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Machine Diagnosis Based Multi-Agent Technology by Autonomous Sensor with Energy Harvesting

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ABSTRACT

A machine diagnosis system based on multi-agent technology is proposed. We mainly focus on developing a multi-agent system for rotating machinery fault diagnosis by vibration sensor with energy harvesting. To estimate the inner rotation of machines in plant frequency analysis is frequently used. Our approach for diagnosis is agent-based, where vibration data is analyzed by a set of software agents coming from distributed servers to the user side. Another feature of this study is the development of autonomous vibration sensors. It earns electric power from vibration so that we are free from battery maintenance, and continuous online monitoring is enabled. Based on the implementation results of the existing multi-agent system design prototype, the harvesting sensor working process can produce total energy of 205µW with a working cycle of about 6.5 minutes, the energy harvester works, and the power accumulates continuously.

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1 INTRODUCTION

Condition monitoring of machines in the industry is a significant factor to maintain its reliability and anticipate machine failure. Maintenance of the devices is crucial to ensure machine performance and maximize the production process. The purpose of our research is to develop a reliable and automated machine diagnosis system that can check for any problem that might occur at any time. Furthermore, based on the checking results, the system thoroughly diagnoses the machine's condition. The goal of machine condition monitoring is to obtain the real-time working status of the devices and use the information to identify potential machine faults and failure before they occur, thus reducing unexpected and costly machine downtime and ensure the highest possible productivity, and for more accurately control the quality of products, which is closely related to the working condition of the machines.

A rotation machine is one of the most common machineries in industrial reduction. The fault diagnosis of rotation machines is an essential job for any factory. Our project uses the vibration monitoring method to diagnose the machine instead of oil particle analysis or other methods. We can use the vibration data generated from the machine itself to monitor the machine's condition. The vibration analysis process plays a significant role in concluding an overall diagnosis result from collection data of vibration that occurs in some parts of the machine. Some energy harvesters which used to collect power from rotation machines, and we constructed a vibration sensor that consumes the power collected by these energy harvesters. After collecting vibration data of the monitored machine, the sensor can send them to the user's PC by Wi-Fi, and all these jobs are done by itself, so we call it an autonomous vibration sensor.

In this research, the underlined technique is to develop machine diagnostics vibration-based, which must catch every vibration data and process the relevant data automatically. The Motivation and target of our research are setting up a multi-agent system for rotating machinery fault diagnosis by vibration sensor with energy harvesting. To process the vibration data collected by the sensors, we set up a multi-agent's system. There are many software methods (also called agents) stored in the web server in this system, and we involve the Planning Algorithm. The planning algorithm is to find a plan guaranteed from the initial states to generate a sequence of agents that leads to desired goal states. When our users access the system, they can download the relevant agents, which may help judge the mechanical faults arising in their machines. This sequence of agents is'' recommended" by planning agents.

As mentioned above, besides the traditional monitoring method, automatic fault monitoring based on vibration waveform became more and more common, especially for the rotation machine's condition monitoring. The problem of automatic fault monitoring and fault diagnosis as part of the maintenance system became more and more critical because of the underlying advantages gained from reduced maintenance costs and improved productivity. Mechanical fault diagnosis can be used to monitor the machine's operating status. Some equipment takes advantage of diagnosis and other innovative technology. The computer could, for example, collect data on vibration while a machine is in operation to find the normal range and determine different levels associated with various functions. If the computer notices that a machine is vibrating too much, it can issue a warning, alerting technicians to a problem. It may be able to offer diagnostic advice and information to help the technician fix the equipment. Our project will use a vibration sensor for mechanical fault diagnosis of rotation machines, so we only need to focus on vibration monitoring. In the vibration

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monitoring field, there are still many artificial intelligence approaches. Artificial intelligence is a field that investigates how computers can be made to exhibit intelligence in different aspects of thinking, reasoning, perception, or action. Different artificial intelligence methods such as expert systems, genetic algorithms, artificial neural networks, etc., have been used to solve non-conventional real-life problems.

