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A Comprehensive Assessment Approach to Evaluate the Trustworthiness of Manufacturing Services in Cloud Manufacturing Environment

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ABSTRACT Cloud manufacturing (CMfg) is an innovative manufacturing paradigm in which geographically distributed various manufacturing resources are encapsulated into manufacturing services (MSs), and also these MSs can provide users with various services. Users can find and choose qualified MSs to form cliques to help them complete their manufacturing tasks via Internet. Trust makes cooperative endeavors happen. Hence, it is an important problem to evaluate the trustworthiness of MSs in CMfg. In this paper, we present a comprehensive assessment approach to evaluate the trustworthiness of a MS in CMfg. The approach evaluates a MS from both objective and subjective perspectives, named as credit assessment and reliability assessment, respectively. Multinomial logistic regression analysis is presented to assess the credit of a MS, while fuzzy analytic hierarchy process is used to assess its reliability. Finally, a case study is presented and the results show the comprehensive assessment approach is efficacious at the trustworthiness evaluation of a MS.

INDEX TERMS Cloud manufacturing, trust evaluation, credit assessment, reliability assessment, FAHP, MLR.

I. INTRODUCTION

Small- and medium-sized enterprises (SMEs) play a crucial role in the healthy development of manufacturing industry and jobs creation [1]. However, many SMEs are still using traditional manufacturing paradigm in their operation and surfer from low productivity and weak competitiveness. The development of advanced information and network technologies in the last two decades give rise to various new manufacturing paradigms that have also attracted great attention from both academia and industries, such as concurrent engineering [2], [3], virtual manufacturing [4]–[6], network manufacturing [7]–[9] and digital manufacturing [10], [11]. With the advent of cloud computing, things of internet, and other new information and network technologies, a service-oriented manufacturing paradigm is proposed, called cloud manufacturing [12], [13].

Cloud manufacturing is a customer-centered manufacturing paradigm that explores on-demand accesses to a shared collection of diversified and distributed manufacturing resources to form a scalable, reconfigurable production system which enhances efficiency, reduces production lead time and costs, and enables optimal resource allocations in responding to variable customer demands [14]. In cloud manufacturing environment, geographically distributed resources are encapsulated into Manufacturing Services (MSs). Customers can gain access remotely without any difference from accessing locally available resources. Nevertheless, with the increasing number of MSs available on the Internet, how to find the trustworthy MSs from the potential candidates becomes one of the most significant questions in cloud manufacturing [15]. Trust is a central component in effective working relationships.

In our society, people usually form collaborative relationships with others they can trust, basing on face-to-face assessment and/or their societal reputation [16], [17]. Trust is an essential component in almost any relationship, such as interpersonal relationship, social structures, and business relationships [18]. Besides, trust in our society is reflected in many aspects, reliability, honesty, truthfulness, dependability, security, competency, punctuality, and quality of service [19]–[21]. On the other hand, in a virtual online environment, members are usually anonymous and do not engage in direct face-to-face communication. Being able to effectively and quantitatively assess trust in such an environment is attracting increasing research attentions [22]–[27]. The concepts of trust and reputation managements have been widely adopted in e-commence [28]–[30], web services [31], [32], ad-hoc networks [33], P2P computing [34], [35], social network [36] and so on. However, there lacks a general concept of trust and it needs much more theoretical analysis and measurement. E-commerce, like C2C (customer -to-customer) and B2C (business-to-customer) improves its popularity because of its inherent benefits of convenience and low costs for the consumer, but it impedes its development further because of its drawbacks such as virtual and anonymous sales and the difficulty in assessing product quality prior to purchase [37]–[39]. Many different kinds of trust evaluation methods have already been applied by the electronic marketplace, such as e-Bay, Amazon, Taobao, Airbnb, and CNet [40]–[43]. But the similarity of these trust evaluation technologies is that the trust computing is based on the feedback information of participants. Usually participants of the e-commerce give three kinds of feedback: positive ratings (+1), negative ratings (−1), and neutral ratings (0), and then the evaluation results are given based on the feedback information. However, trust is characterized by individuality, fuzziness, dynamics, time-dependence and context-dependence. The abovementioned trust evaluation methods just only evaluate trust from subjective views, and certainly they are difficult to be used to evaluate comprehensively. So the trust evaluation approach presented in this paper evaluates trust from subjective and objective views. In the rest of the paper, a framework of trust evaluation, including evaluations of credit and reliability is presented in Section II. In Section III, a comprehensive quantitative assessment model is developed. A case study is presented in Section IV to validate the presented method. It is observed that this approach is able to make decision for supporting the selection of MSs.

