Ontology-based Measurement and Analysis Web Service for Supporting CMMI Level 2 Assessment

Chang-Shing Lee, Jung-Chun Du, Zhi-Wei Jian, Yau-Hwang Kuo and Chaw-Kwei Hung

Department of Information Management, Chang Jung University, Tainan, Taiwan
CREDIT Research Center, National Cheng Kung University, Tainan, Taiwan

Abstract: A Measurement and Analysis Web Service (MAWS) based on CMMI Level 2 Ontology is presented in this paper. The MAWS is composed of four sub-services, including Project Planning Measurement Analysis Web Service (PPMA-WS), Project Monitoring Measurement Analysis Web Service (PMMA-WS), Supplier Agreement Management Measurement Analysis Web Service (SAMMA-WS) and Process/Product Quality Assurance Measurement Analysis Web Service (PPQAMA-WS), that can support other Process Areas (PAs) of CMMI Level 2. In addition, the CMMI Level 2 Ontology that is pre-defined by experts can be used as a basic skeleton for CMMI. Moreover, a Fuzzy Inference Mechanism is applied to assist in the process of MAWS. Then, the genetic algorithm is applied to learn the fuzzy inference rules of the FIM to strengthen the robustness of this system. The proposed MAWS has been set up at DSAI Lab. of Chang Jung University. The experimental results show that this approach can effectively assist in the process of the Measurement and Analysis for CMMI Level 2 assessment.

Key-Words: Ontology, CMMI, Fuzzy Inference, Web Service, Measurement and Analysis, Genetic Algorithm.

1 Introduction
The Ontology is a collection of key concepts and their inter-relationships collectively provide an abstract view of an application domain. There are many ontological applications that have been presented in various domains. For example,Navigli et al. [6] propose the OntoLearn with ontology learning capability to extract relevant domain terms from a corpus of text. Alani et al. [7] propose the Artequakt that automatically extracts knowledge about artists from the web based on an ontology. Lee et al. [5] propose an ontology-based fuzzy event extraction agent for Chinese news summarization. The summarization agent can generate a sentence set for each Chinese news. The CMMI, “Capability Maturity Model -- Integrated”, is a model for improving organization’s processes and ability to manage the development, acquisition, and maintenance of products or services [2]. In the CMMI, the purpose of Measurement and Analysis (MA) is to develop and sustain a measurement capability that is used to support management information needs [2]. M. Morisio [4] mention that software process improvement and measurement are closely linked and measures are the only way to prove improvements in a process [4]. E. Palza et al. [9] propose a measurement repository for collecting, storing, analyzing, and reporting measurement data based on the requirements of the CMMI. This repository is generic, flexible and integrated, supporting a dynamic measurement system. M. Berry et al. [8] propose a trial of the framework involving an assessment of the relationship of measurement with the key process area of project tracking and oversight.

On the other hand, the web service is an emerging web technology in the world. A web service is a software system designed to support interoperable machine-to-machine interaction over a network. It has an interface described in a machine-processable format such as Web Service Description Language (WSDL) [10]. McIlraith et al. [11] propose the markup of web services in the DAML family of semantic web markup languages. This markup enables a wide variety of agent technologies for automated web service discovery, execution, composition, and interoperation. Maximilien et al. [12] propose an agent framework and is realized in the Web Services Agent Framework (WSAF). The WSAF incorporates service selection agents that use the QoS Ontology and an XML policy language that allows service consumers and providers to expose their quality preferences and advertisements. In this paper, a MA Web Service (MAWS) based on CMMI Level 2 Ontology is presented in this paper. The MAWS is composed of four sub-services, including PPMA-WS, PMMA-WS, SAMMA-WS and PPQAMA-WS, that can support other PAs of CMMI Level 2. In addition, the CMMI Level 2 Ontology that is pre-defined by experts can be used as a basic
skeleton for CMMI. Moreover, a Fuzzy Inference Mechanism (FIM) is applied to assist in the process of MAWS. Then, the genetic algorithm is applied to learn the fuzzy inference rules of the FIM to strengthen the robustness of this system. The proposed MAWS has been set up at DSAI Lab. of Chang Jung University. The experimental results show that this approach can effectively assist in the process of the MA for CMMI Level 2 assessment.

