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# A fault diagnosis system for CNC hydraulic machines: a conceptual framework

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***Abstract***
*The fault diagnosis process in Computer Numerical Control (CNC) hydraulic machines for steel processing relies on skills, experiences, and maintenance technicians' understanding of the machine. The problem is many junior maintenance technicians are inexperienced and unskilled. This paper proposes a conceptual framework for a fault diagnosis system for the CNC hydraulic machine to help a maintenance technician in a fault diagnosis process. The framework uses association rule mining to discover hidden association patterns between fault symptoms and causes from historical machine fault data. The framework has consisted of data standardization, knowledge acquisition, and a model of the fault diagnosis system. The data standardization aims to make the data ready to be mined by assigning a fault tag for each record of historical fault data. The tagged repair records are used to produce symptoms–cause associative knowledge. The produced knowledge is refined by corrective actions acquired from expert knowledge. The knowledge is then stored in the fault knowledge database in the form of IF-THEN rules. The reasoning machine is developed to map the fault symptoms as IF and the causes as THEN. Production operators can fill in the fault symptoms by choosing the standardized fault symptom tag. When a maintenance technician reviews a fault report, the system, through a reasoning machine, will access the appropriate IF-THEN rules based on the fault symptoms that the production operator has filled in. The system concludes the fault cause and recommends suitable corrective action.*



***Keywords:***
*Association rule;*
*CNC;*
*Diagnosis;*
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*Framework;*
*Hydraulic;*
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## INTRODUCTION

Fault diagnosis is a process of collecting as many details as possible to determine the fault in a system [1], such as a manufacturing system. The fault in the manufacturing system needs to be dealt with as fast as possible to make manufacturing processes smooth and continuous [2]. The diagnostics procedure is done by observing fault symptoms and using heuristic knowledge of the process to determine the corrective actions.

The hydraulic system is one of the technologies used in many manufacturing machines, especially steel processing machines. This technology allows raw materials to be processed in such a short time. The liquid is pumped by a hydraulic pump, flowing through a circuit designed in such a way as to pierce raw materials in one stroke [3]. Figure 1 illustrates a punch tool pressed by hydraulic pressure to make holes in a raw steel material.

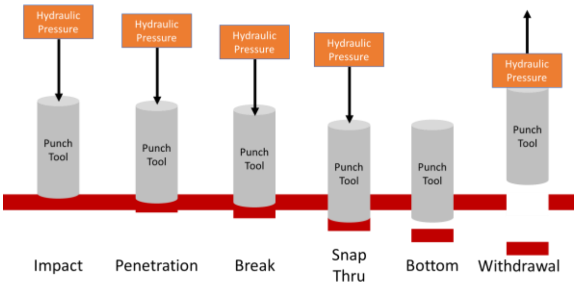


Figure 1. Step-by-step Punching Process that Utilizes Hydraulic Technology

The fault diagnosis has its main challenges, especially regarding knowledge representation, the introduction of prior knowledge, the typical fault symptom distributions, and the data size and representation. The first step in a fault diagnosis process is extracting information regarding the machine fault (feature extraction) [1]. Maintenance technicians then analyze and plan corrective actions based on that information. Skills, experiences, and maintenance technicians' understanding of a machine are important so the maintenance technicians can make the correct way to fix the faults [1]. The issue is that many junior maintenance technicians are inexperienced and unskilled. Lacking skills and experience would lengthen a repair process as it will need much more time to diagnose a machine's fault that causes a company's loss. Based on these problems, a system is needed to assist maintenance technicians in diagnosing machine faults.

Previous works have been carried out to design a fault diagnosis system. Most of these works use sensors to read a condition of a system that is being diagnosed. For example, some studies use vibration signals to diagnose bearing defects [4] and centrifugal machines [5] using neural networks and a wavelet transform. In the case of a hydraulic system, a sensor is used to monitor important parameters such as oil condition, working pressure, and vibration. The data from these sensors is collected to discover fault patterns in the hydraulic system using a wavelet transform [6][7], Kalman filter [6][8], PSE-Autogram [9], neural network [10][11][12], and Dempster-Shafer's theory [13][14]. Table 1 shows a summary of fault diagnosis methods for the hydraulic system in previous works.

As a system, a CNC hydraulic machine for steel processing includes hydraulic components and other components such as electrical and mechanical components. In the previous works, the fault diagnosis system was designed specifically for a certain part of a hydraulic system. Furthermore, these techniques heavily depend on sensor reading, which could not be implemented on machines with no sensors installed. Adding sensors to those machines would incur additional costs, especially if they were implemented in many machines, not to mention the complexity of the installation process and integration required for these sensors to function properly.

