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AN INTEGRATED FRAMEWORK FOR INTELLIGENT RELIABILITY DESIGN AND PROGNOSTIC HEALTH MANAGEMENT OF SPACE ROBOTIC SYSTEMS

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ABSTRACT

Space robotics has received significant attention from both theoretic research and applications. The mission in future will be involving and be heavily supported by different robotic systems, such as planetary rovers and manipulators for orbital servicing, etc[1]. The harsh environment in space can severely affect the operating safety of space robotic systems and therefore the lifecycle reliability problem and prognostic health management have paramount importance to make the space robotic systems more successful and safer in future space missions. Though there has a great deal of research on failure detection, fault diagnosis and condition monitoring for conventional space systems [1-2] and other engineering applications such as nuclear power station[3-4], it has a lack of research on the general methodology for both the reliability design and health management of space robotic systems to improve the operating safety.

This paper proposes an integrated framework (named as iRPHM) in which the higher reliability is designed for space robotic systems by taking advantage of reliability-based intelligent design optimization while considering the expected random loadings. The prognostic health management (PHM) is implemented in the proposed framework to decrease the failures arising from the unexpected events in harsh space environment.

As shown in Figure 1, the integrated framework iRPHM has mainly four steps to deliver its objectives, which include:

(1) Failure mechanism analysis under harsh space environment

During the operation in space, the harsh space conditions such as vacuum, microgravity, extreme temperature, micrometeoroid and space debris will affect the performance of robotic systems. In the vacuum condition, the adsorbed gas providing lubrication volatilizes between the mechanism joints to increase the coefficient of friction, which could lead to dry friction or even cold welding. The microgravity will reduce the pressure between the joints to result in big shocks. The different liner expansion coefficient of components, internal stress due to the time-variant temperature will be formed and the material strength and motion accuracy of mechanism will be influenced as well. Micrometeoroid and space debris will cause shocking to the robotic systems to accelerate the degradation process and even produce fracture. The space conditions exhibit not only randomness but also time-variance. Therefore failure mechanism analysis under complex space conditions is a challenging research topic.

A feasible way to address the above challenge is to construct a bond graph by considering the loading location, loading time and so on to analyze the energy transformation. The dynamic simulation model is then built to study the loading allocation. The failure mechanism could be analyzed by combining the allocated loading with failure modes, effects and criticality analysis (FMECA).