2 METHODS

2.1 Machine Diagnosis

The machine is working in any field and anywhere. It is evident that machines usually work day and night in factories without any rest, but like our human beings, sometimes, when overworked, the machine may also get" sick." For example, when a machine worked for too long and dried up lubricating oil, the machine would not run smoothly, the operation temperature would increase, and the subsequent abnormal sound would occur in most cases. Using a more technical term, some kinds of mechanical faults arise in the machine. In that case, maybe, the maintenance staff need add more lubricating oil or even replace the parts which in bad condition [1].

The engine condition monitoring process diagnoses damage to the machine through specific physical parameters associated with observable working operations to prevent more damage to the machine. The parameter is observed to determine the machine's integrity to determine the action needed for maintenance. Machine condition monitoring, therefore, is a measurement process of various parameters related to the engine's mechanical condition, which makes it possible to determine whether the engine mechanical condition suits the standard of production operation [1-6]. If the engine is in poor mechanical condition, then the condition monitoring makes it possible to detect the cause of the problem. State monitoring is used in conjunction with predictive maintenance, namely maintenance of machines based on indications that the problem is imminent.

The outline of the whole project described in **Figure 1**. which include their parts: knowledge-database provided by experts in different fields; software-agent uploaded by developers who access to our server; and client-part which usually occur in factories.

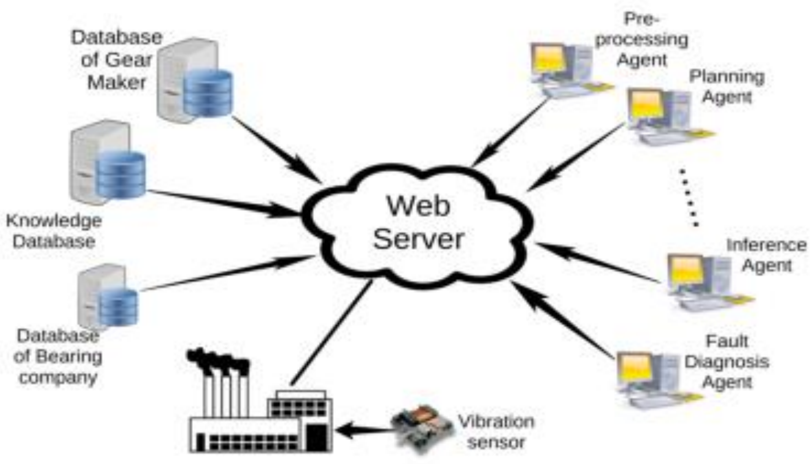

Figure 1. The outline of the whole project.

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2.2 Multi-agent System for Machine Diagnosis

In general, multi-agent techniques are an intelligent system of centralized application procedures in the decision support system. In this research, we focus on implementing multi-agent into a system for condition monitoring of the machines. One of the problems of the condition monitoring system with multi-agent is that it contains complex architectures of intelligent agents that are distributed and interact with each other dynamically. Each agent is an autonomous system that processes the input from several input options and complete interpretation. The diagnosis of the problem itself is achieved through interactions with other agents [5].

2.3 Software Agent

As mentioned before, our motivation and target of the research is setting up a multi-agent system for rotating machinery fault diagnosis by vibration sensor with energy harvesting [7-12]. We use sensors for collecting vibration data from monitored machines, and we can obtain the signal waveform (time-domain signal, of course). Then, usually, we need to process the waveform by utilizing signal processing methods to obtain some helpful information about the signal, such as the frequency, peak value, average, etc. In a multi-agent system, each signal-processing method has been encapsulated into different agents. In order to easily understand, we just regarded the agent as a program method, and each agent represents a method written in an arbitrary program language. However, there are some differences between them.

