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RESEARCH ARTICLE

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Adaptive neuro-fuzzy inference system approach for urban sustainability assessment: A China case study

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Abstract

Urbanization, especially in developing countries, has led to numerous concerns, such as air pollution, traffic congestion and habitat destruction. Within this context, it is important to evaluate urban development as sustainable, and various sustainability assessment methods have been developed, including fuzzy logic approaches. However, predefined fuzzy rules and simple linear membership functions were used, which are largely based on the knowledge of subject experts. Therefore, this paper aims to introduce an adaptive neuro-fuzzy inference systems (ANFIS) approach for urban sustainability assessment. With collected training samples from the Urban China Initiative, and the ANFIS approach was used to rank 185 selected cities in China. The results show that the ANFIS approach is appropriate for assessing urban sustainability, and the nonlinear membership functions fit the training samples better than the linear membership functions. Further discussion indicates that future research on sustainability assessment should be more integrated.

KEYWORDS

ANFIS, artificial neural network, decision-making, fuzzy logic, sustainable development, urban sustainability

1 | INTRODUCTION

Urbanization involves people migrating from rural to urban areas, which has been recognized as a major driver for economic and social development (United Nations, 2016). However, rapid urbanization has also posed various problems such as traffic congestion, air pollution, increased solid waste and rising crime rates (Chen & Lu, 2017; Peng et al., 2018; Shen, Zhou, Skitmore, & Xia, 2015; Shuai, Shen, Jiao, Wu, & Tan, 2017). Sustainable urbanization can be defined as ". . . urbanization practice, which complies with sustainable development principles" (Roy, 2009). Sustainable urbanization is a dynamic process that combines environmental, social, economic and political–institutional sustainability, and which complies with sustainable development principles (Zhou, Zhang, & Shen, 2015). It has been projected by The United Nations Department of Economic and Social Affairs (UNDESA, 2014) that, in China, 76% of the population will live in cities by 2050. The figure for 2014 is already 54%. This rapid urbanization has led to the need to understand urbanization as a major contributor to resource consumption and environmental and social damage (Shen et al., 2018; Zhou et al., 2015). It is necessary for local governments to rethink related policies for the sustainable development of cities (Tan, Xu, & Zhang, 2016).

In line with the promotion of sustainable urbanization, both international institutions and governments at different levels are seeking solutions that integrate, in harmony, environmental, community and economic requirements (Fu & Zhang, 2017). Various assessment tools have been developed to help understand and monitor urban sustainability (Jorgenson & Rice, 2016; Peng, 2015; Peng, Lai, Li, & Zhang, 2015; Shen, Shuai, Jiao, Tan, & Song, 2016; Shen, Yan, Zhang, & Shuai, 2017; Tan, Ochoa, Langston, & Shen, 2015; Tan, Shen, & Langston, 2014; Tan, Shen, & Yao, 2011; Tan, Shuai, Jiao, & Shen, 2017; Wu, Fan, & Chen, 2016). However, these assessment tools have limitations when used in urban sustainability evaluation, such as the one-side assessment principle (Li & Li, 2009), subjective assessment criteria (Phillis, Kouikoglou, & Manousiouthakis, 2010), and unreadable and inapplicable assessment results (Shen et al., 2015).

Fuzzy logic is a widely used method to assess sustainability performance. For instance, Phillis, Grigoroudis, and Kouikoglou (2011) introduced the Sustainability Assessment by Fuzzy Evaluation (SAFE) model to assess overall sustainability performance at the global level. Giordano, Caputo, and Vancheri (2014) applied the Takagi–Sugeno fuzzy model to measure urban ecological efficiency. However, most existing studies use predefined fuzzy rules and linear membership functions (triangular or trapezoidal), which depend greatly on expert knowledge, and may not reflect a real-world situation (Buragohain & Mahanta, 2008; Naderloo et al., 2012).

This paper aims to introduce a new approach, namely, adaptive neuro-fuzzy inference systems (ANFIS) to assess sustainability based on the work by the Urban China Initiative (UCI) (2013). The fuzzy rules and membership functions were generated from training samples and can be adjusted with updated training data, which makes the assessment process closer to the real situation and adaptable to dynamic changes.

2 | LITERATURE REVIEW

Sustainability assessment is a methodology "that can help decision-makers and policy-makers decide what actions they should take and should not take in an attempt to make society more sustainable" (Devuyst, Hens, & Lannoy, 2001, p. 9). With this aim, various sustainability assessment methods and tools have been developed. Based on a comprehensive literature review, eight frequently employed assessment methods were identified, as shown in Table 1.

TABLE 1 Frequently used sustainability assessment methods

Method	Related references
Ecological footprint	Hunter and Shaw (2007); Ferng (2014); Guo et al. (2017); Saravia-Cortez, Herva, García-Diéguez, and Roca (2013); Juknys, Liobikienė, and Dagiliūtė (2017)
Data envelopment analysis	Alfonso Pi a and Pardo Martínez (2016); Wang, Sun, Li, and Zou (2016); Cheon (2017); Halkos and Petrou (2017)
Life cycle assessment	Ren, Manzardo, Mazzi, Zuliani, and Scipioni (2015); Curran (2013); Maier et al. (2016); Belussi and Barozzi (2015)
System dynamics	Xu and Coors (2012); Abdelkafi and Täuscher (2016); Jin, Xu, Xiang, Bai, and Zhou (2016); Allen, Metternicht, and Wiedmann (2017)
Input–output analysis	Onat, Kucukvar, and Tatari (2014);Tsai, Lee, Yang, and Huang (2016); Jia, Li, Wang, Foo, and Tan (2015); Noori, Kucukvar, and Tatari (2015); Li, Beeton, Halog, and Sigler (2016); Kurniawan and Managi (2017)
Substance flow analysis	Yellishetty and Mudd (2014); Kümmerer and Hofmeister (2008); John, Möller, and Weiser (2016)
Comprehensive evaluation	Zhou et al. (2015); Banihabib, Hashemi, and Shabestari (2017); Shen, Shuai, Jiao, Tan, and Song (2017); Geiger, Fischer, and Schrader (2018); Strezov, Evans, and Evans (2017); Guo, Qu, Wu, and Gui (2018)
Fuzzy-set theory	Govindan, Khodaverdi, and Jafarian (2013); Alsulami and Mohamed (2014); Hemdi, Saman, and Sharif (2013); Kommadath, Sarkar, and Rath (2012)

These assessment methods could be classified into two categories in terms of the principle, including efficiency-oriented and output-oriented. Both principles have limitations. For example, data envelope analysis (DEA) is a typical efficiency-oriented assessment method, which has been widely applied in studies such as input–output analysis, life cycle assessment, substance flow analysis and ecological footprint analysis (Yan, Wei, & Hao, 2002). However, the results obtained from the DEA method provide only the relevant efficiency of individual indicators (Li & Li, 2009). The output-oriented assessment method is normally used for comprehensive analysis (Yigitcanlar, Dur, & Dizdaroglu, 2015). For example, Yigitcanlar and Dur (2010) used multiple criteria, including infrastructure, land use, environment and transportation, to assess sustainability performance. Nevertheless, Shen et al. (2015) argued that decision-makers have difficulties in selecting the appropriate development strategy, as the output-oriented principle focuses on outcomes rather than the whole process.

Sustainability is a dynamic and complex concept that integrates multidimensional systems. Cornelissen, Van den Berg, Koops, Grossman, and Udo (2001) stated that sustainability represents the process itself, an ongoing dynamic development, driven by human expectations about future opportunities. Newman (2005) echoed this view and proposed that sustainability must be an ongoing process, not a goal, which includes the inherent complexity and uncertainty of human and natural systems. Moussiopoulos, Achillas, Vlachokostas, Spyridi, and Nikolaou (2010) further stated that sustainability is a multidimensional concept that includes environmental, economic, social and political dimensions. Bentivegna et al. (2002) commented that sustainable development assessment is a dynamic process as it does not have clear absolute outcomes.

