Towards Systematic Approximate Reasoning Methods in Power System Equipment Condition Monitoring and Reliability Analysis

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Abstract - Under the pressure of electric power industry deregulation, the approaches to many traditional power system problems are being reconsidered. Important concerns have arisen with regards to equipment condition monitoring, preventive maintenance and system reliability calculations. Approaches to condition monitoring and maintenance have historically been ad hoc tending to follow broad company guidelines or the experience of company personnel rather than systematic analysis. Recently, there has been increased interest in realizing cost savings by extending equipment lifetimes with focus on a comprehensive view of system reliability. There is not, however, a clear understanding of breakdown mechanisms and equipment stresses that will allow precise probabilistic analysis. This paper formulates an approximate reasoning approach that can incorporate expert judgement into reliability calculations. A novel method for including system constraints to improve the clarity of analysis is proposed. A numerical example illustrates the techniques.

Keywords - Approximate reasoning, condition monitoring, fuzzy logic, fuzzy measure, reliability, maintenance.

1 Introduction

For many years, the electric utility industry has followed maintenance and operating practices that have relied on large design margins in order to ensure safe and reliable operation. Present economic pressures are leading utilities to more carefully consider the costs of this "over-engineered" approach. A utility can enjoy substantial cost benefits by delaying new capital investments in generation and substation equipment. This can be approached by overloading installed equipment to avoid capacity upgrades and or by extending the useful lifetime of equipment through proper maintenance. On the other hand, maintenance programs can be expensive and cost savings can be realized by reducing maintenance on non-critical equipment. In practice, industry has pursued both directions by not only loading equipment significantly beyond manufacturer ratings but also shifting towards longer maintenance intervals on some equipment. Unfortunately, the implications of these practices on system reliability are poorly understood. Traditional reliability analysis of the power system has assumed that probability of failures for system components can be established precisely. These probabilities are normally found from expected equipment lifetimes when manufacturer recommended loadings and maintenance intervals are followed. While it is doubtful whether these probabilities were ever accurate, they clearly do not hold under increased equipment stress. This paper explores fuzzy logic based techniques for addressing reliability and maintenance calculations when failure probabilities, optimal maintenance schedules and operation impacts are not fully known. General conditions are established for the purpose of resolving inexact and conflicting operational data.

In general, equipment breakdown mechanisms are not well understood and developed methods for early detection of equipment failures tend to be imprecise [1]. A rudimentary understanding of the fundamentals of breakdown mechanisms has led to a variety of general diagnostic techniques and maintenance schedules depending on the equipment and application. As these techniques are always approximate, utilities rely on experience to obtain adequate performance. Unfortunately, most utilities find that the necessary experience is rare. This has led to the development of numerous expert systems for diagnostics and maintenance, (e.g. [2, **?**]). While these programs have been useful, the high degree of approximation in the analysis suggests that models of uncertainty are fundamental to successful implementation.

Poor models tend to generate excessive numbers of “false alarms” of equipment failures. Few of the developed systems to date have been capable of complete systematic use of inexact information. Traditional reliability analysis requires probabilistic data for equipment failure rates, repair times and failure effects. In a complex system, Monte Carlo simulations are often the only viable computational approach. The purpose of this research is not to replace such techniques but to integrate expert diagnostic judgements into the analysis. Where previously, probability distributions for failure rates, repair times and dependencies would be assumed known, these relationships will now be considered approximate. Note, this is a natural extension of sensitivity type calculations in reliability [**?**].

Work in the field of approximate reasoning provides some guidelines for addressing problems where relationships are not fully defined [3]. Of particular interest here is the development of information theoretic methods which easily incorporate uncertainties from broad assessments. These information-based approaches can be shown to provide a foundation to unify approximate reasoning techniques with traditional probabilistic methods [5, 4]. Unfortunately, these techniques fail to fully incorporate understanding of the underlying system. The result is an analysis that often provides inconclusive solutions. A novel feature of this work is the ability to incorporate understanding of the system constraints. This paper extends earlier results [6, **?**, **?**] using approximate reasoning techniques to a framework which includes reliability calculations.

This paper is organized as follows. A general description of power system diagnostic and monitoring techniques is given. Background on approximate reasoning techniques is presented. This background is used to develop the main result. A detailed numerical example highlights the approach.

