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A fuzzy knowledge based method for maintenance planning in a power system

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Abstract

The inspection planning in electric power industry is used to assess the safety and reliability of system components and to increase the ability of failure situation identification before it actually occurs. It reflects the implications of the available information on the operational and maintenance history of the system. The output is a ranked list of components, with the most critical ones at the top, which indicates the selection of the components to be inspected.

In this paper, we demonstrate the use of a fuzzy relational database model for manipulating the data required for the criticality component ranking in thermal power systems inspection planning, incorporating criteria concerning aspects of safety and reliability, economy, variable operational conditions and environmental impacts. Often, qualitative thresholds and linguistic terms are used for the component criticality analysis. Fuzzy linguistic terms for criteria definitions along with fuzzy inference mechanisms allow the exploitation of the operators' expertise.

The proposed database model ensures the representation and handling of the aforementioned fuzzy information and additionally offers to the user the functionality for specifying the precision degree by which the conditions involved in a query are satisfied.

In order to illustrate the behavior of the model, a case study is given using real inspection data.

Keywords: Inspection planning; Fuzzy relational database; Criticality analysis; Decision support systems

1. Introduction

Preventive maintenance scheduling of generating units in electric power systems has a considerable impact on power systems performance. Inspection planning helps planners and operators to organize and prioritize maintenance activity and increase the ability to identify a problem before a failure actually occurs. Manufacturers of power plants prescribe recommended preventive maintenance actions and typical major inspection intervals to avoid system malfunction. During a major inspection, all equipments related to the power system are checked for changes that may impair the safe operation, availability and reliability of the units. The major inspection intervals are based on the equivalent operating hours of the system, determined by operating factors like the operating time, the start-up frequency and the load cycle. However, the acceptable technical life for the power plant components is mainly based on the observed defects and disorders rather than on nominal design life. Thus, during the interval between two major inspections, minor inspections are performed either when operating data give indications for required corrective actions or at typical intervals. Minor inspections serve to keep a check on the systems' wear phenomenon and to prevent its progress by suitable remedial measures (clean, replace, leave and recheck during next inspection, etc.) depending on defect findings. In order to minimize time requirements, the minor inspections are focused on high-risk areas where problems are most likely to occur. The objective of this paper is the development of an effective model to support inspection decision-making (pointing out areas that are subjected to higher priorities of checks) in order to identify effective preventive maintenance during minor inspections in thermal power plants. The problem of managing equipment inspection priorities, according to their criticality, incorporates criteria concerning aspects of safety and reliability, economy, variable operational conditions and environmental impacts. This problem is highly complicated, especially for complex systems with many components and requires efficient information manipulation and data assessment.

The problem of maintenance planning in thermal power plant systems has been studied widely in the past. The

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methods for planning maintenance operations in the literature differ both, in terms of the criteria and the mathematical techniques employed to develop maintenance plans.

In all papers surveyed by Kralj and Petrovic [1], power plants maintenance planning problem was stated as a conventional single criterion optimization task. The most important criterion is formulated as the optimization objective, while other criteria are defined as constraints or introduced into the objective function in the form of penalties. A number of different optimization criteria have been considered, expressing either system costs or the expected unserved energy. Dopazo and Merrill [2] described an approach that minimizes the unit maintenance costs using a 0–1 integer linear programming formulation. Yamayee et al. [3] have proposed an optimal maintenance scheduling method wherein production costs are minimized using dynamic programming.

Edwin and Curtius [4] developed a method with production cost minimization via integer linear programming. Satoh and Nara [5] formulated the maintenance scheduling problem as a mixed-integer programming problem and solved it by using the simulated annealing (SA) method. The objective was to minimize the sum of the production costs and maintenance costs. Chen and Toyoda [6] proposed the levelized incremental risks method, which results in a minimum annual loss of load probability (LOLP) maintenance schedule. Their methodology was further extended (1991) for multi-area maintenance planning [7], which takes into account the transmission network constraints. A decomposition method and an iterative two-level optimization technique were developed with the goal to balance the area reserve margins.

Such single objective methods may not meet the requirements of utility planners, whose most important task is the determination of the best compromise solution of the objectives considered. The multi-objective type of the maintenance planning problem was recognized by Mukerji et al. [8], discussing the solutions obtained by optimization of two alternative objective criteria: costs and reliability. They had shown that different optimization criteria gave different 'best' maintenance policies. The first paper in treating simultaneously competing criteria (1995), such as minimum costs, maximum reliable power supply and minimum violation of constraints, was done by Kralj and Petrovic [9]. Vaurio [10] presented a procedure for the optimization of test and maintenance intervals of safety related systems by minimizing testing and maintenance costs while satisfying a risk criterion. The optimization procedure is formulated in terms of single and multiple basic initiating events, the probabilities of which are functions of the test and maintenance intervals, and manipulated by the Fault Tree Analysis method. Moro and Ramos [11] proposed a generator maintenance planning for a real-sized system with multiple objectives using goal programming.

However, all aforementioned proposed mathematical programming optimization methods are unsuitable for the non-linear objectives and constraints of the thermal power maintenance planning problem and their computational time grows prohibitively with problem size. In order to overcome the above limitations, a number of artificial intelligence approaches have been studied. Dahal and McDonald [12] review the development of generator maintenance scheduling using artificial intelligence techniques. Kim et al. [13] applied genetic algorithms (GAs) for maintenance planning using the acceptance probability of the SA method for the survival of a candidate solution during the evolution process. If a newly created solution is an improvement, it is accepted as is, otherwise it is accepted with a defined probability. In Ref. [14] Kim et al. also coupled a tabu search (TS) technique with the GA/SA hybrid method. Marseguerra and Zio developed an approach for optimal maintenance and repair strategies of industrial plants under conflicting safety and economic objectives. The method was based on coupling of a GAs maximization procedure with Monte Carlo techniques. The GAs procedure optimizes the components maintenance and repair strategies, while the Monte Carlo techniques allow to consider relevant aspects of plant operation, such as stand-by modes, aging, preventive maintenance, deteriorating repairs, repair teams, component repair priorities [15]. Busacca et al. proposed a multi-objective GA approach applied to the optimal inspection planning in a nuclear power plant with respect to availability, economic and worker's safety objectives. The method identifies a set of Pareto optimal solutions and their performances with respect to the various objectives. Thus, the decision-maker can select the best compromise among these objectives [16].