This paper proposes a conceptual framework to discover fault patterns from historical machine fault data. To the best of our knowledge, only a few studies discuss fault diagnosis models for hydraulic systems that use historical fault data as the main data source. As a result, association rule mining, introduced in [15], is used to discover association patterns between fault symptoms and fault causes on CNC hydraulic machines for steel processing. The association patterns are generated in the form of IF-THEN rules. Then, the system performs the diagnostic process by mapping the fault symptoms to fault causes based on the IF-THEN rules that have been generated. Compared to other data mining techniques, this technique does not require a large data set and is easy to understand [16]. This is because it only needs historical machine fault data, and the framework does not need sensor reading, so it could be easily implemented in many machines.

Association rule mining has been applied in previous works as a method to extract knowledge related to fault causes. The first study uses association rule mining to diagnose the fault in distribution terminal units [16][17][18]. The mining process is carried out to discover association patterns between fault causes and fault symptoms using historical fault data. The same technique is also adopted to find fault patterns in building energy systems [19], air handling units [20], automatic teller machines [21], thermal power plants [22] and transformers [23][24]. In comparison with Table 1, Table 2 shows a list of studies that have used faulty historical data.

Table 1. A Summary of Fault Diagnosis Methods for The Hydraulic System in Previous Works

| Year | Object | Methods | Data Source |
|---|---|---|---|
| 2010 | Hydraulic Systems | Kalman Filter [8] | Pressure Sensor |
| 2011 | Hydraulic Systems | Fuzzy Logic [25] | Pressure Sensor, Flow Sensor |
| 2014 | Hydraulic Systems | Dempster-Shafer [26] | Pressure Sensor, Flow Sensor, Temperature Sensor, |
| 2012 | Hydraulic Systems | Knowledge Base [27] | Expert Knowledge |
| 2015 | Hydraulic Systems | Multivariate Statistics [28] | Vibration Sensor |
| | Hydraulic Pump | Wavelet Transform, [29] Singular Value Decomposition, Support Vector Machine | Vibration Sensor |
| 2016 | Hydraulic Pump | Neural Network [30] | Vibration Sensor |
| 2018 | Hydraulic Leakage | Neural Network [10] | Pressure Sensor |
| | Hydraulic Pump | Neural Network [11] | Vibration Sensor |
| 2019 | Hydraulic Leakage | Wavelet Neural Network [31] | Pressure Sensor |
| | Hydraulic Leakage | Neural Network [12] | Pressure Sensor |
| | Hydraulic Valves | Principal Component Analysis [32] | Vibration Sensor, Pressure Sensor, Flow Sensor, Electrical Power Sensor, Temperature Sensor |
| 2020 | Hydraulic Pump | Autogram [9] | Vibration Sensor |
| | Hydraulic Valves | Dempster-Shafer [13] | Vibration Sensor |
| | Hydraulic Pump | Wavelet Transform [33] | Vibration Sensor |
| 2021 | Hydraulic Valves | Neural Network [14] | Vibration Sensor, Image Sensor |
| | Hydraulic Pump | Neural Network [34] | Vibration Sensor, Pressure Sensor, Sound Sensor |
| | Hydraulic Pump | Wavelet Transform [7] | Vibration Sensor |
| | Hydraulic Systems | Neural Network [35] | Vibration Sensor, Pressure Sensor, Flow Sensor, Electrical Power Sensor, Temperature Sensor |

Table 2. A List of Studies that Have Used Fault Historical Data

| Year | Object | Methods | Data Source |
|---|---|---|---|
| 2010 | Transformer | Association Rule Mining [24] | Fault Historical Data |
| 2014 | Distribution Network | Association Rule Mining [18] | Fault Historical Data |
| 2015 | Transformer | Association Rule Mining [23] | Fault Historical Data |
| 2016 | Thermal Power Plant | Association Rule Mining [22] | Fault Historical Data |
| 2017 | Power Distribution Unit | Association Rule Mining [17] | Fault Historical Data |
| 2018 | Automatic Teller Machine | Association Rule Mining [21] | Fault Historical Data |
| 2020 | Air Handling Unit | Association Rule Mining [20] | Fault Historical Data |
| 2021 | Distribution Terminal Unit | Association Rule Mining [16] | Fault Historical Data |
| 2022 | Building Energy Systems | Association Rule Mining [19] | Fault Historical Data |

As shown in Table 1 and Table 2, sensors are used in nearly all of the development of fault diagnosis models for hydraulic systems. In addition, association rule mining can be used as an alternative to model fault diagnosis for CNC hydraulic machines, particularly when historical machine data faults are the only available data. Thus, strengthening the suitability of the association rule mining to be applied in this case study.

