Intelligent Fault Diagnosis System for Enhancing Reliability of Coil-Spring Manufacturing Process

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Abstract

The condition of the manufacturing process in a factory should be diagnosed and maintained efficiently because any unexpected disorder in the process will be reason to decrease the efficiency of the overall system. However, if an expert experienced in this system leaves, there will be a problem for the efficient process diagnosis and maintenance, because disorder diagnosis within the process is normally dependent on the expert's experience. This paper suggests a process diagnosis using data mining based on the collected data from the coil-spring manufacturing process. The rules are generated for the relations between the attributes of the process and the output class of the product using a decision tree after selecting the effective attributes. Using the generated rules from decision tree, the condition of the current process is diagnosed and the possible maintenance actions are identified to correct any abnormal condition. Then, the appropriate maintenance action is recommended using the decision network.

Keyword: coil-spring manufacturing process, diagnosis, CBM, data mining

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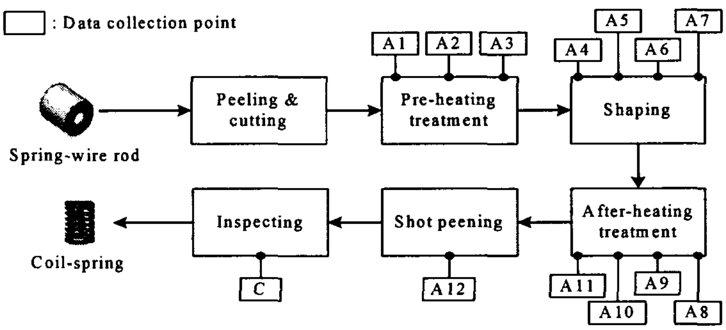
1. Introduction

Even though the quality of a product is more dependant on intelligent facilities, a negligible error or disorder in the process can cause a catastrophic failure in the system. Also, any unexpected process disorder can decrease production capability and the quality of a product. To avoid an unexpected process disorder, it is necessary to increase the reliability of the process with effective maintenance (Lee, 1996). There are three kinds of maintenance: Break-Down Maintenance (BDM), Time-Based Maintenance (TBM), and Condition-Based Maintenance (CBM). In BDM, the maintenance is performed when the disorder occurs. TBM is preventive maintenance based on pre-defined time intervals. Compared to these types, CBM is a more proactive maintenance to minimize the maintenance cost and to maximize the availability of the process (Williams, 1994). The CBM model can be established with data collected in real time.

In this paper, we suggest an intelligent diagnosis model for the coil-spring manufacturing process using data mining. Typically, the coil-spring manufacturing process is consists of six stations: peeling & cutting, pre-heating treatment, shaping, after-heating treatment, shot peening, and inspecting.

Figure 1 shows the coil-spring manufacturing process. In the peeling & cutting station, spring-wire rod is peeled to the appropriate diameter and cut the appropriate length. In the pre-heating treatment station, the rod comes from the peeling & cutting station has a heat treatment for the next shaping station. The pre-heating treatment softens the spring-wire rod to shape a coil-spring more easily. In the shaping station, the rod is coiled. The after-heating treatment station and shot peening station increase the product qualities such as intensity and tenacity. In the inspecting station, the produced coil-spring is inspected for height, hardness, and so on.



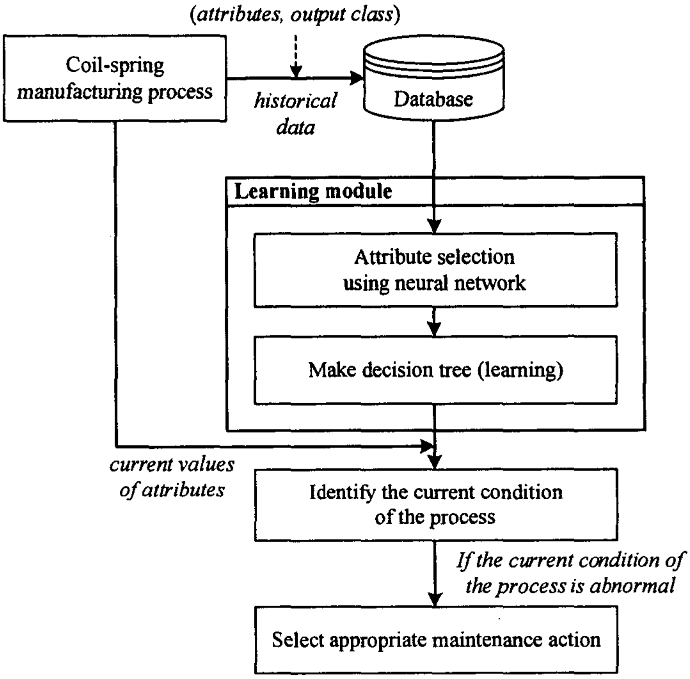
< Figure 1 > Coil-spring manufacturing process.

