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Operational Availability Improvement through Online Monitoring and Advice For Emergency Diesel Generator

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Abstract

This research broadens the prime concern of nuclear power plant operations from safe performance to both economic and safe performance. First, emergency diesel generator is identified as one of main contributors for the lost plant availability through the review of plant forced outage records. The framework of an integrated architecture for performing modern on-line condition for operational availability improvement is configured in this work. For the development of the comprehensive sensor networks for complex target systems, an integrated methodology incorporating a structural hierarchy, a functional hierarchy, and a fault-symptom matrix is formulated. The second part of our research is development of intelligent diagnosis and maintenance advisory system, which employs Bayesian Belief Networks (BBNs) as a high level reasoning tool for incorporating inherent uncertainty for use in probabilistic inference. Our prototype diagnosis algorithms are represented explicitly through topological symbols and links between them in a causal direction. As new evidence from sensor network developed is entered into the model especially, our advisory system provides operational advice concerning both availability and safety, so that the operator is able to determine the likely failure modes, diagnose the system state, locate root causes, and take the most advantageous action. Thereby, this advice improves operational availability.

I. Introduction

Nuclear power plants employ a large amount of alternating current (AC) electric motor-driven equipment. AC electric power also is used for a number of other applications that are important to plant operation and safety, such as instrumentation, control, and battery charging. When normal AC power from the offsite utility distribution network or from the plant main generator is unavailable, then a reliable backup source of power is needed in order to supply necessary power to safety-related equipment. Emergency diesel generator (EDG) units are usually used as backup sources. Due to their safety importance, there has always been a need to monitor the performance of the EDGs, and the plant unavailability experience in PWR in the United States shows that the EDG is one of major systems causing forced outages[1][2].

There is a strong interest in implementation modern condition monitoring. The capability to provide early detection of component deterioration is an essential part of any effective predictive maintenance program. In addition, there are a growing awareness and use of operator advisory systems based upon artificial intelligence (AI) to model, analyze, and diagnose critical plant equipment. It is in this context that the techniques now available and the state of the art movement toward on-line intelligent condition-based monitoring, diagnosis, and maintenance are investigated. Thus, it is the aim of our work to describe the state of development for the condition monitoring and diagnosis. Our work focuses on the condition monitoring and diagnosis of equipment and the development of intelligent systems to integrate process control with condition-based maintenance in order to achieve improved operational availability.

The work comprises two major parts for plant availability improvement : 1) a modern on-line condition monitoring system is developed for early fault detection in complex machines, and 2) by assuming there are valid sensor readings available throughout the sensor validation advisory system, an advisory system for intelligent diagnosis and maintenance is developed.

II. Identification of Major EDG Failure Modes

Three databases are used here to identify the major failure modes of the EDG : the NRC database, NPRDS, and the EPRI database[3].

First, the NRC database covering failures occurring during the interval 1993 to 1995 is used to select the EDG as one of our target systems. But a majority of failure records either do not have a failure description or do not have identified failure causes and affected failure modes. This makes the limited available records even more inadequate for identifying the main failure modes of the EDG. Next, the NPRDS is mainly used to identify the major observed failure modes and their root causes. Among the failure records in the NPRDS we selected such failures for monitoring that frequently occurred and caused high forced outage times. Finally, the EPRI database is used to supplement NPRDS. From the EPRI database we investigated some failures and their root causes. We selected those shown in the NPRDS set having some importance.

III. Development of Sensor Network

3.1 Structural and Functionsl System Hierarchy

A structural and functional system abstraction methodology[1] was developed for purposes of reducing the effective complexity of the EDG system without neglecting the major features of the system's behavior and composition and then for determining the parameters and locations being monitored. This methodology is based upon a hierarchical decomposition of the complex systems under consideration. Each system is modeled by viewing it both as a structural hierarchy and functional hierarchy. This is why the determination of monitoring parameters is directly associated with both the system composition and function.