## METHOD

Formulating the conceptual framework of a fault diagnosis system for CNC hydraulic machines consists of four stages: problem identification, literature review, identification of variables, and development of the conceptual framework. The first stage is started by conducting a study and analysis of the current machine repair procedure and facility in a steel tower company. The second stage is carried out by reviewing relevant literature through search engines on the internet using keywords such as "fault diagnosis", "hydraulic fault diagnosis", "pump fault diagnosis", "valve and accessories fault diagnosis", and "knowledge base fault diagnosis", since 2010. This review aims to determine the suitability of the methods to the company's conditions. This paper also conducted a literature review to study the concept of fault diagnosis by using association rule mining as the proposed method. The keyword "fault diagnosis association rule" is used as an additional keyword in addition to the previously described. The third stage is determining which variable will be used in the framework based on available data and methods. The historical machine fault data will be used as the main data source for the mining process through association rule mining to generate associative knowledge between fault symptoms and fault causes in the form of IF-THEN rules. Finally, the framework can be developed based on the earlier three. The system uses the IF-THEN rule to find the fault causes based on the fault symptoms information received by the system. Figure 2 shows the step-by-step solution framework in this paper.

## RESULTS AND DISCUSSION

### Current Repair Procedures

A machine repair process is begun when an operator issues a fault report using a form in the computer. The report is connected to the maintenance technician and the maintenance technician can review the report from the web browser. The maintenance technician will then check the machine for fault symptoms and ask the operator for other details information. After performing diagnostics procedures by collecting and analyzing machine status and fault symptoms, the maintenance technician then plans corrective actions.

Before performing corrective action, the maintenance technician needs to check the availability of spare parts required for the corrective actions. If the spare parts are not available, the maintenance technician needs to fill in the spare parts purchase request to the procurement department. The repairing process is on hold until the spare parts are received. Otherwise, the maintenance technician can continue to perform corrective actions if the spare parts are already available. Alternatively, the maintenance technician can utilize a used spare part that is still functional with a shorter life span while waiting for the arrival of the new spare part. The maintenance technician can also make a temporary fix so the machine can run again, but some functions need to be turned off.

After performing the corrective actions, the maintenance technician will check whether the fault is solved. If the fault is solved, the maintenance technician updates the fault report by filling in the fault cause and corrective actions. On the other hand, if the fault is not solved, the maintenance technician must recheck the machine status and fault symptoms for other fault probabilities. This repair process is presented in Figure 3.

### Association Rule Mining

Association rule mining is a data mining technique that aims to discover association patterns from a dataset [15]. The formation of associative rules is done by counting the occurrence frequency of the combination of an event compared to all available data (support). The combination has then measured the probability that if event A takes place, then event B will occur as well (confidence). This relationship is demonstrated in (1) and (2).

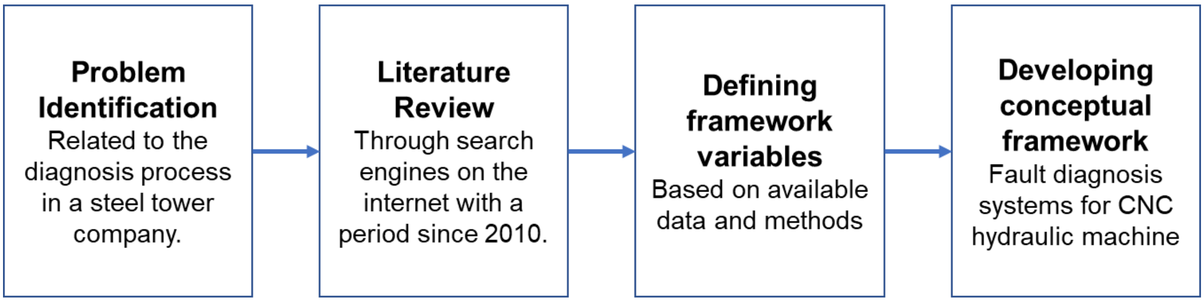


Figure 2. Research Methodology

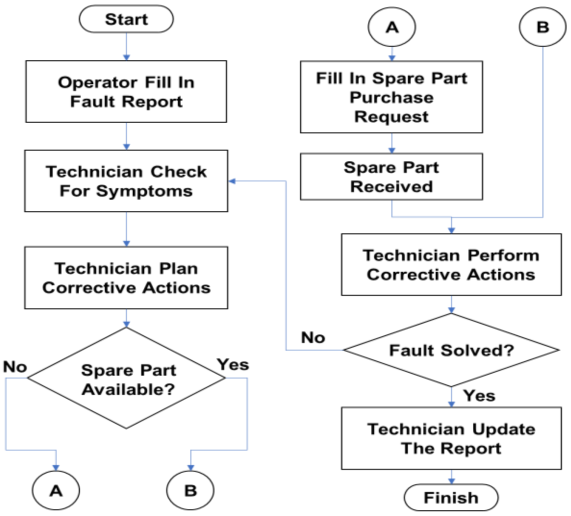


Figure 3. Machine Repair Flowchart

$$Support\ (A \rightarrow B) = \frac{\sum Records\ contain\ A\&B}{Total\ Records} \quad (1)$$