Instead of using strict algorithms, knowledge based and expert systems models have been proposed for producing advice in inspection and maintenance planning. Podbury and Dillon [17] described a prototype of a rule-based expert system with the objective to minimize the variability of the risk level throughout the planning period. The branch and the bound search technique with calculation overestimates were used. Choueiry and Sekine [18] presented a knowledge based system for advising on maintenance scheduling with the objective to maximize the expected power reserve margin over the whole scheduling horizon. Scheduling strategy was a combination of branch and bound like strategy and heuristics.

Nevertheless in planning maintenance operations, the component criticality classification involves multiple criteria frequently expressed in subjective and vague terms, related to the power plants operator perception, instead of numeric values. Therefore, conventional approaches may not be able to model the problem effectively and efficiently. Fuzzy logic provides a formal framework for dealing with imprecision. Lin et al. [19] proposed an optimal generator maintenance scheduling using fuzzy dynamic programming. Jovanovic and Maile [20] described the methodology developed in MPA (State Institute for Testing of Materials, Germany) incorporating fuzzy techniques combined with methods from the multi-criteria area. A combination of a Bayesian and a fuzzy extension of the classical Analytical Hierarchy Process method are used. Fuzzy logic was used in the evaluation of each candidate solution by Bretthauer et al. [21] and a knowledge based technique was employed for load flow calculation within the evaluation function. However, the previous proposed fuzzy approaches cannot manage efficiently large and complex knowledge bases, as is the case of maintenance planning. In such cases, the requirements for efficient information manipulation and retrieval impose the use of database concepts and techniques in the development of inspection planning methods.

In this paper, the proposed model integrates the use of: (a) database concepts and techniques, imposed by the requirements for efficient information manipulation and retrieval and (b) fuzzy methodology for the representation and handling of the fuzzy information. The application of a fuzzy relational database model for manipulating the data required for producing advice in minor inspection and maintenance planning is investigated. The output is a list of components ranked according to criticality or risk, indicating the inspection priority for each component and allowing inspection and preventive maintenance efforts to be focused on areas subjected to higher priorities of checks. The method meets the multi-objective requirements of the problem. The component criticality classification is formed by incorporating multiple criteria like fundamental importance of the component for the plant, existing information on maintenance and operation history, costs associated with testing/maintenance and operation, safety requirements according to potential human hazard, environmental impacts, variable operational conditions and expected unavailability.

The suggested methodology models information following a database approach that organizes frame-based knowledge to relational tables. It ensures the concise representation of the available fuzzy information of the system and displays great flexibility in the handling and evaluation of fuzzy information as contrasted with the previously mentioned proposals appeared in the literature. It exploits the powerful object-oriented semantics for the knowledge representation achieving functionality and model extensibility and the widely used relational systems for the knowledge structure and organization. The proposed fuzzy relational database model provides more natural means for a planner to express his/her preferences in a form of a query containing fuzzy terms. Besides, it permits the user to specify the precision with which the conditions involved in a query are satisfied. The execution of a fuzzy query results to the retrieval of a table in which every attribute of every tuple may have a fulfillment degree associated. This fulfillment degree indicates the level to which this concrete value has satisfied the query condition. This approach is more robust and dynamic and achieves better functionality compared to the rule-based approaches where the inference is limited by the number of rules that have been integrated into the system.

The followed approach incorporates experience and heuristic knowledge and allows a qualitative description of the components' behavior and characteristics by using the fuzzy sets theory. Fuzzy logic provides a powerful tool for directly manipulating the linguistic terms employed by the operator when making criticality assessment. This allows an operator to evaluate and express the risk associated with component failure in a natural way. The proposed fuzzy relational database model is flexible to accommodate a wide range of applications related to the representation and handling of imprecise information; for example in Ref. [22], the proposed model is used for the evaluation of a power unit commitment planning.

The paper is organized as follows: Section 2 presents the formulation of the criticality component classification problem in inspection planning. Section 3 presents the proposed fuzzy relational database model. The organization of the imprecise information in the proposed fuzzy relational database and the performance of the proposed approach are presented in Section 4. Section 5 presents the conclusions.

2. Formulation of the inspection planning problem

The criticality component ranking in inspection planning is highly related to the selection of alternative components and locations to inspect. Due to the size and complexity of power plants, it is essential to designate and classify the plant, its parts and components. In operational aspect, power systems are hierarchically structured. The physical structure of the system is a guideline to choose an adequate decomposition of the power plant into classes of components, suitable to include all elements required for inspection planning. Also, there are general experience-based recommendations for selection of target locations, like earlier indications of defects, suspected material/manufacturing defects and significant overloading or overheating.

The proposed model follows the object-oriented approach [23], which is the most suitable for the modeling of complex knowledge bases, as is the case of inspection planning. Three kinds of abstraction mechanisms are used: classification, composition and generalization. Furthermore, it uses three kinds of relationships between classes: aggregation, inheritance and association relationships. There are also semantic constraints associated with these relationships. A class is the descriptor for a set of objects with similar structure, behavior, and relationships. A composite object represents a high-level object made of tightly bound parts. This is an instance of a composite class, which implies the composition aggregation between the class and its parts. Generalization allows the taxonomic relationship between a more general element (the parent) and a more specific element (the child) that is fully consistent with the first element and that adds additional information. An aggregation relationship implies a logical or physical relationship between the objects of the related classes. There is also an inheritance relationship and an association relationship, which imply a semantic relationship between the objects of the related classes. Each relationship may be seen in two perspectives according to the two classes it connects. In each perspective, one class is the source class while the other is the target class. However, in the case of association relationships the interpretation is the same for both perspectives. In order to visualize and document the aforementioned mechanisms the notation offered by the unified modeling language (UML) [24], is used. UML is a graphical language that offers a standard way to write a system's blueprints, including conceptual things such as business processes and system functions as well as concrete things such as programming language statements, database schemas, and reusable software components.

In our case, the alternative component/locations to inspect are modeled using a hierarchical class structure of the composition type (using aggregation relationships) and the generalization type (using inheritance relationships). A class contains components/locations with the same structure and behavior. Classes are organized into a hierarchy of super-classes and sub-classes. This structure allows the inclusion of new classes for the components of the generation units by defining new classes by inheritance.

The power station class aggregates the generation unit's classes. Each generation unit class aggregates the classes that represent the physical elements of the generation unit such as steam turbine, gas turbine, steam–water–gas-cycles and generator.

Criticality component classification is a complex problem and exhibits multiple goals to be achieved, some of which conflict each other. Utility planners are required to consider several criteria concerning aspects of safety and reliability, economy, variable operational conditions and environmental impacts.

In the proposed formulation, the criteria, associated with the component criticality classification, are categorized in types according to the concerning aspects: importance of the component for the system, component life assessment, component associated costs and component safety requirements.

