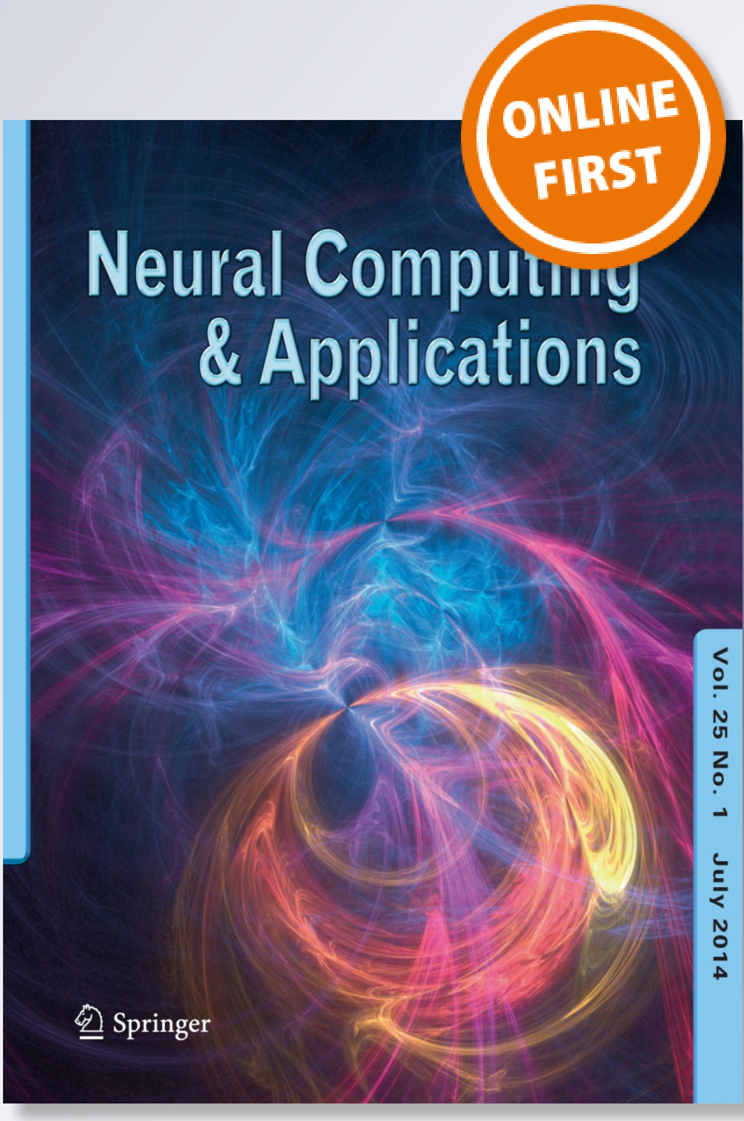
A clustering-based failure mode and effect analysis model and its application to the edible bird nest industry

Kai Meng Tay, Chian Haur Jong & Chee Peng Lim

Neural Computing and Applications

ISSN 0941-0643

Neural Comput & Applic
DOI 10.1007/s00521-014-1647-4



Neural Comput & Applic
DOI 10.1007/s00521-014-1647-4

ADVANCES IN INTELLIGENT DATA PROCESSING AND ANALYSIS

A clustering-based failure mode and effect analysis model and its application to the edible bird nest industry

Kai Meng Tay · Chian Haur Jong · Chee Peng Lim

Received: 24 November 2013 / Accepted: 29 May 2014

Abstract Failure mode and effect analysis (FMEA) is a popular safety and reliability analysis tool in examining potential failures of products, process, designs, or services, in a wide range of industries. While FMEA is a popular tool, the limitations of the traditional Risk Priority Number (RPN) model in FMEA have been highlighted in the literature. Even though many alternatives to the traditional RPN model have been proposed, there are not many investigations on the use of clustering techniques in FMEA. The main aim of this paper was to examine the use of a new Euclidean distance-based similarity measure and an incremental-learning clustering model, i.e., fuzzy adaptive resonance theory neural network, for similarity analysis and clustering of failure modes in FMEA; therefore, allowing the failure modes to be analyzed, visualized, and clustered. In this paper, the concept of a risk interval encompassing a group of failure modes is investigated. Besides that, a new approach to analyze risk ordering of different failure groups is introduced. These proposed methods are evaluated using a case study related to the edible bird nest industry in Sarawak, Malaysia. In short, the contributions of this paper are threefold: (1) a new Euclidean distance-based similarity measure, (2) a new risk interval measure for a group of failure modes, and (3) a new analysis of risk ordering of different failure groups.

K. M. Tay (✉) · C. H. Jong
Faculty of Engineering, Universiti Malaysia Sarawak, Kota Samarahan, Malaysia
e-mail: tkaimeng@yahoo.com; kmtay@feng.unimas.my

C. P. Lim
Centre for Intelligent Systems Research, Deakin University, Victoria, Australia

Keywords Failure mode and effect analysis · Fuzzy ART · Similarity measure · Risk interval measure · Risk ordering

1 Introduction

Failure mode and effect analysis (FMEA) is a popular and effective problem prevention methodology for defining, identifying, and eliminating potential failures and errors of a system, design, process, or service [1]. A search in the literature reveals that FMEA has been used in a wide variety of application domains, e.g., aerospace [2], automotive [1], nuclear [3], electronic [4], manufacturing [5], chemical [6], mechanical [7], health care and hospital [8–10], agriculture [11, 12], and ocean engineering [13, 14]. The main usefulness of FMEA is to identify potential failure modes of a system, understand the causes and effects of each potential failure mode, and determine actions to eliminate or reduce the risk of failure modes [1]. Traditionally, the risk of a failure mode is determined by computing the Risk Priority Number (RPN) [1]. The RPN model considers three factors as its inputs, i.e., severity (*S*), occurrence (*O*), and detect (*D*), and produces an RPN score (i.e., multiplication of *S*, *O*, and *D*) as the output [1]. *S* and *O* are seriousness and frequency of a failure mode, respectively, while *D* is the effectiveness of the existing measures in detecting a failure before the failure effect reaches the customer [1].