A software agent is a persistent, goal-oriented computer program that reacts to its environment and runs without continuous, direct supervision to perform some function for an end-user or another program. Some, but not all, software agents have UI (user interface). We can say that four fundamental notions distinguish agents from programs: reaction to the environment, autonomy, goal-orientation, and persistence [13-15]. Software agents represent an evolutionary step beyond conventional computer programs. They can activate and run by themselves, not requiring input from or interaction with a human user. In addition, there is a common type of agent called mobile-agent, this type of agent can move around the Internet, especially suitable for downloading from agent-server to client. It is fortunate that mobile-agent fits well for our project.

The framework of this project shown in **Figure 2**. which include hardware and software agents' part; the left side indicates the client part; on the right side, it shows the structure of software agents' server.

Figure 2. The framework of the project.

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2.4. Planning Agent

Planning agents have already been used in many other fields but have not been used for machine diagnosis since it is not easy work, because it is difficult to describe the signal processing agents, there are too many agents to implement by ourselves. Furthermore, our research has generated a planning sequence among a limited set of agents, including 26 signal processing functions. In our research about machine diagnosis, PDDL (Planning Domain Description Language) technique for describing the signal processing agents, because PDDL supports the feature of inheritance and has a powerful inference engine. We use the vibration sensor to collect the vibration waveforms as the input signals. Moreover, of course, the input signals are always in the time domain, but for machine diagnosis, it is essential to obtain frequency information of the input signals because we need to do spectral estimation in the frequency domain. Furthermore, there are two spectral estimate methods: AR model and FFT-based spectral estimate.

Figure 3. shows two different signals, the red-coloured wave is smooth, but the blue waveform has both sharply defined peaks and notches, which means the absence of power at frequencies.

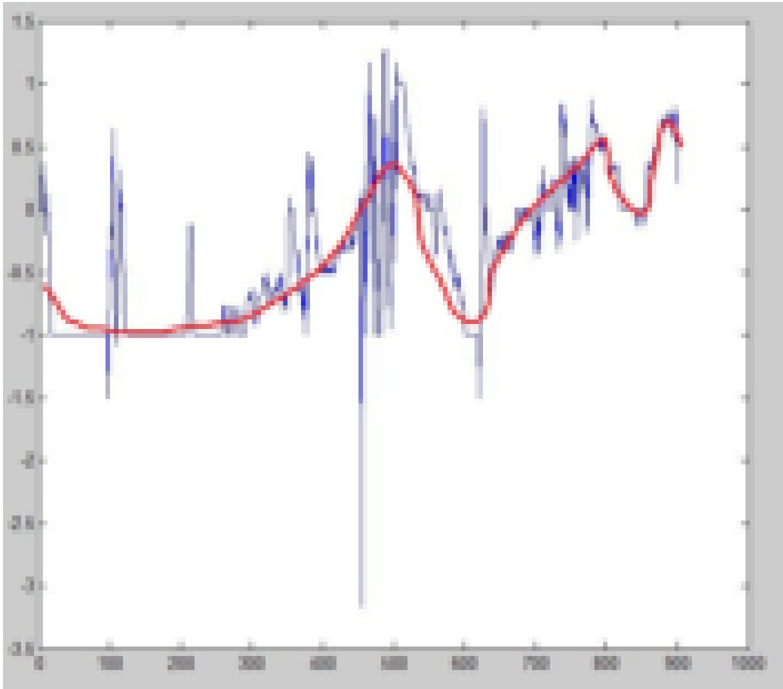

Figure 3. Two different signals.

Moreover, the red-colored signal is suitable for utilizing the FFT-based spectral estimation, but the blue waveform is suitable for using AR model-based spectral estimation in most cases. As shown in **Figure 4**. it is indicated how to distinguish the differences between FFT-based and AR-model-based spectral estimation. If the width of peak value at 50% less than 0.01*peak value and there exists a dominant frequency in the Fourier series of the signal, that means the signal has both sharply defined peaks (dominant frequencies) and notches; then the planning agent will choose the FFT method for spectral estimation.