II. GUIDELINES FOR MANUSCRIPT PREPARATION

In the CMfg environment, geographically distributed various manufacturing resources are encapsulated as MSs and form an immense MS pool. Users can search and choose one or several MSs from this pool to form a niche to work on their manufacturing tasks. These users certainly hope to find those trustworthy potential MSs who can complete manufacturing tasks according to their commitments. Usually trust assessment is conducted in two aspects: credit and reliability. Credit assessment is an objective assessment, meaning it assesses a MS using objective information such as its competency of completing commitments. Reliability assessment is a subjective assessment, meaning it assesses a MS using subjective information such as user feedbacks. Hence the trust evaluation framework contains indexes in both aspects, shown as Figure 1. The credit rating of Small/Medium-Sized enterprises (SMEs) are mainly decided by the factors in Table 1, according to related 60 references and credit evaluation reports. The indexes of reliability assessment are mainly decided by the factors in Table 2, obtained from 75 questionnaire surveys. Factor analysis is used to remove redundancy or duplication from the factors using SPSS, which is a statistical analysis software.

TABLE 1. The inflence factors of credit rating.

Factors	Num	Frequency
Age of enterprise	35	58.3%
Per capita asset	24	40%
Income growth rate	18	30%
Asset growth rate	13	21.7%
Current ratio	21	35%
Interest rate return	29	48.3%
Gross margin	15	25%
Turnover rate	10	16.7%
Total		60

TABLE 2. The influence factors of reliability assessment.

Factors	Num	Frequency
Authenticity of service info	65	86.7%
Response time	35	47.6%
Response attitude	48	64%
Logistics speed	37	49.3%
Delivery time	52	69.3%
Degree of damage	28	37.3%
Production qualified rate	41	54.7%
Cost-effective rate	32	42.7%
Technical advancement	24	32%
Total		75

Table 3 and Table 4 shows significant factors of credit rating and reliability assessing respectively based on factor analysis method. Among credit rating indexes, there are two significant factors: management factor f_{11} and finance factor f_{12}. There are three significant factors in reliability indexes: interaction factor f_{21}, delivery factor f_{22}, and operation factor f_{23}. Table 5 and Table 6 are the rotated factor matrixes of credit rating indexes and of reliability assessing indexes respectively. So the evaluation indexes of trust, involving credit rating and reliability assessing are shown in Figure 1.

III. A COMPUTING APPROACH FOR TRUST EVALUATION

A. PROBLEM FORMULATION

The trust evaluation model of MS is expressed as a seven-tuple ($\boldsymbol{A}, \boldsymbol{X}, \boldsymbol{Y}, \boldsymbol{T}, \boldsymbol{E}_C, \boldsymbol{E}_R, \boldsymbol{E}$,), where

$\boldsymbol{A} = \{a_1, a_2, \ldots\ldots, a_m\}$ denotes the set of candidate services;

$\boldsymbol{X} = \{x_1, x_2, \ldots\ldots, x_k\}$ denotes the set of service providers;

$\boldsymbol{Y} = \{\mathrm{y1, y2}, \ldots\ldots, \mathrm{yl}\}$ denotes the set of service demanders;

$\boldsymbol{T} = \{T_{ij}\}$ denotes the set of the trust evaluation indexes, including credit and reliability assessment indexes

TABLE 3. Total variance explained of credit rating indexes.

Factors	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
T_{11}	4.765	52.942	52.942	4.765	52.942	52.942
T_{12}	2.958	32.862	85.803	2.958	32.862	85.803
T_{13}	0.935	4.504	90.307			
T_{14}	0.585	3.901	94.207			
T_{15}	0.347	2.316	96.524			
T_{16}	0.228	1.518	98.042			
T_{17}	0.192	1.243	99.285			
T_{18}	0.094	0.715	100.000			

TABLE 4. Total variance explained of reliability assessing indexes.

Factors	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
T_{21}	8.350	55.665	55.665	8.350	55.665	55.665
T_{22}	3.343	22.289	77.954	3.343	22.289	77.954
T_{23}	1.152	7.680	85.634	1.152	7.680	85.634
T_{24}	1.085	7.236	92.869			
T_{25}	0.458	3.052	95.921			
T_{26}	0.347	2.313	98.234			
T_{27}	0.093	1.202	99.436			
T_{28}	0.059	0.333	99.769			
T_{29}	0.117	0.231	100.00			

TABLE 5. Rotated factor matrix of credit rating indexes.

Factor loading	Credit rating indexes							
	T_{11}	T_{12}	T_{13}	T_{14}	T_{15}	T_{16}	T_{17}	T_{18}
f_{11}	0.986	0.786	0.301	0.478	0.764	0.125	-0.231	0.936
f_{12}	-0.319	0.061	0.784	0.976	-0.023	0.869	0.751	0.072

TABLE 6. Rotated factor matrix of reliability assessing indexes.

