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Prognostics and Artificial Intelligence- A Step into the Future

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Abstract

This paper focuses on the brief description of aspects of Prognostics and goes on to explore its strategies, types and algorithms to understand the field of Prognostics better and then explains the comprehensive field of Artificial Intelligence (AI) with its types and applications and then exemplifies a very specific example of how a combination of the two enhances our lives and is indeed very practical and futuristic.

1. Introduction

Without the use of Artificial Intelligence, Prognostics is deemed effective but with the prediction theories and apt algorithms that Artificial Intelligence provides this field of Prognostics will reap huge benefits for mankind. We have often thought about our future generations, the usage of prognostics not only secures our future but also safeguards the future of our progeny.

Prognostics on its own has already been experimented with and implemented in certain fields of technology, in particular medicine. However, medicine is just the beginning. With the usage of Artificial Intelligence Prognosis will be an essential tool.

We focus mainly on the aspects of ISHM (Integrated Systems Health Management) which can be best conceived as a pertinent part of systems that would want to implement prognostics.

The combination of Prognostics with Artificial Intelligence (AI) is a very effective combination whose applications are innumerous and still burgeoning. We first start with the description about these two domains: Prognostics, then Artificial Intelligence and later proceed to the applications of the combination.

2. Prognostics

Merriam-Webster defines the term Prognosis as "a judgment about what is going to happen in future" [1].While it is believed that prognostics originated with the French physicians in the nineteenth century, its ken transcends more than just medical applications. Prognostics on its own can be divided into the following of the categories:

2.1. Data-driven prognostics

Data driven prognostics involve a training data-set which takes care of making the system learn. A variety of algorithms then can be applied on this system to generate the prognostic outputs. This method of prognostic indication involves successive estimations on data and is memory-based one which portends the future results on the past estimations and the past results that have been compiled.

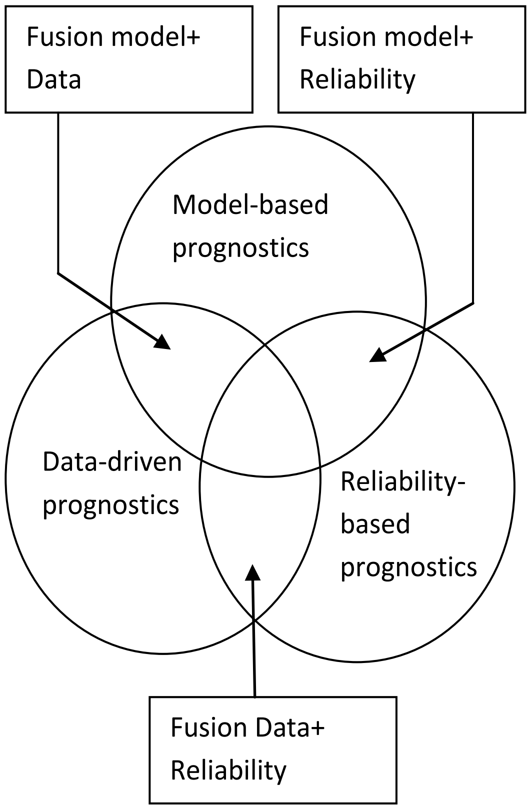

Figure 1. Types of Prognostics- Classification.

2.2. Model-driven prognostics

The model driven prognostics indicate the involvement of all the physical models of the system which establishes the entire platform of prognostics derivation at both- the micro and the macro levels. Micro level models epitomize damage propagation model as the one which includes fatigue life of a ball bearing due to induced stress by Yu and Harris [2]. Macro-level models involve system level mathematical models with a simplified representation of the system input variables, state variables and the output data. It is aimed at encompassing all the possible system components and does not raise an exception to occasional lax of accuracy.

2.3. Hybrid approaches

In recent years, these have been a way to go. With experimentation and the increasing reliance of accuracy of prognostics, hybrid approaches have been resorted to. It is hardly found now-a-days that the researches which take place have been completely data-driven or model-driven.

This approach ramifies itself into two approaches –

- Pre-estimate fusion

Pre-estimate fusion involves the diagnosis and curing of faults before they surface. This means that the resulting failure of any process is known to the machine itself earlier and corrective measures are instilled. However, the downside involves no run-to-fail training set being available. But, it is compensated by presaging the failure and thus avoiding the scheduled maintenance process of the systems and the time investment of maintenance, which is considerable cost-cutting measure and saves the entire system the tedious process of going through with exhaustive maintenance for fault-search.

