors can be seen at Table 4. Fuzzy rules, in bold and blue sign in Table 1, are generated by Wang's method.

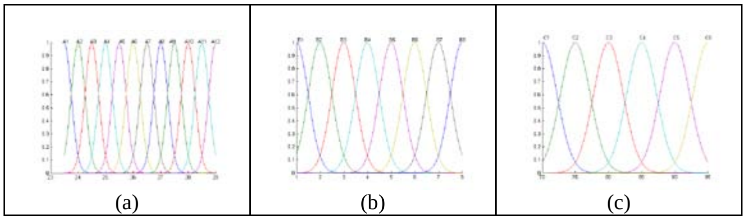


Figure 1. Gaussian membership functions defined on universes of discourse of (a) air temperature, (b) cloud density, (c) humidity

Then, we design fuzzy model that combine the fuzzy rule base and certain fuzzifier, inference engine, defuzzifier. In this paper, we use singleton fuzzifier, product inference engines, center average defuzzifier showed in equation (2). Thus, we use values of mean square error (MSE) and mean absolute percent error (MAPE) of training and testing data to validate the model.

Table 1. Fuzzy rules generated by generalized Wang's method based on time series of air temperature

No	($x(t$-2),	$x(t$-1))	$\rightarrow x(t)$	No	($x(t$-2),	$x(t$-1))	$\rightarrow x(t)$
1	A1	A1	A3	73	A7	A1	A6
2	A1	A2	A3	**74**	**A7**	**A2**	**A5**
3	A1	A3	A3	75	A7	A3	A5
4	A1	A4	A3	**76**	**A7**	**A4**	**A5**
5	A1	A5	A8	**77**	**A7**	**A5**	**A7**
6	A1	A6	A8	**78**	**A7**	**A6**	**A10**
7	A1	A7	A8	**79**	**A7**	**A7**	**A5**
8	A1	A8	A8	**80**	**A7**	**A8**	**A5**
9	A1	A9	A7	81	A7	A9	A8
10	A1	A10	A7	**82**	**A7**	**A10**	**A8**
11	A1	A11	A7	83	A7	A11	A6
12	A1	A12	A7	84	A7	A12	A5
13	A2	A1	A5	85	A8	A1	A5
14	A2	A2	A3	86	A8	A2	A5
15	A2	A3	A3	87	A8	A3	A5
16	A2	A4	A3	88	A8	A4	A6
17	**A2**	**A5**	**A3**	**89**	**A8**	**A5**	**A7**
18	**A2**	**A6**	**A8**	90	A8	A6	A4

19	A2	A7	A8	91	A8	A7	A5
20	A2	A8	A8	92	A8	A8	A9
21	A2	A9	A7	93	A8	A9	A7
22	A2	A10	A7	94	A8	A10	A7
23	A2	A11	A7	95	A8	A11	A7
24	A2	A12	A7	96	A8	A12	A7
25	A3	A1	A5	97	A9	A1	A5
26	A3	A2	A5	98	A9	A2	A5
27	A3	A3	A9	99	A9	A3	A6
28	A3	A4	A3	100	A9	A4	A6
29	A3	A5	A6	101	A9	A5	A6
30	A3	A6	A6	102	A9	A6	A8
31	A3	A7	A7	103	A9	A7	A6
32	A3	A8	A7	104	A9	A8	A9
33	A3	A9	A7	105	A9	A9	A8
34	A3	A10	A7	106	A9	A10	A7
35	A3	A11	A7	107	A9	A11	A7
36	A3	A12	A7	108	A9	A12	A7
37	A4	A1	A5	109	A10	A1	A5
38	A4	A2	A5	110	A10	A2	A5
39	A4	A3	A7	111	A10	A3	A9
40	A4	A4	A9	112	A10	A4	A9
41	A4	A5	A5	113	A10	A5	A9
42	A4	A6	A7	114	A10	A6	A8
43	A4	A7	A7	115	A10	A7	A7
44	A4	A8	A7	116	A10	A8	A8
45	A4	A9	A7	117	A10	A9	A8
46	A4	A10	A7	118	A10	A10	A8
47	A4	A11	A7	119	A10	A11	A7
48	A4	A12	A5	120	A10	A12	A7
49	A5	A1	A5	121	A11	A1	A5
50	A5	A2	A5	122	A11	A2	A9
51	A5	A3	A5	123	A11	A3	A9
52	A5	A4	A7	124	A11	A4	A9
53	A5	A5	A6	125	A11	A5	A9
54	A5	A6	A7	126	A11	A6	A9
55	A5	A7	A5	127	A11	A7	A8
56	A5	A8	A7	128	A11	A8	A8
57	A5	A9	A8	129	A11	A9	A8
58	A5	A10	A8	130	A11	A10	A8
59	A5	A11	A5	131	A11	A11	A8
60	A5	A12	A5	132	A11	A12	A7
61	A6	A1	A6	133	A12	A1	A9

62	**A6**	**A2**	**A6**	134	A12	A2	A9
63	A6	A3	A5	135	A12	A3	A9
64	**A6**	**A4**	**A6**	136	A12	A4	A9
65	**A6**	**A5**	**A4**	137	A12	A5	A9
66	A6	A6	A4	138	A12	A6	A9
67	**A6**	**A7**	**A7**	139	A12	A7	A8
68	**A6**	**A8**	**A5**	140	A12	A8	A8
69	A6	A9	A8	141	A12	A9	A8
70	**A6**	**A10**	**A5**	142	A12	A10	A8
71	A6	A11	A5	143	A12	A11	A8
72	A6	A12	A5	144	A12	A12	A8