Based upon the presented methodology, the structure-based hierarchy (SBH) and the function-based hierarchy in the EDG have been applied to lubrication oil system, cooling system, fuel oil system, and engine mechanical system. The materials used for this work include the fault tree of EDG, the NRC database, and NPRDS. Examples of the two decompositions are shown in Figures 1 and Figure 2.

3.2 Fault Symptom Matrix

Each level of failure modes in the function-based hierarchy (FBH) has its own characteristics, which are indicated by the variations of process parameters and system status parameters. The accumulated expertise obtained from operational experience enables us to select a proper set of monitoring parameters for each failure mode. The fault symptom matrix for the is introduced for the ease of monitoring parameter determination. The monitoring parameters are determined in the fault symptom matrix and are used to determine the corresponding needed sensor types

3.3 Recommendations of New Sensors for EDG Use

The listed sensors shown in Table 1 are ordered based upon the rank order of the related failures according to their contributions to lost availability. From the point of availability improvement such sensors as are related to a high rank of lost availability should be considered for use first. However, some sensors are related to more than one failure, and most failures need to be monitored by several sensors. That situation makes it difficult to recommend one sensor for use over all others. Rather, we grouped the sensors according to their system and gave a rank according to the order of unavailability of that system. Then, within each group we ranked the sensors according to their relative value in detecting incipient failures.

IV. Prototype Diagnostic Network for the EDG

The proposed diagnostic network for the EDG in the advisory system is presented. We divide the EDG into five modules, for convenience. They are the lubrication oil system, fuel oil system, cooling system, start air system, and engine mechanical system. The principle and structure of the advisory system are illustrated by their corresponding Bayesian Belief Networks (BBNs)[4][5][6].

4.1 Lubrication Oil System

The lubrication oil system consists of six basic nodes: F_LO_Lk, F_LO_Pp, F_LO_Fil_Plug, F_LO_Str_Plug, F_LO_Low_Pr, and F_CC_Low_LV. This system is shown in Figure 3.

The F_LO_Lk node describes lubrication oil leakage. The leakage is detected using the sump level and sump pressure sensors. The F_LO_Pp node describes the pump states. The pump states are determined by the pump motor current and pump discharge pressure. The F_LO-Fil_Plug and F_LO_Str_Plug nodes represent the lubrication oil filter and strainer conditions. These are determined by differential pressure sensors sensing the pressure difference across the filter and strainer. The F_LO_Low_Pr node represents the state of lubrication oil pressure. This parameter is affected by lubrication oil leakage, pump state, lubrication filter and strainer conditions. Also, the sump pressure sensor indicates the pressure. Finally, the F_CC_Low_Lv node describes the oil level of the crankcase. It is affected by the lubrication oil pressure state and is detected by the crankcase pressure and crankcase level sensors.

4.2 Fuel Oil System

The fuel oil system consists of six basic nodes: F_FO_Lk, F_T_Fil, F_P_Fil, F_S_Fil, F_FO_Pp and F_Check_Vv. This system is shown in Figure 4.

The F_FO_Lk is the node that describes fuel oil leakage. This leakage is detected using tank level sensors. The F_T_Fil, F_P_Fil and F_S_Fil nodes represent the filter conditions for the transfer filter, primary filter and secondary filter, respectively. Fuel contamination and filter conditions are detected by differential pressure sensors sensing the pressure difference across the fuel filters. The F_FO_Pp node describes fuel pump states. The pump states are determined by pump motor current and pump discharge pressure. Finally, the F_Check_Vv node represents the check valve states. A check valve abnormality is detected by a check valve disc position sensor.

4.3 Cooling System

The cooling system consists of three basic nodes: F_HEx, F_AC and F_CS_Lk. This system is shown in Figure 5.

The F_HEx node represents heat exchanger clogging. This clogging is detected by a coolant temperature sensor from the heat exchanger. The F_AC node represents aftercooler clogging. This clogging is detected by the coolant temperature from the aftercooler. The F_CS_Lk node represents the coolant leakage. This leakage is detected by expansion tank level and coolant system pressure sensors.

