AI Technique in Diagnostics and Prognostics

A.Poongodai (Ph.d)
Pondicherry University
Karaikal Campus,
Karaikal.

S.Bhuvaneswari, Reader,
Pondicherry University
Karaikal Campus,
Karaikal.

ABSTRACT
Artificial Intelligence is the science and engineering of making intelligent machine especially intelligent computer programs. Activities in AI include Searching, Recognizing patterns and Making logical inferences. This paper discuss on Artificial intelligence technique used for System diagnostics and prognostics. Three approaches of AI for diagnostics and prognostics are 1. Rule based diagnostics 2. Model based diagnostics and 3. Data Driven Approaches. System diagnosis is the process of inferring the cause of any abnormal or unexpected behavior. A prognostic is predicting the time at which a system or a component will no longer perform its intended function.

General Terms
AI based approach for Diagnostics and Prognostics

Keywords
Artificial Intelligence, Diagnostics, Prognostics, Rule based system, model based AI approach, Data driven approach.

1. INTRODUCTION
Artificial Intelligence (AI) could be defined as the ability of computer software and hardware to do those things that we, as humans, recognize as intelligent behavior. Traditionally those things include such activities as:

1. Searching: finding best solution in a large search space.
2. Recognizing patterns: finding items with similar characteristics, or identifying an entity when not all its characteristics are stated or available.
3. Making logical inferences: drawing conclusions based upon the given hypothesis.

Many diverse approaches to diagnostic reasoning are Rule based system, Model based diagnostics, Learning systems, Case-based reasoning systems and Probabilistic reasoning systems. The first three approaches follow Artificial intelligence technique The goal of this research paper is to give a how the various AI based technique are used in System Diagnostic and Prognostics
.

2. SYSTEM DIAGNOSIS
System diagnosis is the process of inferring the cause of any abnormal or unexpected behavior. During system operation, indications of correct or incorrect functioning of a system may be available. In complex applications, the symptoms of incorrect (or correct) behavior are observed directly or need to be inferred from other variables that are observable during system operation. Monitoring is a term that denotes observing system behavior. The capability for monitoring a system is a key prerequisite to diagnosing problems in the system.

Diagnostic applications make use of system information from the design phase, such as safety and mission assurance analysis, failure modes and effects analysis, hazards analysis, functional models, fault propagation models, and testability analysis.

In any system, given the complexity of the experimental data and the variety of failure modes, a diagnostic system based on Artificial intelligence technique was designed. A comprehensive analysis of data was carried out to extract a set of uncorrelated features that would not only detect various fault modes but also specify the actionable knowledge to be applied in order to solve the problems.

The system must take as input sensor values and the command stream, and ideally performs

- Fault Detection (detecting that something is wrong)
- Fault Isolation (determining the location of the fault)
- Fault Identification (determining what is wrong i.e., determining the fault mode)
- Fault Prognostics (determining when a failure will occur based conditionally on anticipated future usage)

Diagnostics include not only fault detection but both Fault Isolation and Fault Identification.

3. PROGNOSTICS
A prognostic is an engineering discipline focused on predicting the time at which a system or a component will no longer perform its intended function. Prognostics include detecting the precursors of a failure, and predicting how much time remains before a likely failure. A prognostic is the most difficult of these tasks (Detection, Isolation, Identification and prognostics).

A simple form of prognostics, known as a life usage model, is widely in use. It gathers statistical information about the amount of time that a component lasts before failure, and uses these statistics collected from are sample of components to make remaining life predictions for individual components. We must be able to detect faults before we can diagnose them. Similarly, we must be able to diagnose them before we can perform prognostics.

In addition to fault detection, diagnostics, and prognostics, System should also include support for deciding what actions to take in response to a failure or a failure precursor.

Table 1. Table captions should be placed above the table

Taxonomy	Description	Classification
Model Based Algorithms	Encode human knowledge via a hand-coded representation of the system	Physics based System of differential application Classical AI Techniques Rule-based expert systems Finite-state machines Qualitative Reasoning
Data Driven Approaches	Automatically fit a model of system behaviour to historical data, rather than hand-coding a model	Conventional numerical algorithms Linear regression Kalman filters Machine learning Neural networks Decision trees Support vector machines.

