Distributed Intelligence System for Online Action-Taking in Non Anticipated Situations in Nuclear Power Plants

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Abstract

Non anticipated events during a nuclear power plant operation might lead to accidents with undesirable consequences. Artificial intelligence offers a potential framework for quick and accurate detection of incipient malfunctions and appropriate action-taking to mitigate possible adverse developments through automated planning and scheduling of actions. A new methodology based on a network of intelligent agents for automated planning and scheduling is presented. The multi-agent system uses information coming from different measured quantities and diagnoses the problem. In the case of a severe situation planning of actions takes place in order to tackle with the unexpected state of the plant. Here the architecture of the system and the role of each component are presented and discussed. Two example cases are studied where a spray and a reactor control rod is stuck in the process of effecting control, respectively. Through these examples the applicability and efficiency of the multi-agent system for nuclear plants is examined.

Introduction

Nuclear power plants are large complex systems which are comprised of many smaller and simpler subsystems of various types. Each subsystem performs a specific operation and all of them work synergistically for energy production. It should be noted that a plant's complexity and heterogeneity is an important contributor to the high cost of surveillance and maintenance required. Plants should be monitored continuously and carefully since the potential environmental and financial impact of accidents is prohibitive. Non stop surveillance of a plant components demands significant resources. Also, a number of technical specialists is needed, to evaluate the incoming pieces of information (sensor measurements) and act properly. In case of an emergency, experts should properly identify an operational anomaly and develop a mitigation strategy if needed.

Even experts can have difficulties in understanding and interpreting large volumes of data coming from different channels at the same time. Generally, it is known that humans can not follow and recognize slow changes in a quantity. On the other hand changes that happen in a very short period do not leave sufficient time for reaction. As a result, automated methods for handling unexpected situations are of great interest since they can compensate for such human limitations. Nuclear plant sites are special industrial environments; radiation and temperature concerns limit accessibility to certain areas and components inside the plant.

Artificial intelligence (AI) tools (Russel and Norvig 2002) (Weiss 2000) offer useful possibilities for addressing the challenges of nuclear power plant environments (David and Zhao 1990). Development and deployment of modern and more efficient instruments with embedded intelligence (Zhou and Wu 1993) is an integral part of the overall field of plant and reactor safety. Sensor networks and measurement systems accompanied by high performance computing and smart processing modules are of great research interest.

In this paper, we discuss the application of AI planning (Traverso et al. 2004) in detecting non anticipated functions during power plant operation and recommend the most appropriate actions (Bell et al 2008). The introduced methodology is based on a network of intelligent agents (Uhrig & Tsoukalas 2003) (Uhrig et al. 2008) that measure various quantities. The AI technique adopted by the multi-agent system is fuzzy logic (Tsoukalas & Uhrig 1997) which provides flexibility and a powerful framework for online decision making. In the following sections the intelligent agents and agent systems are discussed and a methodology is presented for automated planning in nuclear power plants. Two cases in which a spray and a control rod are stuck during reactor operation in each of them respectively are studied. In those scenarios the significance of automated planning and the online design and execution of a plan is considered.

Distributed Intelligence Architecture

In the proposed methodology sensors are assumed to possess some intelligent capabilities. Besides collecting measurements from an object, each smart sensor is operated by a special piece of software called intelligent agent.

Intelligent agent

An intelligent agent is a system situated within and as part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future. Intelligent agents are characterized by autonomy (ability to act independently), social ability (ability to communicate with other agents through an inter-agent communication language), reactivity (ability to react to changes in the environment) and proactivity (ability to influence its environment in anticipation of future changes). The intelligent agent is versatile with many useful functionalities. An intelligent agent contains four basic modules (figure 1):

- A receiving module collecting measurements,
- A self-diagnostic module overseeing the performance of the sensor itself,
- A communication interface talking to other sensors and the control console, and
- A data processing module.