Regardless of the popularity of FMEA, the use of the traditional RPN model in FMEA is arguable [2, 15]. In [15], a review of various risk evaluation methods as alternatives to the traditional RPN model was presented. The existing methods are grouped into five categories, i.e., multi-criteria decision-making (MCDM) methods, mathematical programming (MP)

Published online: 01 July 2014

methods, artificial intelligence (AI) methods, integrated methods, and others. In general, MCDM methods interpret *S*, *O*, and *D* as the decision criteria (or sub criteria), and decision alternatives (e.g., causes or failure modes) are evaluated. Note that *S*, *O*, and *D* scores can be precise or imprecise. MP methods consider *S*, *O*, and *D* scores to be precise, or more often imprecise (represented as fuzzy sets). More complicated mathematical techniques (e.g., fuzzy weighted geometric means, fuzzy ordered weighted geometric averaging, and fuzzy envelopment analysis) are used to prioritize the failure modes. AI methods use intelligent algorithms, e.g., rule base system, fuzzy rule base system, fuzzy adaptive resonance theory (ART), and fuzzy cognitive map, in FMEA. The fuzzy rule base system is one of the most popular methods. Both rule base and fuzzy rule base systems use "(fuzzy) If–Then" rules to model the relationship between *S*, *O*, *D*, and RPN. In our previous work [16–18], we argue that it is important to maintain the monotonicity relationship between *S*, *O*, *D*, and RPN scores. The monotonicity relationship is exploited as a useful qualitative information for RPN modeling using fuzzy rule base systems. Integrated methods are methods that attempt to combine more than one methods for risk evaluation, e.g., a hybrid method comprising the fuzzy rule base system and fuzzy analytical hierarchical process, and fuzzy evidential reasoning and gray theory. Example of others methods are Monte Carlo, cost-based model, and kano graph [15].

Some of the above-mentioned methods (influenced by the traditional risk assessment and MCDM practices) attempt to map *S*, *O*, and *D* scores (either precise or imprecise) to a common domain for comparison and ranking. This can be viewed as a mapping or projection of information from a high-dimensional space to one-dimensional space. Making decision with such methods exploits the mapped *S*, *O*, and *D* scores, in one (dimensional) common domain. The use of mapping in FMEA is useful, as it provides a metric to assess *S*, *O*, and *D* scores. However, making decision solely based on the mapped *S*, *O*, and *D* scores can be disadvantageous, as some important information is lost (i.e., projection from a higher-dimensional space to one-dimensional space) or modified (i.e., tuning, optimization, identification, or preprocessing techniques in more complicated risk modeling techniques). In this paper, the focus is on the use of a clustering technique for analysis of failure modes in FMEA. It is worth noting that the use of fuzzy ART in FMEA was examined by Keskin and Özkan [19], with the reason that different combinations of *S*, *O*, and *D* could produce the same RPN scores. In addition to this reason, we further justify the advantages of using clustering techniques in FMEA in this paper, as follows: (1) Clustering deals with the original *S*, *O*, and *D* scores directly; (2) clustering allows failure modes to be compared, or visualized in the *S*, *O*, and *D* space as groups of information; and (3) use of the original *S*, *O*, and *D* scores (instead of the mapped *S*, *O*, and *D* scores into a common domain) avoids loss or modification of important information for decision making.

Motivated from the above-mentioned reasons, the main aim of this paper was to investigate the use of an Euclidean distance-based similarity measure and an incremental-learning clustering technique (i.e., fuzzy ART [20]) for analysis of failure modes in FMEA. The Euclidean distance-based similarity measure quantifies the similarity between two failure modes by taking their *S*, *O*, and *D* scores into consideration. This measure is important as it provides a quantity to indicate whether a failure mode under consideration (represented by its *S*, *O*, and *D* scores) is similar to others; therefore, serving as a solution to one of the key issues in FMEA, i.e., different combinations of *S*, *O*, and *D* can produce the same RPN scores. As an example, consider two failure modes with *S*, *O*, and *D* scores of [1 1 10] and [1 10 1]. With the traditional RPN model, the RPN score of 10 for both failures is produced. However, with the proposed Euclidean distance-based similarity measure (as described in Sect. 3.1), their similarity measure is 0.1835. This implies that even though both failure modes are associated with the same RPN score, they can be differentiated by the similarity measure. It is worth mentioning that the use of the similarity measure in decision-making problems is not new, e.g., in perceptual computing, the Jaccard similarity measure was used [21].

In general, clustering is a process of organizing sets of data samples, which are attributed by multi-dimensional features, into separate groups based on their similarity [22]. The data samples within a cluster share some similar features, as compared to those associated with other clusters [22]. Examples of popular clustering techniques are *k*-means clustering [23], fuzzy ART [20, 24], and fuzzy c-means [25]. In this paper, the focus is on the use of fuzzy ART for clustering failure modes in FMEA into different groups. Fuzzy ART is chosen because of its adaptive and incremental-learning properties. Besides that, failure modes should be prioritized. In [19], each group of failure modes is ranked and prioritized according to its arithmetic mean. In this paper, the risk of each failure mode is evaluated with the (fuzzy) RPN model. Instead of arithmetic mean, the risk of each group of failure modes is represented as a risk interval measure, i.e., the minimum and maximum RPN scores of the failure modes in the group using the (fuzzy) RPN model. In addition, risk ordering of different groups of failure modes is analyzed. Such analysis attempts to provide additional information, i.e., whether the risk of a group of failure modes is higher than that of another group of failure modes.

The contributions of this paper are threefold: (1) an Euclidean distance-based similarity measure to quantify the degree of similarity between two failure modes; (2) a risk interval measure to represent the risk of a group of failure modes; and (3) a risk ordering analysis for different groups of failure modes. The Euclidean distance-based similarity measure provides a measure of ordinary distance of two failure modes in the S, O, and D space (as in **Definition 1**). The risk interval measure provides a measure of risk pertaining to a group of failure modes in the S, O, and D space. The risk ordering analysis of two groups of failure modes further indicates whether both groups can be ordered or one is a subset of another. To evaluate the proposed method, real-world data and information from swiftlets farming and edible bird nest (EBN) processing [11, 12] are used. The experimental results are discussed and analyzed.

This paper is organized as follows. In Sect. 2, the traditional RPN and fuzzy rule base RPN models are explained. In Sect. 3, the use of fuzzy ART in FMEA and our proposed methods are described. In Sect. 4, the experimental results are presented and discussed. Finally, concluding remarks are provided in Sect. 5.

2 Background

In this section, S, O, D, and RPN are defined. The traditional RPN and fuzzy rule base RPN model are explained.

2.1 Severity, occurrence, detect, and Risk Priority Number

Traditionally, FMEA adopts the RPN model, which considers three risk factors, i.e., S, O, and D, for failure mode analysis and risk prioritization [1]. In this paper, these three risk factors are defined as the input space, as follows.