For an intelligent diagnosis in the coil-spring manufacturing process, a decision tree is utilized for analyzing the relationship between the attributes and the output class of the process. As shown in Figure 1, attributes represent the status of stations in the process, and the output class represents the height of coil-spring which is the end-product of the process. In Figure 1, the data collection points are marked. A_i is the attribute(where $i=1,2,..$),12 and C is the output class. Most of the attributes are located in the pre-heating treatment and shaping station because these stations affect the output class more strongly. The attributes and output class are explained in Table 1.

< Table 1 > Attributes and output class in coil-spring manufacturing process.

	Name	Description	Type	Range of value
Attributes	A1	Temperature of burner	Continuous	960±20 ℃
	A2	Moving speed of working beam	Continuous	10.6±0.5 mm/min
	A3	Staying time in pre-heating station	Continuous	49.8±1 min
	A4	Coiling time	Continuous	106.6±1.5 Sec
	A5	Pressure of hydraulic power	Continuous	40~80 Kg/m^2
	A6	The status of the servo valve	Discrete	Normal/Abnormal
	A7	Temperature of hydraulic fluid	Continuous	30~55 ℃
	A8	Temperature of the oil in the direct quenching tank	Continuous	40~60 ℃
	A9	Passing time in the direct quenching tank	Continuous	12.4±20 min
	A10	Temperature of the tempering	Continuous	420±10 ℃
	A11	Passing time in tempering	Continuous	180±5 min
	A12	The status of sand for shot peening	Discrete	Normal/Abnormal
Output class	C	Height of coil-spring	Discrete	--, -, 0, +, ++

Generally, the Markov decision process is used for solving CBM problems expressed as sequential decision making problems. However, the Markov decision process has a drawback in expressing the ideal CBM model, because it has an assumption that the transition probability matrix can express the change of machine status (Putterman, 1994). So, in this paper, we present an intelligent diagnosis model as shown in Figure 2. First, the data for each of the attributes are collected from the process continuously, and stored into the database. To speed up the decision tree learning, attribute selection is performed. In attribute selection module, effective attributes are selected by neural network. After the attribute selection module, a decision tree is generated based on the selected attributes, and the rules are generated by the decision tree. The current values of attributes in the process are applied to the generated rules, and the current condition of the process is diagnosed. If the current condition of the process is diagnosed as abnormal, appropriate maintenance action should be performed.



< Figure 2 > Intelligent diagnosis model.

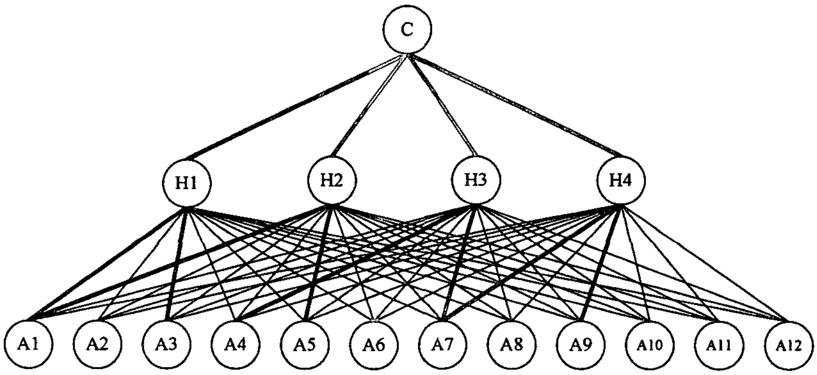
2. Attribute Selection

In today's computerized world, data are abundant, but truly useful information is harder to find. Thus, knowledge discovery in databases and the process of extracting useful information from data are vital. One of the critical aspects of any knowledge discovery process is attribute reduction, also commonly called attribute selection. This determines which attributes contribute something useful for understanding of the data, and should hence be kept, and which attributes can be discarded.