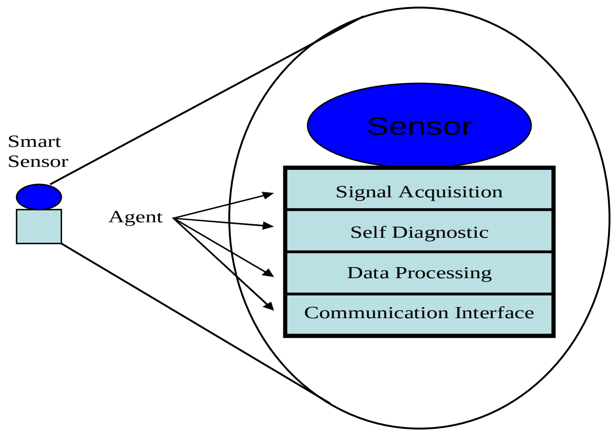

Figure 1: Scheme of a smart sensor

Agents are different from traditional client/server communication because they can migrate from one point to another taking with them, not just their data state, but also their execution state. They can take advantage of local resources at each node in the network, making each node, in effect, a server. This is extremely important from the point of view of robustness. Agent technology significantly improves robustness even in the light of low network bandwidths and unstable connectivity.

Agent Planning Module. Each agent in the system can do some short-term planning. The notion of "short-term" expresses the limitation in data processing and resources which a sensor can handle. As a result sensors do not make long and expensive plans. The plan is being designed by the data processing unit and is indirectly connected with the communication module (figure 2).

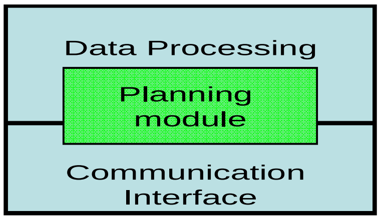

Figure 2: Agent planning module

The planning module of the agent is activated when an unexpected measurement is obtained.

Multi-Agent System

A smart sensor does not work alone. Whenever it detects something worthy of attention, it communicates with other pertinent sensors to seek further evidence to support its judgment. A system consisting of many such autonomous agents is referred to as a multi-agent system (figure 3). Such multi-agent systems provide for a modular, extensible approach to problem solving. The agents in a multi-agent system are collections that can dynamically organize themselves into organizations. These agent organizations can be hierarchical, democratic or have some other structure depending on the task involved. The advantages of having a multi-agent system are highlighted next.

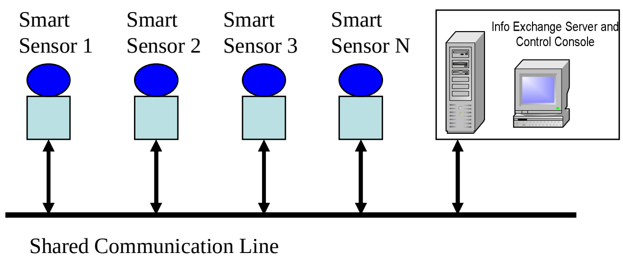

Figure 3: General scheme of a multi-agent system

Having an intelligent agent oversee a particular sensor is an activity that balances the responsibilities shared amongst different sensors. Sensors are focused on monitoring their own measurements, which is more efficient and reliable. The control console, which no longer needs to perform too much data processing, is now able to supervise the performance of the sensors by talking to individual agents at a higher level in the hierarchy to ensure better reliability. The implementation of intelligent agents on individual sensors makes security control possible. The built-in authentication in intelligent agents prevents unauthorized access to certain sensors. Encryption techniques in the communication channels ensure the safety of the information. As a result, distance control over wide spreading locations is readily available. Intelligent sensors are active entities. Human experts are able to control the operation of intelligent sensors by sending commands. This is needed when operators have to know the status of the sensors or want to learn more about a particular scenario.

Control Console Planning Module. The control unit of the multi-agent system has its own planning module. This module is independent from the ones located in each of the agents. Its task is to create an action plan to tackle with the non anticipated state that was detected. There are no limitations in planning in the sense that all the resources and the data of the system can be used. The control console creates a plan if the agents fail to solve the problem. It utilizes the action planning after receiving a signal from the agent which detected a non proper function.

Distributed Planning

In the proposed methodology there are two types of entities that perform automated planning (Leow and Parameswaran 1995) as indicated earlier. This results in utilizing one or more plans during an unexpected situation. Overall, all of them have the same goal: Recognize the problem and react immediately, if possible, or recommend the best series of actions to the human operator. From a macroscopic point of view, since all entities have the same goal and make plans in order to achieve it, it is not very far from the truth to claim that we have a distributed planner. Additionally it should be mentioned that fuzzy logic plays the main role in data processing and supports a *"membership based planning"* by introducing membership functions. Next we describe the steps of the process in case of an emergency.