Furthermore, Phillis et al. (2010) pointed out that sustainability assessment is very subjective and cannot be properly measured using simple hard indicators such as per-capita gross domestic product (GDP), Gini index or employment rate. Some soft indicators that cannot be easily quantitatively measured, such as governance, corruption and poverty, are also important to reflect a city's real sustainability. These soft indicators cannot be quantified by using a crisp number. Instead, these indicators can be represented by using linguistic terms, such as "Good," "Normal," or "Bad." Fuzzy set theory can handle both qualitative and quantitative data, and is a systematic tool for sustainability assessment (Hemdi et al., 2013).

A fuzzy approach to sustainability assessment has been used by many researchers. For example, Govindan et al. (2013) introduced a fuzzy multicriterion approach to measure the sustainability performance of suppliers. Alsulami and Mohamed (2014) presented an innovative model, which combined fuzzy-set theory and fuzzy cognitive maps to assess the sustainability performance of infrastructure. Phillis et al. (2011) developed a SAFE model for sustainability assessment, which contains 75 indicators to evaluate the sustainability performance of 128 selected countries. However, predefined fuzzy rules and linear membership functions (triangular or trapezoidal) and fuzzy rules are commonly used in existing studies (Khalilzadegan, Khoei, & Hadidi, 2012; Kumar & Sundaresan, 2014; Robinson, 2016). Sustainability assessment is a complex, multicriterion and dynamic process, which involves various nonlinear relationships between variables (Hjorth & Bagheri, 2006; López-Ridaura, Masera, & Astier, 2002). Therefore, predefined fuzzy rules and linear membership functions may not reflect the real rules and membership distributions (Buragohain & Mahanta, 2008; Naderloo et al., 2012). Besides, Singh, Kainthola, and Singh (2012) pointed out that it is difficult to define the correct membership functions and rules for a reliable solution, because the trial and error process requires significant time.

To overcome this disadvantage, induction of fuzzy rules and fuzzy membership functions from training samples has been studied. In combining the advantage of artificial neural networks (ANNs) and fuzzy-set theory, Jang (1993) introduced the ANFIS method, which uses training data to generate fuzzy rules and membership functions. Singh, Kainthola, and Singh (2012) showed that it is easy to communicate the neural net weightings by using fuzzy rules. Rule-based memories can be reduced using a nonlinear membership function, and hence the implementation cost can be reduced. Khoshnevisan, Rafiee, Omid, Mousazadeh, and Clark (2014) further opined that ANFIS can determine the proper size and optimal structure of the neural net, which reduces the time for generating the fuzzy rules and membership functions.

Since then, the ANFIS method has been widely used in many research areas, such as prediction (Abdulshahed, Longstaff, & Fletcher, 2015; Hegde & Raju, 2015; Petković, Shamshirband, Abbasi, Kiani, & Al-Shammari, 2015; Rai, Pai, & Rao, 2015), knowledge discovery (Huang, Tsou, & Lee, 2006; Inyang & Akinyokun, 2014; Vahidnia, Alesheikh, Behzadi, & Salehi, 2013), decision-making (Hashemi, Pilevar, & Rafeh, 2013; Li, Yang, & Cao, 2014; Özkan & İnal, 2014) and evaluation (Eldessouki & Hassan, 2015; Maher, Sarhan, Barzani, & Hamdi, 2015; Sangaiah, Thangavelu, Gao, Anbazhagan, & Durai, 2015; Sun, Hu, Lei, Zhu, & Jiang, 2015). For example, Sun et al. (2015) applied the ANFIS method to evaluate the ground source heat pump (GSHP) system, and found that it provided high accuracy and reliability for calculating performance indexes of the system. However, there is, to our knowledge, no research that applies ANFIS to sustainability assessment. This study introduced the ANFIS method as an alternative approach for urban sustainability assessment.

3 | ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

An ANFIS was first introduced by Jang (1993), which incorporates the fuzzy logic concept into neural networks. Integration of fuzzy logic and neural networks is a pre-eminent idea to overcome the disadvantages of fuzzy-set theory. ANFIS integrates the advantages of fuzzy systems for dealing with *explicit* knowledge, and neural networks for dealing with *implicit* knowledge (Singh, Kainthola, & Singh, 2012). The membership function parameters and fuzzy rules are derived from training data instead of predefined when using the ANFIS approach.

For example, if a fuzzy inference system (FIS) has two inputs (x,y), two *if–then* fuzzy rules, one output, and each input has two associated membership functions (MFs). The governing rule set with two *if–then* rules of Takagi–Sugeno type and the ANFIS architecture are shown in Figure 1.

For a typical first-order Takagi–Sugeno fuzzy model (Sugeno, 1985), a basic rule set with two fuzzy *if–then* rules can be expressed as follows:

Rule 1: if x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

where A_1, A_2, B_1 and B_2 are the linguistic labels of the inputs (x, y) respectively, and (p_i, q_i, r_i) (i = 1, 2) are the parameters (Jang, 1993).

As shown in Figure 1b, the architecture of a typical ANFIS consists of five layers, which perform different functions in the ANFIS and are described below (Jang, 1993).

Layer 1. All the nodes in this layer are adaptive, which indicates that the parameters of the membership functions can be modified through training. The outputs of this layer are given by

$$O_i^1 = \mu_{Ai}(x)$$

where x is crisp input to node i, and Ai is the linguistic label, O_i^1 is the membership function of fuzzy-set A_i, which can be linear or nonlinear. For example, a bell-shaped membership function can be defined as follows:

$$\mu_{Ai}(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}}$$

where (a_i, b_i, c_i) are the parameters of the bell-shaped function. If the values of these parameters change, the bell-shaped functions will change accordingly. Parameters in this layer are referred to as premise parameters.

Layer 2. The nodes in this layer are circle nodes labeled Π, indicating that they perform as a simple multiplier. The output is the product of all inputs and can be represented as follows:

$$w_i = \mu_{Ai}(x) \times \mu_{Bi}(x), \quad i = 1, 2$$

Each node output represents the firing strength of each rule.

Layer 3. The nodes in this layer are also circle nodes labeled N. The ith node is the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. It indicates that this is a normalization layer. The outputs of this layer are given by

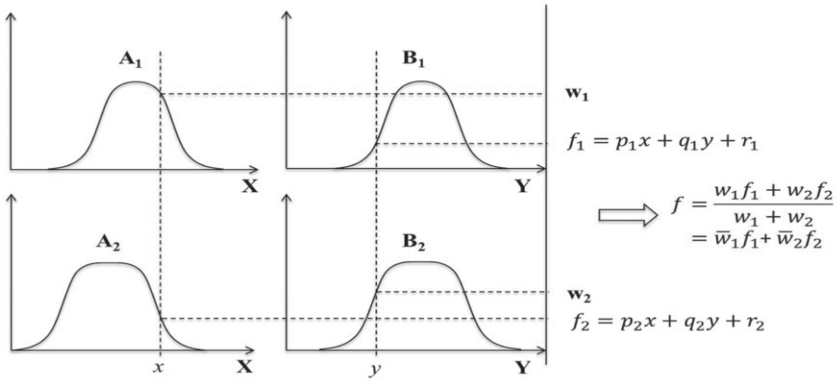
$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2$$

Outputs of this layer are called normalized firing strengths.