4.4 Air Actuated Starting System

The air starting system consists of three basic nodes: F_SA_Lk, F_MV and F_MA. This system is shown in Figure 6.

The F_SA_Lk node represents air leakage from the reservoir tank. This leakage is detected by a pressure sensor at the reservoir tank. The F_MV node represents air leakage from the main air valve. This leakage is detected by a pressure sensor downstream of the mail air valve. The F_MA node represents the concentration of moisture in air. The moisture is detected by a moisture sensor at the reservoir tank.

4.5 Engine and Mechanical System

The engine and mechanical system consists of five basic nodes: F_Blowby, F_RockerArm, F_CC_High_Pr, F_TC and F_TC_Br. This system is shown in Figure 7.

The F_CC_High_Pr node describes crankcase high pressure. The crankcase pressure is measured with a pressure transducer. This problem can be caused by blowby, F_Blowby, and can be monitored by a vibration sensor according to the crank angle. Rocker arm failure, F_RockerArm, can cause temperature to rise in the exhaust outlet flow and can be monitored by a temperature sensor. Impending turbocharger failures, F_TC, that do not yield an increase in the vibration level can be identified through changes in the normal temperature levels or temperature changes across the turbine or compressor. Thermocouples can be used to monitor these temperatures. Bearing failures, F_TC_Br, can be detected by monitoring the turbocharger lubrication oil temperature and the vibration level of the turbocharger

4.6 Expertise-Based Knowledge Implementation in the BBNs

In order to make our HUGIN models work as expected, we have acquired relevant EDG monitoring and diagnosis to obtain the correct quantitative conditional probability values in our HUGIN model.

Information that is needed includes the bounds of sensor ranges, actions that can be taken to mitigate stimulation of the various failure modes, and conditional probability values.

We obtained needed expertise from interviews with power plant system engineers. Currently, on-line monitoring techniques being used for EDGs in power plants are very limited. Condition monitoring of the EDG has mainly been based on off-line monitoring techniques, most of which can also be realized by the corresponding on-line monitoring systems incorporated in our proposed sensor network. From our interviews, the expertise obtained reflects current practices for using off-line monitoring. Data for advanced or new on-line monitoring sensors should be studied further as the needed experience is accumulated.

V. Implementation of BNN Advisory System

There are three modes in the advisory system : the advisory, the diagnostic and the predictive modes. In the advisory mode the sensor outputs are known, and the probability distribution of the failure modes and the expected utility values of the alternative actions are estimated. These estimates indicate to the operation the likely most advantageous action to take[6].

In the diagnostic mode, the advisory systems uses knowledge of the highest level failure mode state and the sensor outputs. The purpose of this mode is to obtain the probability distributions of the subordinate failure modes. This estimate of the most likely subordinate failure mode states is useful in diagnosing the cause of the observed failure, as a basis for planning the needed component recovery actions.

In the predictive mode a particular action in known to have been taken. The purpose of this mode is to estimate the probability distributions of the failure mode states and the sensor reading states. This mode is useful in a forward-looking fashion by indicating to an operator the likely subsequent failure mode state and sensor ouput distributions when a particular action is taken. such estimates provide a basis for comparison of the actual component and sensor set performance to the estimations of the advisory system. Large persistent divergences between the two would indicate that the advisory system is in error for some reason. The need for corrective investigation would be indicated.

When actions are taken, the failure state probability distributions are changed. Also, their likely subordinate sensor readings will reflect the new failure state probability distributions. In this mode the action taken is given as inputs and the probability distributions of the sensor readings are estimated.

VI. Conclusion and Discussions

So far, existing practical monitoring systems have been designed mainly emphasizing improved safety. In them, their corresponding safety related operational procedures are usually computerized by a set of production rules in the form of rule-based advisory system which usually deals with straightforward deterministic problem solving domains or stochastic problem solving domains supplemented by use of an uncertainty factor.

