A Study of Maintenance Planning in a Power System using Fuzzy Logic

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Abstract— The inspection planning in electric power industry is used to assess the safety and reliability of system components and increase the ability of failure situation identification before it actually occurs. It reflect the implications of the available information on the operational and maintenance history of the system. The output ia s 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 critically 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 critically analysis. Fuzzy linguistic terms for criteria definitions along with fuzzy inference mechanisms allow the exploitation of the operator's expertise.

Key words: Inspection Planning; Fuzzy Relational Database, Fuzzy Model Database, Planning Maintenance Operation, Decision Support Systems

I. 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. Manufactures 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 defected and disorder 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 system's 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 effective information manipulation and data assessment.

The problem of maintenance planning in thermal power plant system has been studied widely in the past. The method for planning maintenance operating in the literature differ both, in term of criteria and the mathematical techniques employed to develop maintenance plans.

In all papers surveyed by Kralj and Petrovic (1988), 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 (1975) describe an approach that minimizes the unit maintenance cost using a 0-1 integer liner programming formulation. Yamayeet etal. (1983)have proposed an optimal maintenance scheduling method wherein production costs are minimized using dynamic programming.

Edwin and Curtius (1990) developed a method with production cost minimization via integer linear programming. Satoh and Nara (1991) formulated the maintenance scheduling problem as a mixed-integer programming problem and solved it by using the simulated annealing method. The objective was to minimize the sum of the production costs and maintenance costs. Chen and Toyoda (1990) proposed the levelized incremental risks method, which results in a minimum annual loss of load probability maintenance schedule. Their methodology was further extended for multi-area maintenance planning, 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 (1991), 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 , such as minimum costs, maximum reliable power supply and minimum violation of constraints, was done by Kraj and Petrovic (1995). Vaurio (1995) 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 (1999) 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 (1997) review the development of generator maintenance scheduling using artificial intelligence techniques. Kim et al. (1994) applied genetic algorithms for maintenance planning using the acceptance probability of the simulated annealing 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 define probability. Kim et al. (1997) also coupled a tabu search technique with the GA/SA hybrid method.

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 (1987) 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(1998) 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 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. (1992) proposed an optimal generator maintenance scheduling using fuzzy dynamic programming. Jovanovic and Maile (1996) 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. (1998) 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: (i) database concepts and techniques, imposed by the requirements for efficient information manipulation and retrieval (ii) fuzzy methodology for the representation and handling of the fuzzy information.

The suggested methodology models information following a database approach that organizes frame-based knowledge to relational tables. It ensure 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 fuzzy query result to the retrieval of a table in which every attribute of every tuple may have a fulfilment degree associated. This fulfilment 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 behaviour 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.

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.

II. 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, which is the most suitable for the modelling 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 relationship between classes: aggregation, inheritance and association relationships. Three are also semantic constraints associated with these relationships. A class is the descriptor for a set of objects with similar structure, behaviour 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 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 modelling language is used. Unified modelling language 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 modelled 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 behaviour. 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, 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 critically classification, are categorized in types according to the concerning aspects; importance of the component for the system, component safety requirements.

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

Fig. 2 shows a unified modelling language 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 is based on the Power Station Designation System KSS Bretthaner et al.(1998).

Often, numeric values are not available for the component critically 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 operator's knowledge levels or experience.

The fuzzy sets theory, Zadeh (1978) 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, denotes as $\mu_{\tilde{A}}(u)$, where $u \epsilon U$. This function assigns to each element U f 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 $\tilde{A} = \{(\mu_{\tilde{A}}(u))|u \epsilon U\}$. An important concept for the fuzzy set theory is related with linguistic variables . A linguistic variable admits as value, words or sentence 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 critically 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 criteria 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 inspection 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 requires knowledge about load history and expected changes in load conditions. The criterion of the past operational history is modelled 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 cost and the operation associated cost criteria are {Low, Below Average, Average, Above Average, High}. The 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*}.

