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A Synergetic Intelligent Fault Prognosis Framework to support Product Life Cycle Considering Environmentally Conscious Production

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Abstract

The recent problems of increased oil prices, global warming, and environmental pollution highlighted the urgent need for cost effective, reliable and environmentally conscious production process. Hence to achieve clean and healthy production, the chemical process industry strives to continually improve their preparedness and awareness through adaptive inference logic by effectively extracting and signaturing cascade clues from past experiences and predicting the possible scenarios of risk and its sources. These sources are usually related to equipment life cycle, starting from suppliers' evaluation and ending by its salvage or disposal. Methods are thus needed to effectively utilize data collected and knowledge available in order to make the right decision at the right moment. Despite the considerable technological advancement, these decisions still depend heavily on human expertise, which is, although very valuable, are subject to errors, and may be lost due to death, retirement or resignation. Therefore, an integrated equipment health management system that takes into consideration the equipment life cycle, which leads to environmentally conscious production, is proposed. In order to manage and develop environmentally conscious plant operation, it is essential to provide a synergetic intelligent fault diagnosis and prognosis framework embedded in systematic interoperable platform with respect to product life cycle, process safety and environmental measures. The proposed system employs a systematic expert knowledge structure considering operation execution, process safety and control, warranty policies, and environmental issues during equipment life cycle to assist the user in evaluating uncertainties and the process of decision making.

Introduction

The recent problems of increased oil prices, global warming, and environmental pollution highlighted the urgent need for practical and flexible production chains based on clean process. Chemical process is quite complex, where it involves different views [1,2]. It has been referred as physico-chemical process where there is a link between chemical phenomena and the physical systems and structures. Faults as part of the hybrid phenomena might be triggered by several reasons such as human error, equipment/part deterioration, system error, control device error, environmental stress or material deficiencies which might be associated with negative environmental impacts, out-of specification products and process shutdown. This is a fact that there is always a time delay during fault diffusion between infancy and maturity of abnormality which appears for us through sensors data. Despite the high environment-safety international requirements, physical protection layers and even higher society demands to add mitigation to reduce the consequences of any residual risk, accidents still occur. Hence to achieve clean and healthy production, the chemical process industry strives to continually improve their preparedness and awareness through adaptive inference logic by effectively extracting and signaturing cascade clues from past experiences and predicting the possible scenarios of abnormality and its sources based on real data in plant operation. Thus, plant operation is tightly linked with intelligent fault diagnosis and prognosis. Intelligent fault diagnosis is a complex process where it requires proper understanding of current condition, symptoms and adequate knowledge to identify faults and diagnose root causes and possible consequences. However, the accuracy of current diagnostic and prognostic methods is significantly limited by several critical challenges. (1) Equipment may be subject to multiple degradation processes which lead to multiple failure modes, such as gear tooth root crack and gear surface wear in a gearbox system. Effective methods are needed to evaluate and predict the health condition with presence of multiple degradation processes. (2) The same type of equipment, such as wind turbines and aircraft gas turbine engines, may be used under various operating conditions. Methods are needed to effectively utilize data collected from equipment under various operating conditions so as to achieve more accurate equipment health condition evaluation and prediction performance. (3) Condition monitoring data are typically collected from similar equipment with different specifications, such as gears with different tooth numbers. The accuracy of equipment health evaluation and prediction depends heavily on the availability of sufficient failure and degradation data, which are very limited in many applications. This challenge is coupled with the previous one, and effective methods are needed to fully utilize all the data from equipment with different specifications under various operating conditions. (4) Despite the considerable advancement in condition monitoring and prediction, they still depend heavily on human expertise, which is, although very valuable, are subject to errors. Therefore, intelligent fault prognosis is highly correlated with knowledge based structure semantically describing fault scenarios and plant topology. Plant topology describes process in terms of: a) static dimension which includes facility, materials/products, topology and human through ports, b) dynamic dimension including behaviour models, which are represented as states, transitions, and messages, and, c) finally operation dimension including purposes and methods to be executed as a response to incoming message. In order to manage and develop environmentally conscious plant operation, it is essential to provide a synergetic intelligent fault prognosis framework embedded by systematic interoperability platform with respect to product life cycle, process safety and environmental measures. The proposed framework employs a systematic expert knowledge structure considering operation execution, process safety and control, warranty policies and environmental issues during system life cycle to enable users to effectively predict the time-to-failure (or lead time) and the associated uncertainty in flexible and optimized manner.