Frame of Initializing a Plan

A general framework of the process that the proposed methodology follows includes the following parts: detection, agent planning and central console planning.

Detection of non anticipated events. Smart sensors are located all over the power plant and monitor a specific quantity (for example temperature, radiation etc.). Measurements are taken and processed by the data processing module. In the proposed methodology the processing is performed using fuzzy logic. Towards that direction, the measurement is fuzzified via fuzzy sets. Each sensor has its own sets that are appropriate for the parameter under surveillance. A sample of fuzzy sets for the variable *Temperature* is shown in figure 4. We observe that the space of the variable has been spanned by the sets VERY LOW, LOW, NORMAL, HIGH, and VERY HIGH. The intelligent agent via a fuzzy inference mechanism, which is comprised of a set of empirical rules, controls the procedure. In that direction, fuzzy sets are used as outputs that indicate the possible causes for that malfunction and degree of membership in that (figure 5).

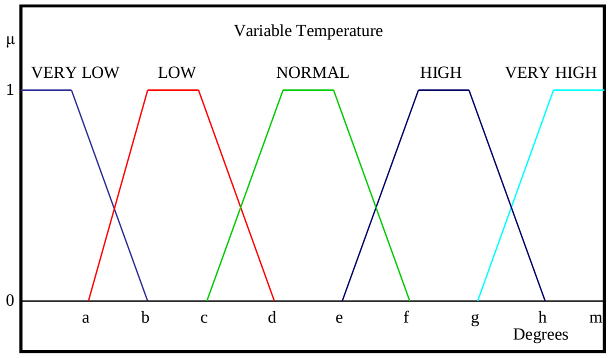

Figure 4: Sample fuzzy sets for variable temperature

It should be noted that only in the case that the measurement is not normal, the fuzzy rules identify possible reasons for that. A few sample rules are shown below:

- If Temperature is NORMAL, then no cause with confidence 1.
- If Temperature is HIGH, then loss of flow is TRUE with confidence c1.
- If Temperature is LOW, then pressure valve is open with confidence c2.

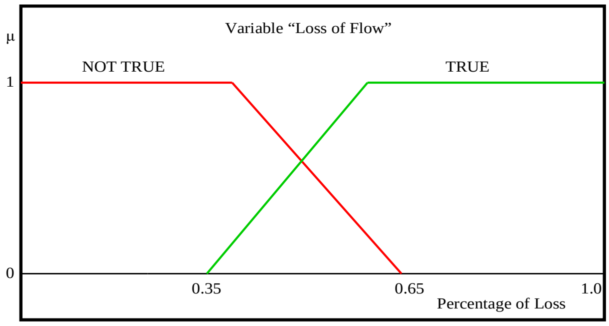

Figure 5: Sample fuzzy sets for variable "Loss of Flow"

The set of rules that possesses each sensor stands for the empirical knowledge of an expert. It should be mentioned that the implication operator applied to the fuzzy relations is the *Mandani Min:*

$$\min \{\mu_A(x), \mu_B(y)\},$$

where $\mu_A(x)$ denotes the membership function of a fuzzy set A. Specifically the system uses the process of *Generalized Modus Tollens* for matching a degree of confidence to each possible reason of malfunction.

Firing of more than one rule marks the start of the agent planning process indirectly. In other words, if a non-anticipated situation occurs then immediate actions should be taken.

Agent Planning

The operation of each agent can be considered as a deterministic plan. Specifically, a smart sensor has as a goal the measurement and processing of values of a quantity. In order to do that, it follows a series of specific actions.

However, a non anticipated action leaves the system in an unexpected state. Such states include those leading to accidents that may compromise safety. That's why online planning of reaction is mandatory.