Factor loading	Reliability assessing indexes								
	T_{21}	T_{22}	T_{23}	T_{24}	T_{25}	T_{26}	T_{27}	T_{28}	T_{29}
f_{21}	0.916	0.886	0.901	0.278	0.352	0.112	0.432	0.229	-0.186
f_{22}	-0.119	0.381	0.274	0.676	0.831	0.869	-0.251	0.072	0.293
f_{23}	-0.221	0.120	0.375	0.293	-0.134	-0.299	0.987	0.936	0.761

$\boldsymbol{T}=\{\boldsymbol{T}_1, \boldsymbol{T}_2\}$ respectively, in which $\boldsymbol{T}_1 = \{\boldsymbol{T}_{11}, \boldsymbol{T}_{12}, \ldots, \mathrm{T}_{1\mathrm{m}}\}$ $(m = 1, 2, \ldots, 8)$ and $\boldsymbol{T}_2 = \{\boldsymbol{T}_{21}, \boldsymbol{T}_{22}, \ldots, \boldsymbol{T}_{2\mathrm{n}}\}$ $(n = 1, 2, \ldots, 9)$;

$E^C_{a_i}$ denotes the computing result of credit evaluation of MS, $a_i \in A$;

$E^R_{a_i}$ denotes the computing result of reliability evaluation of MS, $a_i \in A$;

E_{a_i} denotes the computing result of trust evaluation of MS, $a_i \in A$;

$$E_{a_i} = \lambda^C_{a_i} E^C_{a_i} + \lambda^R_{a_i} E^R_{a_i} \tag{1}$$

where $\lambda^C_{a_i}$ and $\lambda^R_{a_i}$ denotes the weight of credit and reliability for evaluating trust and $\lambda^C_{a_i} + \lambda^R_{a_i} = 1$.

B. CREDIT ASSESSMENT BASED ON MLR

Multinomial logistic regression (MLR) is used to predict categorical placement or the probability of category memebership on a dependent variable based on multiple independent variables. MLR is a simple extension of binary logistic regression that is capble of handling more than two categories of the dependent or outcome variable.

Here the essential information, a credit rank list of 283 SMEs are collected. The credit ranks are listed in table 7. There are 10 levels of the credit rank altogether. Two factors, namely management factor f_{11} and finance factor f_{12} can caputure 8 indexes of credit assessment with factor analysis of SPSS (see Fig. 1). The estimating values for each weight of the abovementioned credit assessment indexes are expressed by the following equation (2) and equation (3) with linear regression. MLR is used to assess the credit rank of SMEs. The MLR model is a simple extension of the binomial logistic regression model. By using MLR in credit rating, the response variable y can take one of serveral discrete value $(0, 1, 2, \ldots, 9)$ and the MLR model of credit rating can be formulated by equation (4).

$$\begin{aligned} f_{11} = {} & 0.365T_{11} + 0.333T_{12} + 0.369T_{13} + 0.007T_{14} \\ & + 0.020T_{15} - 0.019T_{16} + 0.297T_{17} + 0.024T_{18} \end{aligned} \tag{2}$$