In addition, the criteria types are organized in a generalization type hierarchy. Fig. 1 shows a UML static structure diagram that depicts the criteria types' hierarchy, where the arrow ended line indicates the inheritance relationship. Furthermore, the model allows the association of components to multiple criteria types (using association relationships).

Fig. 2 shows a UML class diagram that depicts a representative part of the class hierarchy used in the implementation for all previously described systems aspects, where the diamond ended line indicates a composition relationship, the arrow ended line indicates an inheritance relationship and the single line indicates an association relationship. All elements bear a reference code. This code is based on the Power Station Designation System KSS [25].

Often, numeric values are not available for the component criticality analysis, thus qualitative thresholds and linguistic terms must be used. A fuzzy approach provides a means for the qualitative association of data and posses flexibility to cope with different criteria priorities depending on variable operational conditions (light/heavy load and normal/emergency operation environment) and on operators' knowledge levels or experience.

The fuzzy set theory [26] is a generalization of the set theory and provides a means for the representation of imprecision and vagueness. Each fuzzy set, $\tilde{A}$, is defined in terms of a relevant universal set U by a membership function, denoted as $\mu_{\tilde{A}}(u)$, where $u \in U$. This function assigns to each element u of U a number, in the closed interval [0,1], that characterizes the degree of membership (also designated as degree of compatibility or degree of truth) of u in $\tilde{A}$. A fuzzy set $\tilde{A}$ can be written as $\tilde{A} = \{(u, \mu_{\tilde{A}}(u)) | u \in U\}$. An important concept for the fuzzy set theory is related with linguistic variables [27–29]. A linguistic variable admits as value, words or sentences of a natural language, which can be represented as fuzzy sets. If, about the seriousness of failure/downtime of certain equipment, one states "The seriousness of failure/downtime of the equipment is very high", then the word *very high* can be looked as a linguistic value of the variable *seriousness of failure/downtime*, i.e. is the label of the fuzzy set very high.

Here, after identifying the fuzzy criteria associated with criticality component classification, the fuzzy sets defining these variables are selected. The sets defining the seriousness of failure/downtime in case of failure are {*Very Low*, *Low*, *Medium*, *High*, *Very High*} and represent the importance of the component for the proper operation of the system. The sets defined for the alternative supply patterns criterion are {*Relatively Low Alternative Supply Availability*, *Average Alternative Supply Availability*, *Relatively High Alternative Supply Availability*} and represent the alternative supply availability in the use of this component according to existing alternatives. The results of previous inspections are stated by the sets {*Low Deficiency Level*, *Average Deficiency Level*, *High Deficiency Level*} and model the influence of the damage state of the component. Non-destructive testing methods (NDT) are used to evaluate the defective states [30]. Equipment life assessment requires knowledge about load history and expected changes in load conditions. The criterion of the past operational history is modeled by the sets {*Mild condition Operation*, *Average Operation*, *Severe Operation*} while the expected change in operating condition is defined by the sets {*Least Severe Operation*, *Less Severe Operation*, *No Changes*, *Slightly Increased Condition*, *Strong Increased Condition*}. The sets representing the testing/maintenance associated costs and the operation associated costs criteria are {*Low*, *Below Average*, *Average*, *Above Average*, *High*}. The

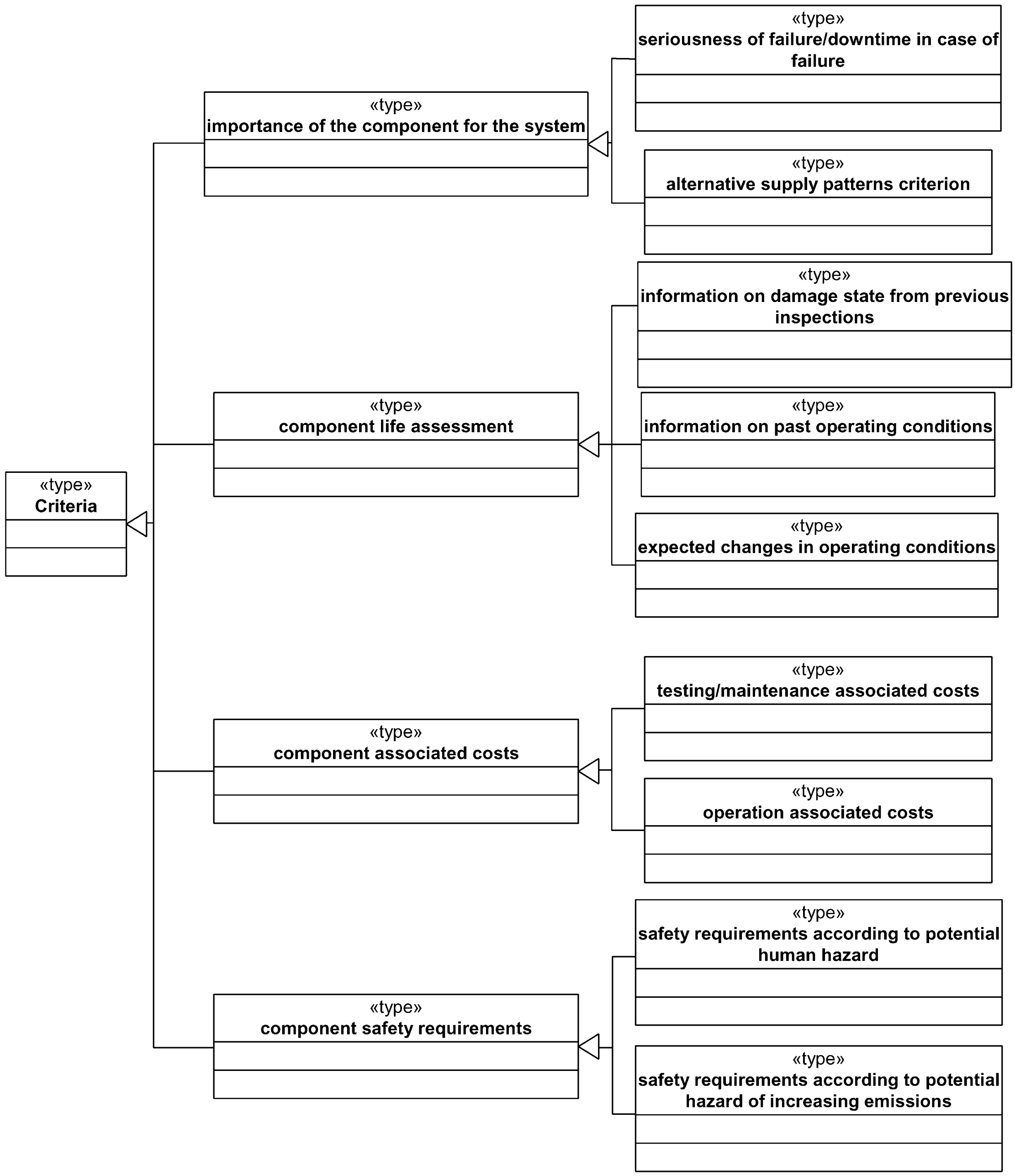


Fig. 1. Criteria types' hierarchy.

criteria of safety requirements according to potential human hazard and the environmental importance according to potential hazard of increasing emissions are given by {*Low*, *Medium*, *High*}.