As seen in **Figure 4.** If the width of peak value at 50% less than 0.01*peak value and there exists a dominant frequency in the Fourier series of the signal, the planning agent will choose the FFT method for spectral estimation.

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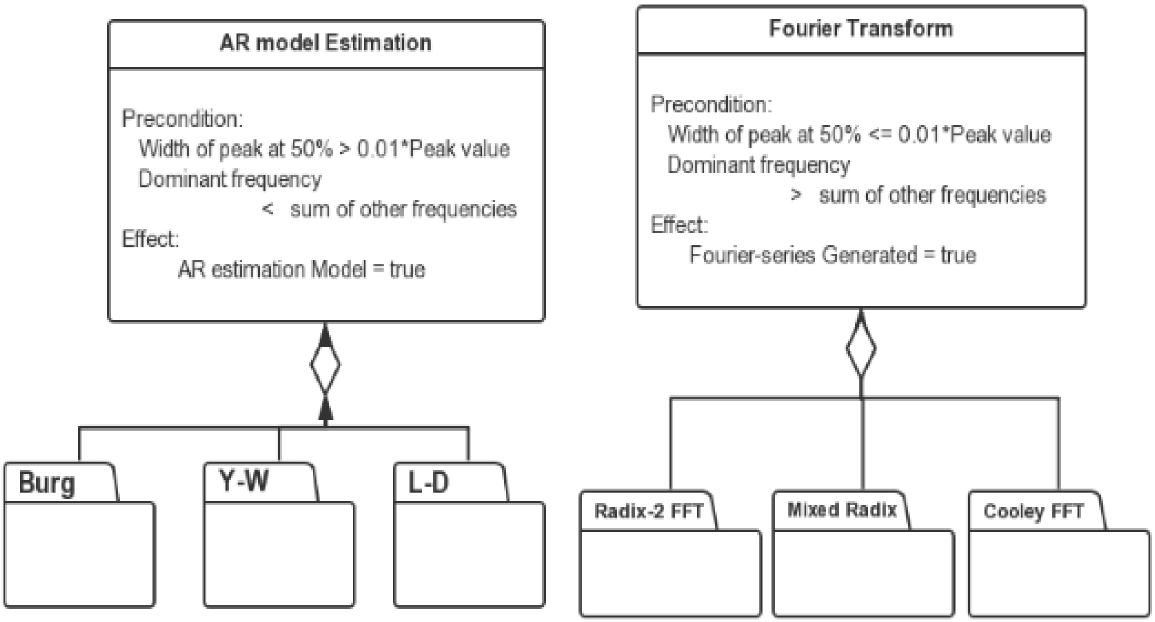

Figure 4. The class diagram shows how to distinguish the differences between FFT-based and AR-model-based spectral estimation.

2.5. Energy Harvesting from Vibration

Vibration Energy Harvesting is a concept that began to take off in the 2000s with the growth of MEMS (abbreviation of the micro-electro-mechanical system) devices. The concept of Vibration Energy Harvesting is to convert vibrations into electrical power. Turning ambient vibration into electricity is a two steps conversion. Vibrations are firstly converted in a relative motion between two elements, thanks to a mass-spring system, then converted into electricity thanks to a mechanical-to-electrical converter [16-20]. As ambient vibrations are generally low in amplitude, the use of a mass-spring system generates a phenomenon of resonance, amplifying the relative movement amplitude of the mobile mass compared to the amplitude of the vibration, increasing the harvested power.