Definition 1: An input space, i.e., $S \times O \times D$, is considered. Variables s, o, and d are the elements of S, O, and D, respectively, i.e., $s \in S$, $o \in O$, and $d \in D$. The lower and upper boundaries of S is represented by $\underline{s}$ and $\bar{s}$, respectively. Similarly, the lower or upper boundaries of O and D are represented by $\underline{o}$ and $\bar{o}$, as well as $\underline{d}$ and $\bar{d}$, respectively.

A set of data samples in the S, O, and D space, as defined in **Definition 1**, i.e., $[s, o, d]$, are considered. Traditionally, the risk of $[s, o, d]$ is compared with other sets of data samples in the RPN space. The RPN space and RPN are defined as follows.

Definition 2: The RPN space is the output space containing all possible RPN scores, i.e., RPN $\in$ RPN space. The lower and upper boundaries of the RPN space is represented by $\underline{\mathrm{RPN}}$ and $\overline{\mathrm{RPN}}$, respectively. The RPN space follows a monotonic, ordered sequence, i.e., the higher the RPN score, the higher the risk.

2.2 The traditional and fuzzy inference system-based RPN models

Traditionally, the risk of $[s, o, d]$ is obtained using Eq. 1 and is designated as the RPN score. Equation 1 can be viewed as a mapping of $[s, o, d]$ to the RPN space.

$$\mathrm{RPN} = s \times o \times d \tag{1}$$

As an alternative to the traditional RPN model, the fuzzy rule base RPN model was proposed [2, 16–18]. Hereafter, the fuzzy rule base RPN model is known as the fuzzy inference system (FIS)-based RPN model. Each S, O, and D domain is defined using a scale table, with m_S, m_O, and m_D partitions, respectively. Each partition in the S, O, and D domains is represented by a fuzzy membership function, i.e., $\mu_X^{n_X}(x)$, and is associated with a linguistic term, i.e., $A_X^{n_X}$, where $n_X = 1, 2, 3, \ldots, m_X$, $x \in [s, o, d]$ and $X \in [S, O, D]$. Note that the fuzzy membership functions follow an ordered sequence, i.e., $\mu_X^{p_X}(x) \preccurlyeq \mu_X^{p_X+1}(x)$, where $p_X \in [1, 2, 3, \ldots, m_X - 1]$. The relationships between S, O, D, and RPN are formulated as a set of fuzzy rules, as follows.

R^{n_S,n_O,n_D}: If severity is $A_S^{n_S}$ and occurrence is $A_O^{n_O}$ and detect is $A_D^{n_D}$, then RPN is B^{n_S,n_O,n_D} where B^{n_S,n_O,n_D} is the fuzzy consequence in the RPN space. Note that b^{n_S,n_O,n_D} is the fuzzy singleton [26] for B^{n_S,n_O,n_D}. With the zero-order Sugeno FIS model [26], the RPN score is obtained using Eq. 2. To ease the explanation, the RPN score obtained from the FIS-based RPN model is called the Fuzzy RPN score, where Fuzzy RPN $\in$ RPN space and **Definition 2** applies.

$$\mathrm{FuzzyRPN}(s, o, d) = \frac{\sum_{n_S=1}^{m_S} \sum_{n_O=1}^{m_O} \sum_{n_D=1}^{m_D} \left(\mu_S^{n_S}(s) \times \mu_O^{n_O}(o) \times \mu_D^{n_D}(d) \times b^{n_S,n_O,n_D}\right)}{\sum_{n_S=1}^{m_S} \sum_{n_O=1}^{m_O} \sum_{n_D=1}^{m_D} \left(\mu_S^{n_S}(s) \times \mu_O^{n_O}(o) \times \mu_D^{n_D}(d)\right)} \tag{2}$$

3 The proposed methods

In this section, the proposed Euclidean distance-based similarity measure is firstly formulated. The use of fuzzy ART for failure modes clustering is presented. The proposed formulations for risk interval and analysis of risk ordering of failure groups are further explained.

3.1 Euclidean distance-based similarity measure

A set of failure modes, each represented as a data sample in the S, O, and D space, as defined in Definition 3, is considered.

Definition 3: A set of data samples with m failure modes is considered. Each failure mode is denoted as $\overline{x_k} =$

$[s_k, o_k, d_k]$ in the S, O, and D space (**Definition 1**), $k = 1, 2, 3, \ldots, m$.

An Euclidean distance-based similarity measure for two failure modes is formulated. The similarity measure between two failure modes, i.e., $\overline{x_k} = [s_k, o_k, d_k]$ and $\bar{x}_j = [s_j, o_j, d_j]$, $j, k = 1, 2, 3, \ldots, m$, is computed using Eq. 3.

$$\text{Similarity } (\overline{x_k}, \overline{x_j}) = 1 - \sqrt[2]{\frac{(s_k - s_j)^2 + (o_k - o_j)^2 + (d_k - d_j)^2}{(\bar{s} - \underline{s})^2 + (\bar{o} - \underline{o})^2 + (\bar{d} - \underline{d})^2}} \quad (3)$$

Note that Similarity $(\overline{x_k}, \overline{x_j})$ = Similarity $(\overline{x_j}, \overline{x_k})$. The higher the similarity measure, the higher the degree of similarity between $\overline{x_k}$ and $\overline{x_j}$. If $\overline{x_k} = \overline{x_j}$, Similarity $(\overline{x_k}, \overline{x_j}) = 1$. If $\overline{x_k} = [\bar{s}, \bar{o}, \bar{d}]$ and $\overline{x_j} = [\underline{s}, \underline{o}, \underline{d}]$, vice versus, Similarity $(\bar{x}_k, \bar{x}_j) = 0$. As an example, if $\overline{x_k} = [1, 1, 10]$ and $\overline{x_j} = [1, 10, 1]$, Similarity $(\overline{x_k}, \overline{x_j}) = 0.1835$.

3.2 Fuzzy ART for clustering of failure modes

The fuzzy ART neural network is adopted for clustering all failure modes. Each failure mode is fed in sequence, i.e., starting from $\overline{x_1}$, $\overline{x_2}$, until $\overline{x_m}$. The architecture of fuzzy ART is depicted in Fig. 1. In layer 1 (or input layer), there are 6 nodes, i.e., s_{nor}, o_{nor}, d_{nor}, s^c_{nor}, o^c_{nor}, and d^c_{nor}. In layer 2 (or recognition layer), there are s cluster prototypes, $s > 0$, and s can be increased over time depending on the availability of data samples. Each cluster prototype is labeled as C_z, where $z = 1, 2, 3, \ldots, s$. The weight connecting C_z and x_{nor} is denoted as $w_{x_{\text{nor},z}}$. As an example, the weight connecting C_1 and s_{nor} is denoted as $w_{s_{\text{nor},1}}$ and that connecting C_s and d^c_{nor} is denoted as $w^c_{d_{\text{nor},s}}$. All weights are contained in a matrix, i.e., $W_{x_{\text{nor},z}}$. Each component of $W_{x_{\text{nor},z}}$ is labeled as $W_{x_{\text{nor},z}}(v)$, where $v = 1, 2, 3\ldots, 6$..

