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MODEL AND ALGORITHM OF FUZZY EVALUATION OF TECHNICAL STANDARDS ALLIANCES MEMBERS – FROM THE PERSPECTIVE OF NETWORK EMBEDDEDNESS

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Abstract. *As the modern marketplace becomes ever more networked, an enterprise can obtain resources such as technology and knowledge, as well as continuous competitive advantage, by "embedding" itself into a technical standards alliance. The question of how to choose partners to achieve a successful alliance is an important one. However, a "paradox" for the embedded relationship in the network exists, and if partnerships were analyzed in isolation as leaving both resources and environment of organization, deviations would appear. Only by bringing the network embeddedness into the analytical framework for surveying the relationships amongst members of technical standards alliances can the network "paradox" be solved. This paper establishes a model for evaluating the partners in a technical standards alliance based on a fuzzy cognitive map (FCM). Firstly, by means of the FCM's causal relationship reasoning and fuzzy measurement, the relationships and mutual influence among evaluation criteria are depicted and understood. Secondly, the non-linear Hebbian learning algorithm is integrated in the establishment of a fuzzy feedback system of knowledge-transfer evaluation. Through the study and training of a cognitive map, the dependence on the experts' opinions is avoided in the evaluation process. Finally, the effectiveness and rationality of the model are demonstrated through calculation examples.*

Keywords: Technical standards alliances, Alliances members, Network embeddedness, FCM

1. **Introduction.** Along with the development of the modern market economy, standards – as a new commanding height in international competition – have become an important means of formulating market rules. Against the backdrop of networked enterprises (referring to both the network development of enterprises and organizations and the networked technological innovation of enterprises), it is increasingly difficult for individual organizations to grasp diverse knowledge and independently develop all technologies. Thus, it has become a common practice for many enterprises to develop their own standards by setting up or joining technical standards alliances (TSAs). However, the long-term development of such enterprises is plagued by instability. Spekman, Dacni, and Hitt and many other scholars were convinced that the failure rate of enterprise alliances was 60%, whereas Woodman suggested that it was as high as 70% [1]. There is a general assumption among scholars that the selection of members by alliances is one of the most important factors leading to such high failure rates.

An enterprise joining such an alliance gains access to technology and knowledge, as well as other resources. However, the question of "what is the best embedding relationship" is in dispute; some studies have found that a higher level of network embeddedness can enhance the performance of enterprises [2,3]. Other empirical studies have shown that strong network embeddedness has a negative influence on enterprise performance [4,5]. These contradictory views call for an in-depth research on alliance relationships.

Recent years have seen many studies on evaluation methods and models for enterprise alliance partnerships, including multi-objective programming (MOP), data envelopment analysis (DEA), fuzzy neural networks (FNN), and fuzzy analytic hierarchy processes (F-AHP) [6-8]. However, these methods are flawed by their inability to automatically update weights and the omission of interactions between indicators, among other problems. Moreover, the constantly changing evaluation criteria of TSA members have curtailed the methods to effectively solve the problem of evaluating members dynamically. Therefore, this study attempts to use fuzzy cognitive mapping (FCM) to construct a fuzzy evaluation model for TSA members that overcomes these limitations and improves the accuracy of evaluation.

2. **Evaluation Index System for TSA Members.** Both foreign and domestic scholars have offered descriptions of TSAs from different perspectives, including organizational mechanisms, causes for alliances, and types of alliance [9,10]. This research proposes that a TSA is a special strategic alliance that is formed by enterprises around key and core techniques to share technical achievements and decrease costs for standardization, which means that it is a contractual alliance with a loose organizational mechanism. The nature of a TSA is a value network that accumulates numerous technical and social resources.

There have been few studies focused on evaluating the TSA members. By combining relevant theories and literature, and by the author's long-term tracking and visiting of domestic TSAs, the present paper argues that the fundamental purpose for members to participate in a TSA is to be continually competitive by being "embedded" in this network and to obtain alliance resources like techniques and knowledge. Therefore, reviewing membership from the perspective of network embeddedness is to adopt it as the evaluation index of membership; this paper also proposes that membership is established on the basis of member selection, and attempts to establish a member-evaluation index system of TSAs from the perspective of a "congenital-factor" (member selection) and an "acquired factor" (network embeddedness).

Adopting Sierra and Cauley's 3C theory as a model, and taking references from the work of Fang et al. and Holm et al. [11,12], this research combines the main purpose for establishing TSAs (i.e., achieving complementary resources, common technological progress, and product and market development) with the classification of the TSA members based on reputation, compatibility, and technical standardization capacity. Here, "reputation" includes brand and product reputations; "compatibility" includes compatibility with rules and regulations and with strategic objectives and core values, etc.; "technical capability" includes technology absorption capacity, technology management capability, and technology innovation capability; and "market capabilities" include marketing cognitive capability, marketing development capability, and the suitability of marketing and R&D.