- Post-estimate fusion

With less amount of training set available at hand, it is often difficult to simulate or to realistically run and understand at what point the failure will occur. Hence what we are left with is a huge domain of uncertainty where the range of such failure occurrence is substantially large. To manage this uncertainty and to prune its range, uncertainty management needs to be performed. This is achieved by fusion of quality assessments employed to individual estimation systems based on a range of inputs.

2.4. Prognostic strategies for learning process and algorithms

2.4.1. Strategies. There are a variety of strategies which can be employed for system learning from the training dataset. An example of such a strategy is as shown [3]:

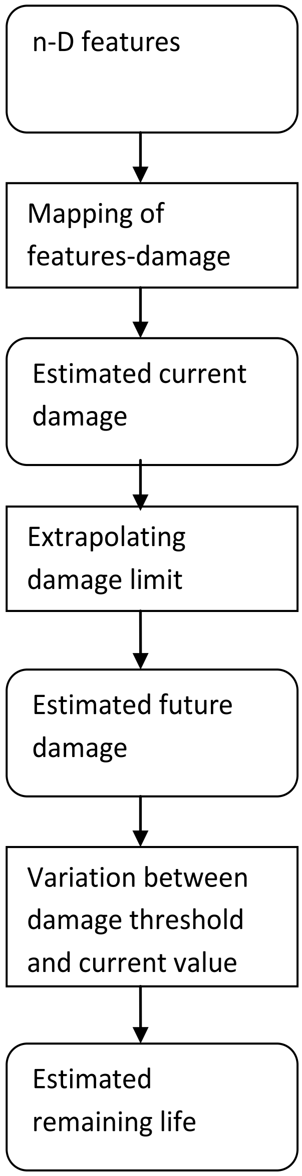

Figure 2. Learning process flowchart of the system with simulation of training set values.

2.4.2. Algorithms. There are a variety of algorithms to implement and get the results in Prognostics. These algorithms are simulated on the training dataset collected. While training dataset may be at hand, but simulations on a large scale are very costly. Usually, the assumptions taken under consideration before starting a Prognostics simulation are:

- The current state of the system
- The overall system damage is accounted for from the current state to the run-to-failure state.

Here the focus is laid on the three important algorithms:

2.4.2.1. Neural Network-based Power Law Parameter Estimation. The distribution of a discrete random variable is referred to as a distribution with a power-law tail if it falls as

$p(k) \sim k^{-m}$
for $k \in N$ and $k \geq k_{min}$ [4].

Because of the erratic nature of m and the invariable range of test data, we consider power law estimation, where we observe the reactions of the Neural Network, the recorded system damage propagation is found to be linear due to log-based representation. In the cases where no training set is available, results may be availed as a smooth curve.

2.4.2.2. Gaussian Progress Regression (GPR). A collection of variables, random in nature, which have a Gaussian distribution define the contents of a Gaussian Process (GP). A real GP f(x) is completely specified by its mean function m(x) and co-variance function k(x, x'). The index set X in R is the set of possible inputs, which need not necessarily be a time vector.

A typical Gaussian Distribution curve [5]:

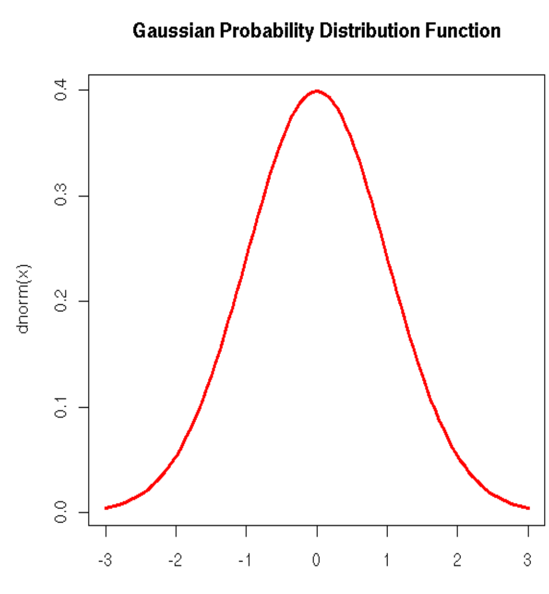

Figure 3. Gaussian Probability Distribution function.

