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A case-based knowledge system for safety evaluation decision making of thermal power plants

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ABSTRACT

Safety assessment of thermal power plants (TPP) is an important means to ensure the safety of production in thermal power production enterprises. Modern information technology can play an important role in TPP safety assessment. The evaluation of power plant systems relies, to a large extent, on the knowledge and experience of the experts undertaking the task. Case-based reasoning (CBR) is introduced for the safety assessment of TPP since it models expertise through experience management. This paper provides a case-based approach for the Management System safety assessment decision making of TPP (MSSATPP). We introduce a case matching method named CBR-Grey, which integrates the Delphi approach and grey system theory. Based on this method, we implement a prototype of case-based knowledge system (CBRSYS-TPP) for the evaluation decision making of the panel of experts. Our experimental results based on a real-world TPP safety assessment data set show that CBRSYS-TPP has high accuracy and systematically good performance.

1. Introduction

Industrial production, especially in the area of power generation, oil and gas, aviation, mining, and nuclear plants, often has significant safety implications on the safety of people's life and property, thus is attracting increasing attention from industry practitioners as well as researchers [1]. As an essential industrial component, thermal power plants (TPP) equip many industrial departments and their production process is very complicated. When operating TPP, the safety of people's lives and work conditions is a major concern. There are numerous TPP all over the world. Taking China as an example, there are over 1200 coal-fired thermal plants. In 2006, the total power generated in China by TPP reached 2834.4 terawatt per hour (TWh) and the total installed capacity reached 622 gigawatts (GW) [2]. As one of the nations with most electric power generation, China produces its electric power mainly from coal [3]. Another country that relies heavily on TPP for power generation is Turkey, where 80% of the total electricity is generated from TPP [4]. Safety assessment of TPP mainly concerns three aspects: Production Equipment Systems (PES), Working Circumstance Systems (WCS), and Production Management Systems. The third is also referred to as the Management System (MS) in current research. Through analyzing and evaluating these three subsystems, TPP can establish necessary corrective, remedial, and preventive measures, and realize the goal of controlling the accidents in advance.

As one of modern management ladders, safety assessment is a powerful tool for automatically diagnosing safety issues. However, numerous existing evaluations for production safety are irregular, unscientific, and capricious.

Because of the lack of powerful information and knowledge support for panel of experts during their decision making process of evaluation, the current used approach of direct expert evaluation is too subjective. Accordingly, there is a sizable margin of error. Hence, it is necessary to reduce its subjectivity. Along with the perfection of safety assessment rules and the development of information technologies, new techniques are being applied to almost all aspects of power systems to improve efficiency [5]. It is of both scientific and social significance for TPP to improve their safety assessment process toward better quantification, scientization, and automatization. MS safety represents an important aspect of the

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safety issue in the production of TPP. Numerous facts show that a large part of safety accidents in TPP occurred due to the managerial inadequateness and not for the equipment malfunctions.

From the perspective of Management Systems Safety Assessment of TPPs (MSSATPP), this paper investigates the whole range of safety assessment in TPPs' production, and applies the case-based reasoning (CBR) technique to the evaluation decision making process of MSSATPP. It presents a case-based decision support method named improved grey CBR (IGCBR) for MSSATPP and a framework of knowledge system for intelligent decision making (IDSS-MSSATPP).

This paper is organized in six sections. Section 2 is literature review regarding the evaluation on the power system and case retrieval methods in knowledge-based decision making, as well as the motivation of this study. Section 3 describes TPP safety evaluation process, introduces the evaluation indexes and defines four statistics for performance evaluation in the later experiments. Section 4 deals with problem's domain knowledge acquisition methodology mainly focusing on the weight determination method based on Delphi method and the retrieval algorithm based grey system theory. Also, the data set for experiments is introduced in this section. Section 5 introduces the system implementation and relevant experiments. And the main results are presented and brief discussion is also given. Section 6 concludes the paper and briefly introduced the trial application in a large-scale thermal power plant.

2. Literature review

2.1. The evaluation on the power system

Common evaluation issues concerning the power industry have been reported in the literature. In view of the special importance of production safety for TPP, it is important to study scientific approaches that fit the characteristic features of the production and management of TPP for safety assessment. However, few research studies focus on the safety assessment of TPP in production – the inside safety itself. Most of the literature focuses on the operational performance [6], energetic and exergetic performance analyses [7], the selection of an optimum power plant [8], air quality impact [9,10], and ecological efficiency [11]. Second, as far as content assessment is concerned, few studies concern safety evaluation of management work.

In terms of evaluation approaches, few approaches are actually able to solve the problems of providing powerful and helpful expert information support for experts' decision making and the reuse of domain knowledge. Until now, rare contributions have been made to the assessment approaches for management safety of thermal power plants. In previous literature, a small amount of prior articles use decision trees [12], structure-preserving energy functions [13], pattern recognition, and fuzzy estimation [14]. In recent years, new methods such as fuzzy decision trees [15], Bayes' classifiers [16], Monte Carlo methods [17], probability methods [18], perturbation methods [19] and Bayesian networks [20] are used for the assessment of probabilistic safety, equipment liability, voltage safety of power transmission system, and construction project safety management. Besides, various artificial neural networks (ANNs) [21,22] are also used to resolve the above problems. Modern ANNs are non-linear statistical data modeling tools and used to model complex relationships between inputs and outputs or to find patterns in data. They process information using a connectionist approach to computation and have become one of the most commonly used approaches for the evaluation regarding the power system. However, few of these research literatures are related to the assessment of management work during TPPs production.