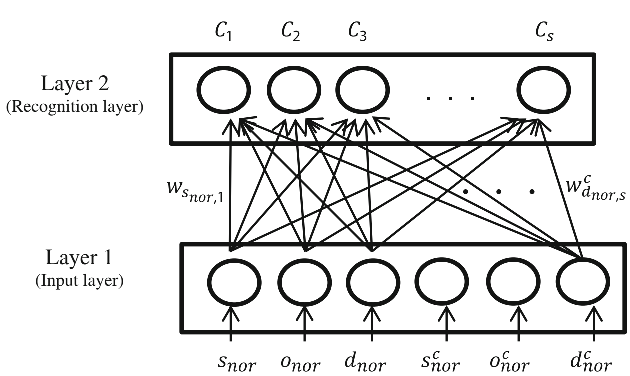


Fig. 1 Fuzzy ART architecture, in which layer 2 is an incremental layer

The dynamics of fuzzy ART can be divided into the following steps.

(i) *Normalization and complement coding*

(a) Normalize S, O, and D to [0, 1].

(b) Normalize each s_k, o_k, and d_k to [0, 1] using Eq. (4). Normalized $\bar{x}_k$ is denoted as $\overline{x_{k,\text{nor}}} = [s_{k,\text{nor}}, o_{k,\text{nor}}, d_{k,\text{nor}}]$

$$x_{k,\text{nor}} = \frac{x_k - \underline{x}}{\bar{x} - \underline{x}}, \text{ where } x \in [s, o, d] \quad (4)$$

(c) Perform complement coding [20] of $s_{k,\text{nor}}$, $o_{k,\text{nor}}$, and $d_{k,\text{nor}}$, i.e., $s^c_{k,\text{nor}}$, $o^c_{k,\text{nor}}$, and $d^c_{k,\text{nor}}$, using Eq. (5).

$$x^c_{k,\text{nor}} = 1 - x_{k,\text{nor}}, \text{ where } x \in [s, o, d] \quad (5)$$

(d) Form the complement-coded failure mode of $\overline{x_{k,\text{nor}}}$, i.e., $\overline{x^c_{k,\text{nor}}} = [s_{k,\text{nor}}, o_{k,\text{nor}}, d_{k,\text{nor}}, s^c_{k,\text{nor}}, o^c_{k,\text{nor}}, d^c_{k,\text{nor}}]$. Again, each component of $\overline{x^c_{k,\text{nor}}}$ is labeled as $\overline{x^c_{k,\text{nor}}}(v)$ where $v = 1, 2, 3, \ldots, 6$. As an example, $\overline{x^c_{k,\text{nor}}}(1) = s_{k,\text{nor}}$.

(ii) *Parameters setting*: The choice ($\propto$), vigilance (ρ), and learning rate (β) parameters are determined. Among these three parameters, ρ plays the key role as it regulates the granularity of the cluster structures formed in fuzzy ART [20]. In this paper, $\propto = 0.0001$ and $\beta = 1$ (i.e., fast learning) are adopted, while ρ is varied, with its effect examined.

(iii) *Initialization*: The number of cluster is set to 1 (i.e., $s = 1$), but is incremental as learning progresses. The weights connecting C_1 and x_{nor} are initialized to 1.

(iv) *Category Choice, Test, and Search*: Each input vector (i.e., $\overline{x^c_{k,\text{nor}}}$) is transmitted from layer 1 to layer 2. The response of each node in layer 2 is computed using the *choice function* (Eq. 6). The node that has the highest response, denoted as node $J \in (1, 2, 3, \ldots, s)$, is selected as the winning node (Eq. 7). If there is a tie on $T_{k,z}$, the node with the smallest index is chosen.

$$T_{k,z} = \frac{\sum_{v=1}^{v=6} \left(\overline{x^c_{k,\text{nor}}}(v) \bigwedge W_{x_{\text{nor},z}}(v)\right)}{\propto + \sum_{v=1}^{v=6} \left(W_{x_{\text{nor},z}}(v)\right)} \quad (6)$$

$$T_J = \max\left(T_{k,z} : z = 1, 2, 3, \ldots, s\right) \quad (7)$$

Winning node J propagates its weight vector back to layer 1. A vigilance test (Eq. 8) is performed to measure the similarity against the vigilance threshold between the transformed category prototype and the input vector.

$$M(J)=\frac{\sum_{v=1}^{v=6}\left(\overline{x_{k,\mathrm{nor}}^{c}}(v)\bigwedge W_{x_{\mathrm{nor},J}}(v)\right)}{\sum_{v=1}^{v=6}\left(\overline{x_{k,\mathrm{nor}}^{c}}(v)\right)} \tag{8}$$

If the vigilance test is satisfied, resonance is said to occur and learning takes place (the next step). However, if the vigilance test fails, node J is inhibited, i.e., it is prohibited from participating in subsequent competitions. Input $\overline{x_{k,\mathrm{nor}}^{c}}$ is re-transmitted to layer 2 to search for a new winner. This process is repeated, consecutively disabling nodes in layer 2, until either an existing winning node is able to pass the vigilance test, or, if no such node is available, a new node is created to encode the input vector.