The agent has the knowledge that its measurement is not a normal one and has a set of possible suspicions about the reasons for that. As a result, the agent starts its plan. The first step is to communicate with other agents that are implicated with the possible causes of the situation. Agents respond with their value and a degree of membership for this. For example a sensor that measures flow could reply that its flow is high to a degree x. Next the sensor collects all the information been sent to it and makes the most possible plan. It should be said that a predefined table with sensor correlations (two quantities might affect each other) helps in making the plan. This means that the actions taken are based on parameters that are somehow related to each other. Indeed this is not surprising since a change that may happen in a single quantity can result in affecting correlated processes in a large system such a plant. Lastly the smart sensor examines availability of resources and computing power to perform the plan and to take the respective actions. In case the resources are not enough for the execution of the recommended action then the control is transferred to the central unit. An overall view of the agent planning is shown below:

Plan
Initial State: Abnormal measurement.
Restrictions: Limitation of sensors in resources.
Number of actions a sensor can utilize depends on the embedded fuzzy rules.
Series of actions depends on degree of membership and correlation of variables.
Actions: Communicate with appropriate agents.
Receive values from other sensors together with a degree of confidence.
Look up correlations among measurements.
Find a series of actions with highest degrees of possibility (*membership planning*).
Search resources for the actions.
If resources not sufficient, then talk to central console.
Final states: i) Highest possible series of actions.
ii) Transfer control to central unit.

The possible final states of the plan are two: Either a series of actions are suggested to be taken or the agent should communicate with the server to pass the responsibility of the actions. In the latter case, the agent is no longer responsible for implementing the planning since action taking is beyond its capabilities.

Central Console Planning

The proposed methodology offers a two level action planning. The first was presented in the previous section and is performed exclusively by the sensor that detects a malfunction. The second and broader planner takes place in the central control unit. The advantages of this planner are summarized as the *universal availability of resources, high computing power, monitoring of the whole system and larger database with fuzzy rules for immediate action taking.*

The central planner is initiated when it receives a respective signal from the peripheral sensors. Specifically the signal is an alert that a non-anticipated situation might have taken place which was verified through communication with other agents. After receiving this signal, the planning module collects information for the current state of the whole system. This determines the initial state of the plan which is not expected by the operation plan. The goal is to stabilize the system (reach a stable state) via action-taking based on: i) the whole state and ii) a database with fuzzy rules accompanied with the respective degrees of membership from the fuzzification of variable space.

The process of actions for tackling with the unexpected state utilized by the central planner follows almost the same path as in the peripheral planning. Initially, the planner has the state of the power plant and determines the possible actions to locate and solve the problem. In that level, the number of correlations among variables is much higher than those in agent planning. Also the fuzzy rules with possible action taking are many more. The fuzzy operator AND is used in order to group the correlated variables and produce the most possible plan. Also alternatives actions are recommended in case the output of the plan is not the one expected. The overall process of planning is summarized:

Plan
Initial state: Current state obtained after receiving an alert from sensors.
Restrictions: Actions are correlated to variables from the whole system.
Actions: Look up correlations among measurements.
Find a series of actions with highest degrees of possibility via fuzzy rules and its operators (*membership planning*).
Find alternatives for each step of the plan.
Final states: i) Stable state of power plant.
ii) Shutdown of the reactor.

As a result, the central planner designs a series of action for online action taking after detecting an emergency. The plan should be followed by the operator of the nuclear plant in order to bring it back to normal operation. Also the shutdown of the reactor is a final goal if no stable state can be reached.

To sum up, the proposed methodology defines a distributed intelligent system which uses planning, based on membership functions of spanned variable spaces. The overall goal is to act online and immediately to address an emerging problem.

Membership based Planning and Scheduling of Online Actions

In this part we present the procedure that is followed to make the final decision for the actions that should be applied. It can be considered as a "subplanning" system which is part of the whole planning process (see previous section). The goal of membership based planning is to find an appropriate way of acting.

The type of planning at agent's level can be represented by a four member tuple:

$$(IS, SoP, RI, F),$$

where IS denotes the initial abnormal situation, SoP the set of all possible scenarios (causes), RI is the received information from other sensors and F the set of final states.

Once in this stage of planning the goal is to promote the most probable scenario and act properly. This should be done by exploiting information coming from other sensors. As a result, the two sets SoP and RI are applied to a set of empirical fuzzy relations. In this case degrees of SoP members are not useful since the best scenario is derived from the received information. The rules are combinations of the measured quantities so as to advance the reason of the unexpected situation. A sample of empirical rules is presented below:

- If Pressure is LOW and Temperature is HIGH and Water Volume is MEDIUM then Loss of Flow with confidence c1.
- If Pressure is LOW and Steam Volume is NORMAL and Water Volume is Low then Leakage with confidence c2.