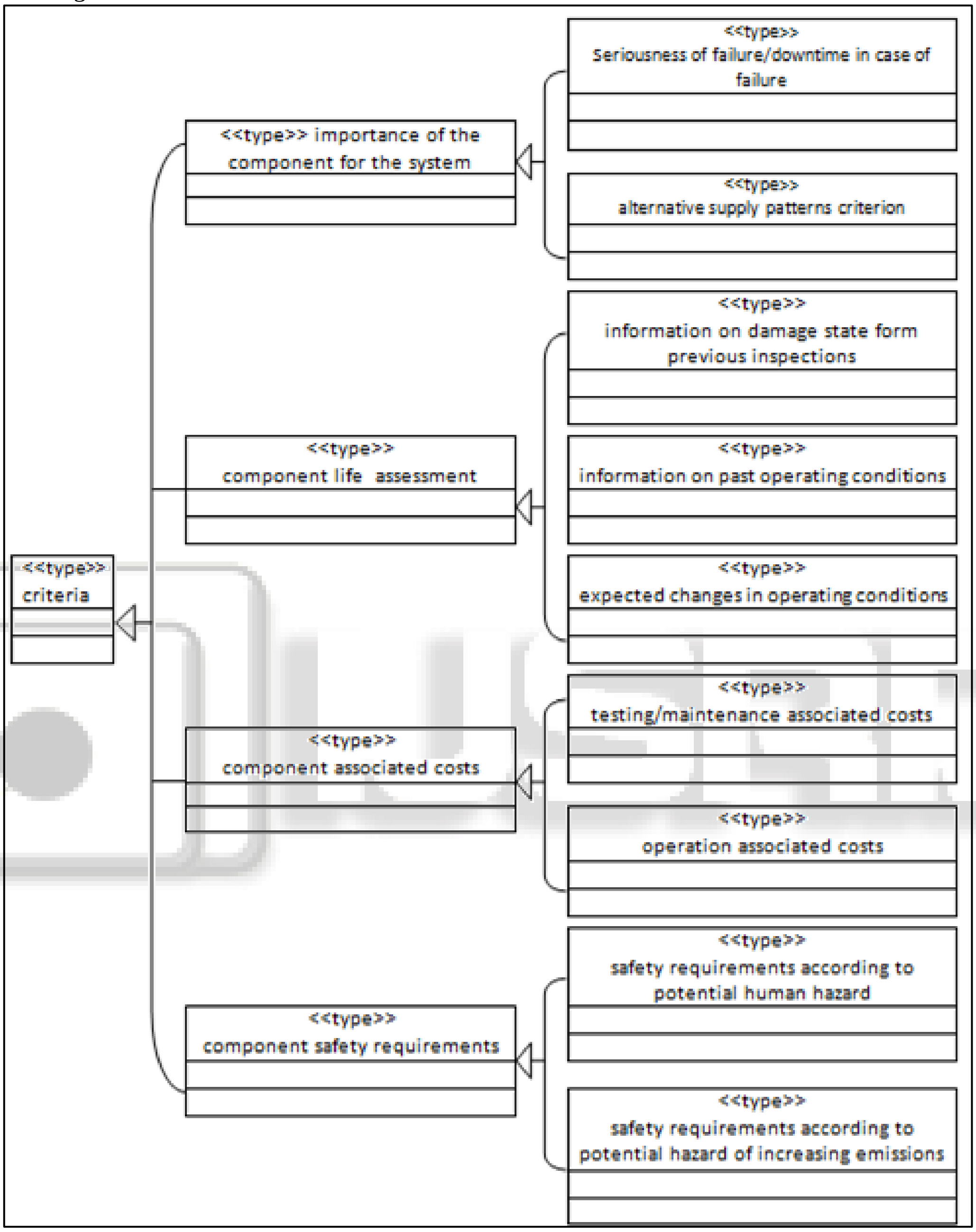


Fig. 1: Criteria type's hierarchy

Regarding the above fuzzy sets, the membership functions are determined for each fuzzy input based on experienced operator's 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.

III. 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 database treat information as records grouped in relations or tables. Vagueness is included in the proposed model either by adding vague information to the database or by making vague queries to the database.