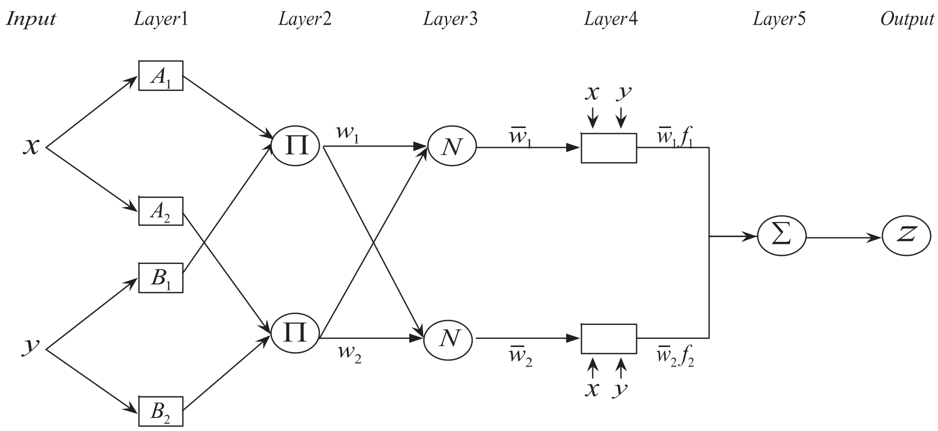
Layer 4. Every node i in this layer is adaptive. The outputs of this layer can be represented as

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i)$$

Parameters in this layer are considered as consequent parameters.



(a) A first order Takagi-Sugeno fuzzy model with two inputs and two rules (Jang, 1993)



(b) The equivalent ANFIS architecture (Jang, 1993)

FIGURE 1 (a) A first-order Takagi–Sugeno fuzzy model with two inputs and two rules (Jang, 1993). (b) The equivalent ANFIS architecture (Jang, 1993)

Layer 5. The node in the last layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals. The overall output is given as

$$\textit{Overall output} = z = O_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_{if_i}}{\sum_i w_i}$$

There are two adaptive layers in the ANFIS architecture, layer 1 and layer 4. The modifiable parameters (a_i, b_i, c_i) in layer 1 are related to the input MFs. The modifiable parameters (p_i, q_i, r_i) in layer 4 pertain to the first-order polynomial. The major task of the training process in the ANFIS architecture is to optimize the fuzzy rules and fuzzy membership functions. Generally, the ANFIS uses the hybrid training algorithm incorporating the gradient method and the least squares estimate to optimize the parameters and quantify the relationships between inputs and outputs. For details, please refer to the study of Jang (1993).

4 | URBAN SUSTAINABILITY ASSESSMENT USING ANFIS

The Urban China Initiative (UCI) (2013) is a joint initiative and is led by three major founding institutions, including Columbia University, Tsinghua University, and McKinsey & Company, and supported by Department of Development Planning of the National Development and Reform Commission. Since 2010, the UCI has been publishing the urban sustainability index (USI), which provides a comprehensive analysis of cities' sustainability in China. The USI data are authoritative and reliable, and can be used as training data for urban sustainability assessment. However, details of the algorithm have not been introduced in the UCI report. It is only noted that the USI can be generated by aggregating values of the basic indicators, which are measured by comparison to the benchmarks in developed economies. Thus, the ANFIS in this research is proposed as an alternative method for urban sustainability assessment. The data relating to basic indicators and the final ranking are provided by the UCI. The data were then used for training the ANFIS models. Furthermore, the bell-shaped membership function has been widely applied to estimate nonlinear relationships (Chang & Chang, 2006; Ekici & Aksoy, 2011; Mingzhi et al., 2009; Sadrmomtazi, Sobhani, & Mirgozar, 2013). Chang and Chang (2006) opined that bell-shaped membership functions have more parameters than other nonlinear functions, so that a nonfuzzy set can be approached when the free parameter is tuned. Bhattacharya and Garhwal (2013) further noted that bell-shaped membership functions are widely used because they give a low rise time and smaller number of fluctuations. Therefore, the bell-shaped membership function will be used in this research. The process of urban sustainability assessment using ANFIS is as follows.

4.1 | Hierarchical structure of the ANFIS model

This study is based on research by the UCI (2013). The UCI adopted a four-level hierarchical structure for urban sustainability assessment. Overall urban sustainability performance is the first level, which is assessed from four aspects, including social, environment, economy and resource, which form the second level. Furthermore, each category comprises subcategories, which are located at the third level. A total of 23 basic indicators are at the fourth level, as shown in Table 2.

Based on the research by the UCI, ANFIS models can be developed and the hierarchical structure of ANFIS models is shown in Figure 2.

TABLE 2 The hierarchical structure for urban sustainability assessment in the UCI research

Category	Subcategory	Basic indicators (unit)
Social	Social welfare	So1: Urban employment rate (%) So2: Number of doctors per capita (per thousand urban population) So3: Middle school students in young urban population aged 0–24 (%) So4: Pension security coverage (%) So5: Healthcare security coverage (%)
Environment	Cleanliness	EnC1: Concentration of SO_2 (mg per cubic meter) EnC2: Concentration of NO_2 (mg per cubic meter) EnC3: Concentration of PM10 (mg per cubic meter) EnC4: Industrial SO_2 discharged per unit GDP (tons per bn RMB) EnC5: Days of air qualified equal or above level II EnC6: Wastewater treatment rate (%) EnC7: Domestic waste treated (%)
	Built environment	EnB1: Persons per square kilometer of urban area EnB2: Passengers using public transit (per capita) EnB3: Coverage of public green space in built area (%) EnB4: Public water supply coverage (%) EnB5: Household access to Internet in total urban households (%)
Economy	Economic development	Ec1: Disposable income per urban capita Ec2: GDP from service industry (%) Ec3: Government investment in R&D (per urban capita)
Resources	Resource utilization	Re1: Total energy consumption (SCE per unit GDP) Re2: Residential power consumption (kWh per capita) Re3: Total water consumption (liters per unit GDP)

Source: Urban China Initiative (UCI) (2013).

SO_2: Sulfur dioxide; NO_2: Nitrogen dioxide; PM10: Particular Matter 10; GDP: Gross Domestic Product; RMB: Renminbi (Chinese Yuan); R&D: Research and Development; SCE: Standard Coal Equivalent