3 RESULTS AND DISCUSSION

Existing multi-agent system design methodologies, the next stage was to implement the prototype. **Figure 5.** shows the test environment of the vibration sensor. The energy-harvester module has been attached to the rotating machine for power generation and supplies power to the vibration sensor by a long cable; on the other side, detectors are working to monitor the condition of the sensor. Shown in **Figure 6.** is the Power (Voltage) Consumption Chart during the sensor's working process. Four harvesters can generate 205µW of energy totally, and the working cycle is about 6.5 minutes. At the chart's beginning, we can see a significant rising curve, which means the energy-harvester is working and power is accumulating continually. When the voltage reaches high enough, the accelerometer and Wi-Fi module starts to work. **Figure 7.** indicates the working cycle. In each cycle, energy was mainly consumed by two components: the accelerometer and the Wi-Fi module.

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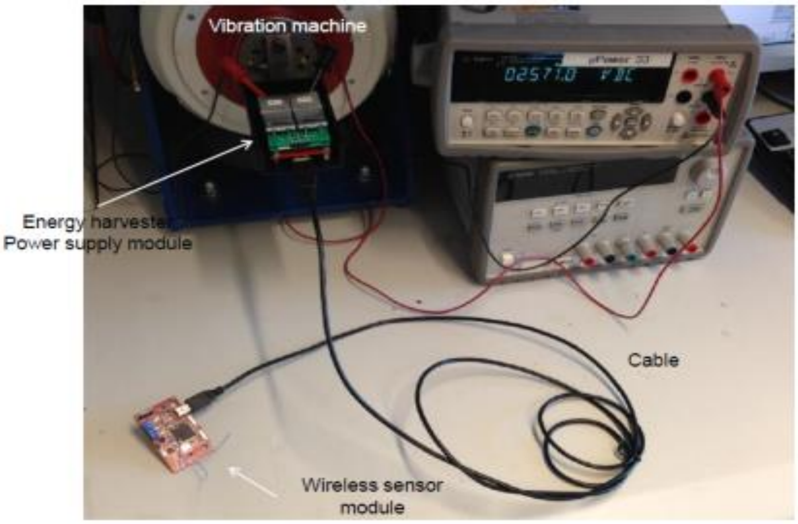

Figure 5. The testing environment of the vibration sensor.

In the beginning, when the energy-harvesters collect enough power (in other words, voltage is high enough), the accelerometer starts to collect vibration data for 10 seconds; then we can the slight decrease, that indicates the accelerometer is collecting vibration data by consuming only few energy; next, the Wi-Fi module starts to transmit collected data to client-PC; particular attention is that Wi-Fi module consumes comparatively more energy, so the data cannot be transmitted at a single time, it should be transmitted in five times, and at each time, when the power exhausted, harvester would collect enough power again, until all the data was transmitted completely.

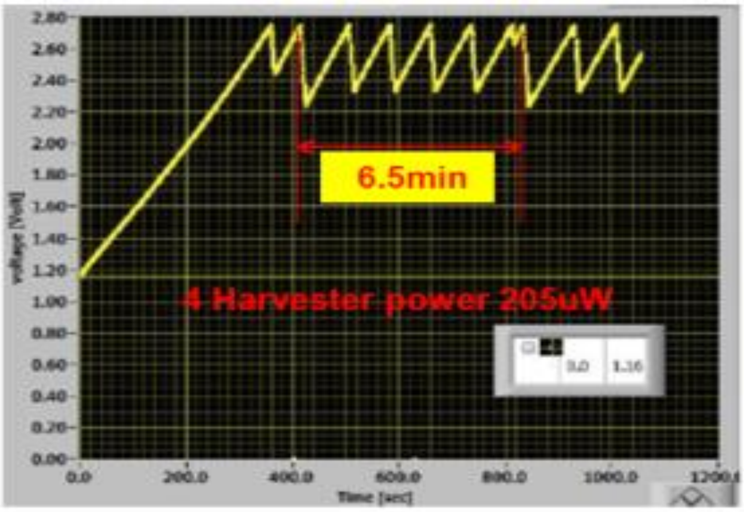

Figure 6. The power consumption chart.