2.2. Case retrieval

In this section, we will review case retrieval methods in knowledge-based decision making. We firstly review the knowledge-based decision making, including case-based reasoning and its applications. In real world, a number of knowledge-based systems are developed for the support of various decisions making. One of typical cases is the knowledge based decision support system (KBDSS) developed by Padma [23]. This systems acquires and quantifies the work-related risks on musculoskeletal disorder specifically, shoulder and neck pain (SNP) that is a prevalent pain complaint within the working environment. Its objective involves knowledge acquisition performed through literature analysis, traditional and concept mapping interviews with neurology, orthopaedic, psychology and physiotherapy experts to identify risk factors that include mechanical, physical and psychosocial categories. In KBDSS, the weight determination of ranking the relative factor importance has accomplished using analytic hierarchy processing (AHP) analysis. As one of important knowledge-based reasoning techniques, CBR can provide an information service and decision support for the whole process of decision making, including knowledge organization, knowledge acquisition, automotive revision and knowledge reuse. Part of its advantage lies in that it can capture expert knowledge, provide methods for knowledge management, and give suggestions for fast problem-solving. Different from ANNs and decision trees, it can address the problem of over fitting. Combined with other intelligent reasoning techniques (such as rule-based reasoning) [24], CBR has been applied widely to health care, engineering design, classification, prediction, recommendation, technologies optimization, organizational behaviour science, social learning, and numerous other fields, while a great many successful application instances have also been achieved [25–29]. In the field of evaluation research, there are also many articles concerning CBR, such as the CBR applications to software cost estimation [30], software effort estimation [31], risk assessment in audit judgment [32], risk analysis for electronic commerce [33], web break sensitivity evaluation in a paper machine [34], safety risk analysis in information safety systems [35], safety evaluation of process configuration [36], and so forth.

The following review is regarding the case retrieval methods. The fundamental idea in CBR is problem solving based on the retrieval of similar cases. Definitely, case retrieval is a key stage in case-based knowledge reasoning. And the global efficiency of CBR systems is greatly determined by their retrieval algorithms. The objective of case retrieval is to identify cases with greatest similarity to the problems described as quickly as possible. In the research area of CBR, researchers have developed various retrieval techniques for different study issues. The most commonly used one is k-nearest neighbour (k-NN) based on Euclidean distance. Euclidean distance metric has the merit that it allows knowledge to be brought to bear on the assessment of similarity. The feature set can be chosen to reflect the important features in the domain. While this metric handles continuous attributes reasonably well, it does a poor job with discrete attributes. Nonmatching discrete attributes contribute maximally to the distance while matching attributes don't contribute at all. Besides k-NN method, various other retrieval techniques, from Fish and Shrink [37] to more sophisticated methods such as mix neural networks [38], genetic algorithms [39], and fuzzy ant colony systems or fuzzy logic [40,41] have been developed. Another key technique to improve accuracy in CBR retrieval is the attribute weighting technology. Attributes with weights of zero are effectively ignored during similarity computation, whereas attributes with high weights have the most impact in determining similarity. There are many approaches to weighting including experience of the expert, analytic hierarchy process (AHP) [42], decisions trees [43], fuzzy logic [44] and neural symbolic feature weighting [45].

In terms of similarity measure among cases, a number of latest researches are also emerging. One example is that Yang and Li [46] builds a similarity measure metric for retrieval in collaborative filtering, considers users' preferences and rating patterns, and promotes rational individual prediction. Another example regarding retrieval approaches is based on rational inference. In real-world, resolving certain situations/problems involves some associated risk, while other situations/problems involve either no associated risk or such a small risk that it is not worth taking into account. Concerning the risk in resolving problems, Castro [47] proposed a new technique of case retrieval in CBR. In this method, the risk information of each attribute is added for the acquisition of the most suitable case to solve the problem. The new information is introduced into the problem using a fuzzy inference system. In addition, Luukka [48] examines a classifier based on similarity measures originating from probabilistic equivalence relations with a generalized mean. This paper concentrates on measures which can be considered to be weighted similarity measures defined in a probabilistic framework, applied variable by variable and aggregated along the features using a generalized mean. Equivalences are weighted and weight optimization is carried out with differential evolution algorithms. Furthermore, a few researchers consider uncertain, incomplete, and vague information in cases, and have conducted some study on fuzzy similarity measurement in case retrieval. Here relevant articles concerning the family fuzzy CBR will be reviewed. Zhang et al. [49] investigated the relationship between entropy and similarity measure of interval-valued fuzzy sets and proved that similarity measure can be transformed by entropy. Wang [50] proposed a new method for assessing concept similarity. This method is based on rough set to evaluate the similarity degree of the two concepts of concept lattice and can be viewed as the development of Tversky's similarity model. Chattopadhyay et al. [51] developed fuzzy logic-based expert systems (ESs) which are able to determine the chance of occurrence of adult psychoses. This work is keen in analyzing the relationships among the inputs and outputs using a fuzzy logic technique. These literatures and other related work can be viewed as important base of our current study.

2.3. Motivation of our research

Although there exist the above numerous methods for case retrieval, there still exists a gap between the abilities of these techniques and the real requirement to improve their accuracy and to provide more detailed decision information. In our research, The MSSATPP case contains not only continuous attributes, but also discrete ones. Also, incomplete "grey" information is the basic characteristic of MSSATPP. Therefore, traditional k-NN based on Euclidean distance algorithms is not appropriate to our current study problems. In this article, grey system theory is integrated into case-based reasoning technology and IGCBR is introduced as a novel retrieval method for case matching. The research novelty of our work lies in that by taking the Management System of whole power systems as an example, we integrate grey system theory and Delphi method into case-based reasoning. Hence, this study applies an improved optimized CBR to the whole decision making process of MSSATPP.

3. TPP safety evaluation: process, indexes and statistics

Power plant safety evaluations are performed by panels of experts through investigation, discussion, and negotiation. This process is explained in this section. Also, we introduce the evaluation indexes and the motivations of our research.

3.1. TPP safety evaluation process

Safety assessment is one of the important measures and safeguards for enforcing the electric safety basis in TPP production and for guaranteeing safe, stable, and economical TPP operation. As an important part of the whole safety assessment work of TPP, MSSATPP is an all-around examination and evaluation of the safety management work in the production of TPP. Two different parts are involved in the safety assessment of TPP: inside evaluation and outside foreign expert evaluation, respectively. The former is operated by a thermal power plant itself. Power companies organize expert groups with relevant personnel to evaluate their safety status, identify issues, and then propose revision suggestions according to the evaluation index, standard, or criterion. The latter is generally organized by the electric power company responsible for a group of TPP. To do so, the electric power companies organize audits in which relevant experts complete their evaluation work. To prepare for the actual audits performed by the electric power companies, most of the electric power incorporations currently complete their internal thermal power plants safety evaluation work through external experts' evaluation. The complete evaluation steps are approximately as follows:

- Step 1. Organize an experts' group to conduct the assessment. The experts can come from a technical layer, a management layer of the electric power companies, the institutes of the electric power, or universities or government departments related to electric power.
- Step 2. Determine the weights associated with the evaluation index or the total score of each index by DELPHI method [52,53].
- Step 3. Organize the experts' visit to the thermal power plants and their scoring through the fact-finding inspection.
- Step 4. Gather the score, conduct group discussions, and finally make decisions. Usually, the evaluation can end in one of two ways: qualified with minor correction and remedy, or unqualified with major correction and remedy[2].

