The Realization of Intelligent Knowledge Adaptive Learning Method in the Field of Substation Operation and Maintenance

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Abstract: In view of the lack of targeted and personalized knowledge learning in existing substation operators, this paper proposes an intelligent adaptive knowledge learning method in the field of substation operation and maintenance. First, an adaptive knowledge learning system is established including domain model, user model, teaching model and adaptive engine. In the user model, the item response theory (IRT) is used to estimate the learner’s master degree of knowledge points contained in the domain model, and then their learning needs are obtained. Meanwhile, the Bayesian network method is used to speculate the cognitive style of learners. On the basis of a comprehensive consideration of learning needs and cognitive style, the particle swarm optimization algorithm (PSO) in the teaching model is used to recommend the optimal learning resource for learners to realize the high-efficiency personalized knowledge learning in substation operation and maintenance.

Key words: substation operation and maintenance, adaptive learning, cognitive style, item response theory, particle swarm optimization algorithm

1. Introduction

The safe and stable operation of substation is of great significance to ensure the safety of the power grid. With the development of ubiquitous power internet of things and smart grid, the application of abundant new technologies, new equipment and new systems in substations has accelerated the updating of the knowledge on substation operation and maintenance, which demands higher abilities of substation personnel. However, the traditional training methods for the personnel featured with large amounts and different ability level are mostly short of pertinence and personalization. Taking the online university platform owned by the State Grid Corporation as an example, it simply moves offline learning resources and examination questions to the web page but cannot generate dynamically the learning content special for each user, descending the training outcomes and quality.

In recent years, the rapid development of artificial intelligence provides the possibility to effectively and further enhance the knowledge and skill level of substation personnel. Among them, the adaptive learning technology [1, 2] is able to select, assemble, and present personalized learning content for users through a deep and real-time analysis of their learning behaviors and requests. This technology has been successfully applied in systems like Knewton, Squirrel AI Learning, etc. on the area of K-12 education. Adaptive learning technology involves a variety of computer science and artificial
intelligence methods, including ontology [3], data mining [4, 5], item response theory [6], fuzzy logic [7], Bayesian network [8], evolution algorithms [9, 10], etc. As for the operation and maintenance training with the test results as one of the main assessment indexes, the item response theory (IRT) establishes the correlation between the ability level and the accuracy of answering questions, based on which each trainee’s ability on different knowledge points can be scientifically tested and estimated. With the aid of genetic algorithm (GA) [9], particle swarm optimization (PSO) algorithm [10] or other evolution algorithms, personalized resource recommendations as well as learning navigations can be offered to trainees to promote themselves effectively. In addition, considering the learning habit and cognitive style when selecting the matching type of learning resources can further improve the training efficiency, continuing to provide intellectual support and talent guarantee for power grid development. In this paper, an adaptive learning method applied to the field of substation operation and maintenance is established. The knowledge level and cognitive style of the trainee selected in this paper are evaluated using IRT and Bayesian network, respectively. Integrating the above two learning characteristics, the PSO algorithm is introduced to recommend the optimal learning resource for the trainee to realize the adaptive learning process.

2. Adaptive learning system

Figure 1 illustrates the fundamental construction of the adaptive learning system designed in this work. The structure refers to the adaptive educational hypermedia system (AEHS), a general reference model proposed by Brusilovsky et al. [11] from the University of Pittsburgh, USA. The system is mainly composed of four parts:

![Figure 1. The fundamental construction of the adaptive learning system](image)

(1) Domain Model: it describes the knowledge structure of substation operation and maintenance and stores the materials including test questions, courseware, etc. Through ontology technology, domain knowledge is summarized and stored in the form of knowledge map with the content covering operating principle, equipment testing, fault recovery and so on. The design and revision of the knowledge map is done by a dozen of experts in this field. Moreover, the experts connect all types of learning resources (video, text, etc.) as well as test questions with different knowledge points.