This research references McEvily, Marcus, and Wang Jiong, and classifies network embeddedness into trust, information-sharing, and joint problem-solving [13,14]. Trust refers to alliance members not attacking each other; information-sharing refers to alliance members sharing information with each other so as to promote the operation and innovation of other members, which is especially critical for TSAs; joint problem-solving refers to network members sharing the responsibility for maintaining the partnership and solving problems, which is also a necessary mechanism for designing and promoting a standards-linked alliance.

On the basis of the above analysis, this paper establishes a member-evaluation index system of TSAs, as shown in Table 1.

Table 1. TSA members evaluation index system based on the network embeddedness

Partners Selection Index	reputation (A)	brand reputation (A_1)
		product reputation (A_2)
	compatibility (B)	compatibility with rules and regulations (B_1)
		compatibility with strategic objectives (B_2)
		compatibility with core values (B_3)
	technical capabilities (C)	technology absorption capacity (C_1)
		technology management capability (C_2)
		technology innovation capability (C_3)
	market capabilities (D)	marketing development capability (D_1)
		marketing cognitive capability (D_2)
		fit of marketing R&D (D_3)
Membership Index-Network Embeddedness (E)		trust (E_1)
		information sharing (E_2)
		joint problem solving (E_3)

3. **FCM Model for Member-Evaluation in TSAs.** The fuzzy cognitive map (FCM) proposed by Kosko is a dynamic system-analysis and modeling method based on Axelrod's cognitive map method and Zadeh's fuzzy set theory, and performs reasoning according to causal relationships [15]. It has been widely applied to research in the social and behavioral sciences, on stock exchanges, and on military policies.

3.1. **Reasoning process for a fuzzy cognitive map.** The diagram and its corresponding weight matrix compose a fuzzy cognitive map. The former is made up of concept nodes: C_i ($i = 1, 2, \ldots, n$, with n being the number of concept nodes); each concept node represents a key element of the system, with a value $A_i \in [-1, 1]$. A_i^k is the state value of the concept node C_i at time k; A_i^{k+1} is for the next time. The weight matrix is the adjacency matrix of interaction between concepts; between A_i^k and A_i^{k+1} is the FCM reasoning process [15].

At each step of reasoning, the state vector A_i^k is multiplied by adjacency matrix W, and then changed to A_i^{k+1} by F. F is the threshold function ensuring that each iteration output is within $[0, 1]$. This paper uses the following threshold function:

$$F(x) = \tanh(x) = (1 - e^{-x})(1 + e^{-x})$$

Since the model being established is qualitative, the threshold function can be adopted to unify the input value at concept nodes. The hyperbolic tangent function $f(x) = \tanh(x)$ is one of the commonly used threshold functions and value of concept nodes can be negative; therefore, this paper adopts this threshold function.

FCM reasoning process is an iterative process. It means that the output of this step A_i^{k+1} becomes input for the next step of reasoning. The interaction between certain specific concepts and other concepts can be calculated by the following iterative formula:

$$C^{(k+1)} = f\left(C^{(k)}W\right),\ C^{(0)} = I_{n\times n} \tag{1}$$

Using a certain number of iterations, a stable state can be considered to be reached when the state value of the concept node reaches one of the following: ① a fixed value; ② a cyclically-changing value; or ③ a chaotic state, i.e., the state value is unpredictable and random.

As can be seen from the above reasoning, the FCM has two significant drawbacks: strong dependence on expert opinion; and the final state may converge beyond the desired state. To enhance the effectiveness and robustness of the fuzzy cognitive map, it is necessary to update the weight matrix by using a learning algorithm, so that the final state can converge within the desired steady state.