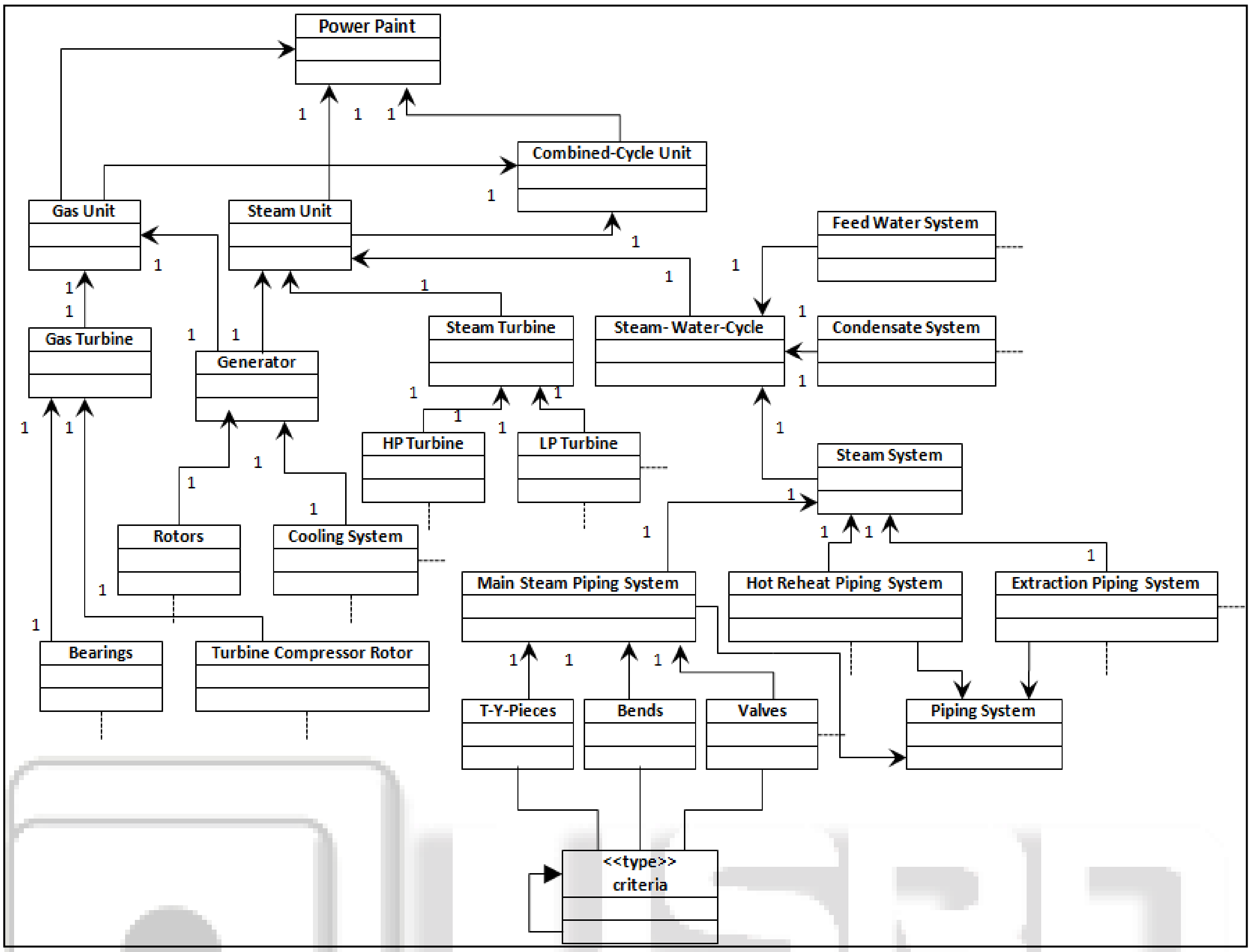
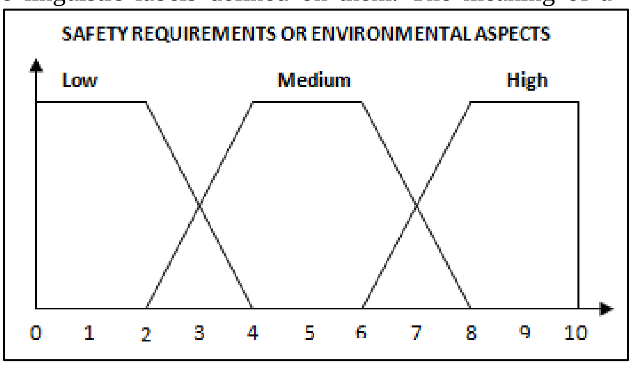