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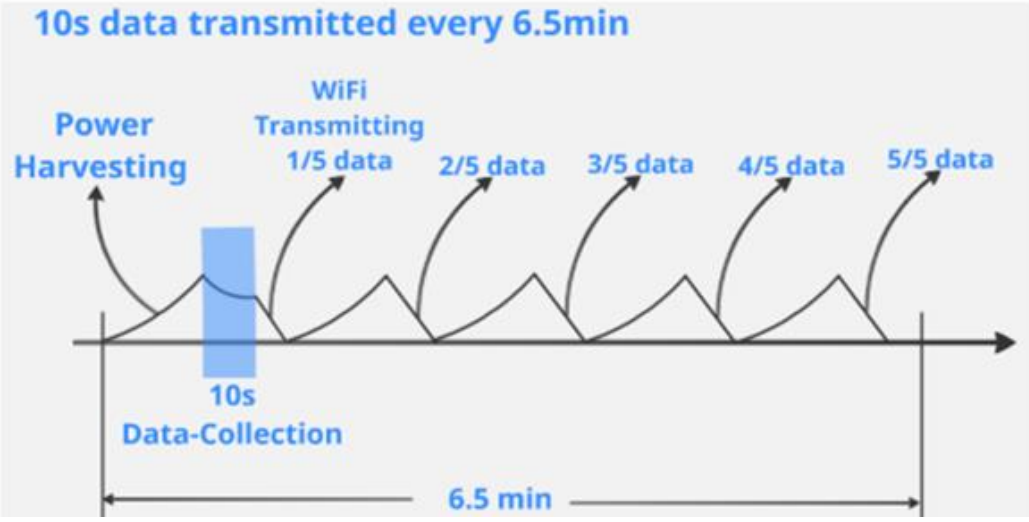

Figure 7. The working cycle of the vibration sensor.

Give a simple example (please pay attention, the values and facts in this example are not certified, it is just an illustrative example). It includes five steps:

1) in client, collecting vibration-data by a sensor, sent to agent-server as incoming data;
2) when agent-server receive the incoming data, (a) invoking planning-agent to find the sequence of agents leading to the desired goal (b) downloading relevant agents from server to client PC 3;
3) by utilizing the agents on the client PC, some facts are figured out, ex. Fs=1.2kHz, Peak=2A (amplitude) and Average=1.6A;
4) inferencing to an expert system for mechanical fault information;
5) According to the facts
   a. Find out the correspondent's fault, ex." Bearing Fracture" in this example;
   b. send the fault information to a client and warn the maintainers that bearings need maintenance or replacement.

Figure 8. Show The work Flow of this project by a simple example. This example shows how to assess the mechanical fault occurring in a machine.

As shown in **Figure 9**. the class diagram indicates how to distinguish Yule-Walker and Burg methods. Yule-Walker is appropriate for the case: 1. big data (length of signal> 104); 2. The signal is not periodic. On the contrary, the Burg method is effective for small data, and it does not care about the periodicity of the signal. Because Yule-Walker method should not be used for autoregressive parameter estimation if the auto-covariance matrix is poorly conditioned, especially for the case that the input signal is periodic.

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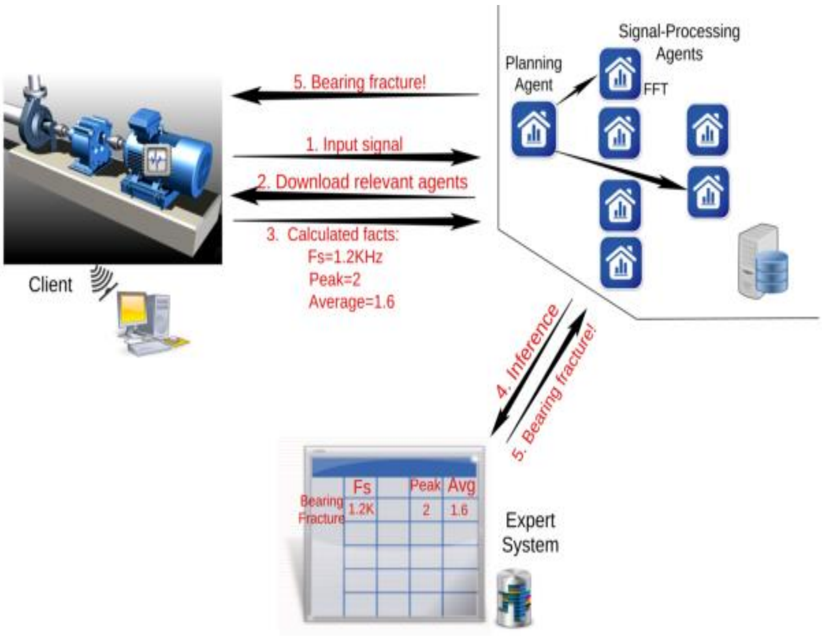