2 Problem description

As indicated above, traditional maintenance schedules were based primarily on manufacturer recommended fixed time intervals. More recently, a reliability centered maintenance viewpoint has been proposed that views all maintenance in terms of system reliability so that, for example, non-critical equipment may receive no preventive maintenance, other equipment is maintained at regular intervals and critical equipment may be monitored on-line. In that a complete discussion on monitoring and maintenance techniques is beyond the scope of a single paper, this section merely provides an indication of the extant techniques and of the complexity of the problems. The equipment under consideration includes power transformers, substation batteries, circuit breakers, relays, generators, insulators and other equipment that can be monitored and maintained. A wide variety of tests can be employed, including:

- Chemical tests - e.g., dissolved gas analysis (DGA) of transformer insulation oil, moisture analysis of SF_6 insulated circuit breakers.
- Electrical measurements - e.g., power factor tests on transformers, harmonic analysis for detection of partial discharges or arcing.
- Acoustic and mechanical measurements - e.g., accelerometer sensed vibration analysis in generators, acoustic sensing of partial discharges or arcing.
- Other methods - e.g., rotor-stator air gap monitoring with optical sensors, thermal probes on generator and transformer windings.

To illustrate the typical diagnostic complexity, consider DGA of transformer insulation oil, one of the most widely applied diagnostic methods. Complete analysis requires historical gas concentration data for a particular transformer as well as for that class of transformers. Further, the specific application is important. For example, a step-up transformer at a nuclear power plant is typically loaded close to manufacturer ratings at all times. As a result, gas concentrations are generally higher and such high concentrations are not necessarily indicative of an incipient fault. These type of rough guidelines are important for analysis.

Note that while improvements in communication systems and sensors has led to interest in on-line monitoring, (e.g. [7]), most maintenance and diagnostic practices are still based on field tests. Thus, many of the above indicators of equipment condition are expensive to obtain on a regular basis. A useful analysis system then should provide guidelines not only for assessing the equipment state based on available data but also the need for further tests and closer inspection.

3 Managing uncertainty

Uncertainty in information concerning a given piece of equipment or given observation may be represented using a variety of methods that will be classified here into one of the following fundamental representations: probabilistic, fuzzy logic or nonadditive measure. The most appropriate description depends on how the information is received. For example, an expert's assessment of equipment by visual inspection would be linguistic and perhaps best represented by a fuzzy set. To be useful, each piece of information must be combined with other diagnostic data in appropriate. This section presents a methodology for representing uncertainty and a unified framework for combining different sources of information.

3.1 Probabilistic analysis

Traditional reliability analysis focuses on determining failure rates of the system components and the impact of such failures [8]. Systems are modelled as parallel, series, series-parallel or non-series-parallel. Non-series parallel can be decomposed into simpler subsystems based on conditional failures. Individual components failures are normally assumed to be independent. For two independent components A and B in parallel, the probability of failure is:

$$P_{\text{fail}} = P_A P_B \tag{1}$$

where P_A and P_B are the probability of failures for components A and B and P_{fail} is the system failure rate. For the same two components in series:

$$P_{\text{fail}} = P_A + P_B - P_A P_B \tag{2}$$

These models may also be used within a state space representation. Normally, the state space model assumes a Markov process so that the failure rates above could be interpreted as state transition probabilities. That development is well-known and is further developed here. For condition monitoring or diagnosis, analysis focuses on hypothesizing the equipment condition based on some observation or piece of evidence. In terms of conditional probability, this can be expressed as:

$$P(h|e) = \frac{P(e|h)P(h)}{P(e)} \tag{3}$$

where h is the hypothese and e the evidence. Given multiple pieces of evidence, one often assumes independence of this evidence and that all conditional probabilities are known. Further, one may assume that the set of hypotheses are mutually exclusive and exhaustive. Under these conditions, the following holds:

$$P(h_i|e_1 e_2 \cdots e_m) = \frac{\prod_{k=1}^{m} P(e_k|h_i)P(h_i)}{\sum_{j=1}^{n} \prod_{k=1}^{m} P(e_k|h_j)P(h_j)} \tag{4}$$

where the h_i are hypotheses and the e_i are evidence. Assuming that the quantities on the right hand side of (4) are more readily available, this simple calculation provides very useful information.

There are three practical concerns that should be incorporated into these calculations [9]. First, the probability values are not known precisely. Second, the components may not be independent. Third, the failure state may not be clearly defined. Each of these conditions are discussed in the following.