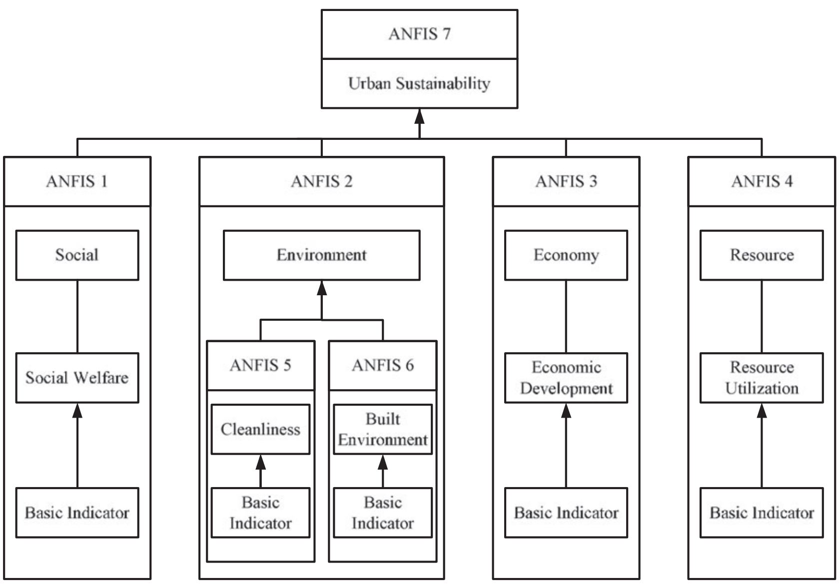


FIGURE 2 Assessment framework of urban sustainability performance

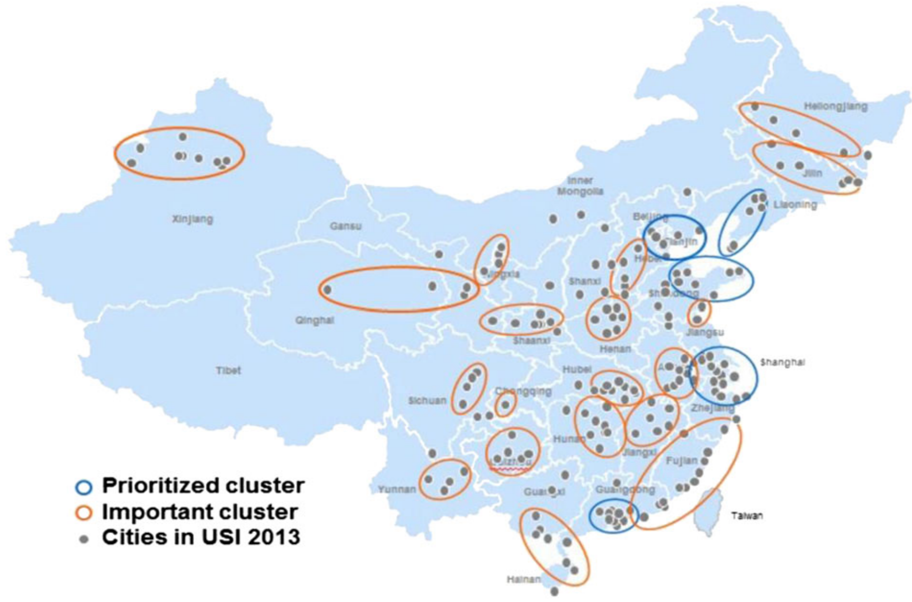


FIGURE 3 The 185 sample cities in China (Source: Urban China Initiative (UCI), 2013) [Colour figure can be viewed at wileyonlinelibrary.com]

Inputs and outputs of ANFIS models can be easily identified through the hierarchical structure. For example, ANFIS 1 has five basic indicators, "Urban employment rate," "Number of doctors per capita," "Middle school students in young urban population aged 0 to 24," "Pension security coverage" and "Health-care security coverage." The scales of these indicators are highly variable. There is a need to normalize the values of the basic indicators within the range from 0 to 1. The five basic indicators can then be used as inputs, and the value of SOCIAL is the output. Similarly, the output of basic ANFIS 1 is used as the input of ANFIS 7. Therefore, seven ANFIS models were developed in this study to assess urban sustainability.

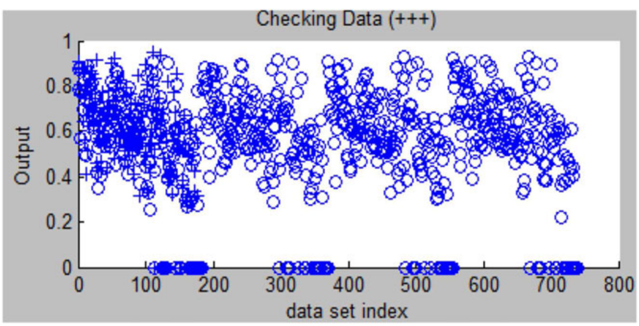


FIGURE 4 Training and checking samples of ANFIS 1 [Colour figure can be viewed at wileyonlinelibrary.com]

4.2 | Data collection

The UCI (2013) applied the same indicator system to assess 185 cities in China over the period 2005–11. Figure 3 shows the 185 selected cities in China. The data generated by the 185 cities from 2005 to 2011 were collected from the UCI for training purposes.

As shown in Figure 3, 23 provincial cities, four municipalities and most of the mega-cities (population over one million) in China are included, accounting for approximately 30% of the total number of cities in China. Therefore, the data from the UCI (2013) will be used as the training and checking samples for the seven ANFIS models. Regarding training and checking samples, Wang and Elhag (2008) suggested that a reasonable ratio between the two is 4:1. In this study, the data from 2005 to 2008, 185 × 4 = 740 datasets, were used as the training samples, and the data from 2009, 185 datasets, as the checking sample. The data from 2010 and 2011 were used as validation samples. Taking ANFIS 1 as an example,

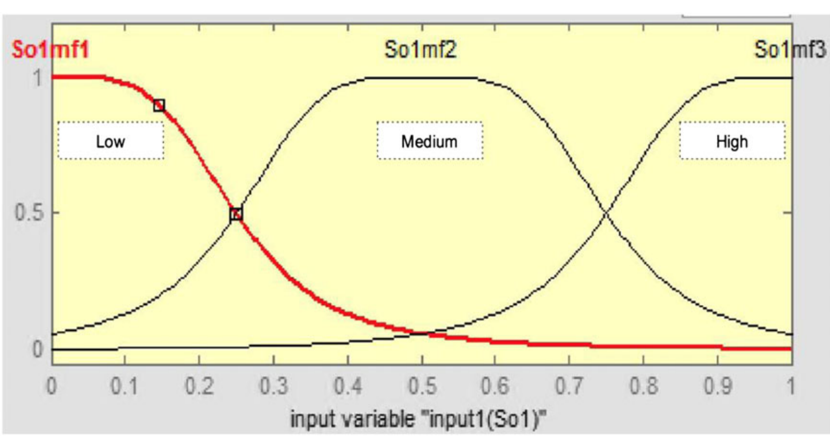


FIGURE 5 Initial membership functions of input 1 (So1) [Colour figure can be viewed at wileyonlinelibrary.com]

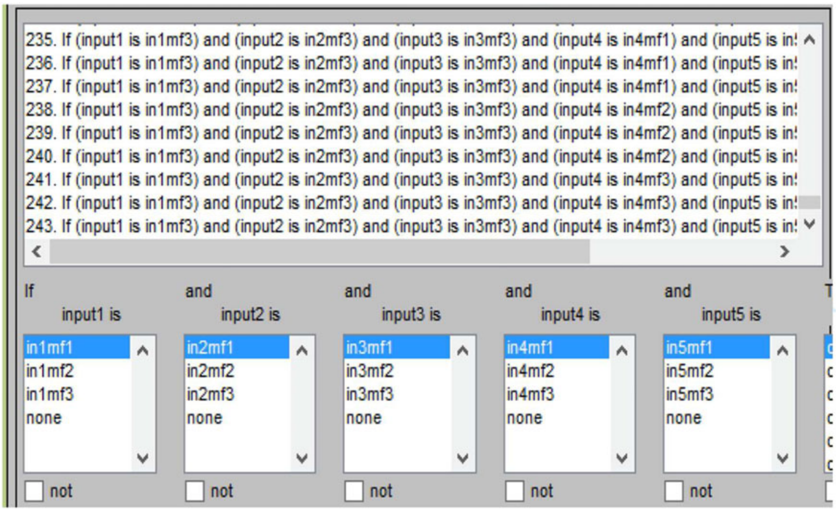


FIGURE 6 If–then rules of ANFIS 1 [Colour figure can be viewed at wileyonlinelibrary.com]

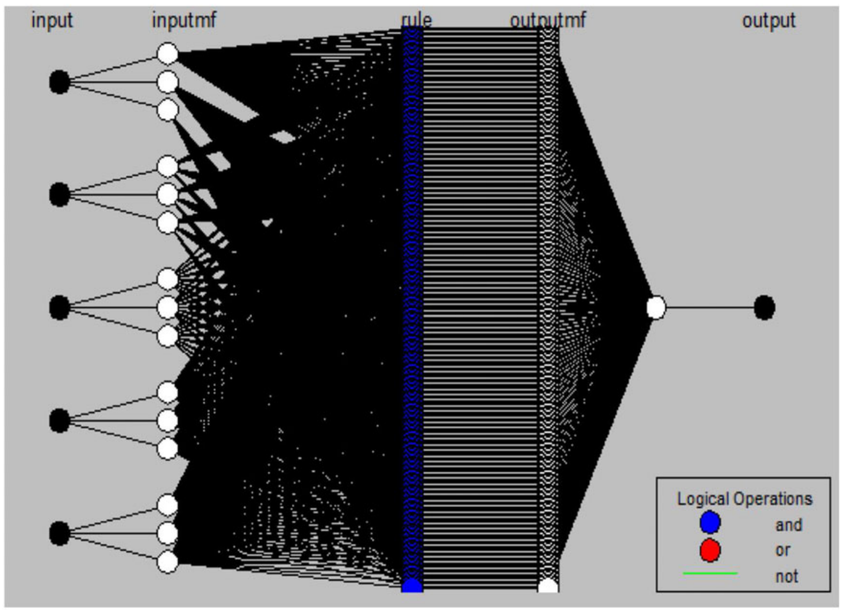


FIGURE 7 Fuzzy inference system structure of ANFIS 1 [Colour figure can be viewed at wileyonlinelibrary.com]