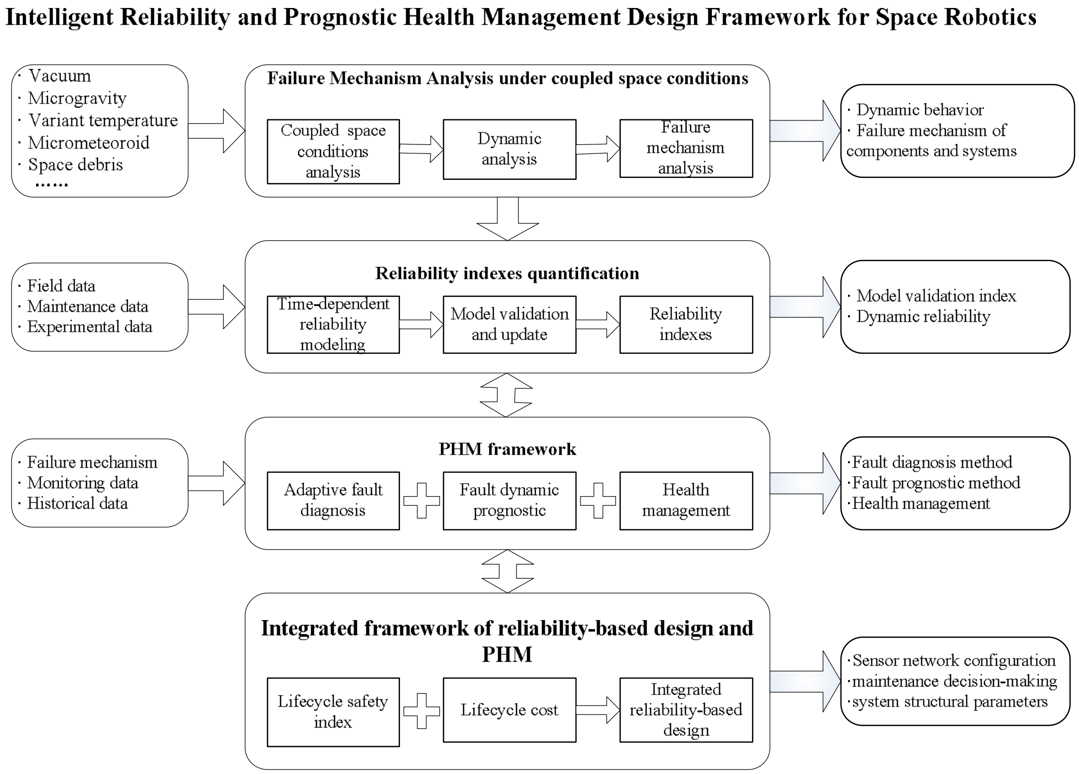

Figure 1: Intelligent reliability and prognostic health management for space robotic systems

(2) Reliability indexes quantification

There are usually several failure modes, which are furthermore time-dependent due to time-dependent loadings and correlated due to the common causes. Time-dependent copula function is a typical representative to describe the time-dependent correlation among time-dependent failure modes. Therefore it is proper to build the time-dependent system reliability model.

Because of the simplification of the model, the approximation of loadings when the time-dependent reliability computer model is built based on physics of failures, the built model may be a little far away from the actual one. Model validation and updating are needed to improve the confidence level. Field data, operating data and experimental data are the information sources for the model validation. Time-dependent B-Distance model validation index could be used to testify the confidence level of the computer model and updating optimization could be conducted for the optimal model parameters.

For the updated time-dependent reliability model, the time-dependent reliability analysis methods, such as crossing rate method [5], extreme value distribution method [6], composite limit state method [7], Gamma process [8] and subset simulation with splitting method [9], could be implemented for time-dependent reliability analysis. The corresponding reliability indexes, such as reliability function, failure rate, mean time to failure (MTBF) can be computed.

(3) PHM framework and analysis

The PHM framework could be built by studying the sensors network configuration, fault diagnosis, fault prognosis, operation decision-making and health management. According to the structure and importance of components, the sensors network configuration is determined under the guarantee of detection accuracy. Adaptive fault diagnosis is one of important trends and fault diagnosis with hidden Markov model is a realization approach, which is an appealing research topic in the fault diagnosis field. As one important part in the proposed framework, fault prognosis can provide information for operational decision-making. Fault prognosis based on wavelet neural network could achieve the goal of dynamic prediction and has attracted some attentions. The preventive operation for space robotic missions could be made according to the reliability or conditions given from the fault prognosis process.

(4) Integrated framework of reliability-based design and PHM

The system reliability-based design model and system PHM design model could be built and then integrate them according to the system lifecycle reliability and cost. With considering the cost produced from design, material, manufacturing, launching, and operations, the overall cost model could be built. With the reliability as constraints and minimal cost as objective, the reliability-based design model is then obtained. Accounting for the cost of sensors network, (e.g.[11]), monitoring, fault diagnosis, fault prognosis and operations, the cost model of the PHM framework could be developed. A function considering the acquisition ability of sensors, fault diagnosis ability, fault prognosis ability is built as the PHM ability. The PHM design model is built by minimizing the cost under the satisfaction of PHM ability. Combining the reliability-based design with the PHM design model, the integrated framework is then constructed. In the proposed framework the CIAD is employed to optimise and resolve the integrated framework for getting the optimal structural parameters, sensors network configuration and operational decision-making to ensure the operating safety of space robots.