One detail deserves to be paid attention to here: the conclusion is not obtained simply by the direct addition of the scores from the experts. The real decision making process is that the experts' group draws the final conclusions through discussion and consultation. The rule of "who gets a high score, who passes" is not necessarily clear-cut. This process is understandable because evaluating the safety on basis of the scores only is not reasonable. Different thermal power plants are evaluated by different experts' groups, and the scoring measures of experts may be different due to their diverse characters, moods, and knowledge background. Therefore, electric power enterprises come to conclusions through comprehensive group evaluation. In this practice, historical or antecedent cases are very valuable for the decision making process of these experts.

Several limitations of in the evaluation process described above can be highlighted as follows. First, the evaluation approach presents too much subjectivity. It generally requires high costs, a long time, and hard labour, but lacks efficiency. In practice, most of this kind of evaluation work is too time consuming with respect to the quality and reliability of conclusions drawn. A second limitation is the lack of knowledge and information available to support the experts' evaluation and decision making process while historical data and information could be resorted to. For the past

[2] This kind of division is not very strict. There is also an exception. A minority of the electric power enterprises only score and do not draw the specific conclusions: qualified or unqualified. However generally, there are only two outcomes: major correction and remedy or not.

ten years or so, thermal power enterprises have accumulated a decent number of SATPP evaluation reports. An evaluation report can be regarded as a case. The cases represent the intelligence gathering activity of experts' and permit to trace their wisdom and knowledge. As an important information resource, a large amount of cases is very valuable for reference. Unfortunately, these MSSATPP cases are left unused and not managed, analyzed, or utilized. During the evaluation process of new thermal power plants, the information resource is hard to be utilized because these evaluation reports have not been organized and analyzed. Some of them have not been standardized nor made electronically available yet. More than that, due to the lack of support of information system in which the cases are effectively organized and analyzed and the knowledge extracted from the case data, Enterprise information resource and the historical knowledge of experts cannot be communicated to the experts' group during the decision making process of MSSATPP. The third limitation is the difficulty of self evaluation and day-to-day real-time evaluation.

Therefore, it is vital for a group of experts to have intelligent information and knowledge support during decision making. Following, one important purpose of our current research is to present a more effective case matching method different from those commonly used in case-based reasoning for the safety assessment issue of thermal power plants. Another aim of our current study is to develop a case-based intelligent decision support system based on historical knowledge to assist the panel of experts in reaching a right decision making for MSSATPP. In the next sections, a novel case matching method combining Delphi method and grey system theory is presented.

3.2. Evaluation indexes

On the basis of actual investigations of coal-fired thermal power enterprises, currently, the safety evaluation of thermal power plants mainly concerns the following six aspects, which are generally regarded as evaluation indexes.

The first is the safety goal (Goal): the implementation of safety principles or policies in production and the safety goal management. Concretely, the implementation of safety policies encompass dimensions such as "Safety first", "Precaution is crucial", and "Comprehensive harnessing", the hierarchical decomposition and pertinence of safety goal management, the familiarity of workers with all potentially unsafe factors in operations locations, and the clarity of supervision and certification systems for safety in production.

The second is the responsible system (ResponsSys): the implementation of the responsibility system for safety in production. It includes the implementation of the responsibility of "The-First-Responsible-Person-In-Production", the safety responsibility of functional departments and workshop directors, the responsibility system of the safety in production for group leaders, and the responsibility system of safety in production of production directions and technical support.

The third is the supervision system for safety in TPPs production (Supervision). It principally contains the implementation of regular safety meetings planning, the implementation of the safety supervision activities, the implementation of the activities related to safety bulletin reports, and the implementation of other safety related supervision systems.

The fourth is the basic activities for production safety (BasicWork). The specific fundamental activities include the use and management of work order and operation order, the management of major hazard installations, the classified performance assessment and management, the production safety management of outsourced projects and contracted projects, and the contingency management of production safety.

The fifth is the training and education about production safety (SafeEdu). It includes the management of training and education production safety, the three-level (Factory-level, workshop-level, enterprise-level) of enrolment safety education. This training is for the recruits and workers who replace the guards and special operational personnel.

The last item is the integrated management (IntergratedM) in which are included mainly the reward and punishment system for production safety and the safety culture creation in enterprises.

In IDSS-MSSATPP, the cases represent actual historical evaluation reports which have been structured. Not only the attributes (i.e. Goal, ResponsSys, Supervision, BasicWork, SafeEdu, and IntergratedM) are included as evaluation indexes, but also additional important attributes, such as the Number of Items with Deducted Marks, the Number of Major Problems, the Assessment Result, the Suggested Amendment Opinions, are represented. The detailed description is shown in Fig. 1. The six indexes on the left are input variables, and four extra attributes on the right are the output variables. The values of input variables are acquired by expert group scoring. Then, the similar cases including ten rather than six attributes are able to be acquired by case matching.

The four extra attributes on the right of Fig. 1 are extremely important and valuable. We shall also provide explanation with respect to their meaning as follows.

Number of IDM: The full name of IDM is Items with Deducted Marks. Generally, the number of IDM may approximately show the safety severity in the management work of TPP.

Number of MP: The full name of MP is the major problems. Some of them exist regarding the equipments, but more are with respect to the management. For example, a small amount of supervisors lack of the consciousness to the steam temperature control and the judgement and treatment ability to abnormal phenomena. Usually, the number of the major problems is small, but they have extremely highly risk and can lead to serious accidents and heavy loss.

Assessment Result: In general, there are two different results after assessment: major correction and remedy required, or no major correction and remedy required.