Regarding the above fuzzy sets, the membership functions are determined for each fuzzy input based on experienced operators' knowledge. The membership functions express the degree with which the linguistic labels defined for the criteria satisfy the decision-maker. A trapezoidal shape is used to illustrate the membership functions considered here. The ranges of the abscissa values, associated with the trapezoidal linguistic labels defined for the criteria, depend on the defined normalization. The membership function definitions used for the criteria are shown in Fig. 3.

3. The fuzzy database model

In this section, the fuzzy relational database model, used for the representation and handling of the above described imprecise information is introduced. Classical relational databases treat information as records grouped in relations or tables. Vagueness is included in the proposed model

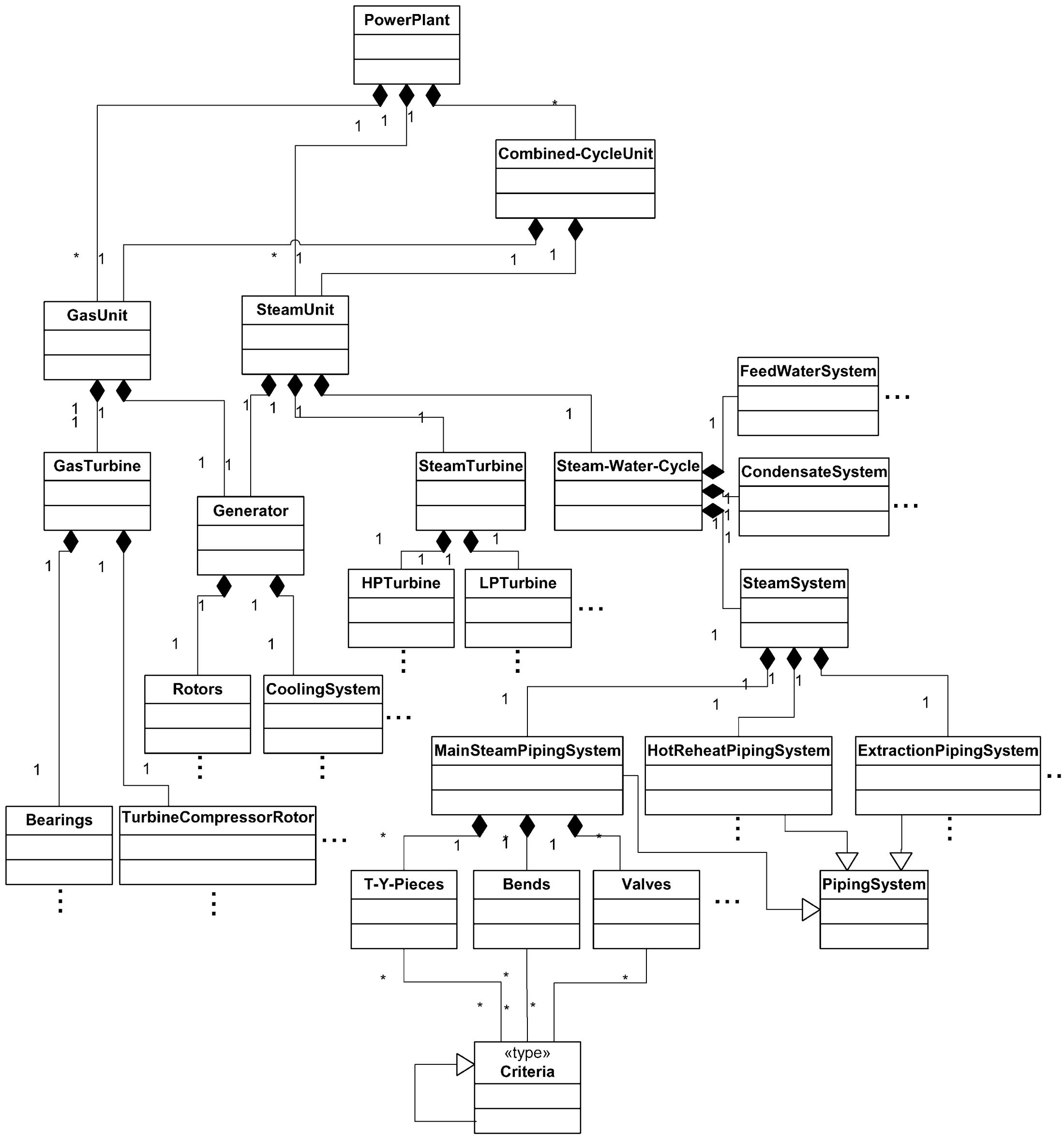


Fig. 2. Systems class diagram.

either by adding vague information to the database or by making vague queries to the database.

In a fuzzy data model, an attribute value of a tuple can be a possibility distribution. Different data types can appear for attributes with imprecise treatment (criteria used for the criticality classification of the components) according to the specific nature of their fuzzy information [31,32]. Incomplete information such as 'unknown' and 'undefined' can also be represented. 'Unknown data type' expresses ignorance about the attribute value, but it is possible for the attribute to take any value in its domain. 'Undefined data type' expresses that none of its domain values are allowed. Even if the 'Crisp data type' is represented for an attribute it is handled as a fuzzy value in a query, according to the linguistic labels defined on the attribute by the experts. Attributes with 'Label data type' have linguistic labels defined on them. The meaning of a fuzzy value (e.g. 'low') is elicited from the user and is represented as a fuzzy set with a trapezoidal membership function. For 'Interval data types', the ranges of the attribute values are input by the user. The membership function of the 'Approximate data type' is assumed triangular with membership value 1 for the attribute value over which the approximation is considered. The margin value is a parameter stored in the database. The classification for the data types that can be represented in the model and the membership functions associated to each data type are shown in Table 1.