.Imprecise probabilities - Probabilities are may be determined by frequency of occurrence. These rates are difficult to determine precisely because of the large number of external influences as well as the typically low failure rates. In general, one can define a possible range for the probability values. For example, one may have a certain confidence that the probability of failure lies within the interval [0.00,0.01]; however, the traditional method of confidence levels based on a t-distribution [10] does not provide for algebraic manipulations of the probabilities. Alternatively, one can define an approximate or fuzzy number (e.g., about 0.5, much less than 0.10 and so on) where a range of values is given for various levels of confidence. In this case, the product or sum of the probabilites can be calculated using interval arithmetic (see [11]). Interval arithmetic computes maximum and minimum values for a given confidence level.

Component dependencies - The expressions (1) and (2) are special cases for independent components. If dependencies exist then the expressions must be modified depending on the nature of the dependencies. For large systems with many dependencies it will be difficult to perform these calculations. It is proposed that formulation of (1) and (2) are modified to reflect the possibility of dependencies by varying the operator. To begin, define the triangular norm, designated by $*$ as satisfying [13]:

1. Identity ($P_A * 1 = P_A$)
2. Commutativity ($P_B * P_A = P_A * P_B$)
3. Monotonicity ($P_A * P_B \leq P_A * P_C$ if $P_B \leq P_C$)
4. Associativity ($P_A * (P_B * P_C) = (P_A * P_B) * P_C$)

Example triangular norms include the minimum and product operators. In addition one can define a triangular conorm, designated here by $\perp$ as satisfying the same conditions except for identity:

1. Identity ($P_A \perp 0 = P_A$)

Example triangular conorms include maximum and probabilistic sum. Operators need to be chosen to correctly reflect the impact of the interdependencies. So for a parrallel connection of components, one could compute the probability of failure as:

$$P_{\text{fail}} = P_A * P_B \tag{5}$$

and for a series connection as:

$$P_{\text{fail}} = P_A \perp P_B \tag{6}$$

It is important to note that these computations result in what can be termed subjective probability evaluations and are no longer probabilities in the strictest sense.

Performance degradation - In the above analysis, failures were assumed to be a clearly defined state. In practice, system performance often degrades before reaching catastrophic failure. Further, a component failure may have either a minor or a significant impact on system performance. It may be easier to express this overall "risk" than to determine the series or parallel combination of a component or to delineate all the system states for state space representation. Fuzzy sets provide a natural and simple way of representing different levels of acceptable performance. These are explored in the next section.

3.2 Fuzzy logic

Fuzzy sets are useful for representing relationships as linguistic descriptions of classes of objects such as those given by experts. An element of a fuzzy set is an ordered pair consisting of an element and the degree of membership in the fuzzy set for that element [5]:

$$\mu : X \rightarrow [0, 1]$$

with fuzzy set A:

$$A = \{(x, \mu_A(x)) | x \in X\} \tag{7}$$

where X is the universe of discourse and $\mu_A(x)$ represents the degree to which x matches the characteristic feature of the set A. The following definitions of fuzzy set operations are most commonly used. If $C = A \cap B$,

$$\mu_C(x) = \min(\mu_A(x), \mu_B(x)) \tag{8}$$

and if $C = A \cup B$,

$$\mu_C(x) = \max(\mu_A(x), \mu_B(x)) \tag{9}$$

and if $C = \overline{A}$,

$$\mu_C(x) = 1 - \mu_A(x) \tag{10}$$

Note that neither the minimum nor the maximum function will necessarily be the appropriate operator for a given decision problem. It is generally accepted that the conjunction (intersection) operator should belong to the triangular norm class and the disjunction (union) operator should be the corresponding triangular conorm [13].

3.3 Nonadditive measures

Probability assesses the "frequency of occurrence" for which some unknown falls within a specified class, for example, how often a component fails. Conversely, fuzzy sets describe the rough boundaries of some class. More generally, one can describe the uncertainty which arises from identifying the class of an object. This uncertainty may be represented by a non-additive or fuzzy measure. See [4] for a rigorous definition. Let g be a fuzzy measure defined over the power set (or a Borel field) of the universe X as:

$$g : \mathcal{P}(X) \rightarrow [0, 1]$$

satisfying the axioms of probability without additivity. With this general definition of a measure, one can define various special cases. For example, if additivity does hold then one has a probability measure. Further, subadditive and superadditive measures, belief and plausibility measures, respectively, can be defined so the following always holds:

$$Bel(A) \leq P(A) \leq Pl(A)$$

where the belief measure is represented here as Bel and the plausibility measure as Pl. Note that due to additivity, probability of some event fixes a value for the complement as well, plausibility and belief measures will specify a bound on the measure for the complement. This adds flexibility to the representation and is very useful for representing uncertainties in expert systems .