Figure 8. The work flow of our project.

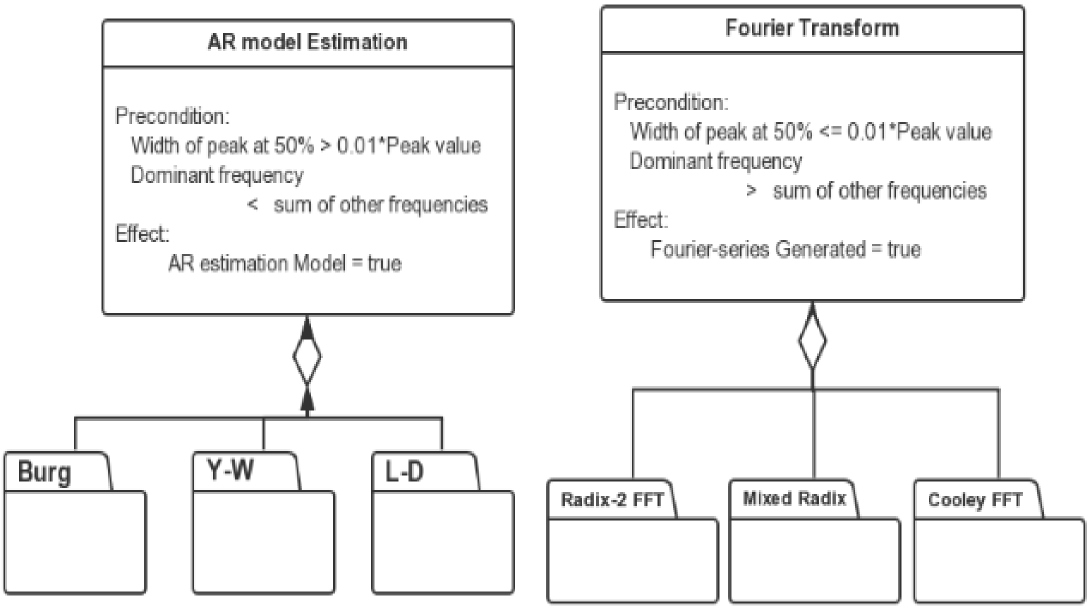

Figure 4. The work flow of our project.

As shown in **Figure 10**. the class diagram shows different kinds of criteria for AR model estimation. If the signal length is less than 104 and the signal is not periodic, then the FPE criterion will be well fitted. As for AIC and MDL criteria, they have the same preconditions, but their effects are different. In this case, we cannot judge which one is more suitable for the input signal, and then we will submit a recommendation list to our users, notice the different effects of each agent, then choose by ourselves.