The work reported here broadens the prime concern of nuclear power plant operations from safe performance to both economic and safe performance through on-line monitoring and advice. Thus, our work is concerned with the advanced design and development of comprehensive sensor networks and new advisory systems in order to improve the operational availability of the EDG. The suggested integrated architecture utilizes comprehensive sensor networks and advisory systems using the Bayesian belief network (BBN) treatment.

For the development of the comprehensive sensor network used for complex systems, the work reported here formulates an integrated method incorporating a structural system hierarchy, a functional system hierarchy, and a fault-symptom matrix. The application of this integrated method to EDG has been judged to be systematic and appropriate as the result of discussions with system experts.

The work reported here is also concerned with the development of intelligent diagnosis and maintenance advisory systems. There are complexities and uncertainties inherent in such intelligent diagnosis and maintenance. Thus, our advisory system employs a Bayesian Belief Network (BBN) as a high level reasoning tool for incorporating inherent uncertainty for use in probabilistic inference. Keeping with the treatment of rule-based expert systems, we conclude that BBNs are far superior to the rule-based approach in their ability to treat modeling of complexities, uncertainty management, systematic decision making, inference mechanisms, knowledge representation, and model modification for newly acquired knowledge. The prototype diagnosis and maintenance algorithms used are represented explicitly through topological symbols and links between them in a causal direction. The output of this network is a diagnostic mapping from sensor readings to a determination of the likely failure mode state or system states. The inference schemes used in calculate the updated probability distribution of alternative component failure states. This probability distribution is then used for making decisions about taking corrective actions. This capability is routinely improved as new evidence is entered into the model.

In conclusion, the advanced design and development of comprehensive sensor networks and Bayesian belief network based advisory systems can lead to the improved plant operation in new power plants, such as is envisioned for the Korea Next Generation Reactor (KNGR).

Needed future efforts include the four items listed below. These are either extensions of this study or efforts needed to complete the study.

First, several essential features should be incorporated for actual applications of our advisory system to practical tasks in nuclear power plants. The sensor validation advisory system should configure on-line validated data files for use in our advisory system. Also, the real-time capability of retrieving and plotting sequential trends using modern graphics are suggested in order to assist the operator in diagnosing a situation as it evolves.

Second, conditional probability values and utility values used in the knowledge base required for the Bayesian belief network based advisory system were elicited through discussions with relevant experts. However, concerning new sensors, recommended in this study, there is insufficient expertise available for computing conditional probability values. Thus, another future effort that could be that of extension from this study is to synthesize newly acquired knowledge concerning new sensors and their corresponding component failure mode states. Furthermore, familiarity with Bayesian Belief network concepts of the operator can enhance the robustness of the advisory system.

Third, currently our advisory system operates only statically giving advice based upon the current state of the monitored system. It does this without considering the pervious system status. This means that its reasoning starts when all the manifestations of abnormal signals are present at such unique time. However, as the sensor output changes dynamically over a time interval, the resulting corresponding failure mode distribution will also change. Thus, the dynamic relationships of the failure mode states and the sensor signal states could be formulated to reflect behavior during a specific time interval. The study on this temporal reasoning process, which depends upon the notion of the time dependence of the system states, could be a valuable future effort.

Lastly, rigorous, extensive testing and validation are essential concerning the adequacy and completeness of our advisory system. In particular, the field tests are recommended as a practical way to ensure that the advisory system can perform as intended in the actual environment. This could perhaps be performed initially using specialized testing devices such as a plant simulator.

References

1. C. W. Kang and M. Golay, "Advanced Monitoring and Advice Integrating a Comprehensive Sensor Network for Improved Operational Availability," Ph.D. Thesis, MIT, 1998.
2. G. M. Grant, et al., "Emergency Diesel Generator Power System Reliability 1987-1993," Idaho National Engineering Laboratory, 1996.
3. G. D. Driscoll, et al., "Surveillance, Monitoring, and Diagnostic Techniques to Improve Diesel Generator Reliability," EPRI NP-5924, 1988
4. S.T. Andersen, et al., "HUGIN – a Shell for Building Bayesian Belief Universes for Expert Systems", Conference on Artificial Intelligence, Vol.2, pp.1080-85, 1989
5. A. Gammerman , Probabilistic Reasoning and Bayesian Belief Networks, Unicom, 1995
6. Frank Jensen, "Bayesian Belief Network Technology and the HUGIN System," Proceedings of International Conference on Intelligent Data Management, London, 1996