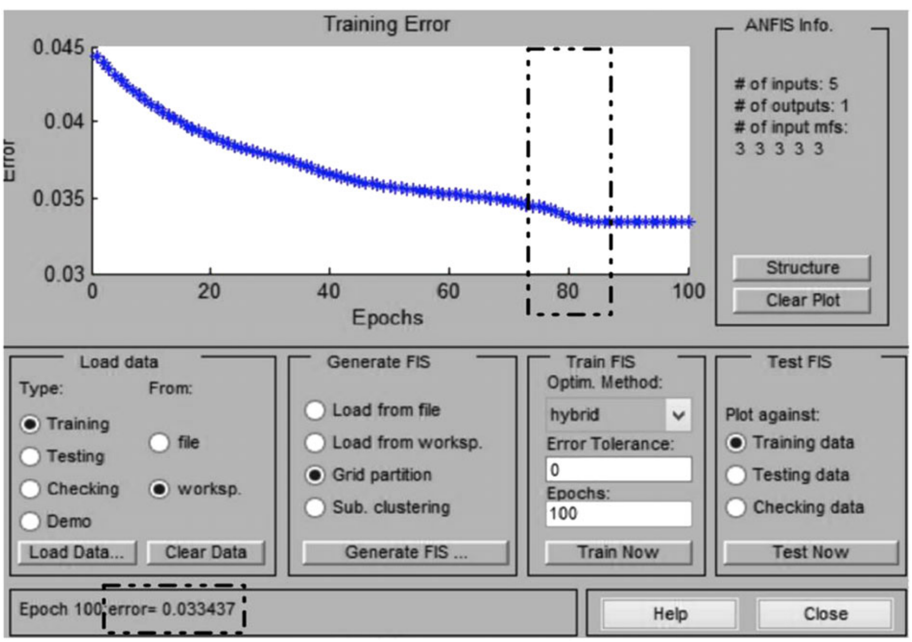


FIGURE 8 Training of ANFIS 1 [Colour figure can be viewed at wileyonlinelibrary.com]

the training and checking datasets samples are shown graphically in Figure 4. The symbols "○" and "+" in this figure denote the training and checking data respectively. In addition, the vertical axis represents the output value of ***Social***, values that are within the range from 0 to 1. The horizontal axis represents the dataset, including 740 training samples and 185 checking samples.

4.3 | Developing ANFIS models

After collecting the training and checking data, the next step is to develop ANFIS models. Basic indicators, subcategories and categories are represented by using fuzzy numbers. Therefore, it is necessary to define the initial fuzzy inference system structure and parameterize the initial membership functions. The membership functions could be linear or nonlinear. In this study, bell-shaped membership functions were used, and each input has three linguistic values, namely weak, medium and strong. Based on the principle of equal distribution, parameters of the initial three bell-shaped membership functions were automatically generated by the MATLAB software. Taking ANFIS 1 as an example, the initial membership functions of the basic indicator "Urban employment rate" are shown in Figure 5.

As shown in Figure 5, there are three bell-shaped membership functions, which denote the three linguistic values, weak, medium and strong. These three membership functions are simple generalized bell-shaped functions with symmetrical distribution (Güler & Übeyli, 2005; Übeylı & Güler, 2005). The vertical axis represents the membership degree of each function, and the horizontal axis represents the normalized value of the input variable. The parameters of the three bell-shaped membership functions are (0.25, 2, 0.0001), (0.25, 2, 0.5) and (0.25, 2, 1). Therefore, the initial bell-shaped membership

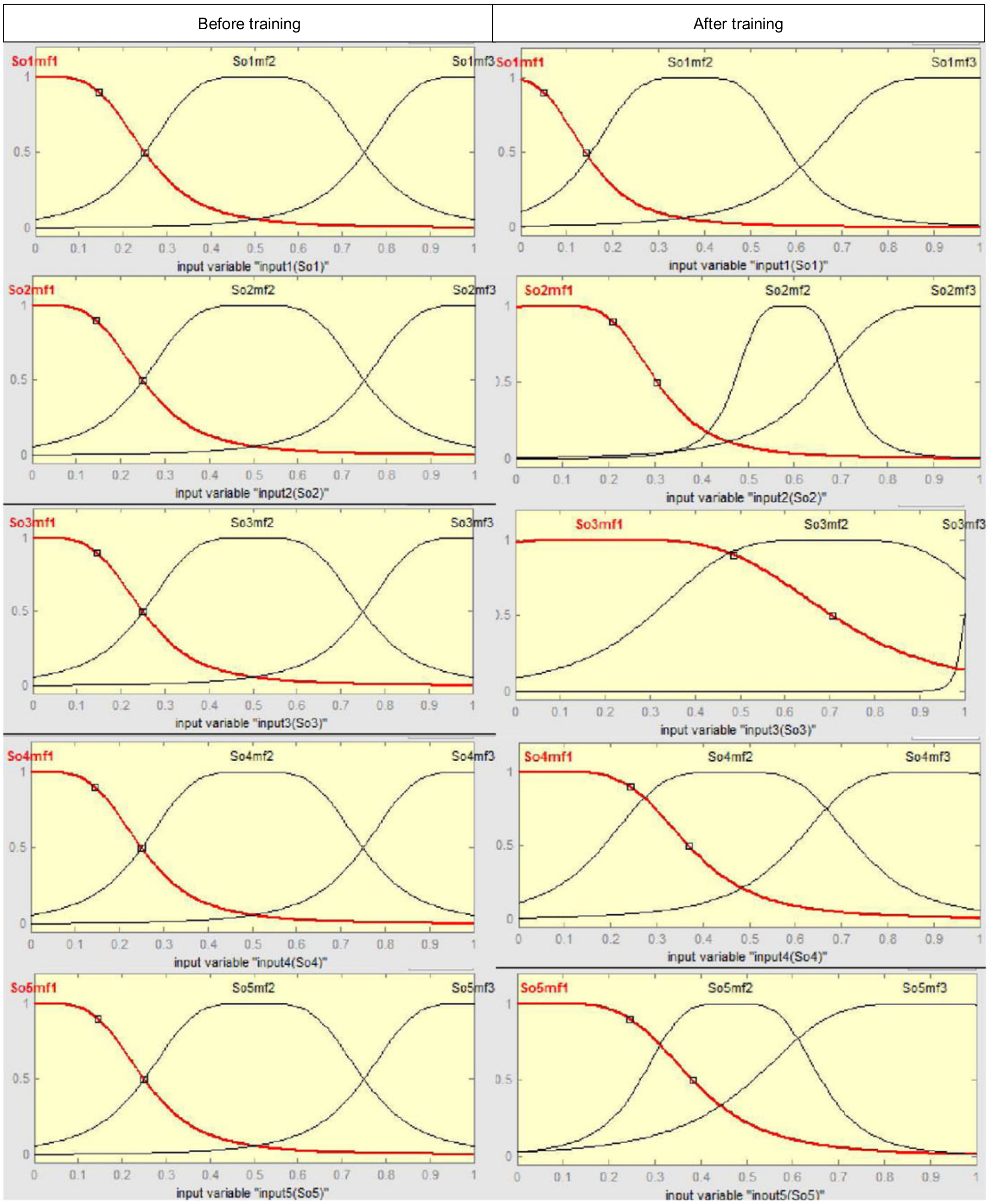


FIGURE 9 Membership functions of five inputs in ANFIS 1 before and after training [Colour figure can be viewed at wileyonlinelibrary.com]

functions of input 1 are denoted as follows. The training will start from the initial membership functions. The final membership functions will be optimized through the training process.