(v) *Learning*: Once the search process ends, learning takes place by adjusting $W_{x_{\mathrm{nor},J}}$ using Eq. (9).

$$W_{x_{\mathrm{nor},J,\mathrm{new}}}(v)=\beta\left(\overline{x_{k,\mathrm{nor}}^{c}}(v)\bigwedge W_{x_{\mathrm{nor},J,\mathrm{old}}}(v)\right)+(1-\beta)W_{x_{\mathrm{nor},J,\mathrm{old}}}(v),\ \text{where } v=1,2,3,\ldots,6 \tag{9}$$

3.3 Risk interval measure

In this study, the risk of a group of failure modes ($\overline{x_k}\in C_z$) is represented as a risk interval, i.e., $\mathrm{RPN}_z=\left[\underline{\mathrm{RPN}_z},\overline{\mathrm{RPN}_z}\right]$. The traditional or FIS-based RPN model (as explained in Sect. 2.2) is used to obtain the RPN score of $\overline{x_k}=[s_k,o_k,d_k]$ and is denoted as RPN_k. The risk interval of C_z is obtained using Eqs. (10) and (11).

$$\underline{\mathrm{RPN}_z}=\min(\mathrm{RPN}_k,\quad \text{for all } \overline{x_k}\in C_z) \tag{10}$$

$$\overline{\mathrm{RPN}_z}=\max(\mathrm{RPN}_k,\quad \text{for all } \overline{x_k}\in C_z) \tag{11}$$

3.4 Risk ordering

In this study, risk ordering of different failure groups is analyzed with the risk interval produced from Sect. 3.3. Consider two failure groups C_{z1} and C_{z2}, where $z1,z2\in 1,2,3,\ldots,s$, with their risk intervals, $\mathrm{RPN}_{z1}=\left[\underline{\mathrm{RPN}_{z1}},\overline{\mathrm{RPN}_{z1}}\right]$ and $\mathrm{RPN}_{z2}=\left[\underline{\mathrm{RPN}_{z2}},\overline{\mathrm{RPN}_{z2}}\right]$, respectively. The ordering relationship between RPN_{z1} and RPN_{z2} is summarized in Table 1. If $\underline{\mathrm{RPN}_{z1}}<\underline{\mathrm{RPN}_{z2}}$ and $\overline{\mathrm{RPN}_{z1}}<\overline{\mathrm{RPN}_{z2}}$, then $\mathrm{RPN}_{z1}<\mathrm{RPN}_{z2}$. If $\underline{\mathrm{RPN}_{z1}}=\underline{\mathrm{RPN}_{z2}}$ and $\overline{\mathrm{RPN}_{z1}}<\overline{\mathrm{RPN}_{z2}}$, then $\mathrm{RPN}_{z1}\le\mathrm{RPN}_{z2}$. If $\overline{\mathrm{RPN}_{z1}}=\overline{\mathrm{RPN}_{z2}}$ and $\underline{\mathrm{RPN}_{z1}}=\underline{\mathrm{RPN}_{z2}}$, then $\mathrm{RPN}_{z1}=\mathrm{RPN}_{z2}$. If $\underline{\mathrm{RPN}_{z1}}>\underline{\mathrm{RPN}_{z2}}$ and $\overline{\mathrm{RPN}_{z1}}<\overline{\mathrm{RPN}_{z2}}$, then $\mathrm{RPN}_{z1}\in\mathrm{RPN}_{z2}$ and C_{z1} and C_{z2} cannot be ordered.

4 A case study

In this section, a case study related to swiftlets farming and EBN processing is presented. The background of EBN [11] and its S, O, and D definitions are explained. The experimental results are analyzed and discussed.

4.1 Background of swiftlets farming and edible bird nest processing

Edible bird nest (or known as "the *Caviar of the East*") is the nest of swiftlets, which is consumed as a type of (healthy) food [27]. With a high demand of EBN from China, swiftlets farming and EBN processing have emerged as a popular urban industry among Southeast Asia countries, including Malaysia [28]. It is worth noting that Sarawak and Sabah (two states of Malaysia in the Borneo Island) are the second ranked resource area (after Indonesia) of the world for EBN production [11]. Despite the popularity of EBN as a food source, it is challenging to ensure its quality of EBN processing. Indeed, many activities on enhancing the quality of EBN have been reported, as summarized in [11]. EBN production comprises five sub-processes [11], i.e., (i) swiftlets farming, (ii) harvesting, (iii) EBN cleaning, (iv) EBN drying and reshaping, and (v) storing and packaging. The use of FMEA (with FIS-based RPN) for improving these sub-processes was reported in [11]. Information and data were gathered from several swiftlets farms and EBN production plants in Sarawak [11]. Based on the preliminary investigation in [11], we extend the work using a clustering-based FMEA technique in this study. Specifically, information and data from [11] are further analyzed with several proposed methods, as mentioned in Sect. 3. Two continuous sub-processes of EBN production, i.e., EBN cleaning as well as EBN drying and reshaping, are examined in details, as follows.

4.2 Severity, occurrence, and detect scale tables

The scale tables of S, O, and D are presented in Tables 2, 3 and 4, respectively. In each scale table, column "Ranking" states the score intervals. These intervals are tagged with a linguistic term, as in column "Linguistic Term ($A_X^{n_X}$)", where $n_X=1,2,3,\ldots,m_X$ and $X\in[S,O,D]$. There are m_X intervals for each S, O, and D, respectively. A detailed description of each interval is summarized in column "Description". As an example, a score from 1 to 2 is assigned with the linguistic term of "Very Low" for S, i.e., A_S^1. This interval is used to indicate a failure with a minor effect, which can be ignored. Besides that, even if the failure occurs, the yield and the product quality are still excellent.

Table 1 Risk ordering of RPN_{z1} and RPN_{z2}

$\underline{\mathrm{RPN}_z}$	$\underline{\mathrm{RPN}_{z1}} < \underline{\mathrm{RPN}_{z2}}$	$\underline{\mathrm{RPN}_{z1}} = \underline{\mathrm{RPN}_{z2}}$	$\underline{\mathrm{RPN}_{z1}} > \underline{\mathrm{RPN}_{z2}}$
$\overline{\mathrm{RPN}_z}$			
$\overline{\mathrm{RPN}_{z1}} < \overline{\mathrm{RPN}_{z2}}$	$\mathrm{RPN}_{z1} < \mathrm{RPN}_{z2}$	$\mathrm{RPN}_{z1} \le \mathrm{RPN}_{z2}$	$\mathrm{RPN}_{z1} \in \mathrm{RPN}_{z2}$
$\overline{\mathrm{RPN}_{z1}} = \overline{\mathrm{RPN}_{z2}}$	$\mathrm{RPN}_{z1} \le \mathrm{RPN}_{z2}$	$\mathrm{RPN}_{z1} = \mathrm{RPN}_{z2}$	$\mathrm{RPN}_{z1} \ge \mathrm{RPN}_{z2}$
$\overline{\mathrm{RPN}_{z1}} > \overline{\mathrm{RPN}_{z2}}$	$\mathrm{RPN}_{z1} \ni \mathrm{RPN}_{z2}$	$\mathrm{RPN}_{z1} \ge \mathrm{RPN}_{z2}$	$\mathrm{RPN}_{z1} > \mathrm{RPN}_{z2}$

Table 2 Scale table for severity (from [11])