The remainder of this paper is organized as follows. Section 2 describes the CMMI Level 2 ontology. Section 3 introduces the FIM for MAWS. In section 4, the genetic learning mechanism is proposed to learn the fuzzy inference rules and membership functions of the FIM. Section 5 shows some experimental results for MA web service. Finally, the conclusions are shown in section 6.

2 CMMI Level 2 Ontology

In this section, we utilized three-layered object-oriented ontology architecture proposed by Lee et al. [1] for constructing CMMI level 2 ontology. In the architecture, it is composed of Domain Layer, Category Layer and Class Layer. Each concept consists of a concept name and attributes in the Class Layer. There are three kinds of relationship, including generalization, aggregation and association in the ontology. The relationship between a domain and its corresponding category is generalization that represents “is-kind-of” relationship. The relationship between each category and its corresponding events is aggregation. The aggregation denotes “is-part-of” relationship. The association represents a general relationship.

Fig. 1 shows that MA Ontology comprehends the concept of “Measurement and Analysis Report (MAR)” and its’ corresponding attributes, including “Each Form Parameter Input (EFPI)” and “Measurement and Analysis Report (MAAR)”. Besides, the MAR concept is related to the concepts of other ontologies such as Purchase Requirement Document (PRD), Supplier Selected Name List (SSNL), Work Product Task List (WPTL) and so on. The MAR concept will receive the important data from the relevant concepts in the MA ontology. Table 1 shows the concepts, attributes and related concepts of CMMI Level 2 MA process area.

3 Fuzzy Inference Mechanism for MAWS

Fig. 2 shows the architecture of MAWS based on CMMI.

Fig. 2. The architecture of the MAWS.

There are four layers, including Web Client Layer, Composite Services Layer, Basic Web Services Layer and Measurement & Analysis Data Layer in MAWS. When using the MAWS in the Web Client Layer,
users have to search the relevant services from UDDI server. In addition, users can also combine some services as the composite service in the Composite Services Layer for using conveniently in the future. On the other hand, users can call the services of the Basic Web Services Layer through SOAP protocol. In the Basic Web Services Layer, there are four fundamental web services, including PPMA-WS, PMMA-WS, SAMMA-WS and PPQAMA-WS in the layer.

In this section, we introduce the Fuzzy Inference Mechanism (FIM) for performing the fuzzy inference analysis of each web service. In the FIM, we utilize and modify the parallel fuzzy inference model of Lee et al. [1]. Fig. 3 shows the proposed FIM. There are five layers, including input linguistic layer, input term layer, rule layer, output term layer and output linguistic layer in the FIM. Now we describe the FIM as follows.

- **Layer 1 (Input Linguistic Layer)**

  The nodes in this layer just transmit input values to the next layer directly. The input vector of layer 1 is
  \[ y_i = (x_{i1}, x_{i2}, ..., x_{ij}) \]
  where \( x_{ij} \) indicates \( j \)-th fuzzy variable of \( i \)-th service. The output vector of layer 1 is as follows:
  \[ y_i = \left[ \begin{array}{c} \mu_{i1} \\
                \mu_{i2} \\
                \vdots \\
                \mu_{ik} \end{array} \right] = \left[ \begin{array}{c} \mu_{i11}, \mu_{i12}, ..., \mu_{i1k} \\
                \mu_{i21}, \mu_{i22}, ..., \mu_{i2k} \\
                \vdots \\
                \mu_{ik1}, \mu_{ik2}, ..., \mu_{ikk} \end{array} \right] \tag{1} \]