3.2. **Weight learning algorithm.** This paper adopts the Papageorgiou's nonlinear Hebbian learning (NHL) algorithm, which is based on the following hypothesis: in each iteration, the simulated values of the concept nodes will cause the state value of the output to change accordingly [16]. Hence, the iteration formula modified by the NHL algorithm is the following:

$$A_i^{(k+1)} = f\left(A_i^{(k)} + \sum\nolimits_{\substack{j=1\\ j\neq i}}^{N} A_j^{(k)} W_{ji}^{(k)}\right) \tag{2}$$

in which $W_{ji}^{(k)}$ is the weight of the relationship between concept nodes C_j and C_i at the kth iteration. The calculation method is as follows:

$$W_{ji}^{(k)} = \gamma W_{ji}^{(k-1)} + \eta A_i^{(k-1)}\left(A_i^{(k-1)} - sgn(W_{ji}) W_{ji}^{(k-1)} A_i^{(k-1)}\right) \tag{3}$$

in which η is the learning rate parameter ($0 < \eta < 0.1$); the trial and error method is usually adopted to determine its value. γ ($0.9 < \gamma < 1$) is the weight-attenuation factor. $sgn(W_{ji})$ is used to ensure that the appropriate weight symbol maintains its original physical meaning. $-sgn(W_{ji})W_{ji}^{(k-1)}\left(A^{(k-1)}\right)^2$ is used to prevent the weight from increasing beyond the desired value.

By updating the weights in each iteration, the NHL algorithm minimizes two standard functions. The first of those standard functions measures the difference between the actual value (DOC_i) and the mean target value (T_i) of each desired output concept (DOC) satisfies experts' requirements:

$$F_1 = |DOC_1 - T_1|$$

If an FCM has m concept nodes, this first function can be written as follows:

$$F_1 = \sqrt{\sum\nolimits_{i=1}^{M} (DOC_i - T_i)^2} \tag{4}$$

The second standard function for the NHL algorithm relates to changes in output concept nodes:

$$F_2 = \left| DOC_i^{(k+1)} - DOC_i^{k} \right| < e \tag{5}$$

Therefore, the learning FCM is constantly updated by the weighted value, thus minimizing the standard functions F_1 and F_2.

3.3. **Calculating steps.** Integrating the weight-learning algorithm with FCM, we establish the following fuzzy evaluation model for TSA members.

First, we obtain the partial weight vector by the characteristic root method after comparing the importance of the member-evaluation index of the TSAs in Table 1.

Next, we depict the interaction between indices by a fuzzy cognitive map, as there are mutual interactions between the various standards. The causality map is shown in Figure 1.

In the cognitive map, each node represents the evaluation index of an alliance partner; the weight value corresponding to the directed arc between nodes $W_{ij} \in [-1, 1]$ represents the causal relationship between nodes; "+" indicates a positive effect, "−" indicates a negative effect, and the absolute value reflects the degree of interaction between concepts [17]. The larger the absolute value, the more obvious the causal relationship between two nodes. When building a fuzzy cognitive map, the relationship between standards is generally described by experts to determine whether the effect of one indicator on another is positive or negative.

The weight matrix is then updated by NHL algorithm and the final values converge to the desired steady state. The specific steps are: ① iterate k times according to the

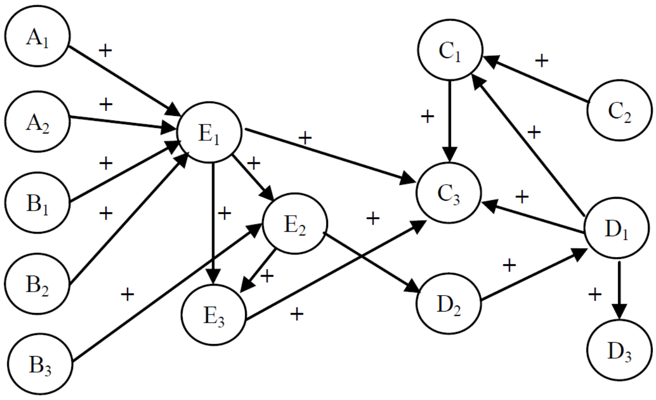

FIGURE 1. Causality diagram of TSA partners evaluation index

Formula (1); ② update the value of $A_i^{(k)}$ according to Formula (2); ③ update the value of $W_{ji}^{(k)}$ according to Formula (3); ④ calculate the two termination conditions based on Formulae (4) and (5) and stop the iterative process until both conditions are met; ⑤ return the final weight matrix W_{final}.

At last, the overall weight vector can be obtained by calculation. The local weight vector Z and the steady state matrix C^* are normalized according to the following method.

$$Z_n = \frac{1}{\lambda} Z \tag{6}$$

$$C_n^* = \frac{1}{\alpha} C^* \tag{7}$$

in which λ is the largest element in the Z vector, and α is the maximal row sum in the matrix C.

The overall vector is obtained according to the following formula:

$$W = Z_n + C_n^* Z_n \tag{8}$$

4. **Simulation Case Analysis.**

4.1. **Fuzzy evaluation of the TSA members.**

We select the biology industry TSA of Zhejiang province in China as research subject. We use the above-established evaluation model to simulate its member evaluation process in its establishment, when there are three alternative alliance members, P_1, P_2, and P_3.