Suggested Amendment Opinions: The inspection team will provide specific problems and detailed amendment suggestions for the evaluated thermal power plants according to their inspection and findings.

The former three items, i.e. Number of Items with Deducted Marks (IDM), Number of Major Problems (MP), and Assessment Result, are influential for the decision results of the current evaluation problem. The last one, i.e. Suggested Amendment Opinions, is extremely helpful as reference for the expert group to derive their suggested corrective and remedial measures based on the specific conditions of the thermal power plant. Accordingly, IDSS-MSSATPP is able to be used by all the expert group members to effectively acquire their knowledge and decision support. The entire safety evaluation procedure of thermal power plants will be eventually completed with the powerful aid and support of IDSS-MSSATPP.

3.3. Statistics for performance evaluation

In this section, several related concepts shall be defined. Definition 3–Definition 5 are the statistics for performance evaluation of the new case retrieval method.

Definition 1. A safety assessment case (SACase) is a structured safety assessment report including scoring index system, standard, scoring value of each index, major problems, final evaluation conclusion, safe strategies, and measures for risk control and the reduction of accidents.

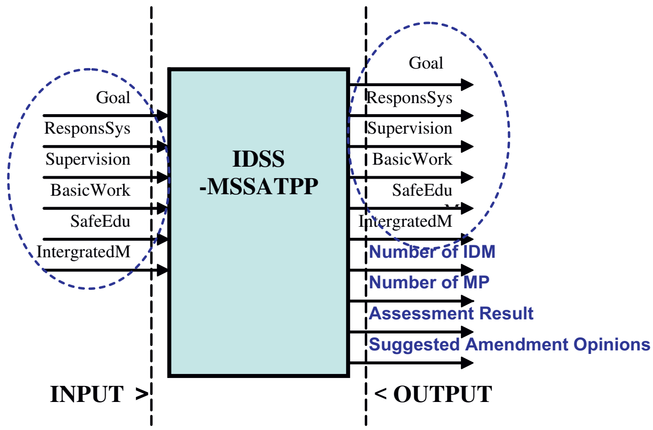

Fig. 1. Evaluation indexes and four extra output attributes in IDSS-TPP.

Definition 2. A MSSATPP Case (MSSACase) is an electronic and structured record of an MSSATPP assessment process and its results that contains the assessment indexes, scoring values from experts, the number of the items Deducted marks, the Number of Major Problems, Assessment Result, Suggested Amendment Opinions, and other related information. The contained information can be presented with numbers, words, tables, pictures, or any other form.Suppose NR1 denotes the number of true positives according to the retrieval requirements, and NUR2 denotes the number of true negatives. Meanwhile, suppose NR2 and NUR1 represent the number of false positives and the number of false negatives respectively. Then we introduce Definition 3, Definition 4, and Definition 5.

Definition 3. Accuracy [54] is the proportion of true results (both true positives and true negatives) in the population. As a parameter of the test, it is often used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition (see Formula (1)).

$$Accuracy = \frac{NR_1 + NUR_2}{NR_1 + NR_2 + NUR_1 + NUR_2} \tag{1}$$

Definition 4. Precision is the proportion of positives in a binary classification test which are correctly identified, which can be calculated by Formula (2).

$$\mathrm{Precision} = \mathrm{NR1}/(\mathrm{NR1} + \mathrm{NR2}) \tag{2}$$

Definition 5. Recall is the fraction of the cases that are relevant to the query that are successfully retrieved in a binary classification test, which can be computed by Formula (3).

$$\mathrm{Recall} = \mathrm{NR1}/(\mathrm{NR1} + \mathrm{NUR1}) \tag{3}$$

Precision and recall can be microscopic or macroscopic. Formula (2) and Formula (3) are microscopic statistics used to evaluate the effect of one retrieval episode. Accordingly, there are also macroscopic precision and recall, as shown in Formula (4) and Formula (5), which can be used to evaluate the effect of multiple retrieval episodes.

$$\mathrm{Precision_{macro}} = \sum \mathrm{NR1}/(\mathrm{NR1} + \mathrm{NR2}) \tag{4}$$

$$\mathrm{Recall_{macro}} = \sum \mathrm{NR1}/(\mathrm{NR1} + \mathrm{NUR1}) \tag{5}$$

Definition 6. $\mathrm{F_{macro}}$-value is a statistic that is used for a comprehensive assessment of retrieval algorithms. It can simultaneously reflect the effects of both sensitivity and specificity. It can be computed via Formula (6).

$$\mathrm{F_{macro}} - \mathrm{value} = 2^{*}\mathrm{Precision_{macro}}^{*}\mathrm{Recall_{macro}}/(\mathrm{Precision_{macro}} + \mathrm{Recall_{macro}}) \tag{6}$$

Additional information for Precision, Recall and $\mathrm{F_{macro}}$-value can be acquired from the research work by García-Nieto, Alba, Jourdan and Talbi [55]. In this study, to evaluate the performance more fully, two statistics are simultaneously used to evaluate the performances of different case matching methods. One is the accuracy, the most commonly popular index for the evaluation of performance. The other is the $\mathrm{F_{macro}}$-value. In the area of statistics and information retrieval, the sensitivity and specificity are generally used for evaluating an algorithm. Sensitivity and specificity are complementary of each other. The simple improvement in sensitivity will lead to a decreasing specificity, and vice versa. Thereby, a good retrieval system should demonstrate both high sensitivity and specificity, but in reality a retrieval system performance tends to be a tradeoff between them avoiding too low sensitivity or specificity. The combined effect can be evaluated by the F–value.