This is important for two reasons. First, determining which attributes are important gives us valuable information in the first place. Second, working with fewer attributes makes the problem of finding classification rules, association, or a prediction model much more tractable. We are currently developing a back propagation network (BPN) analysis of a neural network for the attribute selection problem.

The advantages of neural networks include their high tolerance to noisy data as well as their ability to classify patterns on which they have not been trained. The most popular neural network algorithm is the back-propagation algorithm. The back-propagation algorithm is a supervised learning method for multi-layer perception (MLP) networks with sigmoidal activation units (Fu, 1994). The goal is to find good mapping from input data to output data. When a new data record is fed to a network, the network provides good mapping to the output space by using the intrinsic structure of the training set. This implementation allows the user to use several different training methods. Although the basic training algorithm is slow compared to other methods, it can provide, in some cases, a better representation of the training set.

A major issue in designing a multi-layer neural network is how many hidden units are optimal given a set of training patterns. Some analyses on this issue are avaliable. For example, Micrchandani and Cao (1989) have developed a relationship for this problem. However, their analysis is limited to the case where the activation function is a hard-limiting function. So, in real situations, the number of hidden units can be determined empirically. In our problem, the number of units in hidden layer is determined by SAS Enterprise-Miner® as shown in Figure 3.



< Figure 3 > A neural network for attribute selection.

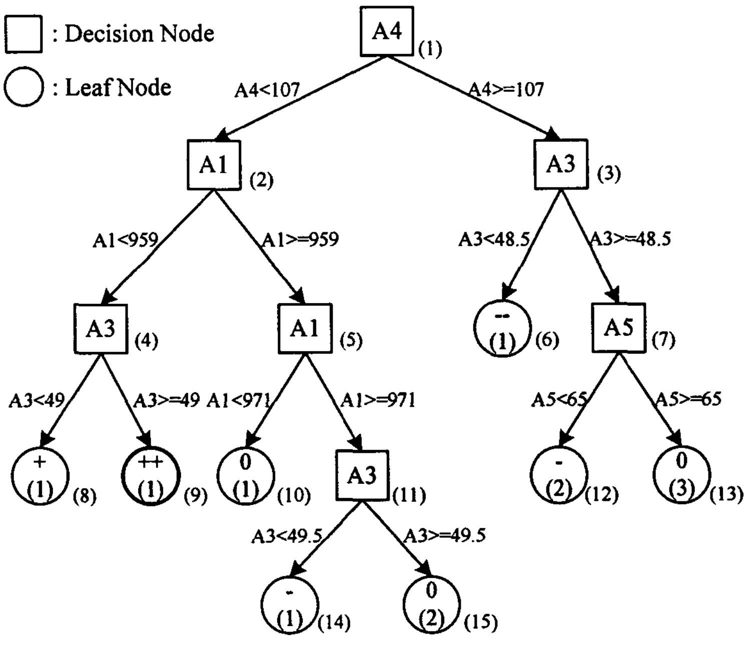
Using Enterprise-Miner®, we evaluated the back-propagation rule with 12 inputs and 1 output. As a result, some attributes affect the output class more strongly. In Figure 3, the strong interconnection is marked as a bold line. We consider a strong interconnection is over 0.5 of weight. This means the interconnections are significantly connected. So, the attributes, A1, A3, A4, A5, A7, and A9 are selected for the decision tree learning.

3. Decision Tree Learning

The decision tree is a powerful and popular tool for classification and prediction. The attractiveness of tree-based methods is due in large part to the fact that, in contrast to neural networks, the decision tree represents rules which can be expressed in English so that humans can understand them easily (Berry, 1997). A decision tree consists of:

- Leaf node that indicates a classification of output class.
- Non-leaf or decision node which contains an attribute name and branch to other decision nodes, one for each value of that attribute.

For constructing a decision tree, C4.5 is used generally. C4.5 is derivative from ID3 (Quinlan, 1986). Information gain is used to select the test attribute at each node in the tree. Such a measure is referred to as an attribute selection measure, or a measure of the goodness of split. The attribute with the highest information gain(or greatest entropy reduction) is chosen as the test attribute for the current node. This attribute minimizes the information needed to classify the samples in the resulting partitions and reflects the least randomness or impurity in these partitions. Such an information-theoretic approach minimizes the expected number of test attributes needed to classify an object and guarantees that a simple tree is found (Han, 2001).