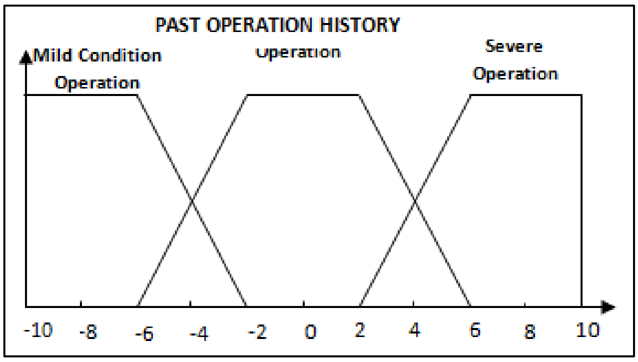
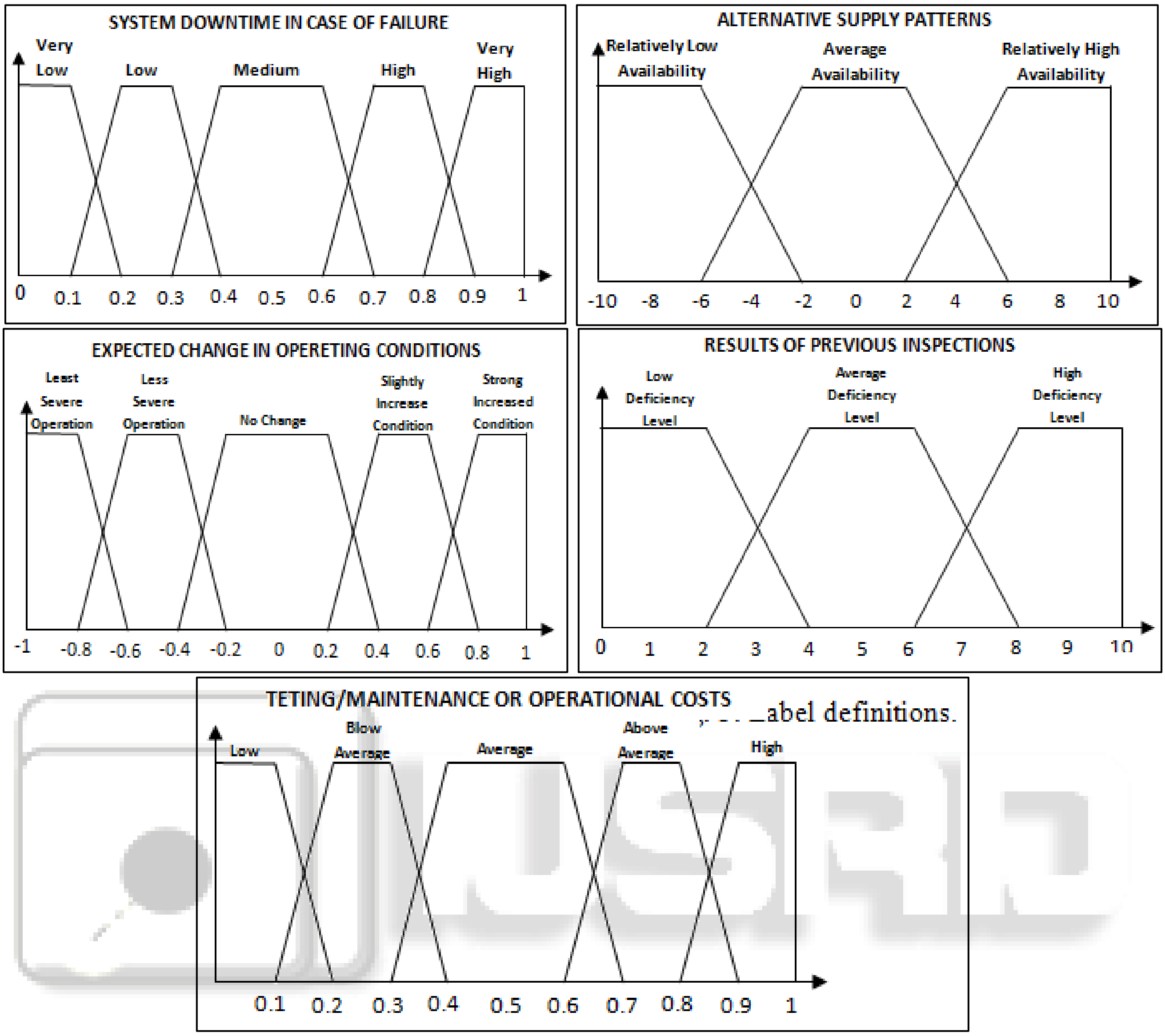