4. Research methodology

Uncertainty of information generally includes four inter-related categories. The first one is random uncertainty which is due to inadequate conditions or the interference from causal factors. The second one is fuzzy uncertainty which is caused by fuzzy extension of unknown information. The third one is grey uncertainty which means part information is known but other is unclear, missing or unavailable. The last one is unascertained uncertainty referring to that decision-makers cannot fully grasp the true state, nature of things, or quantitative relations which causes a subjective uncertainty. But the thing itself may be neither random nor fuzzy. Accordingly, uncertainty information can be divided into four types: information with random uncertainty, information with fuzzy uncertainty, information with grey uncertainty and information with unascertained uncertainty. In 1965, Zadeh introduced fuzzy set theory for treating vague and imprecise information. Fuzzy sets or fuzzy logic is based on many historical data and mainly for dealing with information with unascertained uncertainty. In addition, this approach needs a large amount of judgments from experts of evaluation. This can cause long time and high cost in real operation. Another method used in treating uncertainty is theory of possibility. This method mainly deals with information with random uncertainty and need extensive sampling to ensure its validity. Evidence theory is also one of common methods for dealing with uncertain information. But it is losing its charm due to its overall rigidity in data manipulation and additional information required, such as basic probability assignment and fuzzy set membership. Each of evidences should be independent to the others which cause to bad adaptability.

Grey system theory can deal with all kinds of uncertain information. Compared to traditional approaches to deal with the fuzzy information, it has some prominent advantages. For example: (i) Modelling with small sample. Large scale data set is not necessary for the solution of problem which means less primary data is required in this method; (ii) Dropping the influence of random fluctuations of original data. The sample distribution regularity is unnecessary; (iii) largely reducing the computational requirement. The results can be acquired within shorter time; (iv) High accuracy.

In our current study, the MSSATPP cases contain grey information and other kinds of uncertain information. Grey uncertain information is dominant. In addition, our data sample is small and only 106 records of data (see Section4.3 for further information) are collected for experiments. Fuzzy sets, fuzzy logic, possibility theory, evidence theory and other traditional approaches to deal with the fuzzy information are not appropriate for the solution of our present problem. The use of grey system theory is based on comprehensively consideration on the technical advantages of grey system theory and characteristics of complex case information in our current research.

Our research methodology is presented in three parts. Part one proposes the retrieval method based on grey system theory and our improvement on it combining Delphi approach. Part two describes two statistics for performance evaluation of our proposed method. Part three presents our implemented CBR system and data set for experiments.

4.1. Decision information acquiring method

4.1.1. Weight derivation of MSSATPP cases: Delphi method

In general, to obtain a composite indicator a decision needs to be made upon the weight to assign to each indicator. In the index literature, numerous weighting determination methods can be found. In general, indicator weights can be determined based on correlations (factor analysis), experts' opinions (such as Delphi method), optimization models (data envelopment analysis) or equally distributed (equal weighting) [9]. Herman [56] focused on weights which can represent the idea of experts concerning the importance of the indicators. In the analytic hierarchy process (AHP) [10] experts are asked to judge the relative contribution of one indicator compared to another one. These pairwise comparisons are somewhat time consuming and may involve some level of inconsistency.

Therefore, we opt for the more simple design of Delphi method. The Delphi process today exists in two distinct forms: conventional Delphi and real-lucre Delphi. The former is the paper-and-pencil version which is commonly referred to as a "Delphi Exercise." This form is the most commonly used in practise. Real-lucre Delphi, a newer form, sometimes called a "Delphi Conference," replaces the monitor team to a large degree by a computer which has been programmed to carry out the compilation of the group results. This latter approach may eliminate the delay caused in summarizing each round of Delphi, thereby turning the process into a real-time communications system. However it requires that the characteristics of the communication be well defined before Delphi is undertaken, whereas in a paper-and-pencil Delphi exercise the monitor team can adjust these characteristics as a function of the group responses. Hence, in our research, we use the conventional Delphi. To a degree, this form of Delphi is a combination of a polling procedure and a conference procedure which attempts to shift a significant portion of the effort needed for individuals to communicate from the larger respondent group to the smaller monitor team. A selected panel of experts are asked to mark a weight value for each characteristic index respectively. After a series of procedural steps, the final weight values will be acquired. The higher feature weight value implies the more importance of this index.

In our used Delphi method, some aspects need to be taken into account. First, the selection of experts is crucial and should be well-considered. It is possible that the results are biased if experts assign a high weight to the indicator on which their thermal power plant performs well. In our current research, the following requirements are necessary for a person to be qualified as an experts' panel member:

(1) Professional background and knowledge on power systems, generation systems or electric generation management.
(2) Working experience on electric power systems and familiar with the management work and the risk factors amongst TPP production.
(3) No direct or major interest relationship with the thermal power plants which will be assessed.

In our study, the evaluation panel members consist of six experts selected from both inside and outside of the power enterprise. The selected company for the current research is GreatT Power Generation Group of China (GreatT), one of the largest power generation corporations in Asia. Amongst the experts, four are from corporate headquarter, another one ever worked at a thermal power plant and currently retired, and the last one from a university of electric power. The detailed steps for the weight values of MSSATPP by the conventional Delphi method are as follows:

Step 1. A small monitor team (come from the Department of Safety Production at the group company) designs a questionnaire for the weight values of feature attributes. The scoring values for the feature attributes vary from zero (not important at all) to ten (highly important).
Step 2. The questionnaire is sent to the respondent group, i.e. the six experts mentioned above, and these experts mark weight values by their own knowledge. Then, these questionnaires withmarks for feature attributes are returned.
Step 3. After that the monitor team summarizes the results and, based upon the results, develops a new questionnaire for the respondent group. The new one contains the newest marks from all six experts.
Step 4. The questionnaire is sent to the respondent group again and the experts mark for the second time. And then the questionnaires are returned.
Step 5. Repeat Step 4 and Step 5 for three times. In this phrase, the final evaluation (the final evaluation scoring forms), occurs. Then all previously gathered information has been initially analyzed and the evaluations have been fed back for consideration.

In our study, the respondent group is given three opportunities to re-evaluate its original answers based upon examination of the group response. We performed nonparametric tests (K related samples) by SPSS 16.0. The test results are shown in Table 1, in which Asymp. Sig. is zero smaller than 0.5 and Kendall's W^a is 0.97 bigger than 0.71. Thereby the group of data from the six experts have favourable highly consistency. By calculating the means of six groups of data by column and then divided the sum of the means, we obtained the weight values for the six feature attributes as shown in Table 2.