Ranking	Linguistic term $(A_S^{n_s})$	Description
1–2	Very low	Effect of the potential failure mode is not obvious and can be ignored
		Excellent yield and product quality
3–4	Low	Very minor impact to the production yield
		Failures cause a minor impact to EBN food production process control. The consequence will cause a minor effect to the products' cosmetic appearance and packaging
5–7	Medium	Failures lead to the issue of minor security breaches of the farm, and habitat of the swiftlets is affected by some of the pests and enemies of the swiftlets. The consequence will cause a reduction in the population of the swiftlets and the yield of the farm
		Failures cause a minor impact to the production yield
8–9	High	Failures lead to the issue of serious security breaches of the farm. Safety of the swiftlets will be threatened by its enemies, such as thieves and predators
		Failures cause a major impact to the production yield
10	Very high	Failures lead to impacts to product safety and quality
		Compliance to law
		Major impact to the reputation of the company and the products
		Lead to failure to yield management

Table 3 Scale table for occurrence (from [11])

Ranking	Linguistic term, $(A_O^{n_o})$	Description
1	Extremely low	Failures happen at least once ever
2–3	Very low	Failures happen at least once within 6–12 months
4–5	Low	Failures happen at least once within 1–6 months
6–7	Medium	Failures happen at least once within 1–30 days
8–9	High	Failures happen at least once within 1–8 working hours
10	Very high	Failures happen many times within an hour

4.3 Results and discussions

4.3.1 Risk evaluation and clustering results

Table 5 summarizes the risk evaluation results with the traditional and FIS-based RPN models, together with the clustering results of fuzzy ART. Sub-columns "k" and "Description" are the label and description of a failure mode, respectively. Columns "Sev," "Occ," and "Det" contain the S, O, and D score of each failure mode, respectively. The risk evaluation results with the traditional and FIS-based RPN models are presented in columns "RPN" and "Fuzzy RPN," respectively. Columns C_k are the clustering results using fuzzy ART with three different settings of the vigilance parameter, i.e., $\rho = 0.7$, 0.9, and 0.95. As an example, the first failure mode (i.e., $k = 1$) is described as "Tearing of raw EBN." Its S, O, and D scores are 4, 9, and 1, respectively. With the traditional RPN model (i.e., Eq. (1)) and fuzzy RPN model (i.e., Eq. (2)), the RPN and fuzzy RPN scores for this failure mode are 36 and 422, respectively. With fuzzy ART, this failure mode belongs to the first cluster, for the three ρ settings.

As shown in Table 5, all failure modes are clustered into 1, 3, and 5 groups with $\rho = 0.7$, 0.9, and 0.95, respectively. When $\rho = 0.9$, failure modes 1, 3, and 4 belong to the first group; failure modes 5–13 belong to the second group; failure mode 2 belongs to the third group. When $\rho = 0.95$, there are five groups. Cluster 1 contains failure mode 1; cluster 2 contains failure modes 3 and 4; cluster 3 contains failure modes 6, 7, 11, and 12; cluster 4 contains failure

Table 4 Scale table for detect (from [11])

Ranking	Linguistic term, $(A_D^{n_D})$	Description
1–3	Very high	Detection is excellent
		Control actions can almost detect the failure on the spot and appropriate actions are taken to solve the failure and the weakness.
		Prevent the excursion from occurring
4–6	High	Detection is good
		Control actions can almost detect the failure on the spot within the same process module or steps
		In farm management, control actions can detect the failure within 1 day
		Appropriate actions are available to solve the failure and the weakness
7–8	Medium	Detection is acceptable
		Control actions can detect the failure within one to two process modules or steps
		In farm management, control actions can detect the failure within one to three days
		Appropriate actions are available. However, the failure can be tricky and hard to solve
9	Low	Hard to detect
		Control actions may not detect the failure
		Appropriate actions may not be available and the failure cannot be solved
10	Very low	Detection is almost impossible
		No control action is available
		No solution is available for solving the failure

Table 5 Risk evaluation and clustering results of failure modes

Failure mode		Sev	Occ	Det	RPN	Fuzzy RPN (from [11])	C_k		
k	Description						$\rho = 0.7$	$\rho = 0.9$	$\rho = 0.95$
1	Tearing of raw EBN	4	9	1	36	422	1	1	1
2	Dissolution of EBN	4	6	2	48	339	1	3	5
3	Dirty EBN	3	10	1	30	447	1	1	2
4	Tearing of raw EBN	4	10	1	40	465	1	1	2
5	EBN is not dry enough for the reshaping process	3	7	4	84	532	1	2	4
6	Spraying is uneven	4	7	4	112	549	1	2	3
7	Cracking of the EBN	4	8	4	128	591	1	2	3
8	Cracking of the EBN	3	8	4	96	574	1	2	4
	Too much gaps								
9	Failure in molding	3	8	4	96	574	1	2	4
10	EBN is too dry	3	7	4	84	532	1	2	4
11	Spraying is uneven	4	7	4	112	549	1	2	3
12	Cracking of the EBN	4	7	4	112	549	1	2	3
13	EBN is too dry and may crack	3	7	4	84	532	1	2	4

modes 5, 8, 9, 10, and 13; and cluster 5 contains failure mode 2.

4.3.2 Similarity measures among failure modes

The similarity measures among all failure modes in Table 5 are obtained using the proposed Euclidean distance-based similarity measure (i.e., Eq. (3)). The results are shown in Table 6. As an example, for $j, k = 1$, Similarity $(\overline{x_1}, \overline{x_1}) = 1$. Similarity between the first and second failure modes can be obtained by setting $j = 1$, $k = 2$, i.e., Similarity $(\overline{x_2}, \overline{x_1}) = 0.79714$ (as shaded in Table 6). From Table 6, the minimum and maximum similarity measures are 0.7971 and 1, respectively. These failure modes are close to each other in the $S \times O \times D$ space.