First, multiple-comparison of 14 indicators in Table 1 is done by decision makers, and the judgment matrix is obtained. Then, the local weight value is calculated by AHP method, as shown in Table 2.

Next, according to the FCM in Figure 1, four experts are invited to offer the weight value matrix between 2 indicators as shown in Table 3.

Then, the NHL algorithm trains the above weight matrix. We identify the learning rate, η, as 0.01 and the attenuation factor, γ, as 0.95 by the trial-and-error method; the W matrix after training is shown in Table 4.

According to (8), we calculate the general weights in Table 5.

TABLE 2. Local weight

	A_1	A_2	B_1	B_2	B_3	C_1	C_2
Local weight	0.0270	0.0270	0.0078	0.0211	0.2362	0.0604	0.0558
	C_3	D_1	D_2	D_3	E_1	E_2	E_3
Local weight	0.1048	0.0398	0.0673	0.0717	0.1179	0.0846	0.0785

TABLE 3. Weight matrix of experts

	A_1	A_2	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	E_1	E_2	E_3
A_1	0	0	0	0	0	0	0	0	0	0	0	0.35	0	0
A_2	0	0	0	0	0	0	0	0	0	0	0	0.35	0	0
B_1	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0
B_2	0	0	0	0	0	0	0	0	0	0	0	0.35	0	0
B_3	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0
C_1	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0
C_2	0	0	0	0	0	0.4	0	0	0	0	0	0	0	0
C_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D_1	0	0	0	0	0	0.25	0	0.4	0	0	0.35	0	0	0
D_2	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0
D_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E_1	0	0	0	0	0	0	0	0.55	0	0	0	0	0.35	0.45
E_2	0	0	0	0	0	0	0	0	0	0.35	0	0	0	0.35
E_3	0	0	0	0	0	0	0	0.35	0	0	0	0	0	0

TABLE 4. Weight matrix after training

	A_1	A_2	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	E_1	E_2	E_3
A_1	0	0	0	0	0	0	0	0	0	0	0	0.1672	0	0
A_2	0	0	0	0	0	0	0	0	0	0	0	0.2556	0	0
B_1	0	0	0	0	0	0	0	0	0	0	0	0.2078	0	0
B_2	0	0	0	0	0	0	0	0	0	0	0	0.0891	0	0
B_3	0	0	0	0	0	0	0	0	0	0	0	0	0.5685	0
C_1	0	0	0	0	0	0	0	0.0518	0	0	0	0	0	0
C_2	0	0	0	0	0	0.319	0	0	0	0	0	0	0	0
C_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D_1	0	0	0	0	0	0.6449	0	0.3357	0	0	0.2613	0	0	0
D_2	0	0	0	0	0	0	0	0	0.4507	0	0	0	0	0
D_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E_1	0	0	0	0	0	0	0	0.5270	0	0	0	0	0.4850	0.4450
E_2	0	0	0	0	0	0	0	0	0	0.1948	0	0	0	0.3705
E_3	0	0	0	0	0	0	0	0.2658	0	0	0	0	0	0

TABLE 5. Judging matrix TSA partners evaluation index

	Local weights	General weights
A_1	0.0270	0.0129
A_2	0.0270	0.0398
B_1	0.0078	0.0053
B_2	0.0211	0.0653
B_3	0.2362	0.1826
C_1	0.0604	0.0468
C_2	0.0558	0.0355
C_3	0.1048	0.0327
D_1	0.0398	0.0824
D_2	0.0673	0.0561
D_3	0.0717	0.0783
E_1	0.1179	0.1350
E_2	0.0846	0.1046
E_3	0.0785	0.1227

Table 6. Alliance members' score

	A_1	A_2	B_1	B_2	B_3	C_1	C_2	C_3	D_1	D_2	D_3	E_1	E_2	E_3
P_1	4	4	2	3	4	2	3	4	4	3	3	3	4	5
P_2	4	3	2	3	3	4	4	5	5	3	4	3	2	4
P_3	3	3	3	4	4	4	4	5	4	4	4	2	3	3

Table 7. The evaluation results of alliance partner based on FCM

	P_1	P_2	P_3
Evaluation Result of Local Weights	3.6079	3.4899	3.6437
Evaluation Result of General Weights	3.5375	3.6399	3.5917

In Table 5, the partial weights and the overall weight of the evaluation standards are compared, and it can be found that the reasoning of the evaluation index system by the FCM reflects the interaction between indicators. Therefore, the weights of all evaluation indicators have changed, and those of B_3 (core values of compatibility), D_3 (fit of marketing and R&D), and C_2 (technology management capability) are most significant. It can be found by comparing the overall weights of each indicator that the D_3 indicator is the most important factor when selecting partners of a TSA, followed by E_1 (trust) and C_2 (technology management capability).