These are the main algorithms of Prognostics. With this we now move onto the next domain- Artificial Intelligence.

3. Artificial Intelligence

Artificial Intelligence is the field of Science and Engineering which in focused in making of intelligent machines through the generation of a repository of computer programs that emulate the human behavior or at least intended to do so in every aspect[6].

While some researchers aim to progress in the field of AI by manipulating human mind and its vivid characteristics, some condemners of this thought perceive the progress of AI as an independent and intelligent development with a minimal imitation of the human brain.

3.1. Types of AI

Though AI is of numerous types, some of the important ones are:

3.1.1. Representation AI. Factual world objects have to be represented. Usually languages of mathematical logic are used.

3.1.2. Logical AI. What a program knows about the world in general the facts of the specific situation in which it must act, and its goals are all represented by sentences of some mathematical logical language. The program decides what to do by inferring that certain actions are appropriate for achieving its goals.

3.1.3. Searching and Indexing AI. AI programs often examine large numbers of possibilities, e.g. moves in a chess game or inferences by a theorem proving program. Discoveries are continually made about how to do this more efficiently in various domains.

3.1.4. Inference AI. From some facts, others can be inferred. Mathematical logical deduction is adequate for some purposes. The simplest kind of non-monotonic reasoning is default reasoning in which a conclusion is to be inferred by default, but the conclusion can be withdrawn if there is evidence to the contrary. For example, when we hear of a bird, we may infer that it can fly, but this conclusion can be reversed when we hear that it is a penguin. It is the possibility that a conclusion may have to be withdrawn that constitutes the non-monotonic character of the reasoning. Ordinary logical reasoning is monotonic in that the set of conclusions that can the drawn from a set of premises is a monotonic increasing function of the premises.

3.1.5. Pattern Recognition AI. When a program makes observations of some kind, it is often programmed to compare what it sees with a pattern. For example, a vision program may try to match a pattern of eyes and a nose in a scene in order to find a face. More complex patterns, e.g. in a natural language text, in a chess position, or in the history of some event are also studied. These more complex patterns require quite different methods than do the simple patterns that have been studied the most.

3.1.6. Common sense knowledge and reasoning. This is the area in which AI is farthest from human-level, in spite of the fact that it has been an active research area for many researchers since its inception. While there has been considerable progress, yet more new ideas are needed because such is the vagueness of the outcomes expected.

3.1.7. Learning from experience. Programs do that. The approaches to AI based on connectionism and neural nets specialize in that. There is also learning of laws expressed in logic. Programs can only learn what facts or behaviors their formalisms can represent, and unfortunately learning systems are almost all based on very limited abilities to represent information.

3.1.8. Planning. Planning programs start with general facts about the world (especially facts about the effects of actions), facts about the particular situation and a statement of a goal. From these, they generate a strategy for achieving the goal.

3.1.9. Epistemology. This is a study of the kinds of knowledge that are required for solving practical problems that exist currently in the world.

3.1.10. Ontology. Ontology is the study of the kinds of things that exist. In AI, the programs and sentences deal with various kinds of objects, and we study what these kinds are and what their basic properties are.

3.1.11. Heuristics. A heuristic is a way of trying to discover something or an idea imbedded in a program. The term is used variously in AI. Heuristic functions are used in some approaches to search to measure how far a node in a search tree seems to be from a goal. Heuristic predicates that compare two nodes in a search tree to see if one is better than the other, i.e. constitutes an advance toward the goal.

3.1.12. Gene programming. Gene programming is a technique for getting programs to solve a task by making random Lisp programs and selecting fittest in millions of generations. It is being developed by John Koza and his associates [7].

3.2. Applications of AI

3.2.1. Natural Language Comprehension. Getting a sequence of words into a computer along with parsing the sentences as well as making the computer understanding the domain the text is about has been made possible by Artificial Intelligence.

3.2.2. Computer Vision. The world is composed of three-dimensional objects, but the inputs to the human eye and computers' TV cameras are two dimensional. Artificial Intelligence, though preliminary over here, has been of great help in this domain to transport partial three dimensional information, though not up to the level at which humans see and perceive objects.