4. AI TECHNIQUES

Three approaches of AI for diagnostics and prognostics are 1. Rule based approach 2. Model based approach and 3. Data Driven Approaches.

4.1 Rule based approach

The Rule-based expert systems have wide application for diagnostic tasks. The procedures can be broken down into multiple steps and encoded into "rules." A rule describes the action(s) that should be taken if a symptom is observed. A set of rules can be incorporated into a rule-based expert system, which can then be used to generate diagnostic solutions. In this, expertise and experience are available but deep understanding of the physical properties of the system is either unavailable or too costly to obtain.

Two primary reasoning methods may be employed for generating the diagnosis results.

1. Forward Chaining
2. Backward Chaining

In forward chaining, the process examines rules to see which ones match the observed evidence. If only one rule matches, the process is simple. However, if more than one rule matches, a conflict set is established and is examined using a pre-defined strategy that assigns priority to the applicable rules. Rules with higher priority are applied first to obtain diagnostic conclusions.

If the starting point is a conclusion, a backward chaining algorithm collects or verifies evidence that supports the hypothesis. If the supporting evidence is verified, then the hypothesis is reported as the diagnostic result.

The advantages of rule-based systems include

- increase in the availability and the reusability of expertise but at high cost
- increased safety, if the expertise must be used in hazardous environments
- increased reliability for decision making
- fast and steady response
- consistent performance
- built-in explanation facility

The challenges are

1. Order in which the rules should be matched
2. Determining the completeness, consistency and correctness of derived rules

4.2 Model Based Techniques

Model-based reasoning systems refer to inference methods used in expert systems based on a model of the physical world. Models might be quantitative i.e., based on mathematical equations or qualitative i.e., based on cause/effect models. They may include representation of uncertainty, behaviour over time, normal behaviour, or might only represent abnormal behaviour.
The main focus of application development is developing the model. Then at run time, an engine combines this model, knowledge with observed data to derive conclusions such as a diagnosis or a prediction.
Model Based Algorithms encode human knowledge via a (more or less) hand-coded representation of the system

- Physics based
- AI based

Hand-coded model uses qualitative, rather than numerical, variables to describe the physics of the system. Model-based AI techniques include rule-based expert systems, finite-state machines, Qualitative Reasoning.

4.2.1 Rule Based Expert Systems

An Expert System is an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution.
Early diagnostic expert systems are rule-based and used empirical reasoning whereas new model-based expert systems use functional reasoning. In the rule-based systems knowledge is represented in the form of production rules. The empirical association between premises and conclusions in the knowledge base is their main characteristic. These associations describe cause-effect relationships to determine logical event chains that were used to represent the propagation of complex phenomena. Heuristic-based expert systems can guide efficient diagnostic procedures but they lack in generality.

The limitations of the early diagnostic expert systems are as follows:

- Inability to represent accurately time-varying and spatially varying phenomena

- Inability of the program to detect specific gaps in the knowledge base
- Difficulty for knowledge engineers to acquire knowledge from experts reliably
- Difficulty for knowledge engineers to ensure consistency in the knowledge base
- Inability of the program to learn from its errors

The rule-based approach has a number of weaknesses such as lack of generality and poor handling of novel situations but it also offers efficiency and effectiveness. The main limitations of the early expert systems may be eliminated by using model-based methods. Expert knowledge is contained primarily in a model of the expert domain. Such models can be used for simulation to explore hypothetical problems. Model-based diagnosis uses knowledge about structure, function and behaviour and provides device-independent diagnostic procedures. These systems offer more robustness in diagnosis because they can deal with unexpected cases that are not covered by heuristic rules. The knowledge bases of such systems are less expensive to develop because they do not require field experience for their building. In addition, they are more flexible in case of design changes. Model-based diagnosis systems offer flexibility and accuracy but they are also domain dependent.