Fig. 2: System class diagram

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 critically classification of the components) according to the specific nature of their fuzzy information. Incomplete information such as 'unknown' and 'undefined' can also be represented. 'Unknown data type' expresses ignorance about the value, but it is possible for the attribute to take any value in its domain. 'Undefined data type' expresses that none if 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 $R_{FG} \in (D_1, C_1) \times \ldots \times (D_n\ C_n)$, where D_j (j=1,2, ... n) is the Fuzzy domain of the attribute







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 cij which represents the possibility that $d_{ij} \in R_{FG}$ where d_{ij} represent 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. Here the extended operations are based on the definitions proposed by Zadeh (1978). Consider two Generalized Fuzzy Relations: (i) R_{FG} with a complete tuple $(\tilde{d}_{ij}, c_{ij})$ with i = 1, ..., m, m being the cardinality and (ii) R'_{FC} with a complete tuple $(\tilde{d}'_{ij}, c'_{ij})$ with k = 1, ..., m', m' being the cardinality. Then $R_{FG} \cup R'_{FG}$ define the Generalized Fuzzy Union with a complete tuple $(\tilde{d}''_{\ell j}, c''_{\ell j})$, with ℓ = 1, ..., 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 $R_{FG} \cap R'_{FG}$ with a complete tuple $(\tilde{d}''_{\ell j}, c''_{\ell j})$, with ℓ = 1 , ..., 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_{FG} - R'_{FG} with a complete tuple