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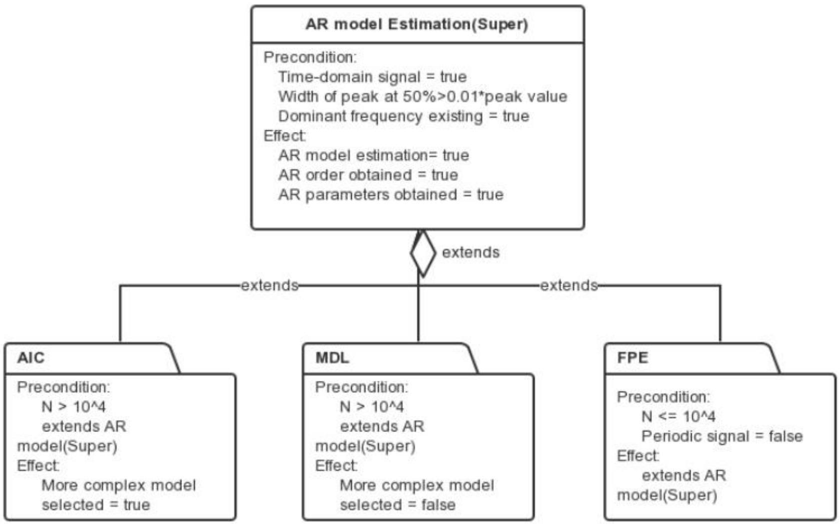

Figure 10. The class diagram shows different kinds of criteria for AR model estimation.

Figure 11. shows the planning process of generating the Fourier transform estimation sequence. The preconditions of FT are 1. Dependency is true; 2. Average removed is true; 3. Dominant frequency exists, which indicates the signal has both sharp peaks and notches.

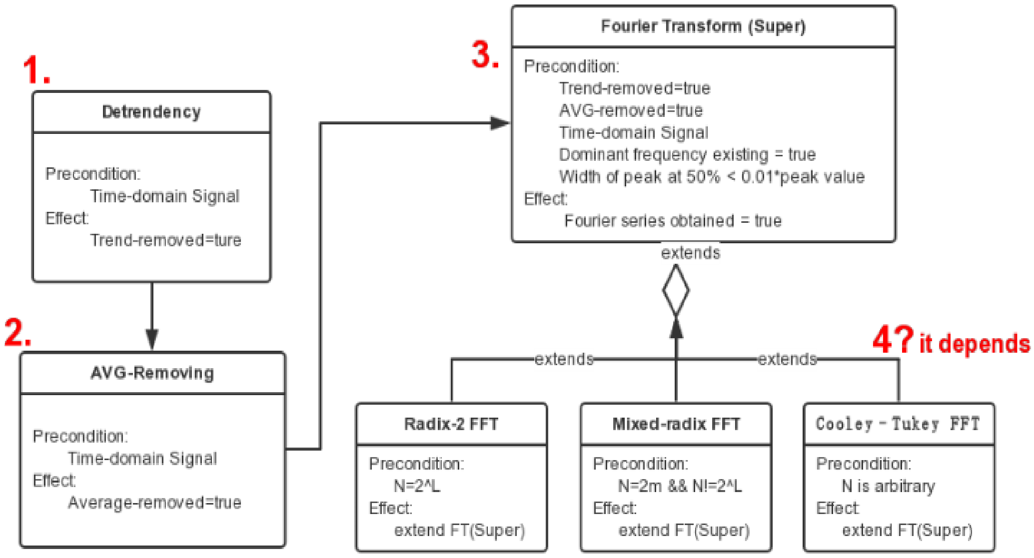

Figure 11. The planning process of generating a Fourier transform estimation sequence.

4 CONCLUSION

In our project, we use the vibration monitoring method to make the machine diagnosis. Some energy harvesters are used to collect power from rotation machines, and our laboratory constructed an autonomous vibration sensor that consumes the power collected by these energy harvesters instead of external power supply, such as batteries and AC power supply. To implement the planning agent, we use PDDL (Planning Domain Description Language) technique and utilize the inference engine of PPDL to do the planning jobs. To implement the planning agent, we use the PDDL technique to set up the inheritance relationship among

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different agents. After involving the inheritance feature, it can improve the efficiency of searching and extendibility of our multi-agent system.

5 AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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