4.1.2. Retrieval algorithm based on grey system theory

In this section, we will firstly review some closely related literatures on the application of grey system theory that are useful to our current study and then introduce our proposed retrieval algorithm based on grey system theory. Wu and Liu [57] introduced the real formal concept analysis based on grey-rough set theory by using grey numbers, instead of binary values. They proposed an extension of the notion of Galois connection in a real binary relation as well as the notions of formal concept and Galois lattice. With the consideration of the retrieval of incomplete information and uncertain relations between effort drivers and the required development effort in software projects, Huang, Chiu and Chen [58] integrated a genetic algorithm (GA) to the grey relational analysis (GRA) to deal with similarity measures of complex relations. The GA method is adopted to find the best fit of weights for each software effort driver in the similarity measures. The integration of GRA with GA presented more precise estimates over the results using case-based reasoning based on traditional k-NN, regression trees (CART) and ANNs method. The grey system theory shows powerful potential for the solution of our current problem which contains incomplete information as well as discrete attributes.

In our study, we use grey system theory combining Delphi approach to complete the acquisition of decision information. In CBR systems, the information acquisition is also called case matching or case retrieval. The most famous case matching method is the traditional CBR retrieval algorithm which is based on Euclidean distance. Besides, other methods such as neural networks, genetic algorithms and fuzzy logic are also studied in previous literatures [59–61].

However, there still exists a gap between the abilities of these techniques and the real requirement to improve their accuracy and to provide more detailed decision information. In this article, grey system theory and Delphi method are integrated into case-based reasoning technology and CBR-KNN is introduced as a novel case matching method.

Grey System Theory was first built by Ju-Long Deng in 1982 [62]. All systems with incomplete information can be regarded as grey systems [63]. The grey system theory seeks only the intrinsic structure of the system given such limited data. It focuses keenly on what only partial information the system can provide, and tries to paint its complete picture from this. The Grey Relational Analysis (GRA) is an important method in the grey system theory which can be viewed as a measure of similarity for finite sequences. With a given reference sequence and a given set of comparative sequences, the GRA can be used to determine the grey relational grade between the reference and each element in the given set. The GRA can also be used as a measure of the absolute point-to-point distance between sequences [64].

Our current study problem has all the above mentioned features: incomplete information, discrete attributes and point-to-point distance calculation. Hence in our current work he case retrieval algorithm for knowledge acquisition of MSSATPP is based on grey relationship analysis. As one of the system analysis techniques, grey relationship analysis is an approach for analyzing the degree of association among different factors. Here, we integrated it into CBR for MSSATPP and proposed CBR-Grey. The fundamental steps using grey relationship analysis for case retrieval in MSSATPP are as follows.

Table 1
Kendall's W test result.

Test statistics	
N	6
Kendall's W[a]	.910
Chi-Square	27.304
df	5
Asymp. Sig.	.000

[a] Kendall's Coefficient of Concordance.

Step 1. Determine the evaluation index system according to the evaluation purpose, and then collect evaluation data. Suppose there are m data series which form the matrix below:

$$(X_1, X_2, \cdots, X_n) = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}$$

where n denotes the number of evaluation indexes, and m is the number of historical MSSATPP cases in the case base.

Step 2. Use the method of Delphi and obtain all weight values of the indexes. The Delphi method is a systematic, interactive forecasting method which relies on a panel of experts. This technique is based on the principle that forecasts from a structured group of experts are more accurate than those from unstructured groups or individuals [65].

Step 3. Determine the reference data series. The reference data series should be an ideal contrast standard. They can be composed of the optimal value or worst-case value of the indexes as well as other reference values that are selected according to the evaluation purpose. In our current research, the reference data series is the target case to be solved and the attribute values are those of the objective case to be solved. Let X_0 denote the reference data series, $X_0 = (x_0(1), x_0(2), \cdots, x_0(n))$.

Step 4. Normalize the data. In our current study, Vector Transforming Method is used for data normalization. This method is suitable for the normalization of index values both under certainty and under uncertainty. The detailed computing algorithm concerning Vector Transforming Method for data normalization can be found in Appendix A.

Step 5. Compute the absolute differences between the corresponding elements of reference data series and comparisons from the case base, namely $|x_{0k} - x_{ik}|$, $i = 1, 2 \ldots m$; $k = 1, 2 \ldots n$, where k denotes the number of attributes, and i denotes the number of evaluation objects.

Step 6. Derive the values of $\min_{i=1}^{n} \min_{k=1}^{m} |x_{0k} - x_{ik}|$ and $\max_{i=1}^{n} \max_{k=1}^{m} |x_{0k} - x_{ik}|$, where $|x_{0k} - x_{ik}|$ is the difference of the absolute value x_{0k} and x_{ik}. In this process, the minimum and maximum deviation values between the characteristic value of objective case and that of each reference case are acquired.

Step 7. Compute the correlation coefficient. By Formula (1), respectively compute the correlation coefficients between each comparative series and reference series. In Formula (1), ρ denotes the resolution ratio, and its values range from zero to one. The smaller ρ is, the bigger the differences among correlation coefficients are, and the stronger the separating capacity is. Generally, the value of ρ is 0.5. i denotes the case number in the case base. $\zeta_i(k)$ represents the correlation between the target case and case i in the case base for index k. The k value varies from one to m.

$$\zeta_i(k) = \frac{\min_i \min_k |x_{0k} - x_i| + \rho \cdot \max_i \max_k |x_{0k} - x_{ik}|}{|x_{0k} - x_{ik}| + \rho \cdot \max_i \max_k |x_{0k} - x_{ik}|} \qquad (1)$$

Step 8. Compute correlative series. Respectively compute the average value of the correlation coefficients between the corresponding elements of the reference series and every evaluation object (comparative series). This average value, named correlation series, can reflect the correlation relationship between the reference series and the comparative series denoted by i. We mark it with r_{0i} as follows.

Table 2
The case attribute weights of MSSATPP(DELPHI).

Attribute	Goal	ResponsSys	Supervision	BasicWork	SafeEdu	IntergratedM
Weight	0.12	0.4467	0.0633	0.2317	0.0267	0.1116

$$r_{0i} = \frac{1}{n}\sum_k \zeta_i(k)(k = 1, 2 \ldots n) \tag{2}$$

Step 9. When the indexes have different roles and importance in comprehensive assessment, we can compute weighted means. We use $S_{global}(i)$ to represent the weighted mean of correlation coefficient and it can be computed by Formula (3).

$$S_{global}(i) = \frac{1}{n}\sum_k w_k \cdot \zeta_i(k)(k = 1, 2 \ldots n) \tag{3}$$

where w_k denotes the weight of index k.