< Figure 4 > An example of decision tree.

In this paper, a decision tree used for the coil-spring manufacturing process diagnosis is constructed by C4.5 using the purified data in attribute selection module. The purified data set consists of {A1, A3, A4, A5, A7, A9}. In the coil-spring manufacturing process, the height of the coil-spring is one of the most important factors. So, in this paper, we use the height of the coil-spring as an output class. Real data and the characteristics of the attributes and output class are informed by D company in Korea.

For diagnosis of the abnormal condition of the process, a decision tree is constructed for generating the rules based on the historical data in database. The output class has 5 values, --(extra less target value), -(less target value), 0(target value), +(over target value), and ++(extra over target value). Automobile manufacturers as customers generally accept the coil spring with the value of output class such as 0, -, or +. So, our policy is to correct the abnormal condition such as ++ or --. We used the Enterprise-Miner® to generate a decision tree as shown in Figure 4. There are 4 attributes (A1, A3, A4, and A5) to affect the output class. From the decision tree in Figure 4, eight rules are generated as shown in Table 2. When the current condition is diagnosed as an abnormal condition by generated rules, the appropriate maintenance action is determined to correct the abnormal condition.

< Table 2 > The rules generated from the decision tree.

Rule 1: **IF**(A4 < 107 AND A1 < 959 AND A3 < 49), **THEN** C = +.
Rule 2: **IF**(A4 < 107 AND A1 < 959 AND A3 >= 49), **THEN** C = ++.
Rule 3: **IF**(A4 < 107 AND A1 >= 959 AND A1 < 971), **THEN** C = 0.
Rule 4: **IF**(A4 < 107 AND A1 >= 971 AND A3 < 49.5), **THEN** C = -.
Rule 5: **IF**(A4 < 107 AND A1 >= 971 AND A3 >= 49.5), **THEN** C = 0.
Rule 6: **IF**(A4 >= 107 AND A3 < 48.5), **THEN** C = --.
Rule 7: **IF**(A4 >= 107 AND A3 >= 48.5 AND A5 < 65), **THEN** C = -.
Rule 8: **IF**(A4 >= 107 AND A3 >= 48.5 AND A5 >= 65), **THEN** C = 0.

4. Maintenance Action

When the current condition of the process is diagnosed as abnormal(Ex: ++(1) in Figure 4), maintenance action should be performed. To select a appropriate maintenance action, we construct a decision network which represents possible paths from the abnormal node to normal nodes. Using a decision network, each possible maintenance action is identified as a path to correct the abnormal condition. After calculating the costs of all possible maintenance actions, the appropriate maintenance action which has the lowest cost is selected.

Methods for constructing decision network and selecting a appropriate maintenance action will be presented in detail. There are two ways of abnormal detection: tight and loose. Loose detection is concerned with a severe situation such as ++ and --. The tight detection is concerned with a severe and possible abnormal situation such as + and - including ++ and --. The loose detection is usually accepted in the field. In our paper, we are dealing with the loose detection.

4.1 Decision Network

The construction procedure of a decision network is simple. When the abnormal situation is detected by loose detection, the procedure to construct the decision network is as follows;

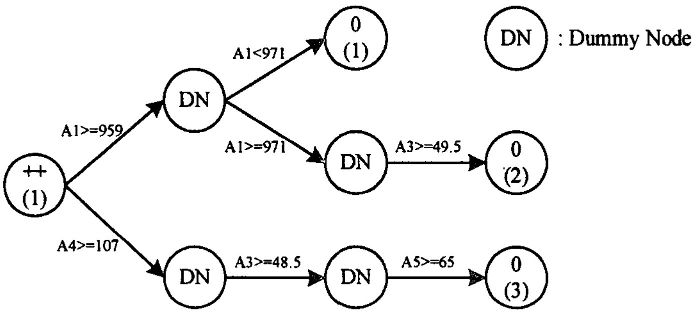
< Table 3 > The procedure for constructing a decision network.