In this case, the left side of most rules consists of more than one condition. Because of that, the operator AND is applied so as to group all the conditions. In fuzzy sets the AND operator denotes the minimum of the implicated membership functions:

$$\mu_{A \text{ AND } B}(x) = [\min \{\mu_A(x), \mu_B(y)\}]$$

The above relation is not only valid for two conditions but can be generalized to N. Once more the implication factor utilized in the set of fired rules is the *Mandani Min.* The end of this step yields the most possible reason for the non anticipated measurement.

In the next step the planner uploads to its memory the set of all actions that can be utilized for the advanced scenario. Additionally, RI set remains active since it is going to be used for firing the actions. Thus, action rules suggest the way that actions should be taken based on the values of the received variables. In general, actions rules encode the accumulated experience of experts. A few rules, which are representative of action rules, are shown:

- If Pump Pressure is LOW then increase Pump Rotation speed with confidence c1.
- If Temperature is HIGH and vessel Pressure is High then move a Control Rod into vessel with confidence c2.
- If Water Volume in Pressurizer is HIGH and Coolant Temperature is High then open relief valve with confidence c3.

It should be emphasized that each fired action rule has a degree of confidence for its action. The planner exploits this and makes an action plan according to descending rule order (figure 6). In other words, the system starts with the most confident action and moves on to the less confident action. Meanwhile, the plan stops if one of the states of the set F is reached. In case the whole plan is executed and no desired results are obtained, then there is a final state in F that passes control of planning to the central console.

PLAN and Scheduling of Actions for Most Possible Scenario: A

Initial state: abnormal measurement

Conditions >> Values coming from sensors

Restrictions: Available rules

Plan:

i)If variable_1 is H1 and variable_2 is H2 then do action_1 with confidence C1.

ii)If variable_1 is H1 and variable_3 is H3 then do action_2 with confidence C2.

iii)If variable_4 is H4 and variable_2 is H2 then do action_3 with confidence C3.

…

xx)If variable_4 is H4 and variable_N is HN then do action_1 with confidence C1.

with C1 > C2 > … > CN

Figure 6: General frame of action planning

At central console's level the procedure is the same as described previously. There are only two differences between them; the first lies in the definition of the planning tuple:

$$(IS, SoP, RES, F),$$

where the set RES has replaced RI. RES includes the values of the parameters of the recorded state of the plant. The second difference derives from a high number of scenarios, parameters and actions taken into consideration. This has as a consequence the existence of more than one possible plan for the same situation. Moreover it is highly probable that planning actions can have almost the same confidence factor. As a result, one action is scheduled while others are considered as alternatives.

Cases of Non-Anticipated Situations

In this section two cases of non-anticipated situations are presented. It is also examined, how the proposed methodology can counter efficiently the problem. The first is a small case in which agent planning is enough. The second one is a much more complicated problem: a reactor control rod is stuck.

Case of a stuck Pressurizer Spray

In this case study we assume that the system is installed in a pressurized water reactor (PWR). The non-anticipated event that occurs is the stuck of spray of the pressurizer. Spray is very important since it helps the pressurizer to increase or reduce the pressure of the steam needed for the circulation of flow in the system.

First, the case in which the pressure of the system needs to be reduced is considered. As a result the spray should pour water into the pressurizer to reduce the volume of the steam. Reduction of steam volume has as a result a drop in the pressure of the system.

If the spray is stuck (not responding in pouring water) then the pressure of the system does not go down. The sensor which measures the pressure in the pressurizer detects that the value does not respond to the expected one. Then the fuzzy system detects the abnormality and sends messages to the agents that might be related with this abnormality. Indeed, sensors reply to the pressure sensor. The smart sensor that measures the level of water responds that the volume is low, the sensor that measures steam replies the steam volume is high, the sensor of the relief valve says that the valve is closed and the flow sensors respond that no flow loss occurs to pressurizer or out of it.

The data processing unit then gets those results and their membership values:

- water volume is low with certainty 0.8,
- the steam volume is high with certainty 0.9,
- relief valve is closed with certainty 1,
- there is no loss of flow with certainty 1.

Then some of the fuzzy rules are used for the action planning:

- If pressure is not normal and water is LOW then inject water.
- If pressure is not normal and water is LOW then loss of flow is possible.
- If pressure is not normal and loss of flow is NORMAL then no action correlated to flow.

The fuzzy inference finds that the most possible action demands that the relief valve should be opened, and water injection should be performed.