Table 1. Sensor Selection Priority List of the EDG

	Monitoring Location	Sensor		Monitoring Location	Sensor
1.	Engine Mechanical Failure		3.	Fuel Oil System Failure	
1	Cylinder	Cylinder vribvation sensor according to crank angle	1	Fuel Transfer Filter	Differential pressure sensor
2	Crankcase	Pressure Sensor	2	Fuel Primary Filter	Differential pressure sensor
3	Exhaust Outlet	Temperature sensor	3	Fuel Secondary Filter	Differential pressure sensor
4	Turbocharger Compressor and Turbine	Temperature sensor	4	Fuel Transfer Pump	Motor current sensor
5	Turbocharger Lubrication Oil Channel	Temperature sensor	5	Fuel Transfer Pump	Discharge pressure sensor
6	Turbocharger	Vibration sensor	6	Fuel Storage Tank	Level sensor
2.	Lubrication Oil System Failure		7	Fuel Day Tank	Level sensor
1	Lubrication Oil Sump	Level sensor	8	Check Valve	Direct current IVMS (inductive valve motion sensor)
2	Lubrication Oil Sump	Pressure sensor	4.	Start Air System Failure	
3	Lubrication Oil Filter	Differential pressure sensor	1	Start Air Reservoir Tank	Pressure sensor
4	Lubrication Oil Strainer	Differential pressure sensor	2	Main Air Start Valve	Pressure sensor
5	Crankcase	Oil level sensor	3	Start Air Reservoir Tank	Moisture-in-air sensor
6	Lubrication Oil Pump	Motor current sensor	5.	Cooling System Failure	
7	Lubrication Oil Pump	Discharge pressure sensor	1	Coolant Expansion Tank	Level sensor
8	Lubrication Oil Heater	Temperature sensor	2	Coolant Channel	Pressure sensor
9	Lubrication Oil Heat Exchanger	Temperature sensor	3	Radiator	Temperature sensor
			4	Heat Exchanger	Temperature sensor
			5	Aftercooler	Temperature sensor