Step 1. Find detected abnormal node
Step 2. Find normal nodes
Step 3. Create paths from the abnormal node to each normal nodes. Repeat sub-step 3.1~3.3 by number of normal nodes founded step 2.
Step 3.1 Set the current location of abnormal node and targeted normal node
Step 3.2 Find the split node for abnormal node and targeted normal node
Step 3.3 Add the arc from the split node to targeted normal node
Step 4. Construct decision network

We will illustrate this procedure with an example. Consider that the current condition of the process is ++(1) in Figure 4. There are three possible normal nodes to correct the abnormal node, ++(1). By step 3 in Table 3, the paths from abnormal node(++(1)) to normal nodes are identified. The three possible paths are as follows:

Path 1 = {(2→5), (5→10)}
Path 2 = {(2→5), (5→11), (11→15)}
Path 3 = {(1→3), (3→7), (7→13)}

The decision network can be constructed based on the possible paths to correct the abnormal condition like the above three paths. As shown in Figure 5, the decision network illustrated is based on the attributes to be adjusted to the correct abnormal condition. In the decision network, the source node is the abnormal node, for example ++(1) and target nodes are the normal nodes. To consider the arcs in decision network, first of all, the actual attributes for adjustment from the abnormal to normal node are identified for each path. Then, the split node is found from the source node and the target node. The arcs are added from the split node to the target node. The arc costs are the adjustment cost for changing the value of the attributes. The end node of each path will be the normal node for each path. Dummy nodes are necessary between arcs as internal nodes.



< Figure 5 > Decision network for ++(1).

4.2 Selecting Maintenance Action

In the constructed decision network for a typical abnormal condition, the possible maintenance actions are identified as paths to correct the abnormal condition. To select the appropriate maintenance action, the cost of each path is calculated, and then the path which has the lowest cost is selected as a appropriate maintenance action. For example, when the condition of the process is diagnosed as abnormal, ++(1), a decision network is constructed like Figure 5. As shown in Figure 5, there are three possible maintenance actions. The cost of each possible maintenance action is calculated as follows:

< Table 4 > Maintenance action cost for each possible maintenance action.

Maintenance action 1 [++(1)→0(1)]: Adjust(A1) = 82500.
Maintenance action 2 [++(1)→0(2)]: Adjust(A1) and Adjust(A3) = 82500+16700 = 99200.
Maintenance action 3 [++(1)→0(3)]: Adjust(A4) and Adjust(A3) and Adjust(A5) = 23000+16700+32600 = 72300.

Table 5 shows the average maintenance cost to adjust an attribute value. These average maintenance costs are presented by D company in Korea. Among three possible maintenance actions, maintenance action 3 has the lowest maintenance cost. So maintenance action 3 is selected as the appropriate maintenance action.

< Table 5 > Maintenance cost (unit: KRW).

Maintenance action	Maintenance cost	Description
Adjust(A1)	82500	Adjust the temperature of burner.
Adjust(A3)	16700	Adjust the staying time in pre-heat treatment.
Adjust(A4)	23000	Adjust the coiling time.
Adjust(A5)	32600	Adjust the pressure of hydraulic power.

5. Conclusion

This paper presents an intelligent diagnosis model for coil-spring manufacturing process using data mining. The intelligent diagnosis model consists of three modules: learning module, identifying the current condition of the process module, and selecting appropriate maintenance action module. The learning module constructs a decision tree with collected data from the process. The identifying the current condition of the process module identifies the current condition of the process using the constructed decision tree and current values of attributes. The selecting a appropriate maintenance action module selects the appropriate maintenance action using decision network. The decision network represents the possible paths from the abnormal node to the normal nodes when the current condition of the process is abnormal. Using a decision network, each possible maintenance action is identified as a path to correct the abnormal condition. After calculating the costs of all possible maintenance actions, the appropriate maintenance action which has the lowest cost is selected.

The further study is applying the CBR (Case-Based Reasoning) technique to our intelligent diagnosis model. Using CBR, a more intelligent diagnosis can be possible and a more effective maintenance action can be selected.

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저 자 소 개

허 준 : 미국 Western Illinois University 경영학과에서 학사 학위를 취득하였으며, 동 대학 대학원 Industrial Technology 학과에서 석사 학위를 취득하였다. 현재 고려대학교 산업시스템정보공학과 박사 과정에 재학 중이며, 관심분야는 데이터 마이닝, KDD, 지능형 기계 진단 등이다.

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