The data is structured through the Generalized Fuzzy Relation model, R_{FG}, given by

$$R_{FG} \in (D_1, C_1) \times \cdots \times (D_n C_n)$$

where $D_j (j = 1, 2, \ldots, n)$ is the Fuzzy Domain of the attribute

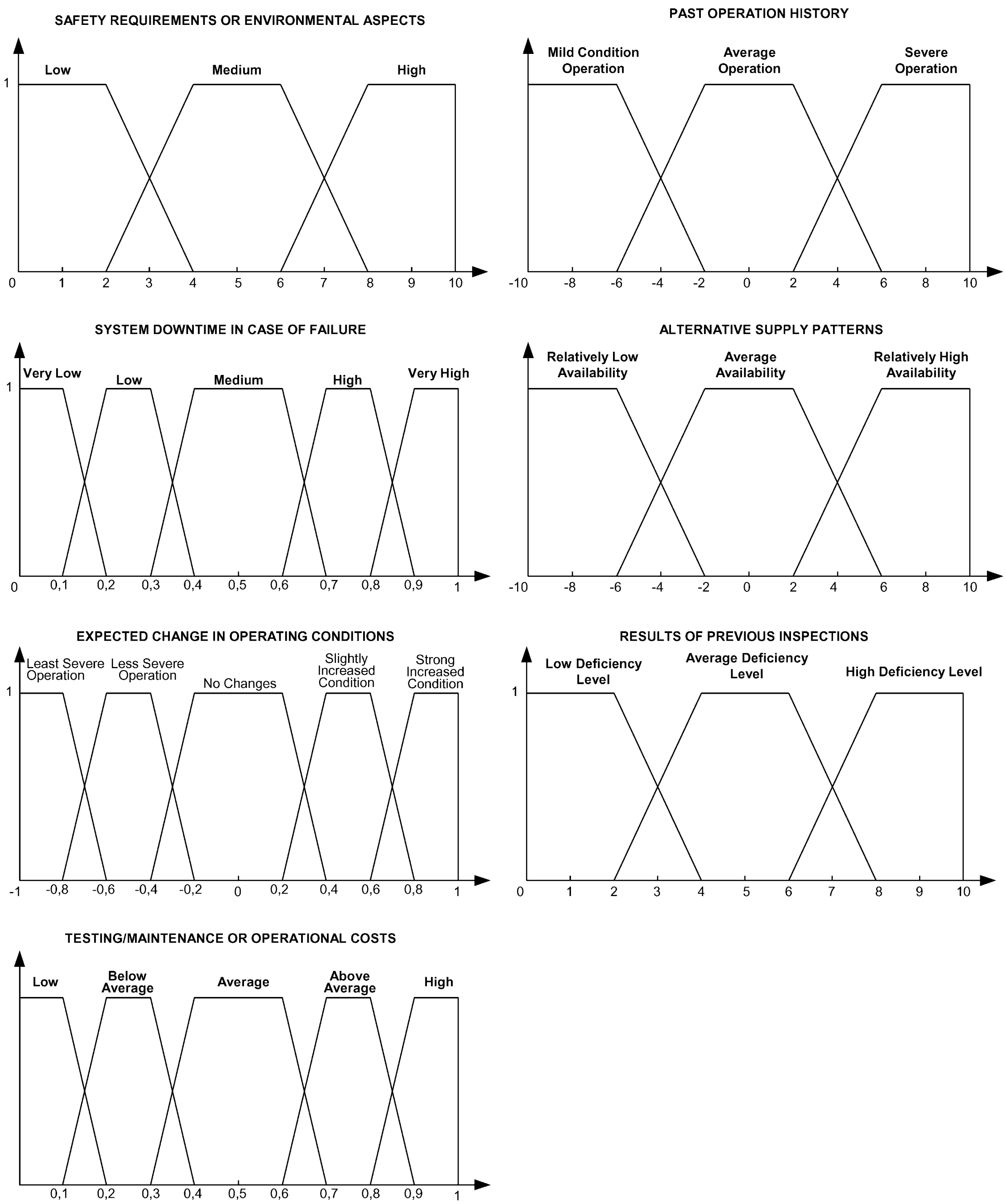
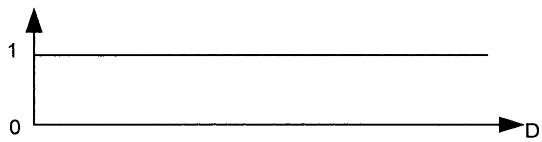
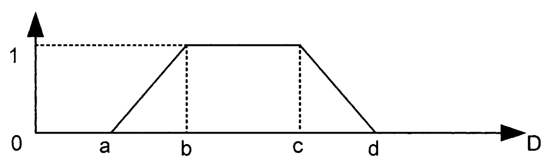
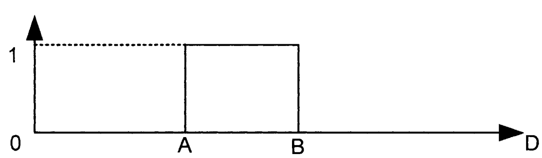
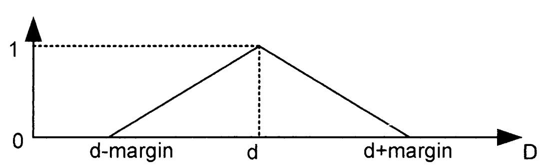


Fig. 3. Label definitions.

A_j and C_j is a compatibility attribute taking values in [0,1]. The Generalized Fuzzy Relation generalizes the conventional theoretic notion of the relation. A complete tuple $(\tilde{d}_{ij}, c_{ij})$ in the Fuzzy Relation R_{FG} includes the compatibility degree c_{ij} which represents the possibility that $\tilde{d}_{ij} \in R_{\mathrm{FG}}$ where $\tilde{d}_{ij}$ represents the domain value for the tuple i and the attribute A_j. The relational algebra must be extended in order to manipulate the defined fuzzy relations. Several definitions for extended operations can be found [32–34]. Here the extended operations are based on the definitions proposed by Zadeh [35]. Consider two Generalized Fuzzy Relations: (a) R_{FG} with a complete tuple $(\tilde{d}_{ij}, c_{ij})$ with $i = 1, \ldots, m$, m being the cardinality and (b) R'_{FC} with a complete tuple $(\tilde{d}'_{ij}, c'_{ij})$ with $k = 1, \ldots, m'$, m' being the cardinality. Then $R_{\mathrm{FG}} \cup R'_{\mathrm{FG}}$ defines the Generalized Fuzzy Union with a complete tuple $(\tilde{d}''_{\ell j}, c''_{\ell j})$, with $\ell = 1, \ldots, m''$, m'' being the union cardinality, where $c''_{\ell j} = \max\{c_{\ell j}, c'_{\ell j}\}$. The Generalized Fuzzy Intersection of R_{FG} and R'_{FG} is defined as $R_{\mathrm{FG}} \cap R'_{\mathrm{FG}}$ with a complete tuple $(\tilde{d}''_{\ell j}, c''_{\ell j})$, with $\ell = 1, \ldots, m''$, m'' being the intersection cardinality, where $c''_{\ell j} = \min\{c_{\ell j}, c'_{\ell j}\}$. The Generalized Fuzzy Difference of R_{FG} and R'_{FG} is defined as $R_{\mathrm{FG}} - R'_{\mathrm{FG}}$ with a complete tuple