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-0.0001}{0.25}\right|^4}, \mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-0.5}{0.25}\right|^4}, \mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-1}{0.25}\right|^4}$$

After parameterizing the initial membership functions, the next step is to develop an ANFIS fuzzy rules framework. Taking ANFIS 1 as an example, there are five input variables in ANFIS 1 and each input has three linguistic values. Therefore, there will be 3^5 = 243 if–then fuzzy rules in ANFIS 1, as shown in Figure 6.

After developing the fuzzy rules of ANFIS 1, the ANFIS model was established with the aid of the MATLAB Fuzzy Logic Toolbox. The fuzzy inference system structure of ANFIS 1 is shown in Figure 7.

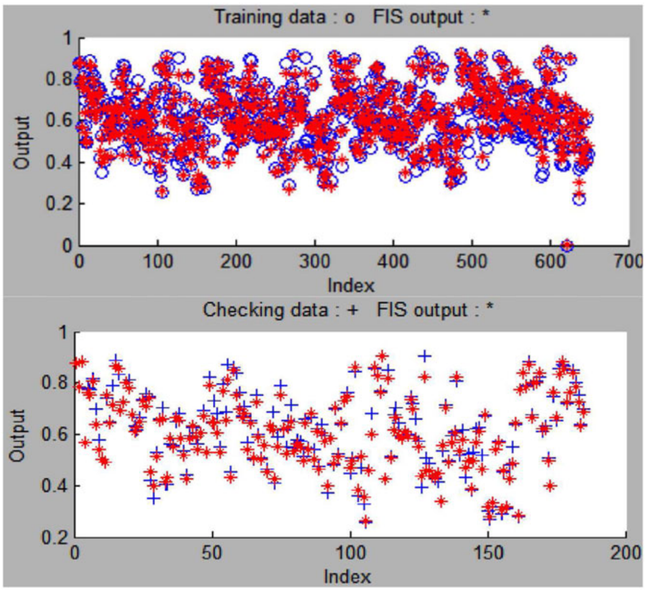


FIGURE 10 Comparison of training data, checking data and the outputs of ANFIS 1 [Colour figure can be viewed at wileyonlinelibrary.com]

4.4 | Training and checking

In this step, the USI data were used for training the parameters of the established ANFIS models. As mentioned above, the ANFIS in the MATLAB software package uses the hybrid training algorithm, which incorporates a gradient method and the least squares estimate. Taking ANFIS 1 as an example, the inputs are the normalized values of five basic indicators, including "Urban employment rate," "Number of doctors per capita," "Middle school students in young urban population aged 0 to 24," "Pension security coverage" and "Health-care security coverage," and the output is the value of ***Social*** category. As mentioned before, the size of training samples is 740. The training process of ANFIS 1 is shown in Figure 8.

In Figure 8, it can be seen that the training error is 0.033 with 100 epochs. The error is 0.033, which is acceptable (<0.1), according to the research of Sun et al. (2015). The training process optimized the parameters of the membership functions, and Figure 9 shows the membership functions of five inputs in ANFIS 1 before and after training.

As shown in Figure 9, the membership functions after training are still bell-shaped with optimized parameters. The optimized parameters reflect the relationships between inputs and outputs in ANFIS 1 based on the USI data. For example, the initial parameter sets of input 1 were changed to (0.242, 2.008, 0.0597), (0.372, 1.977, 0.6299) and (0.348, 1.997, 0.9386) after training, and the membership functions were changed as follows.

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-0.0597}{0.242}\right|^{4.016}}, \mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-0.6299}{0.372}\right|^{3.954}}, \mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-0.9386}{0.348}\right|^{3.994}}$$

After training, the remaining 185 samples were used to check the trained ANFIS models. For example, the training data and checking data of ANFIS 1 are shown in Figure 10.

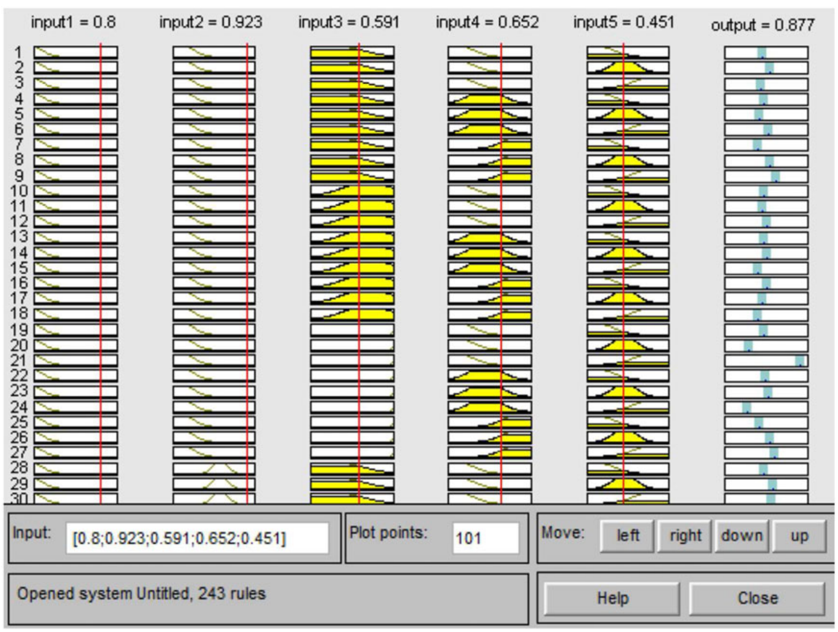


FIGURE 11 If-then rules after training [Colour figure can be viewed at wileyonlinelibrary.com]

As shown in Figure 10, "○" and "+" denote the training and checking data respectively, whereas "*" denotes the value from the ANFIS model. It can be seen that most output values from ANFIS 1 fit the training and checking data very well. Similarly, the training process was also applied to the other six ANFIS models.

With the collected data, the fuzzy if–then rules can also be trained. For ANFIS 1, there are five inputs, and each input is represented by using three linguistic terms. With the input and output data collected from the UCI, the 243 if–then rules were trained, as shown in Figure 11.

In Figure 11, inputs 1, 2, 3, 4 and 5 represent the normalized value of five basic indicators, including "Urban employment rate," "Number of doctors per capita," "Middle school students in young urban population aged 0 to 24," "Pension security coverage" and "Health-care security coverage," and the value of social sustainability performance (***Social***) is the output. Taking Beijing as an example, the values of the five input variables in 2005 are 0.8, 0.923, 0.591, 0.652 and 0.451 respectively, and the output value is 0.875. Values for the input variables for training are 0.8, 0.923, 0.591, 0.652 and 0.451, and the output value of ANFIS after training is 0.877, with an error of 0.2%.

To validate the seven ANFIS models, five cities, distributed over five different regions of China, namely Harbin, Wulumuqi, Xiamen, Haikou and Chongqing, were randomly selected for validation. The values of 23 basic indicators in 2005 were used as the inputs, and the output values from the trained basic indicators were used as the inputs of the next level of ANFIS. The validation results show that the maximum difference of output values between ANFIS and UCI is 8.5%. This indicates that the ANFIS method is suitable for urban sustainability assessment with appropriate training.

5 | DISCUSSION

5.1 | Comparison of assessment results between UCI and ANFIS

After training and checking, the overall sustainability performance of 185 cites was assessed by the ANFIS method using data for 2010 and 2011. The rankings of the 185 cities by UCI and ANFIS are shown in the Appendix. The two rankings are very close. The largest difference is for the city "Lanzhou" in 2010, ranking 116 in UCI and 106 in ANFIS, which is considered acceptable (<10%).