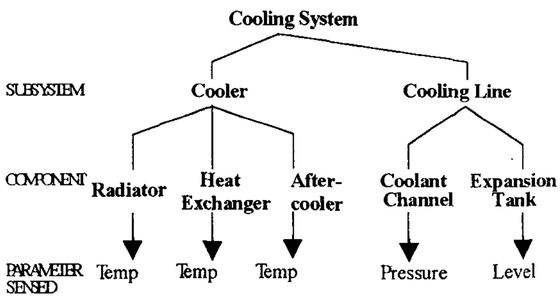

Figure 1. Structure-Based Hierarchy for Cooling System

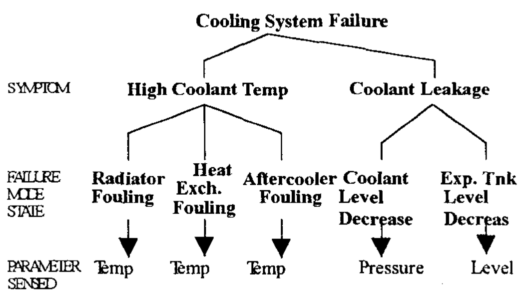

Figure 2. Function-Based Hierarchy for Cooling System

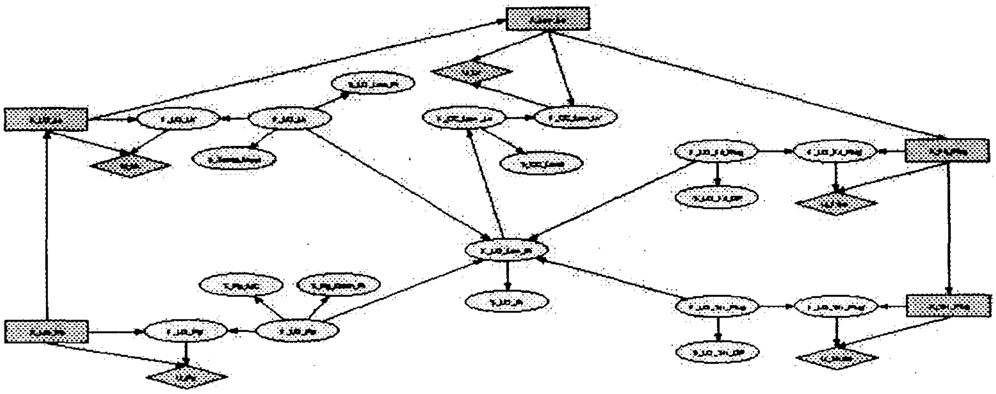

Figure 3. Prototype Diagnostic BNN for Lubrication Oil System

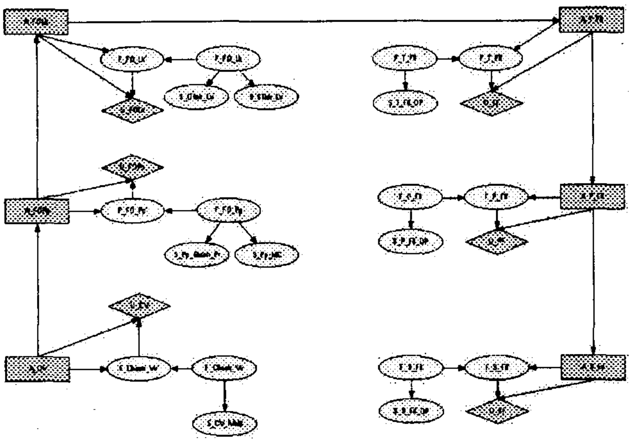

Figure 4. Prototype Diagnostic Network for the Fuel Oil System

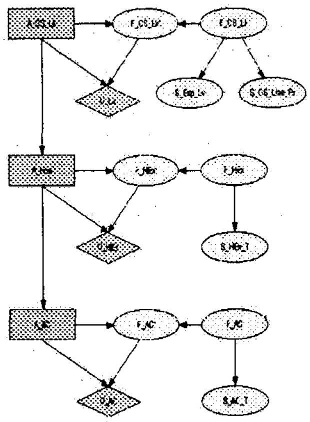

Figure 5. Prototype Diagnostic Network for the Engine Cooling System

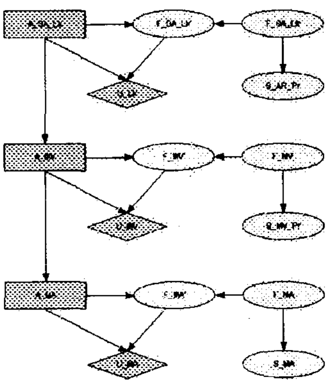

Figure 6. Prototype Diagnostic Network for the Air Actuated Starting System

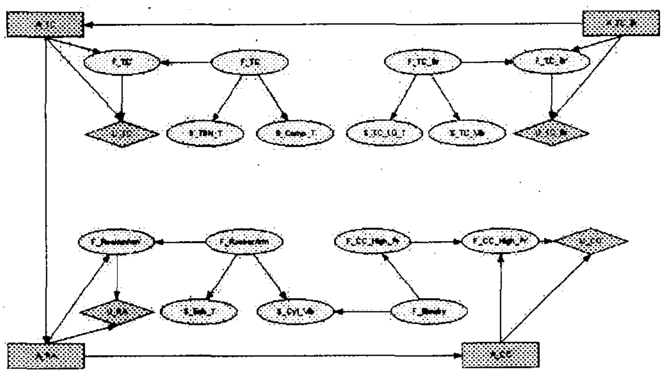

Figure 7. Prototype Diagnostic Network for the Air Actuated Starting System