- **Layer 2 (Input Term Layer)**

  Each fuzzy variable of layer 2 appearing in the premise part is represented with a condition node. Each of the outputs of the condition node is connected to rule nodes in layer 3 to constitute a condition specified in some rules. This layer performs the first inference step to compute matching degrees. If the input vector of this layer is
  \[ y_i^2 = \left[ \begin{array}{c} u_{i11}, u_{i12}, ..., u_{i1k} \\
                  u_{i21}, u_{i22}, ..., u_{i2k} \\
                  \vdots \\
                  u_{ik1}, u_{ik2}, ..., u_{ikk} \end{array} \right] \]
  then it will be transferred as follows:
  \[ y_i^3 = \left[ \begin{array}{c} u_{i11}, u_{i12}, ..., u_{i1k} \\
                  u_{i21}, u_{i22}, ..., u_{i2k} \\
                  \vdots \\
                  u_{ik1}, u_{ik2}, ..., u_{ikk} \end{array} \right] \tag{2} \]

  where \( u_{ijk} \) is the membership degree of \( k \)-th linguistic term of \( j \)-th fuzzy variable for \( i \)-th service. In this paper, we use a triangular membership function specified by three parameters \([\alpha, \beta, \gamma]\) as follows:
  \[ u(x; \alpha, \beta, \gamma) = \begin{cases} 0 & x \leq \alpha \\
                                 (x - \alpha)(\beta - \alpha) / (\beta - \alpha) & \alpha \leq x < \beta \\
                                 (\gamma - x)(\gamma - \beta) / (\gamma - \beta) & \beta \leq x \leq \gamma \\
                                 0 & x > \gamma \end{cases} \tag{3} \]

- **Layer 3 (Rule Layer)**

  The links in this layer are used to perform precondition matching of fuzzy logic rules. Hence, the rule nodes should perform the fuzzy AND operation [1], and the outputs will be linked with associated linguistic node in the fourth layer. In our model, the rules are defined by domain expert’s knowledge previously. Eq. 4 shows the precondition matching degree of rule node \( i \) as follows:
  \[ \mu_{i} = \min\left\{ \mu_{i1j}, \mu_{i2j}, ..., \mu_{ikj} \right\} \tag{4} \]

- **Layer 4 (Output Term Layer)**

  In this layer, the output term node performs the fuzzy OR operation to integrate the fired rules which have the same consequence. Suppose that \( FL, FM \) and \( FH \) are the fired rules connecting to linguistic terms of Low, Medium and High, respectively. Then the output of this layer is as follows:
  \[ \mu_i^4 = \begin{cases} \text{Centroid} & \max_{F \in \{\text{Low}\}} \mu_{iF}^4 \text{ Low} \\
                             \text{Centroid} & \max_{F \in \{\text{Medium}\}} \mu_{iF}^4 \text{ Medium} \\
                             \text{Centroid} & \max_{F \in \{\text{High}\}} \mu_{iF}^4 \text{ High} \end{cases} \tag{5} \]

- **Layer 5 (Output Linguistic Layer)**

  Finally, we compute the center of gravity according to
  \[ Y_i = \frac{\sum_{p=1}^{n} w_p \times F_p}{\sum_{p=1}^{n} w_p} \tag{6} \]
  \[ Y_i = \frac{\sum_{p=1}^{n} w_p \times F_p}{\sum_{p=1}^{n} w_p} \]
  \[ w_p = \sum_{r=1}^{n} w_{ir} \sigma, \text{ where } \sigma = \begin{cases} 1 & \mu_{ir}^4 \text{ is maximum} \\
                             0 & \text{Otherwise} \end{cases} \tag{7} \]