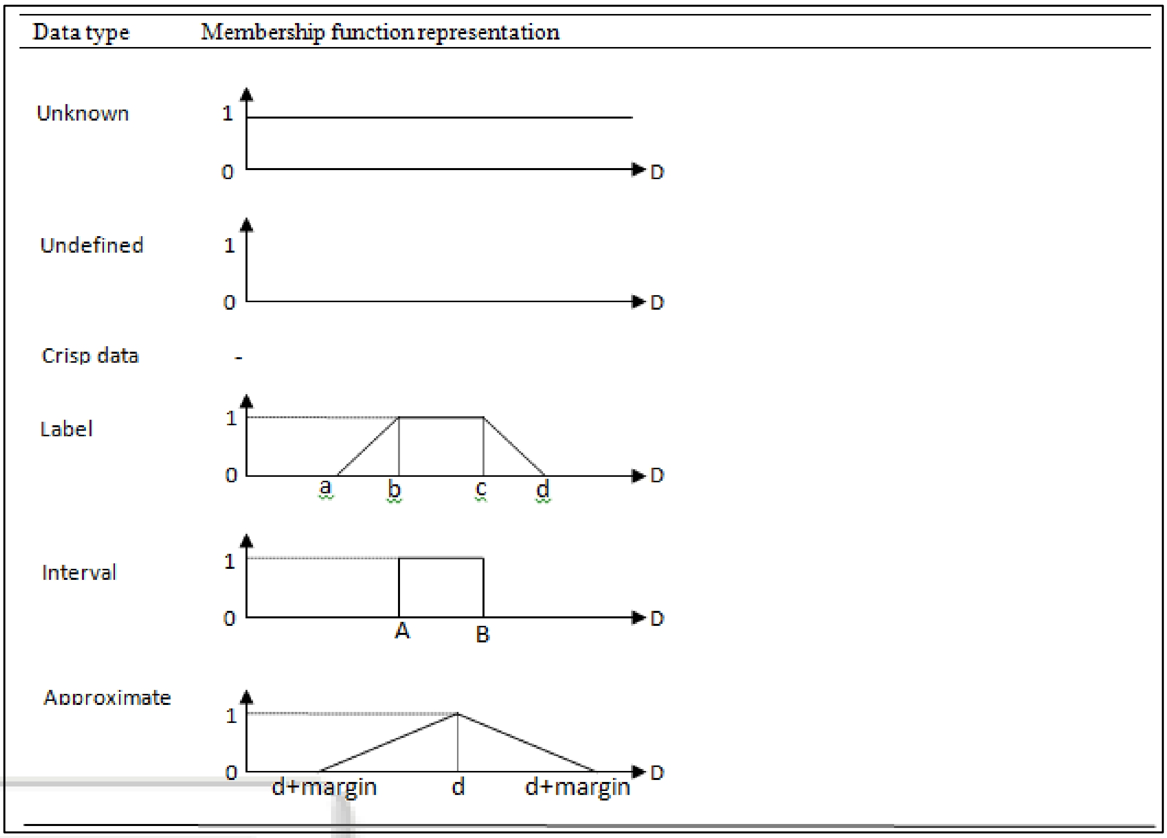


Table 1: Representation of imprecise data type

$(\tilde{d}''_{\ell j}, c''_{\ell j})$, with ℓ= 1, ..., m'', m'' being the difference cardinality, where $c''_{\ell j}$ = min $\{c_{\ell j}, (1 - c'_{\ell j})\}$. The Generalized Fuzzy Cartesian product $R_{FG} \times R'_{FG}$ of R_{FG} and R'_{FG} is defined as the Cartesian product of the (Dj, Cj)× $(D'_{j'}, C'_{j'})$. The Generalized Fuzzy Projection from R_{FG} onto X, where X = $[(D_s, C_{s'}) : s \in S, s' \in S'$; S, S' ⊆ {1, ..., n} is a subset of (D_j, C_j) is defined as PG (R_{FG} ; X) ∈ $(D_s, C_{s'})$. The Generalized Fuzzy Selection carried out on R_{FG} by the condition induced by a generalized fuzzy comparison operator $\Theta_{Gj}(A_j, \tilde{a})$ and a compatibility threshold ϑ_j on the attribute. A_j with $\tilde{a} \in D$ be a constant is defined as SG(EFG; $\Theta_{Gj}(A_j, \tilde{a}) \geq \vartheta_j$) $\in (D_j, C'_j)$ with a complete tuple ($D_{i'j}, C'_{i'j}$) with i' = 1, ..., m', m' being the selection cardinality and $C'_{i'j} = \Theta_{Gj}(\tilde{d}_{i'j}, \tilde{a}) \geq \vartheta_j$. The generalized fuzzy comparison operator $\Theta_{Gj}(\tilde{d}, \tilde{d}') \in [0, 1]$ is an extended comparison operator, such as 'greater or equal', 'equal to', etc. defined to operate on fuzzy information $\tilde{d}, \tilde{d}' \in D$.The Generalized fuzzy join is an extension of the typical relational join operator and is a kind of the Generalized Fuzzy Selection carried out 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 tuple 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 consist 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 obtain 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.

IV. CONCLUSIONS

The aforementioned proposed methodology can be determines a rankled 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. 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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