Table 6 Similarity measures among failure modes, Similarity $(\overline{x_k}, \overline{x_j})$

$\overline{x_j}$ \ $\overline{x_k}$	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	0.79714	0.909278	0.93585	0.759973	0.768704	0.79714	0.787238	0.787238	0.759973	0.768704	0.768704	0.759973
2	0.79714	1	0.727834	0.735503	0.842865	0.856556	0.818556	0.80755	0.80755	0.842865	0.856556	0.856556	0.842865
3	0.909278	0.727834	1	0.93585	0.727834	0.720377	0.759973	0.768704	0.768704	0.727834	0.720377	0.720377	0.727834
4	0.93585	0.735503	0.93585	1	0.720377	0.727834	0.768704	0.759973	0.759973	0.720377	0.727834	0.727834	0.720377
5	0.759973	0.842865	0.727834	0.720377	1	0.93585	0.909278	0.93585	0.93585	1	0.93585	0.93585	1
6	0.768704	0.856556	0.720377	0.727834	0.93585	1	0.93585	0.909278	0.909278	0.93585	1	1	0.93585
7	0.79714	0.818556	0.759973	0.768704	0.909278	0.93585	1	0.93585	0.93585	0.909278	0.93585	0.93585	0.909278
8	0.787238	0.80755	0.768704	0.759973	0.93585	0.909278	0.93585	1	1	0.93585	0.909278	0.909278	0.93585
9	0.787238	0.80755	0.768704	0.759973	0.93585	0.909278	0.93585	1	1	0.93585	0.909278	0.909278	0.93585
10	0.759973	0.842865	0.727834	0.720377	1	0.93585	0.909278	0.93585	0.93585	1	0.93585	0.93585	1
11	0.768704	0.856556	0.720377	0.727834	0.93585	1	0.93585	0.909278	0.909278	0.93585	1	1	0.93585
12	0.768704	0.856556	0.720377	0.727834	0.93585	1	0.93585	0.909278	0.909278	0.93585	1	1	0.93585
13	0.759973	0.842865	0.727834	0.720377	1	0.93585	0.909278	0.93585	0.93585	1	0.93585	0.93585	1

4.3.3 Risk interval and the risk ordering analysis

Table 7 summarizes the risk intervals and risk ordering analyses of failure modes. Column "ρ" is the vigilance parameter setting of fuzzy ART. Column "RPN model" is the RPN model used for risk evaluation. Column "$\mathrm{RPN}_z = \left[\underline{\mathrm{RPN}_z}, \overline{\mathrm{RPN}_z}\right]$" shows the risk interval for each group of failure modes. Column "risk ordering analysis" shows risk ordering of different failure groups. As an example, when $\rho = 0.7$, there is only one failure group. With the traditional RPN and FIS-based RPN models, the risk intervals for RPN_1 are [30, 128] and [339, 591], respectively.

When $\rho = 0.9$, there are three failure groups and their risk intervals are [30, 40], [84, 128], and [48, 48], respectively, with the traditional RPN model. From the risk intervals, it can be observed that $\mathrm{RPN}_1 < \mathrm{RPN}_3 < \mathrm{RPN}_2$. This implies that the degree of risk associated with the second group is higher than that of the third, which is followed by the first group. Using the FIS-based RPN model, the risk intervals are [422, 465], [532, 591], and [339, 339], respectively. A different risk ordering is obtained, i.e., $\mathrm{RPN}_3 < \mathrm{RPN}_1 < \mathrm{RPN}_2$. This is because different RPN models produce different RPN values. Group 1 consists of three potential failures ($k = 1, 3, 4$), and group 3 consists of one potential failure ($k = 2$). It can be observed that group 1 consists of failures with higher O scores (i.e., 9 or 10, which implies once within 1–8 h or many times in an hour, see Table 3) than that of group 3 (i.e., 6, which implies at least once within 1–30 days). All potential failures in both groups 1 and 3 have very good D scores, i.e., 1 or 2, which implies good detection actions and prevention measures are available. Even though potential failures in group 1 has better D score (i.e., 1) than that of group 3 (i.e., 2), the detection actions are still excellent and effective (see Table 4). Therefore, based on the feedback and opinions from domain experts, the risk of group 1 should be higher than that of group 3, owing to its O scores. For group 2, both the RPN and FIS-based RPN models suggest that its potential failures have the highest risk.

When $\rho = 0.95$, there are five failure groups. With the traditional RPN model, it can be observed that $\mathrm{RPN}_1, \mathrm{RPN}_2 < \mathrm{RPN}_5 < \mathrm{RPN}_4 < \mathrm{RPN}_3$, and $\mathrm{RPN}_1 \in \mathrm{RPN}_2$. Again, with the FIS-based RPN model, a different risk ordering is obtained, i.e., $\mathrm{RPN}_5 < \mathrm{RPN}_1, \mathrm{RPN}_2 < \mathrm{RPN}_4 < \mathrm{RPN}_3$. Based on the above-mentioned reasons, feedback and opinions from domain experts suggest that the risk of groups 1 and 2 should be higher than that of group 5. Both the RPN and FIS-based RPN models suggest that the potential failures in group 3 have the highest risk, which is followed by group 4.

Table 7 Risk interval and the risk ordering analysis of failure modes

ρ	RPN model	$RPN_z = \left[\underline{RPN_z}, \overline{RPN_z}\right]$					Risk ordering analysis
		$z = 1$	$z = 2$	$z = 3$	$z = 4$	$z = 5$	
0.7	Traditional RPN	[30, 128]	–	–	–		–
	FIS-based RPN	[339, 591]	–	–	–		–
0.9	Traditional RPN	[30, 40]	[84, 128]	[48, 48]	–		$RPN_1 < RPN_3 < RPN_2$
	FIS-based RPN	[422, 465]	[532, 591]	[339, 339]	–		$RPN_3 < RPN_1 < RPN_2$
0.95	Traditional RPN	[36, 36]	[30, 40]	[112, 128]	[84, 96]	[48, 48]	$RPN_1, RPN_2 < RPN_5 < RPN_4 < RPN_3, RPN_1 \in RPN_2$
	FIS-based RPN	[422, 422]	[447 465]	[549 591]	[532 574]	[339, 339]	$RPN_5 < RPN_1, RPN_2 < RPN_4 < RPN_3, RPN_1 \in RPN_2$

In short, the proposed risk interval and risk ordering analysis allow different failure groups to be ranked and analyzed. The outcome of the analysis is dependent on the RPN model used. The empirical results show that the FIS-based RPN model is able to produce a better risk ordering than that of the traditional RPN model.

4.3.4 Remarks

The applicability of an incremental-learning clustering technique (i.e., fuzzy ART [20]) for analysis of failure modes in FMEA has been demonstrated. Fuzzy ART is capable of rapid and stable learning of recognition categories in response to arbitrary sequences of failure modes [20]. Besides that, its incremental-learning feature [20] allows new failure modes to be included and analyzed from time to time. However, it is not guaranteed that fuzzy ART will always provide an optimal clustering outcome.

