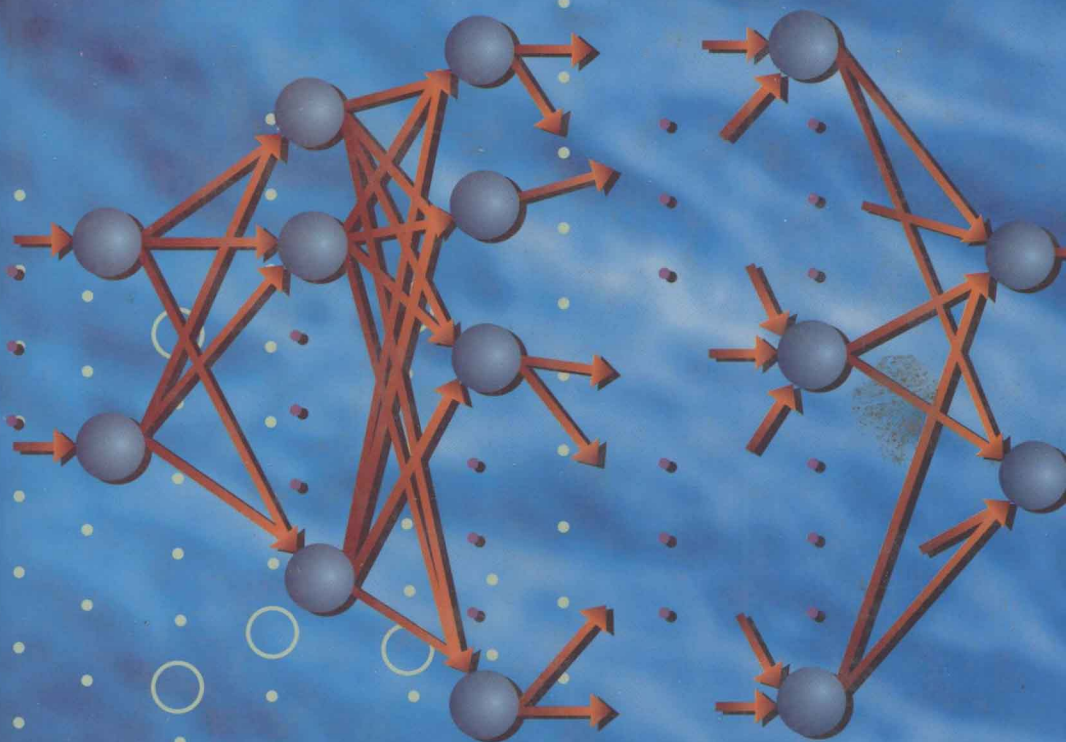


Mo-Yuen Chow.



**Methodologies of
Using Neural Network and
Fuzzy Logic Technologies for
Motor Incipient Fault Detection**

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PREFACE

Humanity has always had the vision and the quest to create new inventions that can help make life simpler, easier and more efficient. From the Industrial Revolution in the eighteenth century to the Information Revolution of the twentieth century, mankind's goal has been to make use of machines in order to reduce the amount of labor work performed by humans and to automate tasks that are repetitive. With the passage of time, machines are evolving to be more complicated, sophisticated and intelligent.

These days, the buzzword is smart: smart homes, smart highways, smart cameras, etc. But where does their intelligence come from? It is not like they can think for themselves, yet given the correct algorithms, they can operate, make decisions and arrive at reasonable thoughts and actions even when incomplete data and input information are used. This is the attractiveness of smart machines.

Smart machines need smart designs and algorithms. Ideally, a smart machine would have the same features, behavior and characteristics as the human brain, including the ability to learn, adapt, grow and make decisions based on previously acquired knowledge and on the present circumstances. To that end, we study and attempt to understand how our brains work because the human brain is without doubt the ultimate intelligent engine. Researchers and scientists are constantly amazed at their new discoveries of the functions, capabilities and complexity of the human brain. It is an overwhelmingly intricate and powerful engine.

To be realistic, smart machines of the level of complexity and capability of the human brain are still many decades away. They only exist in our fantasies and in science fiction literature. However, we are slowly making progress towards that goal. Researchers in the area of Artificial Intelligence use techniques such as expert systems, artificial neural networks, fuzzy logic and genetic algorithms, among others, that in one form or another try to imitate the logic and reasoning process that humans follow in order to make a decision or take an action.