Table 2. Fuzzy rules generated by Wang’s method based on air temperature and cloud density factors

No	($x(t$-1),	$c(t$-1))	→ $x(t)$	No	($x(t$-1),	$c(t$-1))	→ $x(t)$
1	A2	B6	A5	16	A6	B7	A5
2	A2	B7	A6	17	A7	B5	A5
3	A3	B3	A5	18	A7	B6	A7
4	A3	B8	A7	19	A7	B7	A5
5	A4	B4	A6	20	A8	B4	A9
6	A4	B8	A4	21	A8	B5	A7
7	A4	B5	A9	22	A8	B6	A9
8	A4	B7	A6	23	A8	B7	A8
9	A5	B4	A5	24	A9	B5	A7
10	A5	B5	A7	25	A9	B6	A7
11	A5	B6	A6	26	A9	B7	A8
12	A5	B7	A5	27	A10	B4	A8
13	A5	B8	A7	28	A10	B5	A6
14	A6	B5	A8	29	A10	B6	A7
15	A6	B6	A10				

Table 3. Fuzzy rules generated by Wang’s method based on air temperature and humidity factors

No	($x(t$-1),	$h(t$-1))	→ $x(t)$	No	($x(t$-1),	$h(t$-1))	→ $x(t)$
1	A10	C2	A6	12	A6	C4	A8
2	A10	C3	A7	13	A6	C5	A8
3	A2	C5	A6	14	A7	C3	A5
4	A3	C5	A5	15	A7	C4	A5
5	A4	C4	A4	16	A8	C1	A8
6	A4	C5	A5	17	A8	C2	A7
7	A5	C1	A5	18	A8	C3	A8
8	A5	C2	A5	19	A8	C4	A5

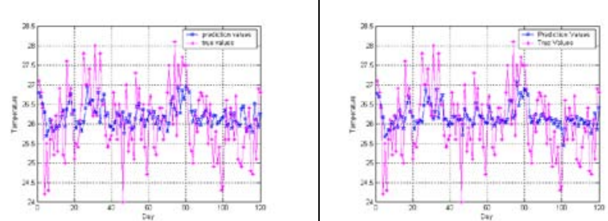
9	A5	C3	A5	20	A9	C2	A7
10	A5	C4	A7	21	A9	C3	A7
11	A5	C5	A5	22	A9	C4	A7

Table 4. Comparison of MSE and MAPE of forecasting air temperature using the Wang's method and generalized Wang's method

Method	factor	Number of fuzzy rules	MSE of training data	MAPE of training data (%)	MSE of testing data	MAPE of testing data (%)
Wang's method	Air temperature	39	0.65572	2.36420	0.68482	2.73140
	Air temperature and cloud density	29	0.76529	2.58660	0.77821	2.75990
	Air temperature and humidity	22	0.73739	2.47400	0.58572	2.53230
Generalized Wang's method	Air temperature	144	0.62534	2.28750	0.62303	2.61620

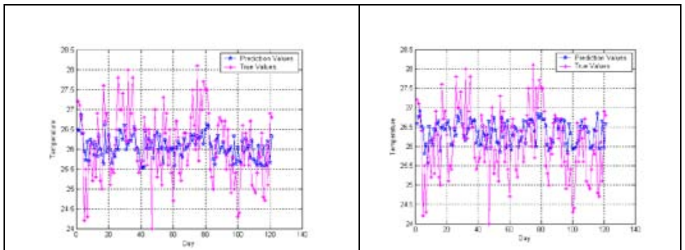
The least number of fuzzy rules are 22 resulted by Wang's method for air temperature and humidity factors. Table 4 shows a comparison of the MSE and MAPE of training and testing data based on the Wang's method and generalized Wang's method. Prediction of air temperature based on air temperature and humidity factors has better accuracy than based on other factors, which values of MSE and MAPE of testing data are 0.58572 and 2.53230% respectively. Furthermore, using generalized Wang's method, prediction of air temperature based on time series of air temperature factor has better accuracy than based on other factors for training data, which values of MSE and MAPE are 0.62534 and 2.28750% respectively.

True and prediction values of air temperature based on time series of air temperature using the Wang's method and generalized Wang's method are shown in Figure 2. Then Figure 3 shows the prediction and true values of air temperature based on the Wang's method using air temperature and humidity factors, and air temperature and cloud density factors.



(a) (b)

Figure 2. The prediction and true values of air temperature using air temperature factor based on (a) Wang's method, (b) generalized Wang's method



(a) (b)

Figure 3. The prediction and true values of air temperature based on the Wang's method using (a) air temperature and humidity factors, (b) air temperature and cloud density factors

5. CONCLUSIONS

In this paper, we have presented a new method for forecasting air temperature in Yogyakarta. The Wang's method and generalized Wang's method are used to construct fuzzy rules. The result is that prediction of air temperature using Wang's method has a higher accuracy than that using generalized Wang's method for testing data. Then prediction of air temperature using generalized Wang's method has a higher accuracy than that using Wang's method for training data. To increase the prediction accuracy, we can define more fuzzy sets in the universe of discourse but defining more fuzzy sets can cause complex computations. So determining the optimal number of fuzzy rules is important to get efficient computations. In future works, we will design the optimal number of fuzzy rules for forecasting air temperature in Yogyakarta.

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