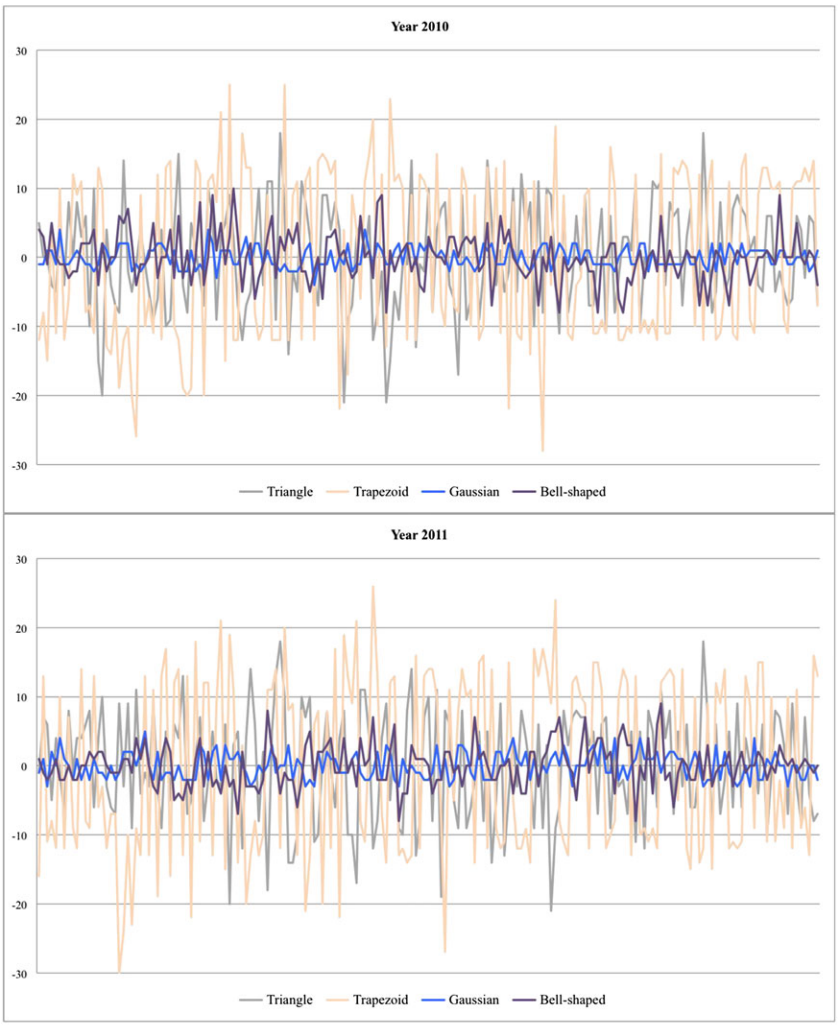


FIGURE 12 Difference in rank between UCI and ANFIS with four membership functions (MFs) in 2010 and 2011 [Colour figure can be viewed at wileyonlinelibrary.com]

5.2 | Membership function selection

As mentioned before, the membership functions could be linear or nonlinear. Also, sustainability assessment involves complexity, dynamics and nonlinearity (Hjorth & Bagheri, 2006). Therefore, this research tested three other types of MFs: triangle, trapezoid and Gaussian. The urban sustainability of 185 cities, from 2010 to 2011, was reassessed by using these three other types of membership functions. The differences in ranking between UCI and ANFIS with four different membership functions are shown in Figure 12.

As shown in Figure 12, the horizontal axis represents the 185 cities, and the vertical axis denotes the differences of ranking between UCI and ANFIS with four different membership functions. It is clear that the nonlinear MFs fit the UCI ranking much better than the linear MFs, which also indicates the nonlinear nature of the sustainability assessment process. Furthermore, the ANFIS models with Gaussian membership functions fit the UCI ranking best. The Gaussian membership function is natural and can be used to approximate any real continuous function with high accuracy (Rasmussen & Williams, 2006).

5.3 | Future research on sustainability assessment

Based on the literature review, most existing sustainability assessment methods lack integration either from a principle perspective or from a technical perspective. The limitations of existing methods, including efficiency-oriented and output-oriented methods, from a principle perspective have been discussed in our literature review. To tackle this issue, integration of the two principles can take advantages of both, and improve the accuracy and dynamics of sustainability assessment.

From a technical integrated perspective, fuzzy-set theory, for example, has been used in sustainability assessment. Nevertheless, predefined fuzzy rules and simple linear membership functions have generally been used in most existing studies. The assessment results may not reflect the real sustainability performance because the predefined rules and membership functions are mostly based on expert knowledge. An appropriate integration of fuzzy-set theory with other methods may provide a solution. ANFIS is a good example. Therefore, integration methods should be considered for future study of sustainability assessment. This view has been echoed by Ness, Urbel-Piirsalu, Anderberg, and Olsson (2007) that the growing experience of sustainability assessment has encouraged a shift from indicator-based to product-related, and the likely trend of sustainability assessment will be toward integrated assessment.

The major contribution of this study is to introduce a new approach, ANFIS, for urban sustainability assessment. The use of ANFIS makes the assessment process close to that of human reasoning, making the results more close to the real-world situation. Furthermore, sustainable development concepts have been promoted at different levels, such as at the country level (Hosseini & Kaneko, 2011; Phillis et al., 2011), city level (Shen, Ochoa, Shah, & Zhang, 2011; Yigitcanlar et al., 2015), industrial level (Bendewald & Zhai, 2013) and project level (Dezhi et al., 2016). The ANFIS method can also be applied in country sustainability assessment, as well as industrial sustainability assessment and project sustainability assessment.

6 | CONCLUSIONS

Sustainability is a complex and dynamic issue. Many assessment methods have been developed. However, the main challenges are vagueness, subjectivity and the dynamics involved in the assessment. To overcome these problems, an ANFIS was introduced in this study for urban sustainability assessment. The fuzzy rules and membership functions can be obtained from training data rather than from expert knowledge. The robust validation process reveals that the ANFIS method is appropriate for evaluation of urban sustainability.

One limitation of this study is that there is only one data source, the UCI. The assessment results are very close to the UCI ranking, and can be further improved by using training data from other sources, such as UN-Habitat and World Bank. Moreover, sustainability assessment is a dynamic process, which requires the assessment method also to be dynamic. Compared with traditional methods, the ANFIS method can meet the dynamic requirements to update the fuzzy rules and membership functions through new training. In future studies, the new source of training data and new training process can be explored to make sustainability assessment more accurate and meet the dynamic changes of the environment.

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APPENDIX A

City	Year 2010 UCI	Year 2010 ANFIS	Year 2010 Difference	Year 2011 UCI	Year 2011 ANFIS	Year 2011 Difference
Shenzhen	1	1	0	2	3	−1
Zhuhai	2	2	0	1	1	0
Guangzhou	3	3	0	5	6	−1
Dalian	4	5	−1	6	8	−2
Xiamen	5	7	−2	4	4	0
Hangzhou	6	6	0	3	2	1
Changsha	7	8	−1	9	9	0
Beijing	8	4	4	8	7	1
Shanghai	9	10	−1	21	23	−2
Qingdao	10	11	−1	12	11	1
Wuxi	11	13	−2	11	13	−2
Zhongshan	12	9	3	14	12	2
Jinan	13	12	1	13	15	−2
FuzhouFJ	14	14	0	7	5	2
Yantai	15	15	0	10	10	0
Weihai	16	17	−1	25	21	4
Ningbo	17	18	−1	15	17	−2
Chengdu	18	20	−2	20	22	−2
Tianjin	19	16	3	18	19	−1
SuzhouJS	20	22	−2	19	16	3
Xian	21	19	2	17	18	−1
Shijiazhuang	22	21	1	26	28	−2
Quanzhou	23	26	−3	36	40	−4
Hefei	24	28	−4	28	31	−3
Qinhuangdao	25	25	0	45	48	−3
Huhehaote	26	30	−4	68	72	−4
Changzhou	27	27	0	22	20	2
Jiaxing	28	24	4	41	42	−1
Shenyang	29	23	6	23	24	−1
Zhenjiang	30	29	1	34	32	2
Dongguan	31	31	0	50	49	1
Shaoxing	32	32	0	24	25	−1
Foshan	33	34	−1	32	30	2
Kunming	34	38	−4	31	27	4
Dongying	35	37	−2	33	37	−4
Yangzhou	36	42	−6	16	14	2
Haikou	37	40	−3	29	34	−5
Taiyuan	38	33	5	27	26	1
Changchun	39	39	0	40	39	1
Kelamayi	40	36	4	39	38	1
Zhoushan	41	43	−2	35	33	2
Nanjing	42	35	7	30	29	1
Maanshan	43	46	−3	42	41	1
Huzhou	44	45	−1	46	47	−1
Wuhan	45	41	4	37	35	2
Huizhou	46	48	−2	38	36	2
Zhanjiang	47	47	0	44	46	−2
Yangquan	48	49	−1	43	45	−2
Zhengzhou	49	44	5	57	61	−4