3.4 Body of evidence

Finally, in this section a common representation is developed which can model the methods described above. Define a body of evidence as[5]:

$$m : \mathcal{P}(X) \rightarrow [0, 1]$$

where $\mathcal{P}(X)$ is the power set of the universe X and m is such that:

$$m(\emptyset) = 0 \tag{11}$$

$$\sum_{A \in \mathcal{P}(X)} m(A) = 1 \tag{12}$$

The value of $m(A)$ is interpreted as the evidence on the set A and only A. Together the values for $m(A)$ provide a body of evidence for the problem under consideration. It can be shown [5] that $m(A)$ uniquely defines the measures defined in the previous section under the following formulas:

$$P(A) = \sum_{x \in X} m(\{x\}) \tag{13}$$

$$Bel(A) = \sum_{B \subseteq A} m(B) \tag{14}$$

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B) \tag{15}$$

Similarly, given the measure one can compute the body of evidence from:

$$m(A) = \sum_{B \subseteq A} (-1)^{|A-B|} Bel(B) \tag{16}$$

Fuzzy sets can be included in this framework by using the so-called "possibility" approach which states that $\mu_A(x)$ indicates the possibility that the variable of interest takes the value x given the fuzzy statement A. The measure is then:

$$Pl(\{x\}) = \mu_A(x) \tag{17}$$

and the subsequently a body of evidence can be found. Note in this case, the body of evidence has non-zero values only on consonant sets so that there is no conflict in the evidence assignment.

The approach taken is to translate information from different sources into a basic assignment and then combine these sources using a decision technique known as the Dempster-Shafer rule of combination. This rule weighs evidence based on the relative certainty as follows for two bodies of evidence m_1 and m_2:

$$m_{1,2}(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - K}, \qquad A \neq \emptyset \tag{18}$$

with:

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C) \tag{19}$$

The factor K is a normalizing factor which accounts for evidence which is dissonant (unreconcilable).

4 Proposed system

In this section, the framework for the developed system is presented. A structure is defined which allows knowledge of the system to be described as a series of relations. Uncertainties of these relations are computed

the application of the approximate reasoning techniques to power system problems is presented. A relational structure is defined. Each relation can be used to determine approximate values based on some observation. An inference engine is defined which utilizes this relational structure.

4.1 Representation

A fundamental requirement for knowledge-based systems is simplicity of modifying the existing knowledge in the system. Missing or erroneous information should not invalidate the analysis and in this sense, each relationship in the knowledge-base should be robust. The proposed structure of the rule-base in the proposed system uses a fuzzy set description for each relation and a measure over the relation. Three classes of rules compromise the system. These rules are discussed in the following.

Diagnostics - For condition monitoring, a measurement is taken and a measure of the truth of a relation is calculated from this measurement. For example, consider the following rule used in a system for DGA of transformers [6]:

High level of acetylene ($\mathbf{C_2H_2}$)
IF the concentration of C_2H_2 is high
THEN this is indicative of an arcing fault
WITH this observation strongly needed

This rule can be understood as follows; if the acetylene concentration is high then it will support other evidence which indicates an arcing fault. The "needed" clause indicates the necessity of observing a high acetylene level in order to conclude there is an arcing fault. The "high concentration" is represented by a fuzzy set which is dependent on the history of the transformer. In general, the rule format for conditioning is as follows:

Condition rule
IF condition A_i
THEN state B_j WITH certainty $g_i(A_i, B_j)$

The sets A_i and B_j can be traditional crisp or fuzzy sets. The certainty clause $g_i(A_i, B_j)$ is a measure as defined in the previous section.

Reliability risk - For consideration of reliability, a fault or equipment state is hypothesized and the effect on system performance computed. For example, consider the following rule associated with a transformer fault.