Step 10. Derive the comprehensive Assessment Result on the basis of the correlation series of all the objects of observation: $S_{global}(1), S_{global}(2), \ldots S_{global}(m)$.

In the above descriptions, the local similarity is represented by the grey association degree of the characteristic attributes. The global similarity is derived by the weighted addition of all the local similarities. For the different importance of the evaluation indexes of thermal power plants, the weight can be integrated into the computing process of a comparative environment when the local similarities are being computed. Therefore an improved local grey association algorithm is derived and further expressed as follows in Formula (4).

$$\zeta_i'(k) = \frac{\min_i \min \mathrm{X}(i,k)_k + \rho \cdot \max_i \max_k w_k{}^* X(i,k)}{(w_k{}^* X(i,k)) + \rho \cdot \max_i \max_k w_k{}^* X(i,k)} \tag{4}$$

where $X(i,k) = w_k|x_0(k) - x_i(k)|$. We use $\zeta_i^{dist}(k)$ to denote the local grey similarity of the index k between the objective case and historical evaluation case. And it can be defined by Formula (5).

$$\zeta_i^{dist}(k) = \frac{1}{\zeta_i'(k)} - 1 \tag{5}$$

Further, we use $\zeta_i^{\mathrm{global}}$ to represent the global similarity between two cases and it can be computed by Formula (6) [66].

$$\zeta_i^{\mathrm{global}} = \sum_{k=1}^{m} \zeta_i^{\mathrm{dist}}(k) \tag{6}$$

Thereby, the global similarity of two cases can be derived by the Formula (7) below. The case chosen for reuse is the one maximizing the global similarity.

$$S_{\mathrm{i}}^{\mathrm{global}} = \frac{1}{\zeta_i^{\mathrm{global}} + 1} \tag{7}$$

4.2. Data set

The data set for our experiments are mainly collected from a mega electric power enterprise group, GreatT Power Generation Group of China (GreatT). As one of the largest power generation corporations in Asia, she owns over one hundred power plants, most of which are coal-fired thermal power plants. The data set are mainly the historical safety assessment data of TPP of GreatT over the years. Most of the data are the newest assessment reports of SATPP occurring between 2007 and 2009. Since these TPP vary in their degree of informatization and electronic data were not even available in parts of them, the task of collecting the data was hard. The current project team collected a total of 120 MSSATPP records, and 106 complete and valid cases were acquired after displaying and analyzing. Among them, the number of positive cases is 56, and the number of negative cases is 50. The assessment reports from the same thermal plants but occurring in different years will be regarded as two different records. Taking LuoHo' Power Plant for example, its two reports in 2008 and 2009 are two different records of the data set. In these data, there are at most three data records occurring for the same thermal plant. These three data records are for three different years.

In this research, we conducted the experiments by 10-fold-cross-validation. The test data are extracted randomly and the experiments are controlled. For each test, 96 cases will be used as historical data in the case base, and the remaining 10 cases represent the testing data which includes five positive cases and five negative cases respectively. For each experiment, the tests will be repeated ten times. Although the data set is not very large, since there are only six attributes in the cases, according to the usual requirement: number of attributes/number of data should equal $1{:}10 \sim 1{:}20$, it can satisfy the experimental requirements (6/106 = 0.057).

5. System implementation and experiments

We implemented the CBRSYS-TPP, a prototype of and IDSS-TPP mentioned earlier, and completed the later experiments regarding the performance of information acquisition. In this section, we completed two distinct randomized controlled experiments. The first one is to test the accuracy, sensitivity and specificity as well as calculate the F_{macro}-Value of our proposed case matching methods which combines Delphi method and grey system theory. And the second one is to test several common classification methods using the same data set. 10-fold-cross-validation tests were conducted. The performance of the methods is evaluated by accuracy, F_{macro}-value and several statistics. In each 10-fold-cross-validation, the data set was randomly divided into ten mutually exclusive subsets with the same distribution using Matlab R2008a. Each fold should be used only once to test the performance of the retrieval algorithms. The most similar cases were generated from the remaining nine folds.

5.1. Comparison tests with k-NN

In the first experiment, tests compare different case matching methods: k-NN based on Euclidean algorithm and our proposed approach. The accuracy of CBR-Grey is 94.00%. The average sensitivity, average specificity, recall and F_{macro}-value are 96.00%, 92.00%, 92.30%, 96.00%, and 94.11% respectively. Meanwhile, the traditional k-NN based is also used as retrieval method to acquire similar cases. In the experiment, the selected value for k is seven. Its accuracy is 90.00%. The average sensitivity, average specificity, precision, recall and F_{macro}-value are 91.00%, 90.00%, 91.00%, 91.07%, and 90.03% respectively. The results are still acceptable. But by comparison, CBR-Grey has significantly higher accuracy and better comprehensive performance.

Table 3
The comparative experimental results of distinct retrieval approaches (Based on GreatT TPP dataset).

Method	Accuracy (%)	Precision (%)	Recall (%)	F-value (%)	Experimental tools
CBR-grey	94	92.3	96.00	94.11	CBRSYS-TPP, Matlab R2008a
Logistic regression[a]	91.50	91.07	92.73	91.89	SPSS15.0
RBF network[b]	84.90	80.00	89.30	84.39	Weka 3.6.2
MLP	79.20	79.20	79.20	79.20	Weka 3.6.2
SMO	83.96	83.96	84.00	83.96	Weka 3.6.2

[a] The cut value is .500 which is the standard and default cutoff value. We can rerun the analysis with a series of cutoff values such as 0.4, 0.45, 0.55 and 0.65 to see if the cutoff value could be adjusted for a better fit. For this particular model, these alternate cutoff values do not lead to better predictions. In this case, the default 0.5 cutoff value is deemed sufficient.

[b] Logistic regression applied to K-means clusters as basic functions here.