  Now, we describe an example of the fuzzy variables and inference rules for SAMMA-WS. In SAMMA-WS, we define three input fuzzy variables, including the Distance of the Supplier (DS), the Difference of the Supplier Budget (DSB) and the Technical Capability of the Supplier (TCS), and one
output fuzzy variable serving as the Selected Possibility of the Supplier (SPS) for FIM. In this case, we denote the membership functions of fuzzy sets $DS_1$={Near, Medium, Far} for fuzzy variable $DS$ as $\{0, 0, 150\}$, $\{0, 150, 300\}$, $\{150, 300, 300\}$, $DS_2$={Less, Medium, Many} for fuzzy variable $DSB$ as $\{0, 0, 250\}$, $\{0, 250, 500\}$, $\{250, 500, 500\}$, $TCS$={Less, Medium, Many} for fuzzy variable $TCS$ as $\{0, 0, 10\}$, $\{0, 10, 20\}$, $\{10, 20, 20\}$ and $SPS$={Very Low, Low, Medium, High, Very High} for fuzzy variable $SPS$ as $\{0, 0, 0.25\}$, $\{0, 0.25, 0.5\}$, $\{0.25, 0.5, 0.75\}$, $\{0.5, 0.75, 1\}$, $\{0.75, 1, 1\}$). Table 2 shows the fuzzy rules defined by the domain experts for the FIM of the SAMMA-WS.

Table 2. Fuzzy inference rules of FIM for SAMMA-WS.

<table>
<thead>
<tr>
<th>Rules</th>
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<th>DSB</th>
<th>TCS</th>
<th>SPS</th>
</tr>
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<td>1</td>
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<td>Less</td>
<td>Many</td>
<td>Very High</td>
</tr>
<tr>
<td>2</td>
<td>Near</td>
<td>Less</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>3</td>
<td>Near</td>
<td>Medium</td>
<td>Less</td>
<td>High</td>
</tr>
<tr>
<td>4</td>
<td>Near</td>
<td>Medium</td>
<td>Many</td>
<td>High</td>
</tr>
<tr>
<td>5</td>
<td>Near</td>
<td>Medium</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>6</td>
<td>Near</td>
<td>Medium</td>
<td>Many</td>
<td>High</td>
</tr>
<tr>
<td>7</td>
<td>Near</td>
<td>Many</td>
<td>Many</td>
<td>High</td>
</tr>
<tr>
<td>8</td>
<td>Near</td>
<td>Many</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>9</td>
<td>Near</td>
<td>Many</td>
<td>Medium</td>
<td>Low</td>
</tr>
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<td>Less</td>
<td>Many</td>
<td>Medium</td>
</tr>
<tr>
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<td>Medium</td>
<td>Less</td>
<td>Medium</td>
<td>High</td>
</tr>
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<td>Less</td>
<td>Medium</td>
<td>Medium</td>
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<td>Medium</td>
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<td>Medium</td>
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<td>16</td>
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<td>Many</td>
<td>Many</td>
<td>Medium</td>
</tr>
<tr>
<td>17</td>
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<td>Many</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>18</td>
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<td>Less</td>
<td>Many</td>
<td>Medium</td>
</tr>
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<td>Far</td>
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<td>Medium</td>
<td>Low</td>
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<td>Medium</td>
<td>Less</td>
<td>Low</td>
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<td>Low</td>
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<td>Medium</td>
<td>Medium</td>
<td>Low</td>
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<td>Medium</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
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<td>Medium</td>
<td>Medium</td>
<td>Low</td>
</tr>
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<td>25</td>
<td>Far</td>
<td>Many</td>
<td>Many</td>
<td>Medium</td>
</tr>
<tr>
<td>26</td>
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<td>Many</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>27</td>
<td>Far</td>
<td>Many</td>
<td>Less</td>
<td>Very Low</td>
</tr>
</tbody>
</table>

4 Genetic Learning Mechanism

In this section, Genetic Learning Mechanism (GLM) used to learn the fuzzy inference rules and membership functions is presented for SAMMA-WS. In the chromosome encoding, we utilized a double coding scheme (CSa + CSb) [1] for both membership function (CSa part) and fuzzy inference rule (CSb part) tuning. Each chromosome is composed of CSa part and CSb part. Fig. 4 shows the linguistic terms of the fuzzy variables where $X_i, \ldots, X_j$ is the input fuzzy variables and $Y_k$ is the output fuzzy variable. The Eq. 8 shows the coding of the fuzzy variables. Fig. 5 shows the CSa part of the chromosome for $i$-th web service.