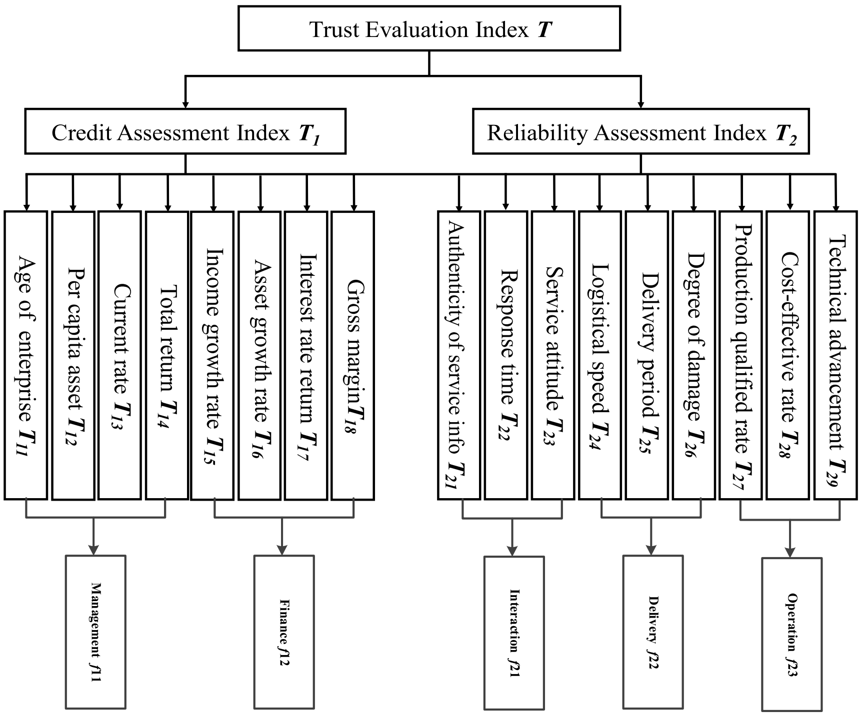

FIGURE 1. **The evaluation index architecture.**

TABLE 7. **The credit ranking of 283 SMEs.**

AAA(E_C=1)	AA(E_C=0.9)	A(E_C=0.8)	BBB(E_C=0.7)	BB(E_C=0.6)	B(E_C=0.5)
28	28	37	34	51	12
CCC(E_C=0.4)	CC(E_C=0.3)	C(E_C=0.2)	D(E_C=0.1)	Total	
34	27	9	13	283	

$$
\begin{aligned}
f_{12} &= 0.008T_{11} - 0.033T_{12} - 0.009T_1 + 0.031T_{14} \\
&\quad + 0.983T_{15} + 0.05T_{16} + 0.014T_{17} + 0.062T_{18} \qquad (3)
\end{aligned}
$$

$$
\begin{aligned}
&\log it(P_r) \\
&= \log it(P(y \le r|f) = \ln(\frac{P_r}{1-P_r}) = \gamma_r - (\beta_1 f_{11} + \beta_2 f_{12}) \qquad (4)
\end{aligned}
$$

where $r = 1, 2, \ldots, 9$; $y = 0, 1, 2, \ldots, 10$ denotes the level of credit rank where 0 is the lowest level and 9 is the highest level. $P_r = P(y \le r|f)$ is the cumulative probablity; γ_r denotes the demarcation point; β_1 and β_2 is regression coefficient. The results of multinomial logistic regression analysis are listed in table 8 with SPSS. And the expansion equation of the equation (4) can be described by the following equation (5), shown at the bottom of the next page.

where $\beta_1 = 0.975$ and $\beta_2 = 0.457$, $\log it(P_r) = \ln(\frac{P_r}{1-P_r}) = \gamma_r - (0.975f_{11} + 0.457f_{12})$. The level R of the credit rank of an company is the maximal value of P_r, namely $R = \arg\max_{0 \le r \le 9} P(y = r|f)$. Then the result of credit assessment is normalized according to equation (6).

$$
E_{a_i}^C = \frac{R_{a_i}}{10} \qquad (6)
$$

where $E_{a_i}^C$ denotes the result of credit assessment for MS a_i; R_{a_i} denotes the credit level of MS a_i.

C. RELIABILITY EVALUATION BASED ON FEEDBACK

1) WEIGHT ANALYSIS OF EVALUATION INDEXES OF RELIABILITY BASED ON FAHP

The Analytic Hierarchy Process (AHP) as an evaluation tool is widely used for multi-criteria decision-making and has successfully been applied to many practical decision making problems. However, the method is quite difficult to handle the inherent uncertainty and imprecision associated with the mapping of the decision-maker's perception to exact numbers. In order to eliminate this limitation, Fuzzy AHP (FAHP) is used to tackle the uncertainty and imprecision of reliability assessment process. There are four steps to be used when using FAHP to assess the reliability.

1) Problem modelling

According to the indexes of reliability evaluation, the hierarchical evaluation system is built as shown in Figure 2.

2) Constructing consistent fuzzy reciprocal comparison matrix

The judgement of the pair-wise comparison of criteria converts the value according to the ratio scale (see table 9)

TABLE 8. The results of the MLR analysis.

Parameters	Coefficients	Standard errors	Wald	Sig.
γ_1	4.825	0.551	43.104	<0.0001
γ_2	3.617	0.432	47.622	<0.0001
γ_3	2.984	0.277	27.529	<0.0001
γ_4	1.451	0.240	0.757	<0.0001
γ_5	-0.209	0.315	30.010	<0.0001
γ_6	-1.725	0.997	27.257	<0.0001
γ_7	-2.702	0.226	18.649	<0.0001
γ_8	-4.082	0.213	4.633	<0.0001
γ_9	-5.207	0.201	5.999	<0.0001
f_{11}	0.975	0.194	0.101	0.031
f_{12}	0.457	0.196	0.773	0.014

TABLE 9. Quantitative scale 0.1-0.9.

Intensity of importance	Definition
0.5	Equal importance
0.6	Moderate importance
0.7	Strong Importance
0.8	Very strong importance
0.9	Extreme importance
0.1, 0.2, 0.3, 0.4	Anti-comparison

and construct the following fuzzy comparison matrix.

$$A = (a_{ij})_{n\times n} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{7}$$

where a_{ij} represents the comparison between the criterion i and j, and $0 \leq a_{ij} \leq 1$, $a_{ij} + a_{ji} = 1$.