(2) User Model: it builds the trainee’s “portrait”, namely learning characteristics. Typical characteristics include multiple dimensions like basic information, knowledge level, cognitive style, user emotion, society relationship, etc. In the training of substation personnel, the knowledge level is always viewed as one of the most important characteristics in evaluation. Therefore, we use IRT in this work to estimate the trainee’s knowledge level of different knowledge points. Based on the results, the current weakness of the trainee is obtained and his learning needs can be further speculated. Besides, our user model also lays emphasis on the dimension of cognitive style. Different from traditional unified teaching materials, the recommended learning resource not only matches the trainee in the aspect of resource contents, but also in resource types, as to improve the efficiency in the personalized learning process.
3. Teaching Model: it declares the rules of recommending the optimal learning resource(s) to the trainee. In this work, the knowledge level and cognitive style are chosen as the two main criteria in making the rule and the PSO algorithm is adopted to search the optimal recommendation.

4. Adaptive Engine: it drives the domain model, user model, and teaching model to realize the adaptive learning process. According to the knowledge map, the engine examines the trainee’s knowledge level of selected knowledge points, and recommends the optimal learning resource with consideration of both the trainee’s knowledge level and cognitive style.

3. Model development

3.1. Domain model

As mentioned above, the knowledge map in the domain model is designed and revised by the expert in the substation operation and maintenance. Taking a 500 kV substation as an example, the knowledge mapping refers to a professional teaching material and starts from chapters to units, which covers fundamental knowledge, basic skills (monitoring, inspection, maintenance, and switching operation), accident handling, and equipment repair. Knowledge points are summarized from the unit content in each chapter and connected with each other forming the network-like knowledge map that follows the principle of accuracy, cleanliness, and uniqueness.

The links between knowledge points and test questions as well as learning resources are further built. Each test question is linked with the most relevant knowledge point and labeled with its difficulty value \( d \), which are done artificially by the expert to guarantee the accuracy. For \( K \) knowledge points with each one linked with \( Q \) test questions, a difficulty matrix \( D=[d_{kq}]_{K \times Q} \) can be established. Based on IRT, \( d_{kq} \) ranges from -4.0 to 4.0. The higher \( d_{kq} \) is, the more difficult the test question is.

Different from test questions, one learning resource on substation operation and maintenance often involves many knowledge points, and the resource type involves video, animation, PPT, text, etc. We establish the learning resource matrix \( R=[r_{mk}]_{M \times (K+1)} \) to describe the relationship between \( M \) learning resources and \( K \) knowledge points. \( r_{mk} \) is defined as:

\[
\begin{align*}
\text{when } k \leq K, & \quad r_{mk} = \begin{cases} 
1 & \text{No. } m \text{ learning resource involves No. } k \text{ knowledge point} \\
0 & \text{otherwise}
\end{cases} \\
\text{when } k = K+1, & \quad r_{mk} = \begin{cases} 
1 & \text{video-type learning resources} \\
0 & \text{text-type learning resources}
\end{cases}
\end{align*}
\]

Here, the video-type learning resources include video, animation, and figure-based PPT, whereas the text-type learning resources include text and word-based PPT.

3.2. User model

3.2.1. Knowledge level. For \( K \) knowledge points, randomly select \( I (I \leq Q) \) test questions from every knowledge point to conduct the test, guaranteeing the difficulty value \( d \) uniformly distributed in the range [-4, 4]. After the test, we can obtain the test result matrix \( A=[a_{ki}]_{K \times I} \) as:

\[
a_{ki} = \begin{cases} 
1 & \text{correctly answer No. } i \text{ question related to No. } k \text{ knowledge point} \\
0 & \text{otherwise}
\end{cases}
\]