Fig. 4. Three linguistic terms for $X_{ii}$-th fuzzy variable.

$$X_i = \left\{ 0.00, 0.10, 0.20 \right\}, \left\{ 0.10, 0.20, 0.20 \right\}, \left\{ 0.00, 0.10, 0.20 \right\}$$

(8)

Fig. 5. The CSa part of the chromosome.

There are three linguistic terms of fuzzy variable $X_{ii}$, which includes $\{0.00, 0.10, 0.20\}$, $\{0.10, 0.20, 0.20\}$ and $\{0.00, 0.10, 0.20\}$. The restriction of fuzzy variable $X_{ii}$ is as follows:

$$X_{ii} \leq X_{ij} \leq X_{ik} \leq X_{ij} \leq X_{ik} \leq X_{ij} \leq X_{ik} \leq X_{ij} \leq X_{ik} \leq X_{ij} \leq X_{ik} \leq X_{ij} \leq X_{ik}$$

(9)

In addition, we utilize concentration linguistic modifier “very” ($\delta = 2$) and dilation linguistic modifier “more-or-less” ($\delta = 0.5$) [1] to tune the fuzzy rules. The equations of the modifier are as follows:

$$u^\text{very}(x) = (u(x))^2$$

(10)

$$u^\text{more-or-less}(x) = (u(x))^5$$

(11)

Fig. 6(a)-(c) show three linguistic terms including normal High ($\delta = 1$), very High ($\delta = 2$) and more-or-less High ($\delta = 0.5$).

Fig. 6. Linguistic terms (normal High, very High and more-or-less High).

The Eq. 12 represents the CSb part of the chromosome, where $\delta_{imn}$ is $r$-th fuzzy inference rule for the linguistic modifier of $m$-th input fuzzy variable, $\delta_{imn}$ is $r$-th fuzzy inference rule for the linguistic modifier of output fuzzy variable. $\{0.00, 0.10, 0.20\}, \{0.10, 0.20, 0.20\}$

$$\delta_{imn} = \left\{ \delta_{imn}, \delta_{imn}, \delta_{imn} \right\} = \left\{ \delta_{imn}, \delta_{imn}, \delta_{imn} \right\} = \left\{ \delta_{imn}, \delta_{imn}, \delta_{imn} \right\}$$

(12)

Fig. 7. The CSb part of the chromosome.

The main components of the genetic learning mechanism are as follows.

- Initial Population
  
  The initial population is composed of four groups.
In the first group, each chromosome is made of original values in the $CS_a$ part and the $CS_b$ part ($\delta = 1$). In the second group, each chromosome is made of original values in the $CS_a$ part and $CS_b$ part generated randomly. In the third group, each chromosome is made of $CS_a$ part generated randomly and the $CS_b$ part ($\delta = 1$). In the last group, each chromosome is made of $CS_a$ part and $CS_b$ part generated randomly.

- **Selection**
  In the selection mechanism, we utilize roulette wheel [3], selection of a new population with respect to the probability distribution based on fitness values, to select the best chromosome. We compute the fitness values of all chromosomes first, and then select the best chromosome by Eq. 14. The roulette wheel is as follows:
  
  1. Calculate the fitness value $MSE(v_i)$ for each chromosome $v_i$ ($i=1,\ldots, \text{population\_size}$).
  2. Find the total fitness of the population
     \[
     F = \sum_{i=1}^{\text{population\_size}} MSE(v_i) \quad (13)
     \]
  3. Calculate the probability of a selection $p_i$ for each chromosome $v_i$ ($i=1,\ldots, \text{population\_size}$).
     \[
     p_i = \frac{MSE(v_i)}{F} \quad (14)
     \]

- **Crossover**
  In the crossover process, we use one-point crossover and randomly generate one point as crossover point. According to the crossover point, two chromosomes will be segmented into two parts. The later part of two chromosomes will exchange each other, and then two offsprings will be generated. The interval of typical crossover probability is [0.1, 0.6] [3].