$$Conf.(A \rightarrow B) = \frac{\sum Records\ contain\ A\&B}{\sum Records\ contain\ A} \quad (2)$$

The frequent item calculation process can be performed using several algorithms. For example, one can use the apriori algorithm. This algorithm was first designed by Agrawal and Srikant in 1994 [36] and has been used successfully in many studies since then. In this algorithm, the frequency of events combination is calculated one by one, so the computer will scan the dataset repeatedly. This algorithm is easy to implement but requires large resources and a long time because it must scan the dataset repeatedly [16].

The formed associative rules are then selected based on the minimum support (minsupp) value and minimum confidence (minconf) value. This means that for every rule whose support value is smaller than minsupp, or the confidence value is lower than minconf, then the rule cannot be used as a valid association pattern. The minsupp and the minconf values are determined by the user at their desire.

## Framework Variables

The whole process, from the operator creating a fault report until the maintenance technician fills in the fault cause and corrective action, is recorded on the historical machine fault data. The record consists of attributes, as presented in Table 3.

Table 3. Historical Machine Fault Data Attributes

| Attribute | Description | Data Type |
|---|---|---|
| Report Time | Time of report created | DateTime |
| Machine ID | Machine that having fault | String |
| Symptoms | Descriptions of known fault symptoms | String |
| Causes | Descriptions of fault causes | String |
| Action | Descriptions of performed actions to solve the fault | String |
| Finish Time | Time of fault | String |
| Operator ID | Person who created the report | String |
| Technician ID | Technician who fixes the fault | String |
| Status | Such as 'OPEN', 'ON GOING', 'FINISH' | String |

## Developing the Framework

The fault symptoms data is obtained when the production operator fills in the fault report. This data contains the production operator's explanations about the machine abnormalities in the form of text (e.g., "Machine cannot clamp raw material"). Whereas the fault causes data is obtained after the maintenance technician finishes repairing the machine in the form of text (e.g., "Hydraulic valve is dirty and clogged up"). Due to differences in the ability of machine operators and maintenance technicians to explain the situation, the data inputted to the database are not standardized, and may contain misspelling (e.g., pump is written as "pumpp"). Non-standard data can result in an ineffective mining process and invalid knowledge.

To overcome this problem, standardization of fault historical data can be done by providing label tags for each fault record. The tagging process is done by reviewing each record. Only after that can the association rule mining be conducted by calculating the support and confidence value for each tag.

The association rule mining process generates symptom–cause associative knowledge with certain minsupp and minconf values. The knowledge is then refined by proper corrective action knowledge obtained from expert knowledge. This can be obtained by interviewing an expert maintenance technician, machine manual, or using relevant literature. The refined knowledge is then stored in the fault knowledge database in the form of IF-THEN rules.

The reasoning machine is then developed to map the fault symptoms as IF and the fault cause as THEN. Production operators can fill in the fault symptoms by choosing the standardized fault symptom tag. When a maintenance technician reviews the fault report, the system, through a reasoning machine, will access the appropriate IF-THEN rules recorded in the fault knowledge database based on the fault symptoms that the production operator has filled in. The system then concludes the fault cause and recommends suitable corrective actions. Figure 4 shows the complete illustration of the conceptual framework of fault diagnosis for CNC hydraulic machines.

## Discussion

Theoretically, the key to the success of implementing this conceptual framework lies in the standardization of fault symptoms and fault cause data. If there are new fault symptoms or fault causes that have not yet been labeled, the maintenance department can register the fault symptoms and causes as new labels.

With the standardization of the fault symptoms and fault causes, the fault knowledge database can be updated regularly to produce more accurate knowledge for the diagnostics process.

The framework is only not limited to CNC hydraulic machines but also in principle, this framework can be implemented to develop various fault diagnosis systems for other machines, as long as, fault historical data is available. Nevertheless, further investigations are needed to measure the effectiveness of the system developed through this framework.