The methodology is a step-by-step process in which various attributes of the plant topology and knowledge base are grouped together at different levels. To support the four integrated steps, the proposed topology engineering captures data semantics with plant representations and formalizes data meanings with ontology to build semantic interoperability of a rule-based adaptive inference engine. The framework integrates the object-based modelling, standard for the Exchange of Plant model data (STEP) approaches with Ontology Web Language (OWL) and fault models to represent, understand, interpret and share the semantically interoperable failure modes, causes, failure mechanisms and HSE consequences to better address fault scenarios and signatures [3]. It involves three areas: ontology engineering, plant model standardization and fault modelling:

Ontology represents formal, explicit and shared understanding about geometric and non-geometric data and maintenance semantics, as fault properties, fault behaviours, inter-part relationships and constraints. They allow classification and precise description of the concepts/terminologies used in a fault diagnosis and enable semantic mappings among fault scenarios.

Plant data model standards serve as a common foundation for interoperating multi-disciplinary applications. In particular, the STEP and XML standards address the information sharability by classifying and defining the standardized information elements and their relationships, and facilitate the data communication between applications by the use of open and neutral file formats and databases.

Fault propagation scenarios are constructed and used to comprehend root causes and consequences and evaluate the associated risks with abnormal situation or process deviation. The proposed qualitative models are further tuned using the developed quantitative models using trouble shooting and correlation matrix that provides information about relationships among process variables contributing to each fault. Risk is evaluated using historical data from maintenance history (e.g. reliability data) which are used along with each fault scenario. There are varieties of sources to collect failure data such as from maintenance history, i.e., from computerized maintenance management systems (CMMS) or via memberships to reliability data banks, e.g. Offshore Reliability Data or OREDA handbook. Failure data can also be extracted from accident/incident databases that are widely developed and maintained for chemical/petrochemical plants, such as those published by Environmental Protection Agency (EPA)/ Occupational Safety and Health Administration [4].

The integrated methodology

This study presents a synergetic intelligent framework to tune fault models and predict future behaviors through maintenance data including historical record and sensor signals, signature extraction, failure mapping in data space. The study is composed of three main processes. The first process is a knowledge acquisition based on the semantic definition of plant topology and past experience corresponding to human experience and operation design, operation execution, process safety and control, supply chain design and operation, and environmental issues. The second process is to develop an adaptive linguistic rule-based inference engine through qualitative and quantitative fault signatures, fault propagation scenarios and knowledge base. The engine is adopted by real time process data, conversion of raw data into trends and the analysis of these trends using sensor and trend fusion algorithms. The rule-based adaptive inference engine is then used to detect, diagnose faults and calculate risks for each fault propagation scenario, which is in the third process. The fourth process is concerned with planning and evaluation of recovery actions based on the diagnosed faults [5,6].

A semantic knowledge acquisition and representation

To achieve the objective, at first knowledge base structure is defined through the OREDA handbook, manufacturer troubleshooting, field expert maintenance personnel, and equipment handbook with respect to the interactive effect of failure modes on the operating parameters. The OREDA handbook includes high quality reliability data for offshore/onshore equipment (which are collected from offshore equipment of ten Oil and Gas companies), and provides both quantitative and qualitative information as a basis for reliability, availability, maintenance and safety (RAMS) analysis [7]. In this taxonomy various items are classified into equipment classes based on one main function (e.g. pumps, valves). These equipment classes are categorized in 5 major categories: machinery (e.g. pumps, compressors), electric equipment (e.g. electric generators), mechanical equipment (e.g. heat exchangers), control and safety equipment (e.g. valves) and subsea equipment (e.g. subsea isolation system). Further, each equipment class is classified according to its design characteristics and type of service (system), e.g. pumps are classified into centrifugal, reciprocating and rotary pumps. Next, the failure and maintenance data of each of the equipment units of these narrow taxonomy classes are described by failure modes, failure mechanisms, causes in different disciplines such as mechanical, material, electrical and instrument.