Overall, the agent detected the malfunction, communicated with agents and got their values. Fuzzy logic indicated the actions to be taken. This plan was short and of low resource cost.

Case of a stuck Reactor Control Rod

In the second study the proposed multi-agent system is used for the action taking in a stuck control rod case. Control rods are of great importance in the reactor operation since they are the main mechanism for reactivity control in a nuclear reactor. Moving of the control rods into the reactor are the only mechanism for reactor shutdown since they are good absorbers of neutrons and cease the fission process.

Initially, the control rods are moved into the reactor core in order to achieve a critical case (neutrons produced are equal to those consumed). While the control system performs the procedure one of the control rods gets stuck in a position different than the expected one. The other rods continue their movement till they reach the proper positions.

When the movement of the control rods finishes, the power sensors detect that the power generation of the reactor core is not as expected. Moreover the neutron flux in the core changes too. Next step is the communication of the power sensor with possible relevant agents in the system. Replies from the other sensor indicate:

- Neutron Flux is changed with certainty 1.
- Temperature in the core is high with certainty 0.9.
- Temperature in the reactor coolant is high with certainty 0.8.
- Fuel clad temperature is high with certainty 0.9.

The power sensor gets the answers and via fuzzy rules verifies the problem. Since the problem is much complicated (all sensors replied: not normal operation with high degree of membership), then the intelligent agent signals the central unit for its detection.

The central unit obtains the alert and then asks for information from the whole system. As a result the central console records the state of the whole system. Recording of the neutron flux yields the graph as in figure 7.
The recording is considered as the initial state for the plan and the goal of the plan is to stabilize the system. Furthermore the central unit obtains all the rules that are fired and creates the most possible plan. In order to create the plan, a table with all correlations among variables is used. Rules are of the following form and include universal info (not local as in agents):

- If core temperature is HIGH then Coolant loss is possible with confidence 0.7.
- If core temperature is HIGH then reactivity is high with confidence 0.9.

- If clad temperature is high then coolant has been degraded with confidence 0.4.
- If reactivity goes up, then control rods are not properly located with confidence 0.9.
- If power increases then neutron flux increases with confidence 1.

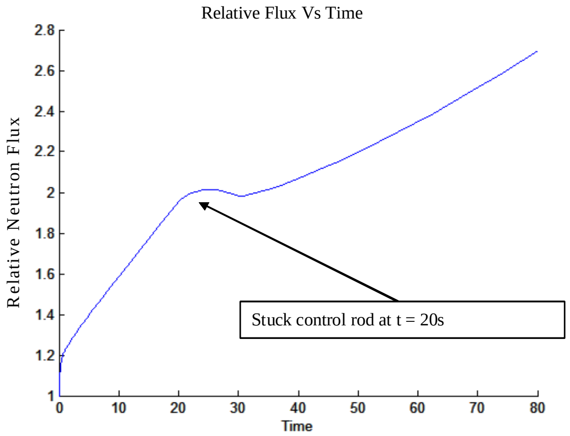

Figure 7: Neutron flux vs. time for the reactor core

In general, the central unit contains several rules like the above ones and exploits them to make the final decision. In our case, considering the rules the problem will be limited to the reactor core and not to other components. This was something that could not be done exclusively by a smart sensor since it does not have an overview of the whole system. Finally the system plans the most possible (from confidence values) way to move the excess heat out of the core by using the secondary heat removal system and reduce the fission process by moving other rods in the reactor. Finally, a stable state is reached. It should be mentioned that in case more than one rod were stuck, shutdown of the reactor was the most possible action.

Conclusions

In this paper a methodology for online action taking in nuclear power plants was presented. Multi-agent systems embedded in sensors comprised of an intelligent grid to enhance safety and automated action in non-anticipated cases and emergencies. An important role is performed by the action planning in the performance of the system. This proposed planner can be classified as a two level planner. At first, planning takes place in the agents considering their limitations. The second level planning, if needed is done by the central console system that monitors the whole plant.

Surveillance systems for nuclear plants are of extreme significance. Nuclear accidents are very destructive and as a result the demand for accurate and immediate prognosis is needed. AI planning offers a strong potential in research for systems that can enhance a plant's operational efficiency and ultimately reliability.

Future work will focus on collecting data for developing a database with many more fuzzy rules and research will be done also to embed other AI methods to smart sensors.

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