4.2.2 Qualitative Simulation in Fault Detection

In this method, fault detection is performed by comparing the predicted behaviour of a system based on qualitative models with the actual observation. Qualitative models of normal and faulty equipment are simulated to describe the range of possible behaviours of the operation of a system without numeric models. The modelling of physical situations contains a set of qualitative equations derived from a set of quantitative equations or from qualitative descriptions about relationships among the process variables and contains knowledge about structure, function and behaviour. Sensor data from actual processes are used to select between the different developed models. The fault diagnosis is realised by matching between predicted and observed behaviour.

The main advantage of this approach is that accurate numerical knowledge and time consuming mathematical models are not needed. On the other hand, this method only offers solutions in cases where high numerical accuracy is not needed.

4.3 Data Driven Approaches

Learning systems are data-driven approaches that are derived directly from routinely monitored system operating data. They rely on the assumption that the statistical characteristics of the data are stable, unless a malfunctioning event occurs in the system.

Data Driven Approaches automatically fit a model of system behavior to historical data, rather than hand-coding a model. Data-driven approaches can either use “conventional” numerical algorithms, such as linear regression or Kalman filters, or they can use algorithms from the machine learning and data mining AI communities, such as neural networks, decision trees, and support vector machines.

The strengths of data-driven techniques are as follows:

- ability to transform the high-dimensional noisy data into lower-dimensional information for detection and diagnostic decisions
- ability to handle highly collinear data of high dimensionality
- substantially reduce the dimensionality of the monitoring problem
- compress the data for archiving purposes
- provide monitoring methods
- facilitate model building via identification of dynamic relationships among data elements

The main drawback of data-driven approaches is that their efficacy is highly dependent on the quantity and quality of system operational data.

The engineering processes needed to relate system malfunctioning events using a data driven diagnosis approach typically involve the following steps.

- Determine the High-Impact Malfunctions
- Data Selection, Transformation, De-noising and Preparation
- Data Processing Techniques
- Testing and Validation
- Fusion

Table 2. Technique used in the system

	Fault Detection	Diagnostics	Prognostics
Model based AI system	Expert system	Finite state machines	-
M/c Learning system	Clutering	Decision Tree Induction	Neural networks

4.3.1 Decision tree Induction

The Decision tree induction is greedy approach which constructs the decision tree in top down recursive, divide and conquer manner. The problem of constructing decision tree is NP-complete problem. Decision tree are built in two phases: Growth and Pruning phase.

In the growing phase, the training data set is recursively partitioned until all the records in a partition belong to same class. For every partition, a new node is added to the decision tree. Initially, the tree has a single root node for the entire data set. For a set of records in a partition P, a test criterion T for further partitioning the set into PI,. . . , Pm is first determined. New nodes for PI,. . . , Pm are created and these are added to the decision tree as children of the node for P. Also, the node for P is labeled with test T, and partitions PI, . . . , P,,, are then recursively partitioned. A partition in which all the records have identical class labels is not partitioned further, and the leaf corresponding to it is labeled with the class. The building phase constructs a perfect tree that accurately classifies every record from the training set.

However, one often achieves greater accuracy in the classification of new objects by using an imperfect, smaller decision tree rather than one which perfectly classifies all known records. The reason is that a decision tree which is perfect for the known records may be overly sensitive to statistical irregularities and idiosyncrasies of the training set. Thus, most algorithms perform a pruning phase after the building phase in which nodes are iteratively pruned to prevent “overfitting” and to obtain a tree with higher accuracy.

A decision tree, or any learned hypothesis h, is said to over fit training data if another hypothesis h2 exists that has a larger error than h when tested on the training data, but a smaller error than h when tested on the entire dataset. The various decision tree induction algorithms are HUNT's algorithm, CART, ID3, C4.5, SLIQ and SPRINT

The classification accuracy of the decision trees is improved by constructing (1) new binary features with logical operators such as conjunction, negation, and disjunction and (2) at-least M-of-N features whose values will be true if at least M of its conditions is true of the instance, otherwise it is false. Gama and Brazdil (1999) combined a decision tree with linear discriminate for constructing multivariate decision trees.