5.2. Comparison with other methods

Logistic regression, Neural networks (especially RBF Network), Multi-layer-perceptron(MLP) and Sequential Minimal Optimization (SMO) are also the commonly used methods for different assessment issues, especially binary classification evaluations [67] [68] [69]. In the current study, comparative experiments were conducted between CBR-Grey and the other methods mentioned above. The first tool for this experiment is Weka 3.6.2 in which RBF Network, MLP and SMO are integrated. The second one is SPSS15.0 which is the platform for logistic regression analysis. The data set for use here are still the GreatT TPP data set. 10-fold-cross-validation tests were conducted. For more valid comparisons among these methods, we used their best possible versions. For example, in RBF networks, we used the best parameter settings to maximize generalization. The random seed to pass on to K-means is set to 1; debug is set to "False"; maximum number of iterations for the logistic regression to perform is set to -1; the minimum standard deviation for the clusters is set to 0.1; the number of clusters for K-Means to generate is set to 2; and the ridge value for the logistic or linear regression is set to 1.0E-8.

The experimental results are shown in Table 3. Among them, CBR-Grey has the best accuracy (94%) and F-value (94.11%). Logistic regression has 91.50% of accuracy and 91.89% of F-value. Nevertheless, RBF Network only has 84.90% of accuracy and 84.39% of F_{macro}-value. SMO with 83.96% of accuracy and 83.96% F_{macro}-value are similar to RBF Network. But the accuracy and F_{macro}-value of MLP are even lower and both of them are less than 80%. Accordingly, the latter three approaches are not recommended for real applications in MSSATPP.

In our proposed approach, Delphi method is also regarded as part of the case retrieval method. Our experimental results highlight that, as far as practical aspects of decision support for expert panel members are concerned, in comparison with KNN based on Euclidean distance algorithm, the most popular retrieval algorithm, our proposed approach seems to present the advantage of combining the strength of Delphi method and grey system theory to complement the weaknesses of traditional case matching approaches. Meanwhile, we completed the comparative experiments among our proposed approach and three other common methods for binary classification evaluation issues. The conclusion is that CBR-Grey is preponderant both in the statistics of accuracy and F_{macro}-value. This further illustrates the validity and high performance of CBR applied to MSSATPP. At the methodological level, the potential advantage of CBR-Grey is in its ability to acquire and reuse the historical knowledge whenever the available information is complete or incomplete.

6. Conclusion

In this paper, we propose a method that integrates grey system theory and the Delphi method into CBR methodologies, with which the intelligent knowledge-based system can provide intelligent decision support for MSSATPP, and the evaluation cycles of experts can be reduced with improved efficiency. This paper provides a novel and effective way for the safety assessment of thermal power plants as well as a new perspective on the use of prototypes through case aggregation, which is one of the popular trends of CBR systems in recent years [70]. Compared to the direct expert evaluation approach, the most commonly used approach in which experts first evaluate each item of safety management work using an evaluation index system then reach a conclusion through face-to-face discussion, our approach has a number of advantages. Firstly, it is more objective than the expert evaluation approach. Furthermore, compared to expert evaluation approach and other common classification methods (such as logistic regression, RBF Network, MLP and SMO), our method has the following features and advantages: (i) more helpful to the utilization of historical knowledge; (ii) higher comprehensive performance; (iii) based on real cases and easy to be understood and operated.

From a practical perspective, this approach can provide not only one but a whole set of evaluation and improvement alternatives for both expert panel members and TPP. Through further trials in Luodian, one of a few high-power stations in East China, the results have shown its feasibility and high performance. The computerized system worked well in providing the knowledge and decision making support for experts during the process of MSSATPP. According to an anonymous survey of 32 assessment experts, 29 of them (90.6%) replied that they were generally satisfied with the performance of the CBRSYS-TPP system. All the experts expressed that they got valuable information support during the decision making process and the conclusions are more scientific and acceptable than those without the support of CBRSYS-TPP. This further reflects the application values of CBR in the safety assessment of TPP.

Our current research presents some limitations. First, due to the small data size, we did not evaluate the efficiency in our current research. The performance, especially the retrieval time under large-scale data is still not clear. In addition, our method partly overcomes the subjectivity of completely relying on experts' evaluation. But we did not eliminate subjectivity, as it still exists in deriving weights when using the Delphi method.

For future research directions, we have several thoughts. First, a new and more objective approach should be explored for weight determination of case retrieval. Second, it is also necessary to integrate the weight determination and case retrieval methods into one system and implement a more powerful CBR system. It is also important to note that the issue of implementation and usability of the CBR systems for MSSATPP are also an interesting and promising direction for future research in this area. In addition, further communications with the electric power enterprises should be strongly encouraged. It is hoped to be able to acquire larger datasets for further experiments, especially to evaluate the performance of retrieval algorithms under the condition of large-scale data. The above problems provide broad horizon for further study. Researchers of this topic could be the professors who are interested in the safety assessment of power systems, the scholars who would like to further improve the performance of case retrieval algorithms, or PHD students who are doing the projects or research on semantic data mining or the case matching under incomplete information.

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Appendix A. Vector transforming method

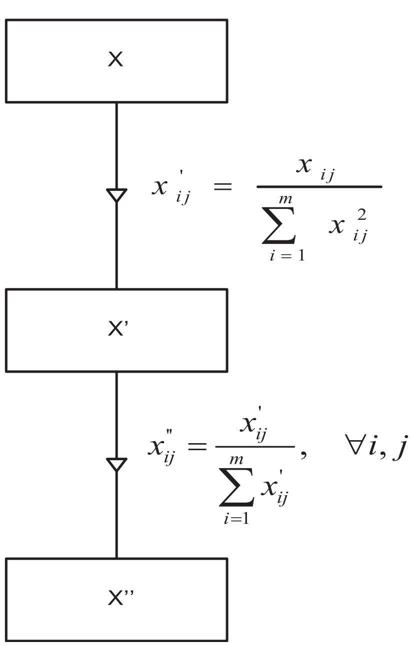
In our current study, we use Vector Transforming Method for data normalization. The main computing formula is as follows.

$$x''_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}}, \quad \forall i, j$$

where

$$x'_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}^2}$$

This method is suitable for the normalization of both index values with certainty and those with uncertainty. The detail process of this algorithm is as follows.



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