The STEP technology and object-based modelling techniques are used for representation of information models which are the computer interpretable and processible. The STEP AP203 is used as the common data representation model for the mechanical domain, and AP210 for the electronic domain in the present study. These two STEP APs are extended with supporting definitions for richer semantics on fault types, fault behaviours, relationships, constraints. Also, supplementary definitions of equipment such as warranty policies, maintenance procedures, safety and environmental emergency procedures are modelled as STEP extensions and populated with equipment maintenance history datasets extracted from user inputs. Two STEP extension mechanisms are investigated to connect the supplementary definitions in the extension models to the relevant fault already existed in the knowledge database according to plant topology. Therefore, representation models formalize the syntax and semantics of failure expressions, such as symbols, terminologies, concepts, or relationships, design aspects and manufacturer recommendations during the lifecycle of equipment. An ontology based on OWL is then applied in an effort to improve the representation of knowledge that is used and produced during qualitative models Failure Mode and Effect Analysis and HAZOP. Traditionally, the information of FMEA studies is registered in text format. The reusability of this knowledge during design or operations is limited due to difficulties in finding and analysing information. The basic ontology is extended so that rule-based inference engine can use more informative queries (instead of text based) to find relevant information during fault prognosis [8-11].

An intelligent inference engine

Proper diagnosis of equipment failure needs to consider many symptoms of hydraulic or mechanical causes, and due to nonlinear, time-varying behaviour and imprecise measurement information of the systems it is difficult to deal with failures with precise mathematical equations. Because of uncertainties and ambiguities about the failure causes, the existing diagnosis methods like vibration signal and condition monitoring are blurred to a great extent. While, human maintenance operators with the aid of their practical experience can handle these complex situations, with only a set of imprecise linguistic if-then rules and imprecise system state. This study combines human experience and mathematical algorithms to enhance inference engine ability as a decision making system.

The inference engine imitates the reasoning process of the domain experts to seek information and relationships from the knowledge base to provide answers, predictions and suggestions possible fault scenarios. The inference process is a combination of five sub-processes: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the antecedent, implication from the antecedent to the consequent, aggregation of the consequents across the rules and defuzzification. Reasoning process is formed by fault signatures defined by qualitative analysis like FMEA and the impact of failure causes on both the hydraulic and mechanical operating parameters of equipment flow rate, discharge pressure, efficiency, vibration, and temperature. Then rule-based knowledge linguistically articulates the signatures through trouble shootings, handbook, and maintenance personnel. At the end condition monitoring techniques such as dissolved gas analysis (DGA), vibration analysis thermo graph analysis are coupled with the rule based knowledge engine to improve flexibility and accuracy of detection in uncertain situation.

3. An adaptive intelligent fault prognosis approach

The last step of the methodology is to an embedded neural network that is capable to be trained by a semantic intelligent inference rule base engine to accurately predict fault behaviour from sensor signals and take necessary maintenance actions. The proposed neural network is expected to take more advantages of adaptive learning, self-organization, real time operation and fault tolerance in comparing to the same available application in the market. The output of the approach is a list of well-arranged most possible scenarios in descending order which can linked to warranty policies, environmental program and safety plan for the essential inspection actions.

Conclusion

This paper proposed an integrated intelligent equipment health management system that takes into consideration the equipment's life cycle and the environmentally conscious production. Our research into intelligent fault diagnosis system is continuing by developing: 1) Knowledge database module of maintenance records, sensor signals resulting from the simulation of different faults, under different component specifications, different warranty policies and working conditions through Oil and Gas standards such as OREDA, ISO14224, EPA and OSHA. This knowledge base will be represented according to OWL, STEP to maximize shareability, interoperability and integration across system software, 2) An intelligent inference engine module to effectively articulate reasoning process and the interpretation of different faults under varying conditions supported by human experience. 3) An adaptive intelligent fault diagnosis and prognosis module that considers varying conditions and multiple degradation processes. 4) Novel supplier evaluation methodology embedded in the software that considers product life cycle cost and green performance.

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