Table 1
Representation of imprecise data types

Data type	Membership function representation
Unknown	
Undefined	
Crisp data	–
Label	
Interval	
Approximate	

$(\tilde{d}''_{\ell j}, c''_{\ell j})$, with $\ell = 1, \ldots, m''$, m'' being the difference cardinality, where $c''_{\ell j} = \min\{c_{\ell j}, (1 - c'_{\ell j})\}$. The Generalized Fuzzy Cartesian product $R_{\mathrm{FG}} \times R'_{\mathrm{FG}}$ of R_{FG} and R'_{FG} is defined as the Cartesian product of the $(D_j, C_j) \times (D'_{j'}, C'_{j'})$. The Generalized Fuzzy Projection from R_{FG} onto X, where $X = \{(D_s, C_{s'}) : s \in S, s' \in S'; S, S' \subseteq \{1, \ldots, n\}\}$ is a subset of (D_j, C_j) is defined as $P_{\mathrm{G}}(R_{\mathrm{FG}}; X) \in (D_s, C_{s'})$. The Generalized Fuzzy Selection carried out on R_{FG} by the condition induced by a generalized fuzzy comparison operator $\Theta_{\mathrm{G}j}(A_j, \tilde{a})$and a compatibility threshold ϑ_j on the attribute A_j with $\tilde{a} \in D$ be a constant is defined as $S_{\mathrm{G}}(R_{\mathrm{FG}}; \Theta_{\mathrm{G}j}(A_j, \tilde{a}) \geq \vartheta_j) \in (D_j, C'_j)$ with a complete tuple $(\tilde{d}_{i'j}, c'_{i'j})$, with $i' = 1, \ldots, m'$, m' being the selection cardinality and $c'_{i'j} = \Theta_{\mathrm{G}j}(\tilde{d}_{i'j}, \tilde{a}) \geq \vartheta_j$. The generalized fuzzy comparison operator $\Theta_{\mathrm{G}j}(\tilde{d}, \tilde{d}') \in [0, 1]$ is an extended comparison operator, such as 'greater or equal', 'equal to', etc. defined to operate on fuzzy information $\tilde{d}, \tilde{d}' \in D$. Here the extended comparison operators are based on the definitions proposed in Ref. [36]. The Generalized Fuzzy Join is an extension of the typical relational join operator and is a kind of the Generalized Fuzzy Selection carried out on the Generalized Fuzzy Cartesian Product of the involved relations.

Applying a vague query on the fuzzy relation R_{FG}, a new relation is obtained that adds to every tuple, for every value of the attribute involved, a new compatibility degree according to the condition imposed in the query. This compatibility degree is a measure of the appropriateness of the tuple to the given query. The tuples of the derived relation are selected according to the compatibility threshold established in the query. The established threshold controls the precision with which the condition of the query is satisfied. This threshold is in the interval [0,1] and can be represented through linguistic labels, which have subjective meaning; for example, the threshold label 'high' can be established to accept all tuples whose compatibility degree is greater or equal to 0.8. When a query consists of simple conditions connected with conjunction operator, the intersection of the relations obtained from every condition is computed. The value of the compatibility attribute of every tuple of the intersection is updated to the minimum of those in the respective initial simple conditions. For simple conditions connected with disjunctive operator, the union of the relations obtained for every condition is computed and the compatibility attribute is updated with the maximum value. For a negated simple condition, the compatibility attribute value is updated with the complement to 1 of the present value in every tuple.

4. Implementation of the fuzzy relational database approach

This section introduces the organization of the imprecise information in the Fuzzy Relational Database. To achieve the desired functionality, the information should be modeled according to the application requirements only and not according to the way that it is structured to the database. The information model refers to the elementary entities, which are important for the application along with their relationships. Also, it is used as the basis for the user interface model, as well as for the retrieval and the presentation of the information.

The database model [37] includes: (a) the logical model—which should reflect the information model and satisfy the user requirements—that is related to the external level of the system architecture and (b) the implementation model, which relates to the conceptual level of the architecture. Here, the logical model follows the object-oriented paradigm, which appears to be the most suitable one for modeling knowledge following the frame-based approach.

On the other hand, the implementation model is based to the relational model, mainly due to the wide acceptance of the relational database systems. The implementation of the relational model is mainly the formal conversion of the logical data model to a collection of relations that can be represented in the form of tables.

According to the proposed methodology, the criticality classification of the components is formed incorporating fuzzy criteria, which are attributes with imprecise treatment. The Fuzzy Relational Database model has been developed with the Microsoft Access package and organizes all the information concerning the imprecise nature of these attributes using tables or relations. The organization of the most important tables is shown schematically in Fig. 4. A more detailed description of each table follows. The 'UserInput' table contains the user description for the system components according to the criteria inputs. The 'datatype_id' attribute contains information about the data type of the criterion value given by the user, according to the classification established in the 'DataType' table. The 'input_1' and 'input_2' attributes represent the criterion input data. For the 'Interval' data type both attributes are used. For all other possible data types shown in Table 1, the data is represented using only the input_1 attribute. The 'margin_value' attribute of the DataType table contains information concerning the 'Approximate' data type. The