3.2.3. Game playing. By brute force and known reliable heuristics, it requires being able to look at 200 million positions per second, which is possible only by AI.

3.2.4. Speech Recognition. In the 1990s, AI made it possible for computer speech recognition to reach a practical level for limited purposes. The main beneficiary was airlines sector among which mainly the United Airlines took the initiative by replacing its keyboard tree for flight information by a system using speech recognition of flight numbers and city names [8].

3.2.5. Expert Systems. A ``knowledge engineer'' interviews experts in a certain domain and tries to embody their knowledge in a computer program for carrying out some task. One of the first expert systems was MYCIN in 1974 [9], which diagnosed bacterial infections of the blood and suggested treatments. It did better than medical students or practicing doctors, provided its limitations were observed. Namely, its ontology included bacteria, symptoms, and treatments and did not include patients, doctors, hospitals, death, recovery, and events occurring in time. Since the experts consulted by the knowledge engineers knew about patients, doctors, death, recovery, etc., it is clear that the knowledge engineers forced what the experts told them into a predetermined framework. In the present state of AI, this has to be true.

3.2.6. Heuristic Classification. Heuristic Classification provides one of the most feasible kinds of expert system given the present knowledge of AI which puts some information in one of a fixed set of categories using several sources of information. An example is advising whether to accept a proposed credit card purchase. Information is available about the owner of the credit card, his record of payment and also about the item he is buying and about the establishment from which he is buying it (e.g., about whether there have been previous credit card frauds at this establishment).

After the understanding of these two big fields, we see one specific application and the way in which such a merger would shape the future.

4. Application of Prognostics merged with Artificial Intelligence (One Way mission to Mars)

NASA and as well as private organizations specially, like the Mars One intend to have a proposed one-way manned mission scheduled around 2023 which is a one way mission for the masses who wish to explore Mars. It is popularly known as Mars To Stay. Usage of Prognostics in such missions will be the need of the mankind. With meticulous AI and Prognostics algorithms described above and the employment of Prognostic sensors and equipments will not only keep the critical parameters of such an important mission in check, but also will foretell failures and amend them, by making extensive use of Pre-estimate or Post-estimate fusion techniques of prognostics. It would involve millions of calculations based on AI algorithms just to diagnose the successful running of the system.

An important contributor to that reliability will be an on-board Integrated Systems Health Management (ISHM) system. It chiefly provides two advantages:

- It can increase safety, by detecting problems, quickly diagnosing them, and assessing remaining life before they become serious, so that controllers can respond rapidly and prevent major failures.
- It will reduce costs by enabling corrective action to be scheduled more efficiently. Corrective action such as maintenance scheduling is most important for reusable systems.

An ISHM system takes 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; that is, determining the fault mode), and fault prognostics (determining when a failure will occur based conditionally on anticipated future usage). We define diagnostics to include fault isolation and fault identification, so that full diagnostics requires determining the specific fault mode, rather than just reporting which sensor has an unusual value. We define prognostics to be detecting the precursors of a failure, and predicting how much time remains before a likely failure. Prognostics is the most difficult of these tasks. One must be able to detect faults before one can diagnose them. Similarly, one must be able to diagnose faults before one can perform prognostics. In addition to fault detection, diagnostics, and prognostics, ISHM also includes support for deciding what actions to take in response to a failure or a failure precursor.

The success of such critical missions where billions of dollars are spent and innumerable months of man-hours are put in must not rely on an occurrence of an error or a miscalculation of an otherwise insignificant nature. Thus, it forms a very important application to which the combination of Prognostics and Artificial Intelligence comes to the rescue.

5. Conclusions:

Technologists, Scientists and Inventors have spent and are spending their time extensively for inventions that would precipitate technology to higher notch; it would be unwise if this time is spent in reinventing the solutions to the problems which are already arising out of past inventions. This is what Prognostics with Artificial Intelligence is actually designated to provide. Over the years since the advent of Industrial Revolution, mankind has been accused of dispensing the job of people to the machines. The future lies in the fact that the human race will be the in charge of the present time technology and new inventions, while the machines would take care of the future (resulting errors and predicting faults)- Prognostics with Artificial Intelligence.

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