If the matrix A is consistent, then the equation (7) holds for all comparisons:

$$a_{ij} = a_{ik} - a_{jk} + 0.5 \tag{8}$$

If $a_{ij} \neq a_{ik} - a_{jk} + 0.5$, the matrix A is inconsistent. The matrix A needs to be modified to form a consistent comparison matrix A' according to the equation (9).

$$A' = (a'_{ij})_{n\times n}, \quad a'_{ij} = \frac{a_i - a_j}{n} + 0.5 \ (i \neq j) \tag{9}$$

where $a_{i(j)} = \sum_{k=1}^{n} a_{i(j)k}$, $i, j = 1, 2, \ldots, n$ $i \neq j$.

3) Solving the matrix A' to obtain the weight of each criterion with equation (10).

$$\omega_i = \frac{1}{n} - \frac{1}{(n-1)} + \frac{2\sum_{j=1}^{n} a_{ij}}{n(n-1)} \quad (i = 1, 2, \ldots, n) \tag{10}$$

Here three experts are invited to construct comparison matrix for determining the importance degree of the group criteria.

$$A_1 = \begin{array}{c} \\ f_{21} \\ f_{22} \\ f_{23} \end{array} \begin{array}{c} \begin{array}{ccc} f_{21} & f_{22} & f_{23} \end{array} \\ \begin{bmatrix} 0.5 & 0.3 & 0.2 \\ 0.7 & 0.5 & 0.6 \\ 0.8 & 0.4 & 0.5 \end{bmatrix} \end{array}$$

$$A_2 = \begin{array}{c} \\ f_{21} \\ f_{22} \\ f_{23} \end{array} \begin{array}{c} \begin{array}{ccc} f_{21} & f_{22} & f_{23} \end{array} \\ \begin{bmatrix} 0.5 & 0.4 & 0.3 \\ 0.6 & 0.5 & 0.5 \\ 0.7 & 0.5 & 0.5 \end{bmatrix} \end{array}$$

$$A_3 = \begin{array}{c} \\ f_{21} \\ f_{22} \\ f_{23} \end{array} \begin{array}{c} \begin{array}{ccc} f_{21} & f_{22} & f_{23} \end{array} \\ \begin{bmatrix} 0.5 & 0.4 & 0.1 \\ 0.6 & 0.5 & 0.6 \\ 0.9 & 0.4 & 0.5 \end{bmatrix} \end{array}$$

As the three comparison matrixes are not subjected to equation (8), the equation (9) is used to respectively modified the three matrixes to form the following three matrixes A'_1, A'_2 and A'_3.

$$A'_1 = \begin{bmatrix} 0.5 & 0.233 & 0.267 \\ 0.767 & 0.5 & 0.533 \\ 0.733 & 0.467 & 0.5 \end{bmatrix}$$

$$\begin{cases} P(y=1) = P(y \leq 1|f_{11}, f_{12}) = \dfrac{e^{logitP_1}}{1+e^{logitP_1}} \\ P(y=2|f_{11}, f_{12}) = P(y \leq 2|f_{11}, f_{12}) - P(y \leq 1|f_{11}, f_{12}) = \dfrac{e^{\log itP_2}}{1+e^{\log itP_2}} - \dfrac{e^{logitP_1}}{1+e^{logitP_1}} \\ \vdots \\ P(y=0|f_{11}, f_{12}) = 1 - P(y=1|f_{11}, f_{12}) - P(y=2|f_{11}, f_{12}) - \ldots - P(y=9|f_{11}, f_{12}) \end{cases} \tag{5}$$

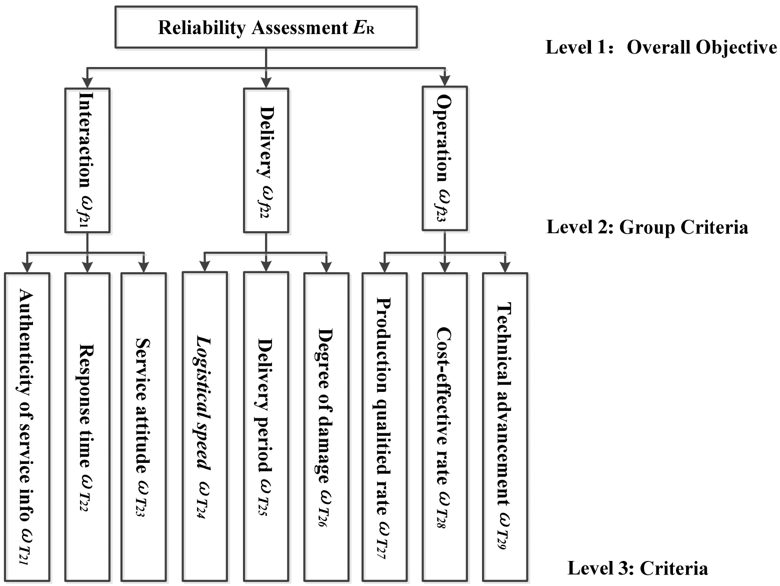

FIGURE 2. The hierarchical evaluation system of reliability.