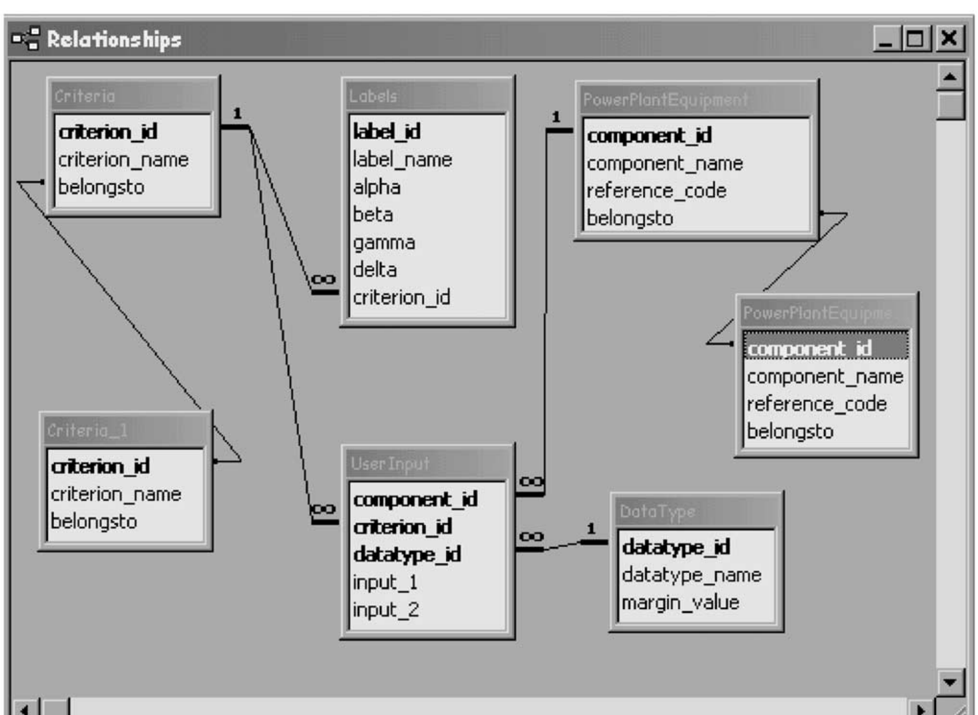


Fig. 4. Fuzzy relational database organization.

Table 2
Indicative input for the Chania example (the symbol # means approximate data type and the symbol * interval data type)

No	Ref. code	Comp. ID	Comp. name	Downtime criterion	Alt. supply avail.	Results of prev. insp.	Past oper. cond.	Exp. changes in oper. cond.	Test/maint. costs	Oper. costs	Safety hum. haz.	Safety env. imp.
1	LBA02BR	30	Y piece	High	Relat. low	High	Severe	No changes	Average	Average	Medium	Low
2	LBA02BR	19	T piece	High	Relat. low	High	Average	No changes	Average	Average	Medium	Low
3	LBA05BQ	10	Bend	Medium	Relat. low	High	Severe	No changes	10 KECU	Average	High	Low
4	LBA81AA	45	Reduct. valve	Medium	Relat. high	Average	Mild	No changes	#45 KECU	Average	Medium	Low
5	LBA80AA	7	Main valve	High	Relat. low	Average	Severe	No changes	High	Average	Medium	Low
6	LBA31AV	12	Deaer. nozzle	Medium	Average	Average	Mild	No changes	*2,5 KECU	Average	Low	Low

'criterion_id' attribute associates a numeric identifier to each criterion. The 'Labels' table contains the parameters that determine the membership functions corresponding to the trapezoidal type linguistic labels defined for the criteria.

For the UserInput table, an interface has been developed which takes the user inputs for every component and criterion and calculates the corresponding compatibility degrees associated with the labels defined on the criterion, by using the customized modules. The resulting 'Results' table involves the ' component_name', 'criterion_name', 'label_name' and 'mfValue' attributes.

Microsoft Access represents a query using the SQL formalism. The queries are applied on the Results table. The WHERE clause of a query specifies conditions which the records of the table ought to follow. When applying a query containing fuzzy terms, the SQL formula calculates a new compatibility degree to every tuple, for every value of the criterion involved, according to the compatibility threshold and the fuzzy comparison operator in the query. The established threshold controls the precision with which the condition of the query is satisfied and can be represented through linguistic labels. When a query consists of simple conditions associated with conjunctive or disjunctive operators, the intersection or the union, respectively, of the relations obtained from every condition is performed.

When an inspection task is performed, the operator forms a query containing fuzzy terms expressing his/her preferences about the components condition. In order to avoid the SQL complexity we provide a standard set of predefined queries where depending on the query selected, the planner has the ability to give the appropriate values (i.e. thresholds, criteria, components). Nevertheless an expert user may also form his/her own SQL queries. The result is a list containing the power plant components and their respective matching degree, stating how well a component meets the conditions specified in the query.

In order to illustrate the behavior of the proposed model, a case study for the power system of the island of Crete is performed. However, this example does not exploit all the possibilities of the model either in the representation or in the data handling.

In this case study, we consider the main steam piping system for a gas and steam turbine combined-cycle block (1323 MW) in the power station of the city of Chania (Greece). It consists of 115 components/locations of potential interest. Some of the more critical ones are shown in Table 2. The underlying domains for the criteria are expressed by the data types described in Section 3. All attributes (criteria used for the criticality classification of the components) may take 'unknown', 'crisp', 'label', 'interval' or 'approximate' value but, given the nature of the relations, the value 'undefined' is not possible.

An example of a query with two simple conditions connected with conjunction follows:

Query: "Give the name and the satisfaction degree of the conditions for those components whose 'PreviousInspResults' criterion is 'Average Deficiency Level' (degree ≥ 0.6) and 'PastOperationCondition' criterion is 'severe' (degree ≥ 0.8)"

The SQL query is given as:

SELECT Results.component_name,min(Results.mfValue)**AS** MINVALUED**FROM** Results **INNER JOIN** Results **AS** T1 **ON** Results.component_name = T1.component_name**WHERE** (Results.criterion_name= PreviousInspResults **AND** Results.label_name = Average Deficiency Level **AND** Results.mfValue ≥ 0.6 **AND** T1.criterion_name = PastOperationCondition **AND** T1.label_name = severe **AND** T1.mfValue ≥ 0.8) **OR** (Results.criterion_name = PastOperationCondition **AND** Results.label_name = severe **AND** Results.mfValue≥0.8 **AND** T1.criterion_name = PreviousInspResults **AND** T1.label_name = Average Deficiency Level **AND** T1.mfValue ≥ 0.6)**GROUP BY** Results.component_name;

The component priority list for the example (Table 2), resulting from the proposed model is the following ranked list (in descending order): No. 5, 1, 3, 2, 4 and 6.

The result is in a very good agreement with the decision made by the power plants engineers. Besides, the decision-making is fast and consistent with the pre-set criteria and posses flexibility to cope with different criteria priorities depending on variable operational conditions. Furthermore, the proposed decision is independent of the number of components.