Item response theory (IRT) is a modern psychometric theory that establishes the association between test results and potential characteristics. In this paper, the single-parameter Logistic model (termed as Rasch model) based on this theory is used to estimate the knowledge level \( c_k \) [13]. Rasch model describes the probability of a person with knowledge level \( c_k \) correctly answering question \( (a_{ki}=1) \) as:
\[
p(a_{ki} = 1) = \frac{1}{1 + e^{-(c_k - d_{ki})}}
\]  

(3)

The probability of not correctly answering equals to \(1 - p\). Based on the test result matrix \(A\), the maximum likelihood estimation (MLE) method is adopted to estimate the knowledge level \(c_k\), using the following likelihood function \(L\):

\[
L(a_k | c_k, d_k) = \prod_{i=1}^{I} p(a_{ki} | c_k, d_{ki})
\]  

(4)

The knowledge level on the No. \(k\) knowledge point equals to the \(c_k\) that makes \(\ln(L)\) reaches its maximum. We use the Newton-Raphson iterative algorithm to solve this mathematical problem and finally obtain the knowledge level vector \(C=\{c_k\}_K\) related to the \(K\) knowledge points. \(c_k\) ranges from -4.0 to 4.0.

The learning need is further deduced from the knowledge level. Basically, if one owns a low knowledge level at a certain knowledge point, he/she has a high level of learning need at this point. Therefore, we use the following function to quantify the relationship between the knowledge level and the learning need:

\[
n_k = 1 - \frac{1}{1 + e^{-c_k}}
\]  

(5)

\(n_k\) stands for the learning need on the No. \(k\) knowledge point and ranges from -1.0 to 1.0. Based on the knowledge level vector \(C\), the learning need vector \(N=[n_k]_K\) is calculated.

3.2.2. Cognitive style. The cognitive style considered in this work mainly refers to the preference on the type of learning resources, and is quantified with the cognitive style vector \(S=\{s_1, s_2, s_3\}\). Specifically, \(s_1\) stands for the percentage of video-type (including animation) learning resources in all learning resources that are ordinarily learned. In similar, \(s_2\) and \(s_3\) stand for the percentage of PPT-type and text-type learning resources, respectively. Before the adaptive learning, the incipient cognitive style can be obtained by a questionnaire investigation. The update of the cognitive style afterwards can be done on the basis of the online learning record.

The Bayesian method is used to ascertain the cognitive style. Bayesian network is a probability-based directed acyclic graph (DAG). Referring to literature [14], we design a video-style/text-style probability scale, as shown in Table 1. √ stands for selecting this type of learning resources while × stands for not selecting. Based on the cognitive style vector \(S\), the cognitive style \(Sty\) can be calculated as:

\[
Sty = 0.85s_1s_2s_3 + 1.0s_1s_2\bar{s}_3 + 0.6s_1\bar{s}_2s_3 + 0.7s_1\bar{s}_2\bar{s}_3 + 0.4\bar{s}_1s_2s_3 + 0.7\bar{s}_1s_2\bar{s}_3 + 0\bar{s}_1\bar{s}_2s_3 + 0.5\bar{s}_1\bar{s}_2\bar{s}_3
\]  

(6)

Here, \(\bar{s}=1.0-s\). \(Sty\) ranges from 0 to 1.0. If \(Sty\) approaches to 1, the cognitive style is more like video-style. Otherwise, it is more like text-style.

| Video (including animation) | √ | × |
|-----------------------------|---|---|
| PPT                         | √ | × |
| Text                        | √ | × |
| Video-style                 | 0.85 | 1.0 | 0.6 | 0.7 | 0.4 | 0.7 | 0 | 0.5 |
| Text-style                  | 0.15 | 0 | 0.4 | 0.3 | 0.6 | 0.3 | 1.0 | 0.5 |

Table 1. Video-style/text-style probability scale used in this work
3.3. Teaching model

Based on the learning need and cognitive style, the optimal learning resource will be selected in this part. First, we define a decision vector \( X = [x_m]_M \) in which:

\[
x_m = \begin{cases} 
1 & \text{select No. } m \text{ learning resource and recommend} \\
0 & \text{otherwise} 
\end{cases}
\]