$$A'_2 = \begin{bmatrix} 0.5 & 0.367 & 0.333 \\ 0.633 & 0.5 & 0.467 \\ 0.667 & 0.533 & 0.5 \end{bmatrix}$$

$$A'_3 = \begin{bmatrix} 0.5 & 0.267 & 0.233 \\ 0.733 & 0.5 & 0.467 \\ 0.767 & 0.533 & 0.5 \end{bmatrix}$$

Calculating with equation (10) respectively, the weight vector of each consistent comparison matrix is as follows:

$$\omega_{f21}^1 = 0.1667 \quad \omega_{f21}^2 = 0.2333\ \omega_{f21}^1 = 0.1667$$
$$\omega_{f22}^1 = 0.4333 \quad \omega_{f22}^2 = 0.3667\ \omega_{f22}^2 = 0.4$$
$$\omega_{f23}^1 = 0.4 \quad \omega_{f23}^2 = 0.4\ \omega_{f23}^3 = 0.4333$$

Then we can obtain the weight vector ω_{f_2} of the three group criteria for reliability evaluation, $\omega_{f_2} = (0.1889, 0.4, 0.4111)$.

In the same way, the weight vectors of the criteria for the three group criteria are obtained.

$$\omega_{f21} = (0.4762, 0.261, 0.2619),$$
$$\omega_{f22} = (0.2815, 0.3826, 0.3359),$$

TABLE 10. Quantitative-scale of user rating.

No.	Rating	Value
1	Very bad	0.2
2	Bad	0.4
3	Medium	0.6
4	Good	0.8
5	Very good	1

$$\omega_{f23} = (0.4926, 0.2025, 0.3049).$$

Hence we can obtain the weight vector ω of each criterion for reliability evaluation.

$$\omega = \begin{bmatrix} \omega_1 \\ \cdots \\ \omega_9 \end{bmatrix} = [0.09, 0.0495, 0.0495, 0.1126,$$
$$0.153, 0.1344, 0.2025, 0.0832, 0.1253]'.$$

2) THE DETERMINATION AND QUANTIFICATION OF FEEDBACK INFORMATION

Supposedly after using a certain MS k ($k = 1, 2, \ldots, m$), each user i ($i = 1, 2, \ldots, n$) has already used the MS k feeds back, a rating fb_{ij}^k for this MS k from the rating set

TABLE 11. The essential information of three companies.

Credit indexes	$C_1(S_1)$	$C_2(S_2)$	$C_3(S_3)$
Age (year) (T_{11})	5	12	3
Per capita asset (RMB) (T_{12})	323.6197	537.4637	127.2201
Current ratio (T_{13})	1.8029	2.0346	1.0673
Total assets turnover (T_{14})	0.0634	0.0921	0.05149
Increase rate of business revenue (T_{15})	5.9023	6.5491	4.0199
Asset growth rate (T_{16})	0.2457	0.3021	0.1372
Return on total assets (T_{17})	2.2495	2.7038	1.9802
gross profit rate (T_{18})	23.71	24.60	19.82

TABLE 12. The probability of each credit assess level.

	C_1	C_2	C_3		C_1	C_2	C_3
AAA	0.337	0.097	0.028	*B*	0.02	0.074	0.079
AA	0.199	0.063	0.112	*CCC*	0.079	0.028	0.044
A	0.051	0.019	0.372	*CC*	0.018	0.087	0.083
BBB	0.144	0.46	0.082	*C*	0.01	0.006	0.037
BB	0.107	0.061	0.112	*D*	0.035	0.105	0.042

{very bad, bad, medium, good, very good} according to each index of reliability assessment T_{2l} $(l = 1, 2, \ldots, 9)$, in which $j = \mathrm{T}_{2l}$. The ratings are quantified according to table 10. Considering that the influences of the ratings of users on the conclusive results of reliability assessment will be degraded with time passing by, namely the importance degree of user feedback for MS reliability assessment reducing with time passing by. The time weight $wT_i(t)$ is introduced to express the importance degree of the feedback information at the different time (equation 11) for assessing reliability.

$$wT_i(t) = \frac{-\frac{1}{\Delta t_i}\ln\frac{1}{\Delta t_i}}{\frac{1}{n} - \sum_{j=1}^{n}\frac{1}{\Delta t_j}\ln\frac{1}{\Delta t_j}} \tag{11}$$

where n denotes the total number of the feedback information; Δt_i denotes the difference between the assessment time t and the feedback time t_i. Hence the reliability assessment is as followings:

$$E_k^R = [wT_1(t), wT_2(t), \ldots, wT_n(t)] \times \begin{bmatrix} fb_{11}^k & \ldots & fb_{19}^k \\ \ldots & \ldots & \ldots \\ fb_{n1}^k & \ldots & fb_{n9}^k \end{bmatrix} \begin{bmatrix} \omega_1 \\ \ldots \\ \omega_9 \end{bmatrix} \tag{12}$$

where E_k^R denotes the result of reliability assessment and k denotes the MS k $(k = 1, 2, \ldots, m)$; $wT_\mathrm{i}(t)$, ω_j denotes the weight of time and of index of reliability assessment respectively.