This book describes the use of artificial neural networks and fuzzy logic for predicting the condition of induction motors, so incipient faults can be detected early enough to minimize expensive repair costs and to increase the reliability of the motors. My goal here is to illustrate how artificial neural networks and fuzzy logic can be integrated to create a powerful tool that is trainable, adaptive, robust and inexpen-

sive to solve an engineering problem. The readers should bear in mind that although a specific problem is illustrated in this book (i.e., predicting a motor's condition), it is the methodologies and techniques for applying and integrating artificial neural networks and fuzzy logic that are the main focus of the book. After reading this book, the readers should feel comfortable in choosing any real-world problem and using the methodologies that are presented in the following chapters for their application.

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CHAPTER 1

INTRODUCTION TO MOTOR INCIPIENT FAULT DETECTION

The monitoring, diagnosis and incipient fault detection of motors are important and difficult topics in the engineering field. Applications range from the small DC motors used in intensive care life support units to the huge motors used in power plants. With proper machine monitoring and incipient fault detection schemes, early warning can be achieved for preventive maintenance, improved safety and reliability of different engineering system operations. The importance of incipient fault detection is found in the cost savings realized by detecting potential machine failures before they occur. For example, in the world of manufacturing, machine tools are used extensively to shape objects to suit specific needs. Recent studies indicate that as many as 90% of the failures of machine tools occur because of a malfunction of internal components such as the main motor. These motor malfunctions need to be detected and corrected before quality is degraded and the overall system is jeopardized.

Many industries still perform maintenance on their equipment in a *reactive* and *breakdown* mode because traditional monitoring systems can only detect machine faults after they occur. *Reactive* maintenance is expensive because of the unplanned downtime and possible damages caused by equipment failures. To avoid expensive machine downtime, some companies have adopted principles of *preventive* maintenance. *Preventive* maintenance is based on the belief that since degradation generally occurs before failures, monitoring the trend of machine degradation allows the degraded behavior or faults to be corrected before they cause failure and machine breakdown. In the near future, high performance industrial processes will not be able to tolerate significant degradation of machine performance. Therefore, many industrial customers request manufacturers and suppliers to provide smarter equipment that would require less technical support.

1.1. Importance of Incipient Fault Detection for Induction Motors

Induction motors are the workhorses of many different industrial applications due to their ruggedness and versatility. Many articles have been written outlining key

issues for reliable, cost effective motor operations. Among these key issues are: a motor of high quality, a thorough understanding of the motor application, properly choosing the type of motor for the specific application, and properly maintaining the motor.

System availability is a function of several factors. *Absolute system availability* can be defined as the percentage of the actual time that the system is available. *Relative system availability* can be defined as the percentage of *scheduled* operation time that the system is available. In most motor operations, the relative availability is a more important issue because downtime can be scheduled!

Although rotating machines are usually well constructed and robust, the possibility of incipient faults is inherent due to the stresses involved in the conversion of electrical energy to mechanical energy and vice versa. Incipient faults within a machine generally affect the performance of the machine before major failures occur (Timperley 1983; Sood, Fahs et al. 1985; Sood, Fahs et al. 1985; Douglas, Edmonds et al. 1988; Reason 1988; Chow and Yee 1990; Chow and Yee 1991; Bonnett and Soukup 1992; Gupta and Culbert 1992; Chow, Sharpe et al. 1993; Sottile and Kohler 1993; Trutt, Cruz et al. 1993; Campbell, Stone et al. 1994; Finley and Burke 1994; Timperley and Michalec 1994). Early fault detection allows preventative maintenance to be scheduled for machines during scheduled downtime and prevents an extended period of downtime caused by extensive motor failure, improving the overall availability of the motor driven system. With proper system monitoring and fault detection schemes, the costs of maintaining the motors can be greatly reduced, while the availability of these machines can be significantly improved.

The use of induction motors in today's industry is extensive, and the motors can be exposed to different hostile environments, misoperations, and manufacturing defects. Internal motor faults (e.g., short circuit of motor leads, interturn short circuits, ground faults, worn out/broken bearings, and broken rotor bars), as well as external motor faults (e.g., phase failure, asymmetry of main supply, mechanical overload, and blocked rotors), are inevitable. Furthermore, operation within hostile environments can accelerate aging of the motor and make it more susceptible to incipient faults (Boothman and Elgar 1974; Burke, Douglass et al. 1983; Smeaton 1987; Cambrias and Rittenhouse 1988; Douglas, Edmonds et al. 1988; LaForte, McCoy et al. 1988; Reason 1988; Schump 1989; Tavner and Penman 1989; Fenton, Gott et al. 1992). These incipient faults, or gradual

deterioration, can lead to motor failure if left undetected. Motor problems usually cause crises that are expensive and annoying, especially if the problems could have been prevented in the first place. Many motor faults can be avoided if the application, the environment, and the cause-effect of motor faults were understood (Maier 1992). Reliability demands for electric motors are constantly increasing due to the importance of motor applications and the advancement in technologies.

Usually, induction motors are protected by devices such as fuses, overload relays, and circuit breakers. So far, research has been focused on:

- (i) different motor failure mechanisms;
- (ii) analyses of the causes of stator and rotor failures;
- (iii) methodologies to determine whether a motor is suitable for extended service;
- (iv) test methods and test equipment and their applications and limitations; and
- (v) data gathering, specific benefits, and costs (Bonnett and Soukup 1988; Schump 1989; Soukup 1989; Maier 1992).

In addition to developing motor protection schemes in reaction to faults caused by misoperations, disturbances, and sudden failures, *on-line monitoring* of induction machines in critical applications has been increasingly necessary to improve the machines' reliability and to minimize catastrophic failures. *Microprocessor-based monitoring* systems are of particular interest because they can be used for regular analyses of machine variables and for predicting possible fault conditions, so that preventive maintenance can be organized in a cost-effective manner.

Many technical articles have addressed the importance and economic benefits of on-line monitoring and fault detection schemes for motors. General methods of cost-benefit analysis have been applied to investigate the financial viability of such systems. A method for the evaluation of the improvement of machine reliability made by such monitoring systems can be found in (Pailletti and Rose 1989; Siyambalapitiya and McLaren 1990).

1.2. Current Methods of Motor Fault Detection

Many engineers and researchers have focused their attention on incipient fault detection and preventive maintenance, which aims at preventing major motor faults from occurring. Different *invasive* and *non-invasive* methods for motor incipient fault detection (from disciplinary areas such as electrical, mechanical, and chemical)

have been reported in (Boothman and Elgar 1974; Timperley 1983; Sood, Fahs et al. 1985; Sood, Fahs et al. 1985; Keyhani and Miri 1986; Nassar 1987; Cambrias and Rittenhouse 1988; LaForte, McCoy et al. 1988; Natarajan 1989; Chow and Yee 1990; Das 1990; Chow and Yee 1991; Chow and Yee 1991; Isermann and Freyermuth 1991; Isermann and Freyermuth 1991; Gupta and Culbert 1992; Chow, Sharpe et al. 1993; Costello 1994). *Non-invasive* schemes are those which are based on easily accessible and inexpensive measurements to predict the motor condition without disintegrating the motor structure. These schemes are most suitable for on-line monitoring and fault detection purposes. An objective of incipient motor fault detection should be to detect faults within the existing motor design without reducing the reliability of the motor. Due to their economical and non-destructive features, most engineers often prefer non-invasive techniques.

Many motor incipient fault detection schemes can be applied *non-invasively* on-line without the need of expensive monitoring equipment by using microprocessors. With proper monitoring and fault detection techniques, the incipient faults can be detected in their early stages. Thus, maintenance and downtime expenses can be reduced while also improving safety.

The usual motor incipient fault detection procedure requires engineers and researchers to devote a significant amount of time and effort to investigate the specific motor system with which they are working. They use their knowledge and experience to identify appropriate variables to be monitored, design appropriate fault detection schemes and choose the correct parameter settings for their tasks. They may rely upon machine theory or system theory to design their fault detection schemes. The end result is a highly compact motor incipient fault protection scheme that is not transparent and understandable for other people. Usually, the detection schemes and parameter settings developed are very specific to the system under investigation. Today, we still do not have a generic theory or methodology suitable and convenient for solving most incipient fault detection problems. Because of this, and due to the lack of *heuristic* explanations and the flexibility to adapt the developed schemes to different motor systems, knowledge in the area of motor incipient fault detection is difficult to disseminate to the public, thus hindering the growth of knowledge in this area.

1.2.1. Model-Based Methods

Each of the fault detection methods developed to date has its own advantages and disadvantages. Some techniques require expensive diagnostic equipment and/or off-line fault analysis to determine the motor condition. For instance, the *radio frequency* scheme injects radio frequency signals into the stator winding of a machine and measures the changes of the signal waveform to determine whether the winding insulation contains faults. This technique requires expensive equipment and is justified only for use with large and expensive machines. Another popular technique is *particle analysis*, which requires bringing motor oil samples to a laboratory for analysis to determine the motor condition and is therefore more suitable for overhaul or routine check-up rather than for on-line monitoring and fault detection. Other methods of fault detection include *vibration analysis* and *thermal signature* (Boothman and Elgar 1974; Stone, Lyles et al. 1991).

Motor owners and engineers alike prefer non-invasive, inexpensive, and reliable fault detection techniques. Many of the inexpensive and non-invasive techniques available for fault detection and diagnosis in motors, such as *parameter estimation* (Keyhani and Miri 1986) and other *model based* techniques, are based on mathematical models of the system of interest (Isermann and Freyermuth 1991; Isermann and Freyermuth 1991). However, since most machine dynamics are non-linear and stochastic, many assumptions must be made regarding the system to arrive at a simple and reasonable mathematical model of the machine. In other words, the fault detection or diagnosis system is not robust enough in the presence of noise and perturbations because the underlying mathematical model of the system is not well represented.

The *parameter estimation* technique is widely used, even though it requires an accurate mathematical model and an elaborate understanding of the system dynamics based on a set of system parameters. These system parameters are usually chosen to reflect the motor conditions. For example, the motor's *bearing* condition will affect the *damping coefficient* of the motor's *mechanical equation*. As the bearing wears out, the damping coefficient increases. So, the parameter estimation approach uses the motor's mechanical equation and measurements (such as rotor speed) to estimate the value of the damping coefficient. After estimating the numerical values of the chosen parameters, in this case the damping coefficient of the motor, a means to translate the estimated numerical values to a qualitative description, such as a *good* or *bad* bearing, is required. The major difficulty with the

parameter estimation technique is that an accurate mathematical system model (e.g., the motor's mechanical dynamic equation) is required, which in most cases is difficult to obtain. In addition, the interpretation of the fault conditions — which is a fuzzy concept (Zadeh 1965; Klir and Folger 1988; Zimmermann 1991; Chow 1997) — using rigorous mathematical formulations is generally impractical and inaccurate.

1.2.2. Human-Based Methods

An *experienced* engineer or maintenance person can diagnose a motor's conditions based on its operating environments and measurements (Figure 1.1) without knowing the exact mathematical model of the motor. The approach is simple and often reliable, and the complicated relation between the motor fault conditions and the measurements is implicitly embedded in the engineer's knowledge about the motor.

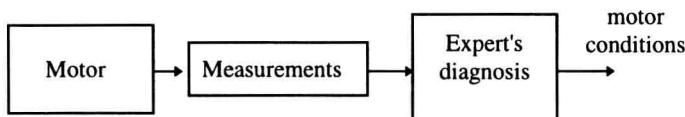


Figure 1.1. Experts' motor fault detection and diagnosis process.

This *human expertise* approach has many advantages over several mathematical model-based fault detection schemes, such as the *parameter estimation* approach. An experienced engineer can usually detect and diagnose motor faults by observing the motor's operating performance, without knowing or understanding the exact system dynamics. Unfortunately, experienced engineers are expensive and difficult to train. It is desirable to automate system monitoring and fault detection schemes rather than to rely on a few experienced engineers to perform continuous on-line monitoring. Furthermore, such experienced engineers may not be able to give detailed explanations regarding the reasoning and logic used to make the decisions, simply because experience is difficult to describe accurately in exact terms and be transferred and automated. Researchers and engineers usually transfer experience and knowledge through linguistics and mathematics, which can be time consuming, ambiguous and inaccurate. In actuality, the experience and knowledge used by expert engineers to perform motor fault detection and diagnosis are also implicitly *embedded* in the historical fault detection data previously gathered by the experts.