The decision vector \( X \) determines which one in the \( M \) learning resources is ultimately recommended. Corresponding to the decision vector, the target functions are formulated as follows:

\[
F_1 = \sum_{m=1}^{M} \sum_{k=1}^{K} x_m |r_{mk} - n_k| \\
F_2 = \sum_{m=1}^{M} x_m |r_{m(K+1)} - Sty| \\
F = \min \left( \xi_1 F_1 + \xi_2 F_2 \right)
\]

\( F_1 \) function presents the proximity between the knowledge points involved by the learning resource and those related to the learning need. \( F_2 \) presents the proximity between the type of the learning resource and the cognitive style. The lower the value of \( F_1 \) and \( F_2 \) are, the more suitable the selected learning resource is. \( F \) is the sum of \( F_1 \) and \( F_2 \), with the weighting factor of \( \xi_1 \) and \( \xi_2 \). Thus, the decision vector that makes \( F \) reaches its minimum will be regarded as the best one.

As above, the recommendation process has been simplified into an optimization problem. The particle swarm optimization (PSO) algorithm is one of the typical optimization algorithms that simulates the process of bird flock foraging and have unique advantages in solving multi-object optimization problems. In this algorithm, a group of particles are first generated and each of them carries a possible solution to the problem. In every generation, each particle will adjust its velocity (value and direction) according to the particle best position and the group best position. During the competition and cooperation, the best position in the solution space will be ultimately found. In this work, we adopt this algorithm to find the best decision vector \( X \).

Each particle is given a decision vector \( X_{id} \) when first generated. \( id \) is the identity of the particle and every initial \( x_{id} \) in \( X_{id} \) is randomly set as 0 or 1. The searching velocity, \( v_{id} \), is calculated with the following equation:

\[
v_{id}(t) = \omega v_{id}(t-1) + l_1 \text{rand}(1) \left( p_{best_{id}} - x_{id}(t-1) \right) + l_2 \text{rand}(1) \left( g_{best} - x_{id}(t-1) \right)
\]

Here, \( t \) stands for the generation number. \( p_{best_{id}} \) is the best position of the No. \( id \) particle and \( g_{best} \) is the group best position, which are chosen in the \( t-1 \) generation. \( \text{rand}(1) \) generates a random number in (0, 1). \( l_1 \) and \( l_2 \) are the model coefficients. \( \omega \) is the inertia weight. In the early stage, big \( \omega \) is preferred to enhance the searching ability of the algorithm in the entire solution space. When it comes to the late stage, small \( \omega \) is beneficial to the local precise searching. Referring to literature [15], we assume a linearly changing \( \omega \):

\[
\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{T} t
\]

\( T \) is the total generation number. \( \omega_{max} \) equals to 0.9 and \( \omega_{min} \) equals to 0.4. Considering the discreteness of \( x_{id} \) (only 0 and 1), we use the following equation to update the position of particles [16]:
\[ x_{id}(t) = \begin{cases} \frac{1}{1 + e^{-\omega(t)}} > \text{rand}(1) \\ 0 \text{ otherwise} \end{cases} \] (11)

4. Results and discussion

4.1. Case setting

We select 30 knowledge points on switching from the knowledge map of substation operation and maintenance \((K=30)\), together with 15 related learning resources \((M=15)\). The knowledge points cover the switching operation of high-voltage line, bus, voltage transformer, compensation device, secondary equipment, etc. and the types of learning resources include video, animation, PPT, and text. All selected knowledge points and learning resources are re-numbered with \(K_{n} = 1-K_{30}\) and \(R_{e} = 1-R_{e} 15\), respectively. Based on eq. (1), the learning resource matrix \(R\) is established. For each knowledge point, 10 relevant test questions are selected \((I=10)\) with the marked difficulty ranging from -4.0 to +4.0. We use all these questions to test the trainee and then record his test result to establish the test result matrix \(A\). Afterwards, the knowledge level vector \(C\) as well as the learning need vector \(N\) are derived based on eq. (2)-eq. (5). By means of a questionnaire investigation, we obtain the trainee’s current cognitive style \(S_{ty}=0.708\). The parameters in the PSO algorithm are set as: total number of particles=200, \(T=100\), \(\zeta_{1}=0.6\), \(\zeta_{2}=0.4\), \(l_{1}=l_{2}=1.49618\).