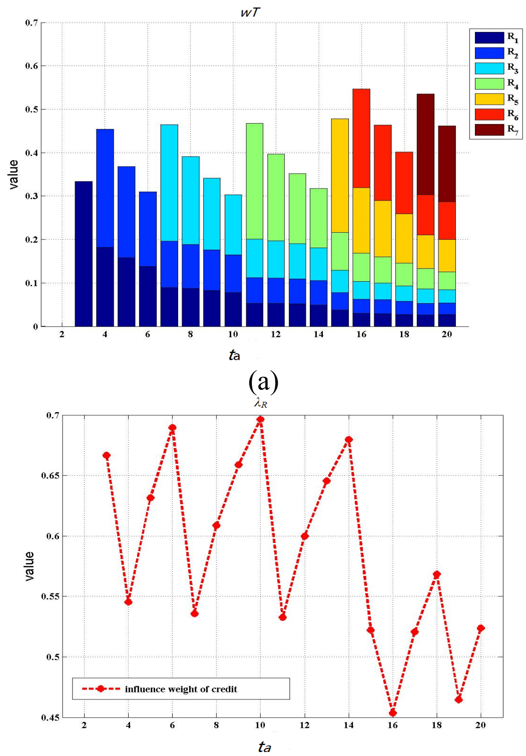

FIGURE 3. Influence weight comparison.

IV. A CASE STUDY

There are three companies C_1, C_2, C_3 who provides three different MSs, namely S_1, S_2, S_3 respectively. The essential information of these three companies are listed in table 7. According to the equations (2) and (3), the management capacity coefficient f_{11} and the operation capacity coefficient f_{12} are calculated. And the probability $P(y = j)$ is calculated according to the equation (4), where j $(j = 0, 1, 2, \ldots 9)$

TABLE 13. The feedback information of MS S1.

No.	Reliability Assess Indexes									Feedback Time
	T_{21}	T_{22}	T_{23}	T_{24}	T_{25}	T_{26}	T_{27}	T_{28}	T_{29}	*Time*
R_1	1	1	1	1	1	1	1	1	1	1
R_2	1	1	1	1	0.8	0.8	1	1	1	2
R_3	0.8	1	1	1	0.8	0.8	1	1	1	2
R_4	0.8	1	0.8	1	0.8	0.8	1	0.8	0.8	3
R_5	0.8	0.8	0.8	0.8	0.8	0.8	1	0.8	0.8	4
R_6	0.8	0.8	0.8	0.6	0.8	0.6	0.8	0.8	0.8	4
R_7	0.8	0.8	0.6	0.8	0.6	0.6	0.8	0.8	0.6	6
R_8	0.6	0.6	0.6	0.6	0.6	0.6	0.8	0.6	0.6	7
R_9	0.6	0.4	0.4	0.6	0.6	0.6	0.6	0.6	0.6	8
R_{10}	0.6	0.4	0.4	0.4	0.6	0.6	0.4	0.6	0.6	10
R_{11}	0.6	0.4	0.4	0.6	0.4	0.4	0.6	0.4	0.4	13
R_{12}	0.4	0.4	0.4	0.6	0.4	0.4	0.4	0.4	0.4	14
R_{13}	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	15
R_{14}	0.4	0.4	0.2	0.4	0.2	0.4	0.4	0.4	0.4	18
R_{15}	0.4	0.2	0.2	0.2	0.4	0.4	0.4	0.4	0.2	19
R_{16}	0.4	0.4	0.2	0.4	0.2	0.2	0.2	0.4	0.2	25
R_{17}	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	31
R_{18}	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	42