- **Mutation**
  In the mutation process, the gene of the chromosome will be changed if a random value is larger than mutation probability. In one chromosome mutation proceeding, the $CS_a$ part of the chromosome must observe restrictions (Eq. 9) and the $CS_b$ part of the chromosome is 0.5, 1 and 2.

- **Evaluation Function**
  The fitness function will be to minimize the well-known mean square error (MSE) as follows:
  \[
  MSE = \frac{1}{2 \times T} \sum_{t=1}^{T} (y_{t|d} - y_{t|d})^2 \quad (15)
  \]
  where $T$ is the training data size, $y_{t|d}$ is the output for $t$-th training data of $i$-th web service, $y_{t|d}$ is the desired output for $t$-th training data of $i$-th web service.

## 5 Experimental Results

We have constructed an experimental website to test the performance of the proposed approach. The website is located at “Decision Support & Artificial Intelligent Lab.” of Chang Jung University in Taiwan, and implemented with VB.Net on Windows operating system.

In the experiment, we select 110 suppliers divided into two groups including 100 training data and 10 testing data for $SAMMA\_WS$. In GA learning experiment, we setup a population size of 20 chromosomes and 50 generations. Fig. 8 shows the average results of population for each generation. Fig. 8, GLM have two parameters, where one parameter is crossover probability and the other is mutation probability. Fig. 9 shows the best results of population for each generation. After learning, the membership functions of fuzzy sets are as follows: $DS=\{\text{Near, Medium, Far}\}$ for fuzzy variable $DS$ as $\{[0, 0, 142.74], [13.35, 152.34, 208.8], [205.62, 232.47, 232.47]\}$, $DSB=\{\text{Less, Medium, Many}\}$ for fuzzy variable $DSB$ as $\{[0, 0, 195.17], [40.29, 196.46, 321.32], [318, 458.16, 458.16]\}$, $TCS=\{\text{Less, Medium, Many}\}$ for fuzzy variable $TCS$ as $\{[0, 0, 6], [5, 6, 17], [13, 18, 18]\}$ and $SPS=\{\text{Very Low, Low, Medium, High, Very High}\}$ for fuzzy variable $SPS$ as $\{[0, 0, 0.15], [0.11, 0.22, 0.38], [0.23, 0.49, 0.65], [0.6, 0.7, 0.78], [0.72, 0.84, 0.84]\}$.

![Fig. 8. The average results of population for each generation.](image1)

![Fig. 9. The best results of population for each generation.](image2)

We select 20 data among 110 suppliers to make inside testing and outside testing. Table 4 shows the results that are gained both before and after learning.
In the experimental results, the results of learning before are better than after when crossover probability and mutation probability were setup 0.9 and 0.1, respectively.

Table 4(a). The inside testing results of GA learning.

<table>
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<tr>
<th>Inside Testing Data</th>
<th>Desired Output</th>
<th>The results GLA</th>
<th>0.0/0.05</th>
<th>GLA</th>
<th>0.6/0.05</th>
<th>GLA</th>
<th>0.9/0.01</th>
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<th>0.6/0.1</th>
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Table 4(b). The outside testing results of GA learning.

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6 Conclusions

In this paper, we propose a measurement and analysis web service based on CMMI Level 2 ontology and utilize the parallel fuzzy inference mechanism to assist in MA process areas. The MA web service provides four sub-services including PPMA Web Service, PMMA Web Service, SAMMA Web Service and PPQAMA Web Service. In the future, we will construct the ontologies of CMMI Level 3, Level 4 and Level 5 for supporting all MA process areas in the CMMI.

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References: