

# The Investigation of Motor Production Test Indicators in Qualitative Research Methods

Yao-Chin Lin, Ching-Chun Yeh, Yi-Shien Yang, Wei-Hung Chen, and Jyun-Jie Wang

**Abstract**—This research is based on the concept of smart manufacturing, with the case of a motor manufacturing line. Explore the relationship between the project content in the finished motor data and all processes of pre-engineering, coils, and assembly. The objective of this study is to improve the efficiency of motor quality control inspection. The method is mainly to use expert interviews and secondary data to collect case company data. This study finds that: 1. This research is based on the initial 88 testing items, of which 14 items can be referenced in the motor manufacturing process. 2. This study proposes the relevant parts and production steps corresponding to these 14 items, which can evaluate the error points from the values of the motor finished product inspection items and simplify the time spent in quality control inspection. Finally, this study proposes practical implications and future research recommendations.

**Index Terms**—Motor production, test indicators, qualitative research methods.

## I. INTRODUCTION

This study takes the case of the company's motor production line as the research object. The motors produced must be tested before they can be shipped, because the test indicators of the motor are very important, and the customer order for the motor production line is quite large. In the operation and assembly of personnel, the operation is not adjusted in accordance with the production data, which is likely to cause the loss of secondary products and subsequent costs. Therefore, this study analyzes the motor test indicators.

Research questions are as follows:

1. What are the indicators for motor testing? How to reduce these indicators?
2. What indicators correspond to the processes that need to be improved on the production line?

## II. LITERATURE REVIEW

A study pointed out that in order to achieve Industry 4.0, horizontal integration, vertical integration, and networked manufacturing systems through value-added networks, and

end-to-end data integration of engineering in the entire value chain should be considered. Through data, production line management can be more comprehensive. Product data can see all problems that occur in the production process [1]. The potential applications and key advantages of big data in traditional manufacturing are the ability to sense and predict market demand, improve product and service design, improve product quality and output, optimize workshop logistics, control and reduce energy consumption, provide predictive maintenance services and Intelligent spare parts prediction service, accurate prediction of remaining life, optimization of recovery decisions and reduction of environmental impact. The application of big data is almost indispensable [2]. Human resources issues in urban smart production [3], issues of reducing environmental pollution through smart manufacturing [4], intelligent information security management fields of various industries involved in safety information technology [5], etc., both internally and externally As so many topics are related to data, it is one of the necessary tools to reach the smart factory.

Therefore, the case company should introduce the necessary data application mode in smart manufacturing when making operational decisions, link the data of motor finished product inspection with the manufacturing process, and quickly select from them when secondary products occur. Make mistakes, and clarify the reasons and steps for negligence, so as to continue to improve motor products.

The key indicators of motor manufacturing can be summarized as follows [6]:

The latest trend in the manufacturing of squirrel-cage induction motors is to replace the manufactured copper rotors with aluminum die-casting rotors to reduce manufacturing costs. During the die-casting process, the pores of aluminum die-casting squirrel-cage rotors will inevitably be introduced, which will cause the performance of the motor to decline [7]. Multiple RFID sensors can be used to continuously identify castings and process-related data for decentralized storage. Combining KBS and ML technologies can be used to optimize process parameters in the casting process [6]. A study mentions condition monitoring technology for rotor fault detection, which can be used in the production process to accurately diagnose defective products [8], or special signals injected into the stator terminals by a filter to stimulate rotor fault modes [9]. The rotor size, material and topology were studied, and the torque, mechanical constants and tangential hard force values of the squirrel-cage rotor volume were analyzed, and a solution for high-speed operation was proposed [10]. As for how manufacturers should strive to comply with the

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minimum energy consumption standards, research indicates that the rotor parameters change with slip, and a new method for separating the short-circuit reactance in the stator and rotor components has also been proposed [11].

Especially for the stamping process, which uses different techniques to cut out the circuit board, there are several sensor methods that can monitor tool wear based on conventional microscopic measurements, measured punch pressure, audio signals or vibration signals [6]. Based on this, machine learning technology can be used to monitor or control the stamping process. In finite element simulation technology, the relevant accurate values such as the width of the damaged material area are determined, and then analyzed to improve the operating parameters and efficiency [12]. Monte Carlo simulation (MCS) method was used to evaluate the reliability of the residual magnetism in the rotor core of the induction motor. The data model was used to analyze the failure density function, cumulative failure distribution function, survivor function, danger model, success and failure probability [13]. Certain manufacturing steps may produce by-products in the form of scrap, which, for the most part, are electrical scrap produced when stamping stator and rotor core laminates. Therefore, the quality inspection of the cut piece and the entire laminated core can be performed with the help of computer vision [14].

There are different alternatives to stator slot insulation, such as insulating paper, powder coatings, or cast polymer insulation materials. Machine learning algorithms can help model the process and determine the optimal process parameters [6]. One study used DoE statistical methods to identify the effects of different operating factors and their corresponding interactions on insulation life, conducted accelerated aging tests, and analyzed the results to track the parameters that have the most effect on insulation life [15]. Another study analyzed the changes in voltage, current, and temperature of high-temperature heating during the coil immersion process, and concluded that polyimide-coated fiber coils have a better theory of thermal stability [16].

2D transient and eddy current field analysis values are called through MATLAB to calculate the typical full load performance of stator windings with different air gap lengths. It is found that the factors of stator windings and air gap lengths can effectively improve the efficiency of induction motors [17]. The ML-based method can conveniently model the relationship between process parameters (such as wire tension and winding speed) and winding errors (such as excessive contact resistance or insulation damage) [6]. Through the analysis of torque and magnetic flux pulsation, the angle between the shaft, the current and the switching frequency data, using graphics analysis and other methods to improve the operating performance of the entire system. Frequency [18]. In addition, the robotic arm captures force feedback data from the force sensor through the haptic device and a force sensor installed at the end of the robotic arm to drive the haptic device to feedback the tactile feedback to the operator. Computer vision may be suitable for automatically detecting faults in the supplied wires or finished coils [19].

The term "contact" refers to the process step of connecting

conductive components to each other in order to establish mechanical and electrical contact to ensure good current flow [20]. There is a condition monitoring system for the thermos-compression process, which evaluates the potential of the ML algorithm in ultrasonic crimping by evaluating two different use cases [6]. Crimping is common in power and data cables. One study increased the electrical conductivity of carbon nanotube (CNT) materials to a level that competes with metal conductors, while maintaining other advantages to reduce weight and improve environmental toughness, and monitor data from it. Changes in bending resistance, environmental stability, and contact resistance have successfully demonstrated that nanoscale conductors may become a new technology in wiring design [21]. Big data technology also helps the safety of workers and the maintenance of the environment. For example, a study mentioned the ultrasonic welding process, the heat, radiation, noise, gas and other data generated by it can cause skin damage, finger injury and burns. Such as occupational injuries, environmental pollution will also cause pollution, these factors will affect the operation and reputation of a company in the long term [22]. In order to quickly evaluate the quality of electrical contact, a simple continuity test was performed on the test samples to determine the number of single wires for electrical contact. This part was also optimized using machine learning techniques [23].

Sensor-based sensor bearing signal fusion has high accuracy, fast diagnosis efficiency, and the diagnosis result is significantly better than other motor bearing fault diagnosis, which can be used to diagnose the actual motor bearing fault [24]. ML can be used for quality management, process control and predictive maintenance in the milling process. The proposed model focuses on the prediction of surface roughness and cutting force, and the estimation of tool life and wear [6]. Tool wear is one of the important parameters to be considered for machining sustainability. By monitoring and predicting tool wear data, it can reduce poor surface integrity and then reduce the scrap rate, thereby improving sustainability. In the experiment, an image of the worn side of the cutting insert was captured through a camera on the system without having to remove it from the tool holder [25]. The spindle power data method is used to observe the data such as the wavelength frequency and the sound pressure amplitude range to determine the cutting speed to facilitate the improvement in the subsequent processes. An electric milling spindle was also installed on the spindle test bench and equipped with multiple sensors to identify temperature and shaft deflection when the spindle was running [26]. One study may achieve weight reduction through AM of shaft parts, while reducing pollution during manufacturing [27].

A study pointed out the best design of "manufacturing process loss", analyzing the relationship between the magnetic flux barrier, rotor slot arrangement and motor performance to ensure that the motors are synchronized while meeting ultra-high efficiency [28]. For HRC fault diagnosis in permanent magnet synchronous motor drive systems, the fault phase can be located through the calculated resistance deviation, and the severity of the fault can be

estimated [29]. In the manufacturing process of magnets, machine learning selects and installs magnets or magnet stacks according to algorithms to minimize deviations from the ideal rotor simulated magnetic field [6]. The model in this article can reproduce the time evolution of the electrical and mechanical quantities of the motor (such as current, power, torque speed, etc.). The purpose is to maintain fast and accurate models for the induction motor state. These models are self-training, Expert system for monitoring and identifying these failures [30].

The final assembly of the motor assembly includes connection steps such as press-in operation, gluing, shrinking, tightening or welding. In addition to the improvement of a single connection technology, a data-driven approach can also be added from a wide range of applications [6]. In the research, machine learning technology was used to create a new method of visual servo control to improve the control speed and accuracy of the robot winding copper wires on the narrow stator teeth of the motor, thereby avoiding collisions. In addition, cost planning also has great advantages. Manufacturing costs include tool costs, machine costs, and labor costs [31]. A study analyzes the cost of the stamping machine when manufacturing the motor stator. The blanking force, thickness, length, area, cost and other data are provided as a reference for designers [32].

According to the above indicators, motor production can be summarized into 8 steps:

1. Production of housings and squirrel-cage rotors, 2. Laminated core production, 3. Insulation and impregnation Winding, 5. Contact, 6. Shaft production, 7. Production of permanent magnet rotor, 8. Final assembly and testing.

The above cases illustrate the importance of importing data. Whether it is the data of the production process or the data of the respective state of the product, it can make the production process flexible and diversified. This study intends to observe the data of the finished motor product. The abnormal value of the project indicates that the related parts and processes have been neglected, and finally the problem point is found in the production process.

### III. RESEARCH DESIGN

#### A. Instrument

In this study, a Japanese company commissioned a case company to produce a motor production line and explored the test data of its testing machine to establish a standard procedure for quality management.

This study method used the method of secondary data collection and expert interview. This study invited two case company managers to interview, one is the head of production line design, and the other is the head of the motor design department. The outline of the interview is as follows:

##### 1) The first interview

Questions about motor test data and secondary data, time: November 27, 2019, interviewees: Manager Chen, Manager Xu. Motor test data and secondary data related issues:

(1) What role does the number item of defective products

represent?

(2) The number of defective products shows which part of the motor has a defective test result?

(3) The measurement conditions are No. 201 to 235, No. 245 to 247, and No. 250. In which step do I need to look at the measurement conditions?

##### 2) The second interview

For these 48 detection items (the original 88 items were deleted, the 40 items that detect clockwise rotation were deleted, because there is only one direction now), the problem was proposed, time: February 14, 2020, interviewee: Manager Chen. Questions related to 48 testing items:

(1) Which structure and component of the motor are tested for these test items?

(2) Is there any error in the initial inference process corresponding to the project of the M4 measurement standard?

#### B. Data Analysis

Collection of secondary data includes: Motor production line SOP, Motor tester manual. Interviews: conducted using audio recordings and verbatim versions.

TABLE I: MOTOR TEST ITEM LIST

| Items of Motor test equipment Measurement Standard |            |   |  |
|--|------------|---|--|
| No   | Code       | Operating   | Influences   |
| 1  | No Max     | Set no-load speed.<br>(Be sure to set)  | Motor performance confirmation.  |
| 2  | No Min     |   |  |
| 3  | IO Max     | Set no-load current.<br>(Be sure to set)  | Motor performance confirmation.  |
| 4  | IO Min     |   |  |
| 5  | Nr Max     | Set rated load speed.<br>(Be sure to set)   | Motor performance confirmation.  |
| 6  | Nr Min     |   |  |
| 7  | RI Max     | Set rated load current.<br>(Be sure to set)   | Motor performance confirmation.  |
| 8  | RI Min     |   |  |
| 9  | Is Max     | Set starting current.<br>(Be sure to set)   | Check motor coil specifications and magnetization.   |
| 10   | Is Min     |   |  |
| 11   | Ts Max     | Set starting torque.<br>(Be sure to set)  | Check motor coil specifications and magnetization.   |
| 12   | Ts Min     |   |  |
| 13   | Kt Max     | Set torque constant.<br>(Be sure to set)  | Check motor torque.  |
| 14   | Kt Min     |   |  |
| 15   | To Max     | Set loss torque.<br>(Be sure to set)  | Check the size of mechanical damage.   |
| 16   | To Min     |   |  |
| 17   | TouchR Max | Set the contact resistance between the brush and the commutator.  | Check brush contact.   |
| 18   | TouchR Min |   |  |
| 32   | IoUnst     | Upper limit of no-load current change during inspection time.   | For detecting defects that increase rapidly after startup.   |
| 33   | SurgeV     | Set the upper limit of the surge voltage between the motor terminals when the voltage is applied to the motor on/off. | Detect the damage and welding failure of the ring varistor in the motor.                           |
| 35   | Chatte     | Set the upper limit of the total time for the Io waveform to fall to GND in one turn.                                 | Check the bounce when the brush and commutator rotate.   |
| 36   | StartV     | Set start voltage and start time.   | If the time is too short, the shaft may not rotate. Check the interference when the motor rotates. |
| 82   | Insu V     | Insulation voltage, resistance and voltage rise be sure to set.   | Is the coil insulated, will it be electrified, confirm the short circuit of the motor?             |

### C. Summary of Interview Results

There were originally 88 detection items mentioned in the secondary data, 1 ~ 40 items detected the clockwise rotation (CW) motor, 40 ~ 80 items detected the counterclockwise rotation (CCW) motor, 81 ~ 88 items were judged badly, but The motor produced by the company has only one counterclockwise rotation direction, so the testing items are considered as 1 to 40 items, 81 to 88 items, and reduced to 48 items to discuss. After the first interview and the second interview, the items that need to be detected are found in the SOP secondary data, which are the no-load rotation number, no-load current, fixed-load rotation number, fixed-load current, starting current, and starting torque. , Torque constant, loss torque, brush contact resistance, fluctuation, surge voltage, chattering, start-up voltage, insulation resistance, and then the operation and influence are discriminated (see Table I).

Through the second interview, this research analyzes which components will affect the project results and cause abnormal conditions. Some of the more special components, such as the rotor core, can be seen from the loss of torque data to see if they are abnormal. The data of brush contact resistance, fluctuation, surge voltage, chattering and start-up voltage are checked for abnormality. Therefore, this study deduces that the abnormality of components is used to find the relevant production line, which is convenient for personnel to make corrections and detection.

## IV. FINDING

The complete production process of the motor is divided into the front engineering production line, the coil production line and the assembly production line. The first two production lines are the various parts and assembly products required for manufacturing the assembly production line, such as a single part base connected to a single part. The brush is an assembly product, and the assembly production line is the final assembly operation of each assembly product, that is, the final stage of production of the finished product. Next, the SOP manual provided by the company is used as the secondary information and discussed in the previous interview. The results are analyzed for these testing items. When the value is not within the standard range, it means that there is an error in the middle of these production processes. The following numbers correspond to it:

As shown in Fig. 1, if the number of no-load rotations, no-load current, fixed-load rotations, fixed-load current, starting current, starting torque, and torque constant are abnormal, it can be deduced that the bearing group in the production line before the motor Insertion, magnetic ring assembly, permanent magnet cast magnetic assembly and spring, permanent magnet magnetization, Flux test process, winding in the motor coil production line, bearing assembly, bearing distance inspection process, coil assembly in the motor assembly production line, Motor press assembly process, these steps may be negligent.

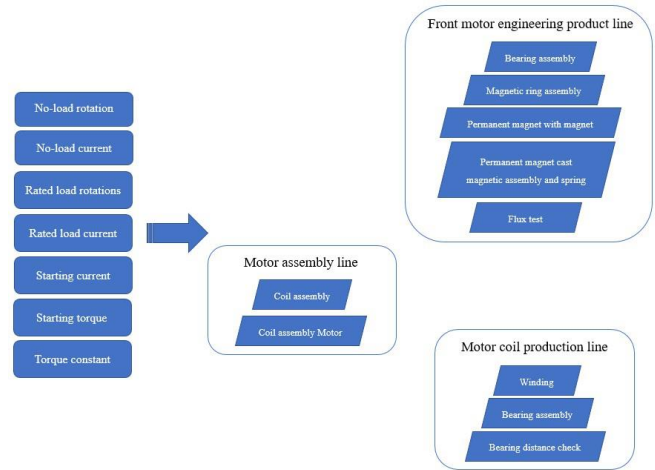


Fig. 1. Production process to be reviewed for the first 7 test items.

As shown in Fig. 2, if the value of the lost torque is abnormal, it can be inferred that the rotor assembly, magnetic ring assembly, permanent magnet cast magnetic assembly and spring, permanent magnet magnetization, Flux test process, and motor coil production in the motor front engineering production line. The rotor spot welding and rotor cutting processes in the line, and the motor press-fitting assembly process in the motor assembly line, these steps may be negligent.

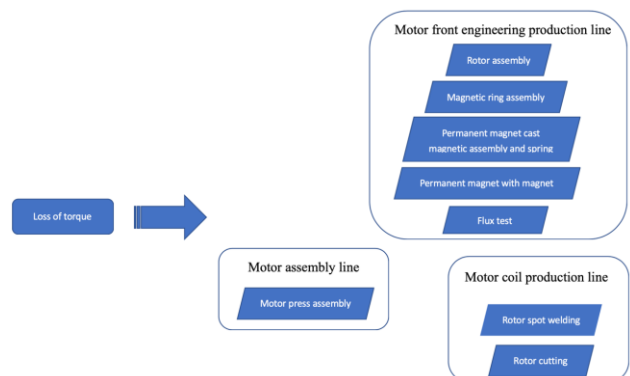


Fig.2. Production process to be reviewed for the 8th test project.

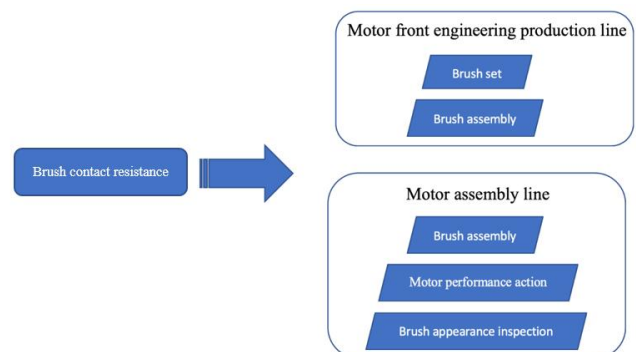


Fig. 3. Production process to be reviewed for the 9th test project.

As shown in Fig. 3, if the value of the brush contact resistance is abnormal, it can be deduced that the brush assembly and brush assembly assembly processes in the motor front engineering production line, and the brush assembly assembly and electric assembly in the motor assembly production line. Brush appearance inspection, motor performance action flow, these steps may be negligent.

As shown in Fig. 4, if the values of fluctuations, surge voltages, and chattering are abnormal, it can be deduced that the brush assembly, brush assembly assembly process in the motor front engineering production line, and the winding process in the motor coil production line. The coil assembly, brush assembly assembly, brush appearance inspection, and motor performance action flow in the motor assembly production line may be negligent.

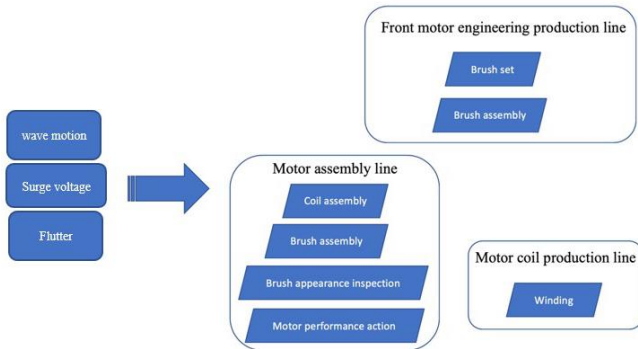


Fig. 4. Production process to be reviewed for the 10th, 11th, and 12th test items.

As shown in Fig. 5, if the value of the starting current is abnormal, it can be inferred that the brush assembly, brush assembly assembly, permanent magnet casting magnet assembly and spring, permanent magnet magnetization process, and motor coil in the motor front engineering production line. The winding process in the production line, the coil assembly in the motor assembly production line, the brush assembly assembly, the brush appearance inspection, and the motor performance action flow. These steps may be negligent.

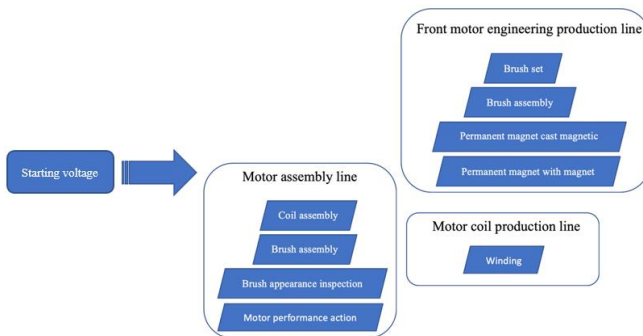


Fig. 5. Production process to be reviewed for the 13th test project.

As shown in Fig. 6, if the value of the insulation resistance is abnormal, the winding process in the motor coil production line and the coil assembly process in the motor assembly production line can be deduced. These steps may be negligent.

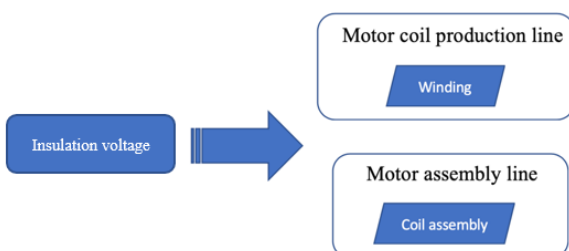


Fig. 6. Production process to be reviewed for the 14th test project.

In summary, when there is a defect in the finished motor product, it will be more efficient to use the data review method to find the faulty process. As for the problem of which part of the production line, it can infer from the status of the motor operation. Using the assembly sequence of the motor parts to reverse test or disassemble, judge that it should be a problem that belongs to the former engineering production line, coil production line or assembly production line, in order to correct and review the mistakes.

## V. DISCUSSION AND CONCLUSIONS

### A. Conclusions

This study is consistent with the research literature [6]. Big data analysis and prediction can be used to manage the motor production line. The 14 detection indicators analyzed through this study can improve all the processes of the previous motor production line by human inspection. Instead, it will affect the shutdown of the production line and cause a large amount of loss. At the same time, the accumulation of motor secondary products will continue to increase. Therefore, by simplifying the correction process through the numerical changes of the items in the data, it can quickly know the possible problems of each component in the production process.

### B. Practical Implications

The motor test indicators of this study were analyzed from the original 88 test items and found that the test data had only the same direction, so it was reduced to 40 items. Through interview methods, only 14 indicators are important reference items in this study.

In terms of management practice, these 14 indicators can be explored in depth. The problems of future motor production lines can be reflected in the improvement of the production process through the 14 indicators analyzed in this study.

### C. Recommendations for Future Research

Future research can be carried out in several directions. Big data analysis is performed through the 14 indicators analyzed, and related data and information of other existing component production processes are analyzed to find out the correlation with the data of motor products. You can also analyze other products other than motors, such as the research of medical equipment, sanitary equipment, water valves and other products.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

Yao-Chin Lin, Ching-Chun Yeh, Yi-Shien Yang, Wei-Hung Chen and Jyun-Jie Wang jointly designed the research and prepared the manuscript. All authors have read and approved the final manuscript.



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