5 Summary

In this paper, the use of fuzzy ART for clustering failure modes in FMEA has been investigated. Three new concepts in FMEA have been proposed. First, the new Euclidean distance-based similarity measure allows the similarity of failure modes to be quantified. Next, fuzzy ART allows failure modes in FMEA to be clustered into different groups effectively, even if a new failure mode(s) is included. Then, the risk interval measure allows the risks associated with failure mode groups to be obtained and ordered. The usefulness of these proposed concepts have been demonstrated using real data and information gathered from the EBN industry in Sarawak [11]. Positive results have been obtained. The results have also been properly analyzed and discussed. The outcomes are in line with the opinions of the domain experts. For further work, visualization of failure modes in FMEA using a self-organizing map [29] and an evolving tree [30, 31] will be investigated. Besides that, the use of clustering and visualization techniques in other decision-making and assessment problems, e.g., education assessment [32], will be further examined.

Acknowledgments The authors gratefully acknowledge the Exploratory Research Grant Scheme (ERGS/1/11/TK/UNIMAS/03/05), Fundamental Research Grant Scheme (FRGS/ICT02(01)/997/2013(38)), and Research Acculturation Collaborative Effort (RACE/F2/TK/UNIMAS/5) for supporting this research work and Universiti Malaysia Sarawak for the facilities.

References

1. Stamatis DH (2003) Failure mode and effect analysis: FMEA from theory to execution. ASQ Press
2. Bowles JB, Peláez CE (1995) Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. Reliab Eng Syst Safe 50:203–213
3. Guimarães ACF, Lapa CMF (2004) Fuzzy FMEA applied to PWR chemical and volume control system. Prog Nucl Energy 44:191–213
4. Zafiropoulos EP, Dialynas EN (2005) Reliability prediction and failure mode effects and criticality analysis (FMECA) of electronic devices using fuzzy logic. Int J Qual Reliab Manag 22:183–200
5. Tay KM, Lim CP (2006) Fuzzy FMEA with a guided rules reduction system for prioritization of failures. Int J Qual Reliab Manag 23:1047–1066
6. Garrick BJ (1988) The approach to risk analysis in three industries: nuclear power, space systems, and chemical process. Reliab Eng Syst Safe 23:195–205
7. Korayem MH, Iravani A (2008) Improvement of 3P and 6R mechanical robots reliability and quality applying FMEA and QFD approaches. Robot Comput Integr Manuf 24:472–487
8. McNally KM, Page MA, Sunderland VB (1997) Failure-mode and effects analysis in improving a drug distribution system. Am J Health Syst Pharm 54:171–177
9. Kahraman C, Kaya İ, Şenvar Ö (2013) Healthcare failure mode and effects analysis under fuzziness. Hum Ecol Risk Assess 19:538–552
10. Geum Y, Shin J, Park Y (2011) FMEA-based portfolio approach to service productivity improvement. Serv Ind J 31:1825–1847

11. Jong CH, Tay KM, Lim CP (2013) Application of the fuzzy failure mode and effect analysis methodology to edible bird nest processing. Comput Electron Agric 96:90–108
12. Jong CH, Tay KM, Lim CP (2014) A single input rule modules connected fuzzy FMEA methodology for edible bird nest processing. In: Snášel V, Krömer P, Köppen M, Schaefer G (eds) Soft computing in industrial applications, vol 223. Springer, Switzerland, pp 165–176
13. Helvacioglu S, Ozen E (2014) Fuzzy based failure modes and effect analysis for yacht system design. Ocean Eng. doi:10.1016/j.oceaneng.2013.12.015
14. Zaman MB, Kobayashi E, Wakabayashi N, Khanfir S, Pitana T, Maimun A (2014) Fuzzy FMEA model for risk evaluation of ship collisions in the Malacca Strait: based on AIS data. J Simul 8:91–104
15. Liu HC, Liu L, Liu N (2013) Risk evaluation approaches in failure mode and effects analysis: a literature review. Expert Syst Appl 40:828–838
16. Tay KM, Lim CP (2008) On the use of fuzzy inference techniques in assessment models: part I—theoretical properties. Fuzzy Optim Decis Mak 7:269–281
17. Tay KM, Lim CP (2008) On the use of fuzzy inference techniques in assessment models: part II—industrial applications. Fuzzy Optim Decis Mak 7:283–302
18. Tay KM, Lim CP (2011) On monotonic sufficient conditions of fuzzy inference systems and their applications. Int J Uncertainty Fuzziness Knowl Based Syst 19:731–757
19. Keskin GA, Özkan C (2009) An alternative evaluation of FMEA: fuzzy art algorithm. Qual Reliab Eng Int 25:647–661
20. Carpenter GA, Grossberg S, Rosen DB (1991) Fuzzy ART: fast stable learning and categorization of analog patterns by an adaptive resonance system. Neural Netw 4:759–771
21. Mendel J, Wu D (2010) Perceptual computing: aiding people in making subjective judgments. Wiley, Hoboken, New Jersey
22. Rui X, Donald CW (2009) Clustering. IEEE Press/Wiley, Hoboken, New Jersey
23. MacQueen J (1967) Some methods for classification and analysis of multivariate observations. In: Proceedings of the fifth Berkeley symposium on mathematical statistics and probability, pp 281–297
24. Carpenter GA, Grossberg S, Rosen DB (1991) ART 2-A: an adaptive resonance algorithm for rapid category learning and recognition. Neural Netw 4:493–504
25. Pal NR, Pal K, Keller JM, Bezdek JC (2005) A possibilistic fuzzy c-means clustering algorithm. IEEE Trans Fuzzy Syst 13:517–530
26. Jang JSR, Sun CT, Mizutani E (1997) Neural-fuzzy and soft computing. Prentice-Hall, Upper Saddle River, New Jersey
27. Hobbs JJ (2004) Problems in the harvest of edible birds' nests in Sarawak and Sabah, Malaysian Borneo. Biodivers Conserv 13:2209–2226
28. Jordan D (2009) Globalization and bird's nest soup. Int Dev Plan Rev 26:97–110
29. Kohonen T (2001) Self organizing maps, 3rd edn. Springer, Berlin
30. Pakkanen J, Iivarinen J, Oja E (2006) The evolving tree-analysis and applications. IEEE Trans Neural Netw 17:591–603
31. Chang WL, Tay KM, Lim CP (2014) A new evolving tree for text document clustering and visualization. In: Snášel V, Krömer P, Köppen M, Schaefer G (eds) Soft computing in industrial applications, vol 223. Springer, Switzerland, pp 141–151
32. Jee TL, Tay KM, Ng CK (2013) A new fuzzy criterion-referenced assessment with a fuzzy rule selection technique and a monotonicity-preserving similarity reasoning scheme. J Intell Fuzzy Syst 24:261–279