Aging substation transformer
IF transformer condition indicates premature aging
THEN risk of failure at peak loads WITH a strong possibility

This rule can be understood as follows; if tests have indicated advanced aging in the transformer, then there is increased risk of complete failure during a high load period. In general, the format for the reliability risk is:

Reliability rule
IF state B_j
THEN risk C_k WITH certainty $g_i(B_j, C_k)$

The risk C_k represents some failure state.

Corrective actions - Based on the diagnostic and reliability analysis , some form of action should be taken be it corrective, preventive or further data gathering. The cost of actions should be considered as well as the impact on reliability. Further, actions which hold out some possibility of clarifying equipment condition should be incorporated in the framework. For example, consider the following rule associated with scheduled maintenance:

Transformer inspection
IF transformer has an electrical fault
AND the transformer windings are physically inspected
THEN electrical fault identified WITH high possibility

This rule can be understood as follows; electrical faults have a high chance of being identified through physical inspection of the windings. In general, the format for a corrective action rule is:

Corrective action rule
IF state B_j AND action D_l
THEN state B_m WITH certainty $g_i(D_l, B_j)$
AND cost E_n.

Typical actions would include scheduling maintenance, removing equipment for service, modifying operational constraints, obtaining a field measurement and so on. Note in the above example, gathering data may lead to a clarification of the equipment condition but there will no change in the state and there will still be a probability for device failure. The costs allows inclusion of economic objectives into the inference and should provide for the cost of the outages as well. This is not explored more fully in this paper.

4.2 Domain constraints

The above postulated several components of a representation: (1) observations, A_i (2) equipment states, B_j (3) risks, C_k (4) actions, D_l and (5) costs, E_n. The rule base provides the relationships between these items. In addition, it has been found that there is a need to incoporate system constraints into the rule base. This can be thought of as a modified model-based approach. For example, consider a problem where the measurement indicated either that a piece of equipment had been heavily loaded or that a fault was developing. If that equipment had been operating in overloaded conditions, then there would be less concern of an incipient fault. Typically, system constraints can help eliminate many of the false alarms that tend to be generated in approximate analysis. It is proposed to model the constraints in terms of the measures of those states so that the constraints are represented by:

$$f_i(g_1(B_1), \ldots, g_p(B_p)) \leq 0 \tag{20}$$

where p is the number of sets with measures. The system constraints can be enforced by adjusting the measures calculated from a given rule base during the inference. As there may be many ways to reassign evidence in order to satisfy the constraints, general procedures must be defined within the inference to consistently perform the reassignment. This is developed in the next section.

4.3 Inference algorithm

Inference in the proposed system moves through several steps each involving specific computations. Given some observation, a measurement of A_j can be calculated. Based on this value and g_i, an assessment for the conclusion, B_j, is found. The result of applying all relevant rules must be computed. The necessary computations depend on the sets A_i and B_j and the form of the uncertainties g_i. Rules can be applied through conjunction, disjunction or as independent bodies of evidence. Rules which apply to a conclusion B_k in terms of conjunction are combined as:

$$g(B_k) = \mathop{*}_{\substack{R_i \text{ with} \\ B_j \subseteq B_k}} g_i(B_j) \tag{21}$$

and in terms of disjunction as:

$$g(B_k) = \mathop{\perp}_{\substack{R_i \text{ with} \\ B_j \cap B_k \neq \phi}} g_i(B_j) \tag{22}$$

When rules have been applied to a set of observations, a body of evidence values $m(\cdot)$ can be computed by satisfying (11)-(15) and the underlying system constraints (20) and to ensure the validity of the analysis. The reapportionment of evidence for constraint violations works as follows:

1. Select the smallest sets with non-zero evidence.
2. If possible without violating constraints, assign evidence for these sets to achieve the measures calculated from the rule base.
3. If a constraint violation exists, then assign the conflicting quantity to the "unknown" set (the universe).
4. Repeat (1)-(3) above for increasingly larger sets until all evidence has been assigned.