(Continued)

City	Year 2010 UCI	Year 2010 ANFIS	Year 2010 Difference	Year 2011 UCI	Year 2011 ANFIS	Year 2011 Difference
Wuhu	50	52	−2	70	73	−3
Zibo	51	50	1	53	52	1
Luoyang	52	51	1	59	57	2
Nantong	53	53	0	47	43	4
Zhaoqing	54	58	−4	49	44	5
Fushun	55	54	1	85	86	−1
Yinchuan	56	61	−5	66	64	2
TaizhouZJ	57	56	1	60	56	4
Guiyang	58	55	3	56	59	−3
Taian	59	62	−3	83	76	7
Jiangmen	60	57	3	73	68	5
Daqing	61	59	2	79	77	2
Benxi	62	66	−4	52	50	2
Yanan	63	70	−7	76	78	−2
Tangshan	64	67	−3	69	69	0
Langfang	65	65	0	81	85	−4
Jiujiang	66	60	6	64	60	4
Shaoguan	67	64	3	65	66	−1
Chongqing	68	63	5	54	55	−1
Shantou	69	69	0	61	63	−2
Liuzhou	70	68	2	106	104	2
Sanya	71	71	0	62	62	0
Changzhi	72	78	−6	55	58	−3
Weifang	73	81	−8	72	74	−2
Baoding	74	76	−2	90	92	−2
Qiqihaer	75	77	−2	134	136	−2
Datong	76	73	3	87	79	8
Yingtan	77	79	−2	63	65	−2
Anshan	78	75	3	77	81	−4
Lianyungang	79	84	−5	80	75	5
Baotou	80	74	6	98	96	2
Nanchang	81	72	9	48	51	−3
Yichang	82	82	0	89	88	1
Wenzhou	83	80	3	71	67	4
Chaozhou	84	88	−4	74	71	3
Jingdezhen	85	92	−7	95	93	2
Tongling	86	94	−8	58	54	4
Ningde	87	95	−8	112	106	6
Handan	88	86	2	84	87	−3
Nanning	89	83	6	105	109	−4
Jiaozuo	90	90	0	82	90	−8
JinzhouLN	91	87	4	51	53	−2
ZhuzhouHUN	92	89	3	91	91	0
Harbin	93	85	8	88	84	4
Jieyang	94	97	−3	86	83	3
Mianyang	95	93	2	67	70	−3
Guilin	96	99	−3	75	80	−5
Baoji	97	98	−1	93	95	−2
TaizhouJS	98	105	−7	100	103	−3
Xuzhou	99	96	3	92	89	3
JiningSD	100	91	9	96	98	−2

(Continued)

City	Year 2010 UCI	Year 2010 ANFIS	Year 2010 Difference	Year 2011 UCI	Year 2011 ANFIS	Year 2011 Difference
Binzhou	101	104	−3	104	108	−4
Changde	102	101	1	108	112	−4
Panzhihua	103	100	3	94	94	0
Wulumuqi	104	102	2	97	97	0
Jilin	105	103	2	99	101	−2
Xuchang	106	109	−3	130	132	−2
Xinyu	107	114	−7	103	100	3
Xingtai	108	116	−8	118	111	7
Yuxi	109	113	−4	120	120	0
Zhangzhou	110	108	2	78	82	−4
Huangshi	111	110	1	115	119	−4
Xinxiang	112	112	0	131	127	4
Deyang	113	120	−7	101	99	2
Yibin	114	111	3	109	102	7
Zaozhuang	115	107	8	137	139	−2
Lanzhou	116	106	10	114	116	−2
Jingzhou	117	119	−2	121	118	3
Putian	118	124	−6	111	107	4
Kaifeng	119	118	1	126	130	−4
Beihai	120	115	5	102	105	−3
Huanggang	121	123	−2	128	122	6
Mudanjiang	122	117	5	107	113	−6
Pingdingshan	123	121	2	122	126	−4
Zhangjiajie	124	129	−5	142	141	1
Xining	125	122	3	117	124	−7
Shanwei	126	127	−1	113	121	−8
Linfen	127	130	−3	110	114	−4
Rizhao	128	126	2	133	133	0
Songyuan	129	131	−2	135	135	0
Anyang	130	132	−2	123	117	6
Jinchang	131	125	6	125	125	0
Tongchuan	132	128	4	116	115	1
Yueyang	133	137	−4	124	123	1
Xiaogan	134	136	−2	143	145	−2
Xiangtan	135	135	0	141	140	1
Shizuishan	136	134	2	152	152	0
Anqing	137	139	−2	127	128	−1
Chuzhou	138	138	0	132	131	1
Ezhou	139	133	6	119	110	9
Qujing	140	141	−1	145	143	2
Chizhou	141	143	−2	136	134	2
Xuancheng	142	140	2	139	137	2
FuzhouJX	143	145	−2	144	147	−3
Zunyi	144	146	−2	149	148	1
Shangluo	145	144	1	155	157	−2
Chifeng	146	149	−3	147	146	1
Xianyang	147	142	5	129	129	0
Xianning	148	147	1	150	151	−1
Hengyang	149	148	1	153	153	0
Yiyang	150	150	0	154	156	−2
Weinan	151	151	0	151	150	1

(Continued)

City	Year 2010 UCI	Year 2010 ANFIS	Year 2010 Difference	Year 2011 UCI	Year 2011 ANFIS	Year 2011 Difference
Chaohu	152	152	0	148	144	4
Tianshui	153	153	0	156	154	2
Zhongwei	154	154	0	158	158	0
Suifenhe	155	155	0	157	155	2
Loudi	156	156	0	140	142	−2
Leshan	157	158	−1	146	149	−3
Baiyin	158	159	−1	160	161	−1
Luzhou	159	157	2	138	138	0
Fangchenggang	160	160	0	162	162	0
Changji	161	161	0	161	160	1
Chuxiong	162	164	−2	164	164	0
Anshun	163	162	1	159	159	0
Bole	164	163	1	163	163	0
Yanji	165	166	−1	165	166	−1
Qinzhou	166	165	1	166	167	−1
Duyun	167	167	0	167	165	2
Huanghua	168	169	−1	169	169	0
Wuyishan	169	168	1	168	168	0
Kaili	170	170	0	170	171	−1
Yining	171	171	0	172	173	−1
Wuzhong	172	172	0	171	170	1
Kuitun	173	173	0	174	174	0
Tianmen	174	175	−1	173	172	1
Fukang	175	179	−4	175	175	0
Xiantao	176	177	−1	179	185	−6
Wusu	177	178	−1	178	177	1
Wenchang	178	181	−3	176	176	0
Qianjiang	179	182	−3	180	181	−1
Longjing	180	180	0	177	182	−5
Shihezi	181	176	5	182	183	−1
Tumen	182	183	−1	181	179	2
Geermu	183	174	9	183	180	3
Xingping	184	184	0	184	184	0
Hunchun	185	185	0	185	178	7