## CONCLUSION

This paper proposes a conceptual framework for a fault diagnosis system that is not mainly dependent on a sensor reading. The framework is developed using historical machine fault data mined through association rule mining to generate associative rules between fault symptoms and fault causes. The fault diagnosis framework for CNC hydraulic machines for steel processing consists of three parts. The first part is data standardization of historical machine fault data.

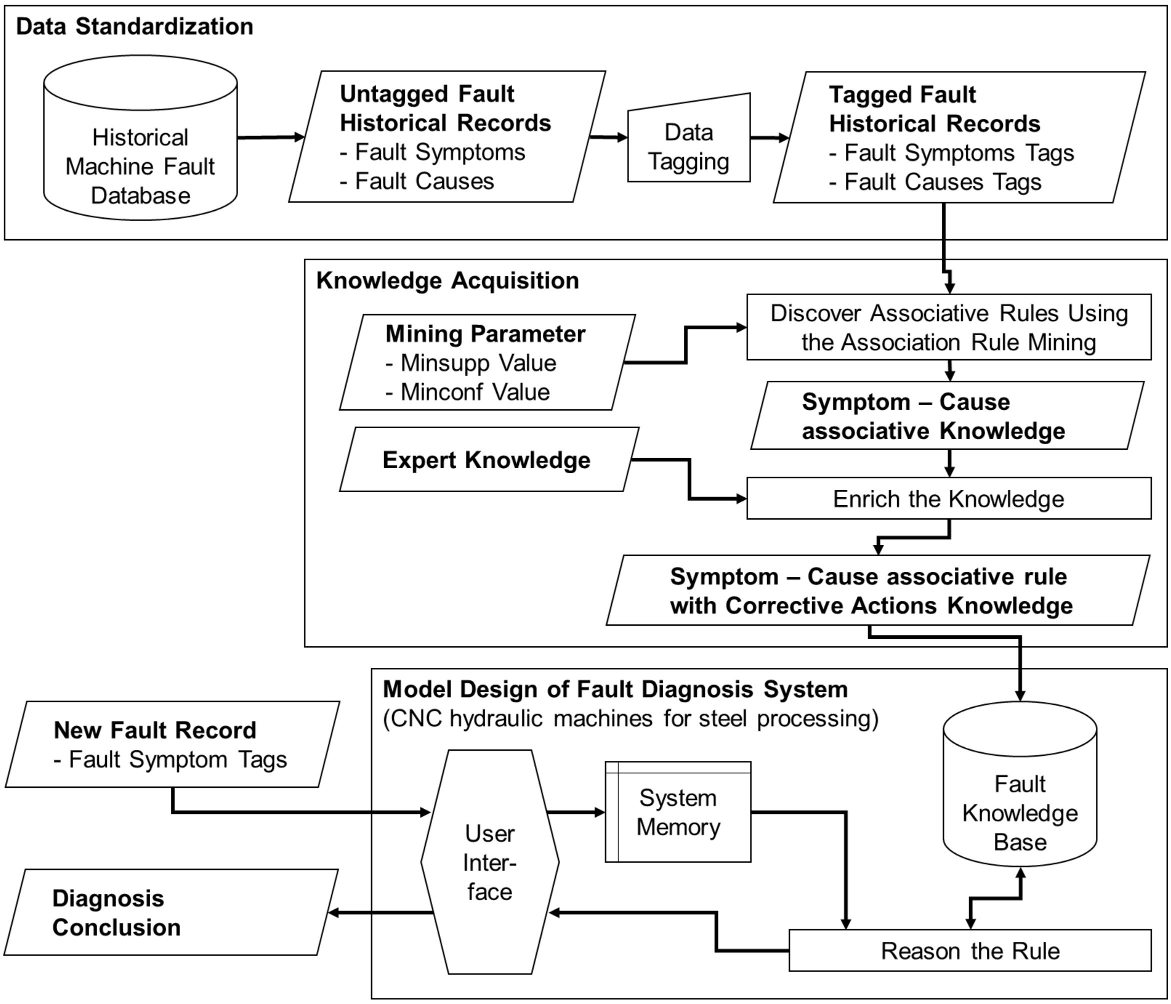


Figure 4. Conceptual Framework of Fault Diagnosis System for CNC Steel Processing Hydraulic

The standardization is performed by providing label tags for each fault record. The second part is knowledge acquisition. The association rule mining is applied to produce symptom–cause associative knowledge in the form of IF-THEN rules. The knowledge is refined with corrective action knowledge from experts. The third part is the model design of the fault diagnosis system for CNC hydraulic machines. The system uses a reasoning machine to fault symptoms into fault causes. Further research is advised to compare technicians' performance with and without the system to assess the system's efficacy.

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