4.2. Result analysis

Figure 2 illustrates the value of target function \(F\) as a function of the generation number. As present, the PSO algorithm finds the best solution of the our case after 18th generation and the best decision vector is \(X_{\text{best}}=[0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]\). The result indicates that \(R_{e}.10\) is most suitable learning resource to recommend to the trainee.

![Figure 2. The value of F as a function of the generation number t](image)

In order to verify whether the recommended learning resource matches the learning need of the trainee, we compare the knowledge points involved in the learning resource with those related to the learning need, as shown in Fig. 3. It can be seen that the recommended learning resource involves 16 knowledge points in the aspect of switching operation. Among them, all the three knowledge points of which the knowledge level is less than -1.5 (learning need \(\geq 0.818\)) are covered. For the knowledge points of which the knowledge level is less than -1.0 (learning need \(\geq 0.731\)), the learning resource
covers 66.7% (four of six) of them. The recommended learning resource meets the trainee’s learning need pretty well.

To further clarify the fitness of the recommended learning resource in all the selected ones, we define the deviation $\sigma$ between the learning resources and the learning need as:

$$\sigma = \sqrt{\frac{1}{K} \sum_{k=1}^{K} (r_{mk} - r_{kn})^2}$$  \hspace{1cm} (12)

From the viewpoint of learning need, the lower $\sigma$ is, the more suitable the resource is. Fig. 4 illustrates the $\sigma$ of all the fifteen selected learning resources. Among all, Re. 14, Re. 10, and Re. 15 are the top 3 resources that are closest to the learning need, with $\sigma$ equalling to 0.552, 0.555, and 0.561.

![Figure 4](image-url) \hspace{1cm} Figure 4. The deviation between the learning resources and the learning need

Specifically, the details of Re. 14, Re. 10, and Re. 15 are extracted from the resource matrix and listed in Table 2. It is demonstrated that Re. 10 and Re. 15 are video-type, while Re. 14 is text-type. For a trainee with a cognitive style of $Sty=0.708$, video-type Re. 10 is the optimal recommendation.

![Figure 3](image-url) \hspace{1cm} Figure 3. The knowledge points corresponding to the recommended resource and the learning need

| Kn. 1 | Kn. 2 | … | Kn. 30 | Type |
|-------|-------|---|--------|------|
| Re. 10 | 1     | 0 | …     | 1    |
| Re. 14 | 0     | 0 | …     | 0    |
5. Conclusion
In this paper, an intelligent knowledge adaptive learning method is proposed and realized in the training of substation operation and maintenance. Item response theory (IRT) and Bayesian network are adopted to obtain the knowledge level and cognitive style of the trainee, respectively. Based on these two key characteristics, the particle swarm optimization (PSO) algorithm is used to successfully find the optimal learning resource. For a case with 30 knowledge points and 15 relevant learning resources, the optimal solution is obtained at ~20th generation in the PSO algorithm. The recommended learning resource using our adaptive learning method covers 100% of the knowledge points with the knowledge level of the trainee less than -1.5, and 66.7% of those with the knowledge level less than -1.0. Under the premise of meeting the learning need, the recommended resource type well fits the video-preferred cognitive style of the trainee. The adaptive learning method proposed in this work integrates knowledge level and cognitive style to realize the personalized learning process. Further studies can focus on more learning characteristic dimensions or more detailed recommendation rules, which, along with the method in the work, has broad application prospects in the intelligent training of substation operation and maintenance.

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