5. Conclusions

The aforementioned proposed methodology determines a ranked list for components according to their criticality in thermal power systems, by taking into account the multiple criteria. This allows organizing and prioritizing inspection and maintenance activities. Results from the present study reveal that the proposed model provides more natural means for an inspection planner to describe the components behavior and characteristics and to express his priorities, according to variable operational conditions (light/heavy load and normal/emergency operation environment). The proposed fuzzy relational database model features great flexibility in handling and evaluation of fuzzy information and in controlling the degree to satisfy the individual conditions of a query. Thus, it is flexible to accommodate a wide range of applications related to the representation and handling of imprecise information and complex systems.

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References

[1] Kralj B, Petrovic R. Optimal preventive maintenance scheduling of thermal generating units in power systems. A survey of problem formulations and solution methods. Eur J Opl Res 1988;35:1–15.
[2] Dopazo J, Merril H. Optimal generator maintenance scheduling using integer programming. IEEE Trans Power Appar Syst 1975;94(2):665–71.
[3] Yamayee Z, Sidenblad K, Yoshimura M. A computationally efficient optimal maintenance scheduling method. IEEE Trans Power Appar Syst 1983;102(2):330–8.
[4] Edwin W, Curtius F. New maintenance scheduling method with production cost minimization via integer linear programming. Int J Elect Power Energy Syst 1990;12:165–70.
[5] Satoh T, Nara K. Maintenance scheduling by using simulated annealing method. IEEE Trans Power Syst 1991;6:850–7.
[6] Chen L, Toyoda J. Maintenance scheduling based on two-level hierarchical structure to equalize incremental risk. IEEE Trans Power Syst 1990;5:1510–6.
[7] Chen L, Toyoda J. Optimal generating units maintenance scheduling for multi-area system with network constraints. IEEE Trans Power Syst 1991;6:1168–74.
[8] Mukerji R, Merrill H, Ericson B, Parker J, Friedman R. Power plant maintenance scheduling. Optimizing economics and reliability. IEEE Trans Power Syst 1991;6:476–83.
[9] Kralj B, Petrovic R. A multiobjective optimization approach to thermal generating units maintenance scheduling. Eur J Opl Res 1995;84:481–93.
[10] Vaurio J. Optimization of test and maintenance intervals based on risk and cost. Reliab Engng Syst Safety 1995;49:23–6.
[11] Moro L, Ramos A. Goal programming approach to maintenance scheduling of generating units in large scale power system. IEEE Trans Power Syst 1999;14:1021–8.
[12] Dahal K, McDonald J. A review of generator maintenance scheduling using artificial intelligence techniques. Proceedings of the 32nd University Power Engineering Conference (UPEC). Manchester, 1997. p. 787–90.
[13] Kim H, Nara K, Gen M. A method for maintenance scheduling using GA combined with SA. Comput Ind Engng 1994;27:477–80.
[14] Kim H, Hayashi Y, Nara K. An algorithm for thermal unit maintenance scheduling through combined use of GA, SA and TS. IEEE Trans Power Syst 1997;12:329–35.
[15] Marseguerra M, Zio E. Optimizing maintenance and repair policies via a combination of genetic algorithms and Monte Carlo simulation. Reliab Engng Syst Safety 2000;68:69–83.
[16] Giuggioli Busacca P, Marseguerra M, Zio E. Multiobjective optimization by genetic algorithms: application to safety systems. Reliab Engng Syst Safety 2001;72:59–74.
[17] Podbury C, Dillon T. An intelligent knowledge based system for maintenance scheduling in a power system. Proceedings of the Ninth Power Systems Computation Conference (PSCC). Lisbon, 1987. p. 708–14.
[18] Choueiry B, Sekine Y. Knowledge based method for power generators maintenance scheduling. Proceedings of the Expert Systems Applications to Power Systems (ESAP). Stockholm-Helsinki, 1988. p. 9.7–14.
[19] Lin C, Huang C, Lee S. An optimal generators maintenance approach using fuzzy dynamic programming. Proceedings of the IEEE/PES Summer Meeting, Seattle, 1992. p. 401–10.
[20] Jovanovic A, Maile K. Management of remaining life of power plant components by means of intelligent software tools developed at MPA Stuttgart. Int J Press Vessel Piping 1996;66:367–79.
[21] Bretthaner G, Gamaleja T, Handschin E, Neumann U, Hoffmann W. Integrated maintenance scheduling system for electrical energy systems. IEEE Trans Power Deliv 1998;132:655–60.
[22] Sergaki A, Kalaitzakis K. Evaluation of a power unit commitment

planning using a knowledge based system featuring fuzzy knowledge representation. Proceedings of the European Symposium on Intelligent Techniques (ESIT), Crete 1999. p. 45–50.

[23] Rumbaugh J, Blaha M, Premerlani W, Eddy F, Lorensen W. Object-oriented modeling and design. New Jersey: Prentice-Hall, 1991.

[24] Object Management Group. Unified modeling language specification. Version 1.3. OMG, 2000.

[25] VGB (Technical Association of Large Power Plant Operators), Technical Committee on Technical Classification Systems. KKS (KraftwerkKennzeichenSystem) Power Station Designation System, 1988.

[26] Zadeh L. Fuzzy sets. Inform Control 1965;8:338–53.

[27] Zadeh L. The concept of a linguistic variable and its application to approximate reasoning—part I. Inform Sci 1975;8:199–249.

[28] Zadeh L. The concept of a linguistic variable and its application to approximate reasoning—part II. Inform Sci 1975;8:301–57.

[29] Zadeh L. The concept of a linguistic variable and its application to approximate reasoning—part III. Inform Sci 1975;9:43–80c.

[30] Becker R, Dobmann G, Kroning M, Reiter H, Schneider E. Integration of NDT into life time management. Int J Press Vessel Piping 1997;73:11–17.

[31] Buckles B, Petry F. A fuzzy representation of data for relational databases. Fuzzy Sets Syst 1982;7:213–26.

[32] Petry F. Fuzzy databases, principles and applications. Boston: Kluwer Academic Publishers, 1996.

[33] Klir G, Yan B. Fuzzy sets and fuzzy logic, theory and applications. New Jersey: Prentice Hall, 1995.

[34] Bosh P, Kacprzyk J, editors. Fuzziness in database management systems. Heidelberg: Physica-Verlag, 1995.

[35] Zadeh L. Fuzzy sets as a basis for a theory of possibility. Fuzzy Sets Syst 1978;1:3–28.

[36] Lee K, Lee-Kwang H. Fuzzy matching and fuzzy comparison in fuzzy expert systems. Fuzzy Logic Neural Networks 1992:313–6.

[37] Ullman J. Principles of database and knowledge-base systems. Computer Science Press, 1988.