(5) Computational intelligence aided design for iRPHM

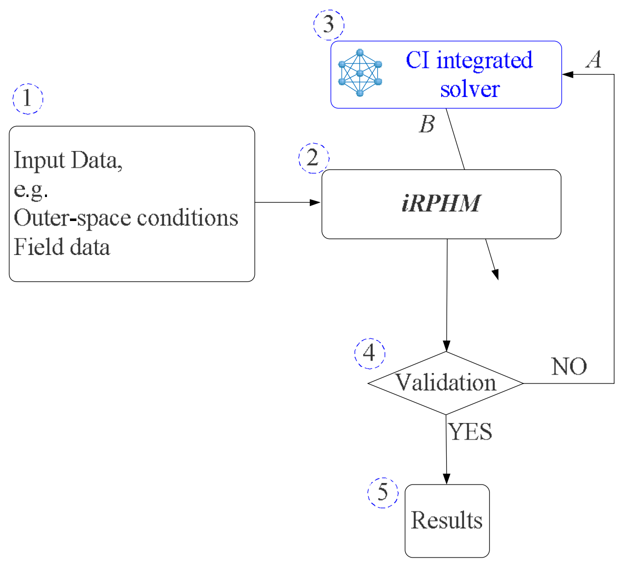

Figure 2: Computational intelligence aided design for iRPHM

The computational intelligence aided design (CIAD)[10] approach will be utilized to construct and optimise the iRPHM, as given in Figure 2, there are five steps as follows: step1, the input data, for example, Field data under specific outer-space conditions for space robotics; step2, the iRPHM process for space applications; step3 is the `CI integrated solver' that optimises the parameters for the fitness function of the IRPHM; step4 is the validation step. In particular, performance criteria are employed to assess the optimal results, and then decide whether the optimisation process should continue (NO), or it should be terminated and move to step5 (YES); step5 produces the final results and completes the post-processing tasks. More specifically, this step reports the optimal solution, analyses and visualises the results, and presents the recommendations to robotics engineers or mission operators.

As shown in Figure 3, the conceptual framework of `Computational intelligence integrated solver (CIS)' comprises three parts: data input, CI Integrated solver and result output, in which, Part 1: Data Input (point A). This part prepares the data input for the CI Integrated solver. It collects, filters, stores, and pre-processes data originated from various sources, such as statistical data, simulation analyses, and system design reports, etc.

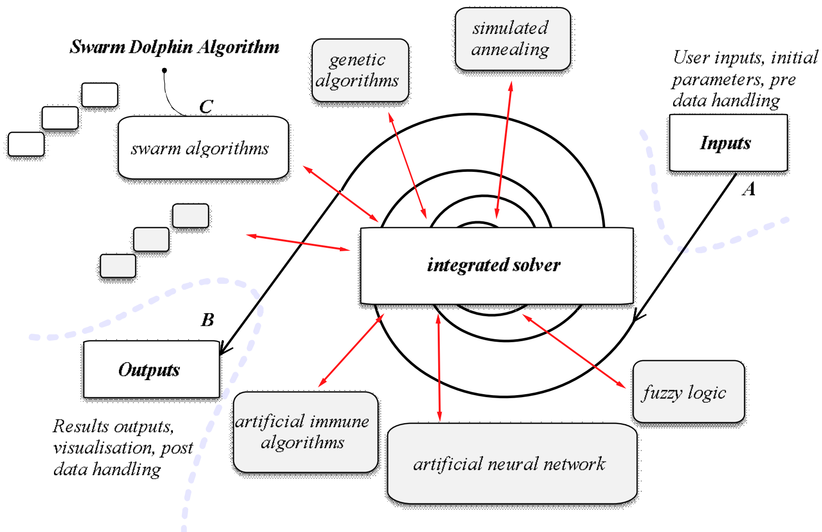

Figure 3: Computational intelligence integrated solver (CIS)[10]

Part 2: CI Integrated solver. In this part, a set of nature-inspired intelligent computational approaches are integrated into one solver to optimise complex real-world problems, which primarily involves one or more of the following methods: artificial neural networks, genetic algorithm, fuzzy logic, simulated annealing, artificial immune algorithms, and swarm intelligence algorithms, etc.

Part 3: Result Output (point B). This part reports the final results from Part 2. As also shown in Figure2, the data-flow from Steps 4 to 3 is the input of the `CI integrated solver' interconnected with point A, and the data-flow from Steps 3 to 2 is the output of the `CI integrated solver' interconnected with point B.

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