An algorithm was developed which applied a reduced form of the above constraint or conflict resolution for a simplified representation [6]. This

Equipment State	x_1	x_2	x_3	x_4
Unknown - B_1	x	x	x	x
Faulted - B_2	x	x	x	
Electrical - B_3	x	x		
Partial Discharge - B_4	x			
Arcing - B_5		x		
Thermal - B_6			x	
Normal - B_7				x
System Failure - C				

Table 1: Domain Definitions

Approach	Conclusions
1	$Pl(B_2) = 0.8$, $Pl(B_3) = 0.6$ $Pl(B_7) = 0.3$, $Bel(B_4) = 0.1$ $Bel(B_7) = 0.2$
1*	$Pl(B_2) = 0.8$, $Pl(B_3) = 0.8$ $Pl(B_7) = 0.5$, $Bel(B_4) = 0.1$ $Bel(B_7) = 0.2$
2	$P(B_3) = 0.5$, $P(B_6) = 0.2$ $P(B_7) = 0.3$
3	$Bel(C\|B_2) = 0.20$, $Bel(C\|B_7) = 0.01$

Table 2: Condition Monitoring Observations

paper extends that work to the representation proposed in Sec. 4.1 The body of evidence between different sets of observations are combined using (18). Subsequently, calculations proceed for computing the appropriate actions to be taken. The impact of an action depends on the assessment of equipment states. Measure computations again follow (21)-(22). For multiple actions, cost is additive.

5 Numerical example

Equipment State	$m(B_i)$	$Pl(B_i)$	$Bel(B_i)$
Unknown	0	1.0	1.0
Faulted	0	.77	.77
Electrical	.54	.62	.62
Partial Discharge	.08	.62	.08
Arcing	0	.54	0
Thermal	.15	.15	.15
Normal	.23	.23	.23
System Failure	–	.16	.16

Table 3: Resultant Body of Evidence

In this section, a numerical example is presented in some detail to show the application of the proposed techniques. Table 1 defines the possible equipment states where an 'x' indicates the element is present in that set. The problem here is generic but is intended to loosely represent either generator or transformer windings. Table 2 lists two assessments of the equipment state after appropriate application of diagnostic rules based on two different diagnostic techniques. The first approach results in fuzzy measure values and the second approach results in a probability measure. No system constraints are modelled but the constraints in (11)-(15) are checked. The measures which are obtained from the first method do not satisfy these constraints, so '0.2' of the evidence is added to the unknown assignment. The new measure values are shown as 1* in Table 2. The two bodies of evidence are then combined using (18). Table 3 shows the result of this computation. The third method shown in Table 2 establishes the system risk for the given equipment failure.

Now, the impact of various courses of action are considered. Three actions are considered in the present example. The first would repeat a measurement. The second would involve removing equipment from service for maintenance. The third action would replace the piece of equipment. Table 4 lists the associated costs and estimates of the conclusion certainty depending on the actual state. These values are then combined to give a

Action	State	Conclusion Certainty	Cost
Retest	B_2	$Pl(B_2) = 0.80$	\$1,000
	B_7	$P(B_7) = 0.95$	
Maintain	B_2	$Bel(B_7) = 0.90$	\$10,000
	B_7	$Bel(B_7) = 0.95$	
Replace	B_2	$P(B_7) = 0.99$	\$1,000,000
	B_7	$P(B_7) = 0.99$	

Table 4: Possible Actions and Reliability Risk

Action	Conclusion Certainty	Reliability Risk
Retest	$Pl(B_2) = .80$, $Bel(B_2) = .77$ $P(B_7) \leq .22$	$Bel(C) = 0.16$
Maintain	$P(B_2) = .08$ $P(B_7) = .91$	$Bel(C) = 0.03$
Replace	$P(B_2) = .01$ $P(B_7) = 0.99$	$P(C) = 0.01$

Table 5: Final Recommended Actions

final assessment of the course of action. The result is shown in Table 5. In this simple example, the prudent course of action is to pursue maintenance. Repeating a test adds little to the certainty of the conclusion and the added cost of replacement doesn't justify the expected improvement in reliability unless the fault becomes certain.

6 Summary and Conclusions

This paper has proposed representations of uncertainty and new computational algorithms that will allow power engineers to improve the overall monitoring and maintenance of equipment condition. The representation includes the ability to model domain constraints as well as expert knowledge of diagnostic, maintenance and reliability concerns. The proposed framework requires the following design steps:

1. Specification of the measurements, equipment states and corrective actions.
2. Identification of measurement and equipment constraints.
3. Establishment of rule base based on
   - Relations between measurements, equipment states and corrective actions.
   - Appropriate uncertainty measures for all relations.
4. Definition of logical operators for all rule groupings.

The developed methodology has been implemented as an expert system shell and to date systems have been written for transformer and simple hydro generator diagnostics. Further work will focus on developing complete expert systems in the area of hydro condition monitoring and improved understanding of conflict resolution techniques.

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