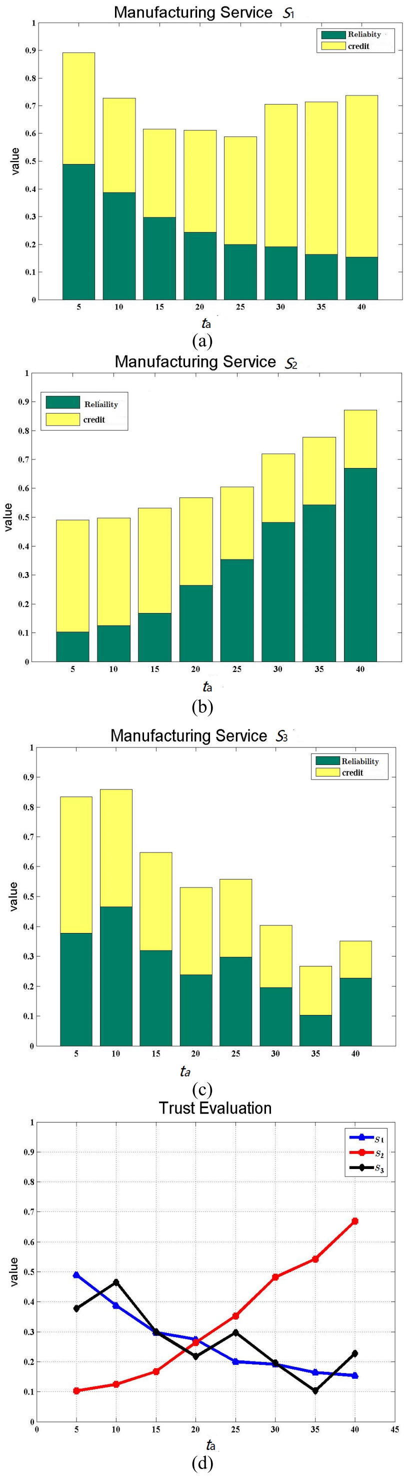

FIGURE 4. **Trust evaluation results.**

denotes the credit assess rank and directly corresponds to the credit rank. Level 0 is the highest level, corresponding to *AAA* and level 9 is the lowest level, corresponding to *D*. The results are listed in table 11. The credit rank of the company C_1 is *AAA*, because its probability at rank *AAA* is the highest among the other ranks. Similarly, C_2 is *BBB*, and C_3 is *A* (see table 12).

The feedback information of the MSs from users are collected for assessing the reliability of the three services S_1, S_2, and S_3 provided by the three companies respectively. Table 13 lists the feedback information of S_1 from customers. There are altogether 18 pieces of feedback information. The t_a denotes the time that gives the result of reliability assess. For example, there are six pieces of feedback information $\{R_1, R_2, R_3, R_4, R_5, R_6\}$ when t_a is at 5 unite time. And then the time weight of feedback information wT^1 and the weight of credit λ_R^1 of S_1 is calculated as equation (13), shown at the bottom of the page.

The longer the interval time between the feedback time and the assessment time is, the less the effect of feedback information on the reliability assess is (see FIGURE 3(a)).

The trust evaluation of MS S_1 is as follows.

$$E_1 = \lambda_1^C E_1^C + \lambda_1^R E_1^R = 0.4895 + 0.4207 = 0.8922 \tag{14}$$

Similarly, the trust computing of S1, S2, and S3 at different t_a are shown as figure 4 respectively.

The Figure 4 (d) reflects the evolutionary process of MS's trust from the beginning to join the platform, and the changing tendency of the trust value is compared with the line graph.

A MS just join the platform, users are usually dependent on its credit assessment for evaluting its trustworthiness. When this MS is used by users and obtains feedback information, the feedback information will affect its trustworthiness. In this case (fig. 4(d)), the trust value of S1 is gradually reduced, the S2 is gradually rised, and the S3 is waved. Hence, the S2 is the best candidate.

V. CONCLUSIONS

In this paper, a trust computing approach is proposed to assess the trustworthiness of MSs in CMfg environment on basis of constructing the evaluation architecture of credit and reliability. The trust evaluation approach considers objective and subjective two aspects respectively, involving credit assessment and reliability assessment. And two algorithms are used for assessing credit and reliability: one is the ordinal multinomial logistic regression analysis for assessing credit; the other is FAHP for assessing reliability. At last a case is presented to validate the approach.

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$$\begin{cases} \lambda_1^R = \sum_{j=1}^{6} wT_j^1 = \sum [0.06711 \quad 0.080537 \quad 0.08054 \quad 0.1007 \quad 0.1342 \quad 0.1342] \\ \lambda_1^C = 1 - \lambda_1^R = 0.4027 \end{cases} \tag{13}$$

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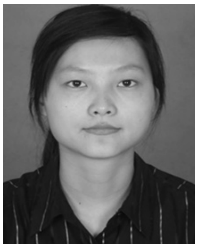

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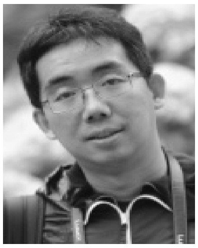

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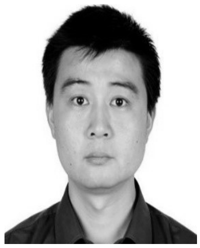

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