4.3.2 Support vector machine (SVM)

SVM is a statistical classifier that analyzes data and recognizes patterns. Also SVM is a non-probabilistic binary linear classifier as it takes a set of input data and predicts, for each given input, which of two possible classes comprises the input. It is also used for regression analysis. SVM is more capable to solve the multi-label class classification. SVM can classify successfully when combined with other classifier for reducing the number of dimension.

4.3.3 Neural Network

Backpropagations algorithm is a neural network algorithm which works on multilayer feed forward network, a type of neural network. A neural network classifier is a network of units, where the input units usually represent terms, the output unit(s) represents the category. BP neural network can improve the accuracy of classification. There are several theoretical advantages of BP neural network that make it especially adaptable to be employed in interacting prediction. It can process a batch of testing dataset and gain the predicting results quickly. The advantage of neural network technique is their high tolerance to noisy data and their ability to classify the new object on which they have not been trained.

Neural networks find application in fault detection due to their main ability of pattern recognition. The network is trained to learn, from the presentation of the examples, to form an internal representation of the problem. For diagnosis it is needed to relate the sensor measurements to the causes of faults, and distinguish between normal and abnormal states. Input vectors are introduced to the network and the weights of the connections are adjusted to achieve specific goals.

One of their limitations in the on-line fault detection process is, the high accuracy of the measurements needed in order to calculate the evolution of faults. Fault detection usually makes use of measurements taken by instruments that may not be sensitive enough or that may produce noisy data. In this case the neural network may not be successful in identifying faults. It is nearly always necessary to pre-process the data so that only meaningful parameters are presented to the net.

Neural networks are able to learn diagnostic knowledge from process operation data. However, the learned knowledge is in the form of weights which are difficult to comprehend. Another limitation compared to expert systems is their inability to explain the reasoning. This is because neural networks do not actually know how they solve problems or why in a given pattern recognition task they are able to recognise some patterns but not others. They operate as "black boxes" using unknown rules and are unable to explain the results.

5. CONCLUSION

One of the biggest challenges for AI-based prognostics is verification and validation (V&V). The complexity of AI systems makes them very difficult to verify and validate before deployment. AI based V&V may offer the potential to help solve this problem. Several biology-inspired AI and Neural network techniques are currently popular. Neural Networks model a brain learning by example—given a set of right answers, it learns the general patterns. Reinforcement Learning models a brain learning by experience—given some set of actions and an eventual reward or punishment, it learns which actions are good or bad. Genetic Algorithms model evolution by natural selection—given some set of agents, let the better ones live and the worse ones die. Typically, genetic algorithms do not allow agents to learn during their lifetimes, while neural networks allow agents to learn only during their lifetimes. Reinforcement learning allows agents to learn during their lifetimes and share knowledge with other agents.

6. REFERENCES

[1] Ann Patterson-Hine, Gordon Aaseng, Gautam Biswas, Sriram Narasimhan, Krishna Pattipati, A Review of Diagnostic Techniques for ISHM Applications

[2] Mark Schwabacher and Kai Goebel, NASA Ames Research Center, A Survey of Artificial Intelligence for Prognostics

[3] C. Angeli, A. Chatzinikolaou, On-Line Fault Detection Techniques for Technical Systems: A Survey,International Journal of Computer Science & Applications © 2004, Vol. I, No. 1, pp. 12 – 30

[4] Beshears, R. and Butler, L. 2005. Designing For Health; A Methodology For Integrated Diagnostics / Prognostics. Proceedings of IEEE Autotestcon. New York: IEEE

[5] Thair Nu, Phyu, Survey of Classification technique in data mining. Proc International Multi Conference on Engineers and Computer Society, Volume 1, 2009

[6] Beshears, R. and Butler L,. 2005. Designing For Health; A Methodology For Integrated Diagnostics/Prognostics Proceedings of IEEE Autotestcon. New York: IEEE.