The member-evaluation indicators for TSAs in Table 1 are all qualitative. Thus, each indicator for each of the three alliance members is scored by experts; the evaluation statements set $v = \{very\ low, low, medium, very\ high, high\}$; the corresponding values are $v = \{1, 2, 3, 4, 5\}$; therefore, a score sheet of alliance partner candidates is obtained as shown in Table 6.

We comprehensively evaluate each indicator of all candidate enterprises by the vector of the overall weights in Table 5, and the evaluation results are shown in Table 7.

The above table also shows the evaluation results according to the weighted values of indicators without FCM iteration; the order of the three companies is $P_3 > P_1 > P_2$, that is, the Union should take P_3 as the best candidate for membership, then P_1, and finally P_2. The result obtained by the fuzzy evaluation model on the basis of the FCM is $P_2 > P_3 > P_1$; P_2 has the highest score and should be given priority when absorbing enterprises as members of the alliance, whereas P_3 turns out to be the second, and thus the second candidate.

The results of the FCM method are consistent with the actual situation of this technical standards alliance. The member P_2 is now well integrated in the alliance and has thus developed well and fast, whereas P_1 has withdrawn from the alliance. Although P_2 is in the alliance, both the resources it obtains from the alliance and its contribution are limited.

4.2. **Analyzing the simulation results.** The fuzzy evaluation model based on the FCM and NHL algorithms considers the interaction between all metrics when evaluating TSA members and therefore reflects members' comprehensive advantages and capabilities. Some novel and interesting information is obtained from the simulation results.

① Highlighting the market capabilities of TSA members

The average local weight of AHP-computed market capabilities is relatively low (only 0.0596). After the relationship between market capabilities and other evaluation indices is considered, its overall weight is the second highest among one class index in the evaluation system. The good market capabilities of the partners mean that TSA already has a substantial pool of users for installation; this is the key to further development of TSA. Therefore, technical standards are reliant on the marketing prowess of members to promulgate and then embed as the industry's technological paradigm.

② Earnestly enhancing trust among TSA members

In the fuzzy cognitive map, we find that the indicator of "trust", which is embedded in the network sector, is very active; that is, it makes contact with all factors in the network and other sectors. The overall weight of trust is relatively high at 0.1350. Therefore, TSA should focus on cultivating and upgrading trust among members to enhance the efficiency of TSA's knowledge integration and technology diffusion.

③ Emphasizing the compatibility of bilateral cooperation

The local and overall weights of the three secondary indicators of "compatibility" are not very high; this reflects their stability as a quality that exists objectively. This has also been reflected in fuzzy cognitive maps that the compatibility sector is barely affected by other factors but affects other factors as a "cause". Therefore, an enterprise should carefully examine their alliance partners' compatibilities in terms of culture, objectives, and organizational structure to ensure trust-based good relations and smooth communication and to optimize TSA network relations.

5. **Conclusions and Research Prospects.**

5.1. **Conclusions.** The main conclusions of this study are listed as follows.

(1) In the context of network, the selection of partners in a technical standards alliance has an influence depending upon specific situations. This paper establishes an evaluation system for partners in such alliances from the perspective of network embeddedness, highlighting the significance of the member's relationship to the development of TSA. Therefore, the evaluation indicator system in this study includes two dimensions, namely, partner selection as the "innate factor" and network-embedding as the additional factor influencing TSA.

(2) In view of the mutual influence and feedback features of the evaluation system, this study performs an FCM-based fuzzy evaluation of TSA members. Using expert knowledge, FCM causal reasoning, and fuzzy measurement methods, this study depicts the relationships and influences between each index. Integration with the NHL algorithm improves the FCM model, forming a complete evaluation model that supports adaptive and intelligent behavior with expert knowledge. Its learning and feedback mechanisms render the evaluation model updatable and gear the evaluation results toward the actual situation of TSA.

5.2. **Research prospects.** It is clear from a review of the few previous studies on the evaluation of TSA members that this paper introduces network embeddedness into the evaluation system for the first time. There may exist two problems, namely incomplete consideration and biased setup of influence factors. Therefore, the study of path-dependence for technological innovation should be tracked domestically and abroad in the future, and a more extensive investigation should be carried out. Moreover, the original model of influence factors should be further optimized and perfected, so as to improve its effectiveness and scientific rigor.

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