

# Decision Support System for Principal Factors of Grinding Wheel Using Data-Mining Methodology

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**Abstract.** The recommended grinding conditions are described in five factors (abrasive grain, grain size, grade, structure, and bonding material) of the three main elements (abrasive grain, bonding material, and pore) in the grinding wheel catalog data-set. As systematic arrangement is not made, grinding conditions (cutting speed, table feed, depth of cut) have to be decided on the basis of an experienced engineer's information or experience. Moreover, although the setting of the five factors of the three elements of a grinding wheel is important parameter that affects the surface quality and grinding efficiency, it is difficult to determine the optimal combination of workpiece materials and grinding conditions. In this research, a support system for effectively deciding the desired grinding wheel was built by using a decision tree technique, which is one of the data-mining techniques. This system extracts a significant tendency of grinding wheel conditions from catalog data. As a result, a visualization process was proposed in correspondence to the action of the grinding wheel elements and their factors to the material characteristics of the workpiece material. In this report, we produced patterns to support selection of grinding wheels by visualizing the surface grinding wheel selection decision tendency from more amount of data, based on data mixed with JIS (Japan Industrial Standards) and maker's catalog data.

## Introduction

A grinding wheel has three main constituents (abrasive grain, bonding material, and pores), and five principal factors that affect the performance of each constituent (grain type, grain size of the abrasive grain, strength of the bonding material (bonding strength A–Z), degree of porosity (structure 1–14) and type of bonding material). When using a grinding wheel, the results are affected by interactions between multiple factors, so it is necessary to determine the grinding wheel shape and grinding conditions and the most appropriate specification of the above three elements and five factors after considering the material and finish precision of the workpiece. If these conditions are set incorrectly, it can cause loading, shedding, dulling, leaving burn marks, rough finish on the workpiece, resulting in unacceptable end finish and reduced productivity [1]. The setting of grinding wheel parameters is currently a difficult and important issue. In the precedence research, some of the research about decision making of grinding wheel were conducted and promoted automated-decision mechanism of five factors [2]. Machine-learning methods such as neural networks and genetic algorithms have been applied, and many papers on proposals of optimization systems and problem-prediction methods have been written manufacturing field. However, although those predictions are extremely accurate, it is difficult to clearly determine significant factors and conditions for solutions derived from predictive models. Furthermore, it is not possible to visualize the correlation and case classification of factors such as complexly-related variables. Therefore, before applying a machine-learning method, it is important to visualize the structure and correlation of data in advance. In this study, we used the catalog data of grinding wheel makers and JIS standard to perform catalog data mining [3] in order to develop an optimal grinding wheel selection support system. To conduct so, data mining method

called "decision trees" [4] was focused on to construct a system that visualizes the grinding wheel selection decision process and produces patterns to support the selection of grinding wheels for surface grinding.

## Data Mining Method for Grinding Wheel Data-set

### Decision tree algorithm used in this study

The decision trees used in this study are trees for determining principal factors of grinding wheel. To explain this decision tree algorithm, indicators of entropy and gain were used. First, in the state where  $i$  different factors are included among the attributes, if  $p_i$  is the ratio of the total number in an attribute to the total number of each factor, then the entropy ( $H$ ) can be expressed as follows:

$$H = -\sum_{i=1}^c p(i|t) \log_2 p(i|t_i) \quad (1)$$

$t$  is node of decision tree. When this attribute branches into  $k$  classes under certain conditions,  $GI$  (Gini index) is calculated as Eq. (2).

$$GI = 1 - \sum_{i=1}^c [p(i|t)]^2 \quad (2)$$

In the decision tree algorithm, factors for which  $GI$  has a large value are used for branching. By repeating this step, we arrive at a simpler decision tree with greater branching accuracy. Using the decision tree makes it possible to not only visualize the structure and correlation of the entire dataset but also find parameters and criteria important for class determination. By creating a decision tree for each database, it is possible to determine whether certain factors concerning grinding wheels are determined with respect to which attributes of grinding wheels take priority and consider the features and commonalities of branches; as a result, it is possible to construct a system to support grinding-wheel selection. R (CART) as the analysis software for deriving decision trees was used in this study.

### Target data for making decision tree

Table. 1 Data ranges for each predictor and criterion variables

	Maker X	JIS (B4051)
Outside diameter $D$ [mm]	152~762	$D \leq 255$ , $255 < D \leq 455$ , $455 < D \leq 760$
Abrasive grain type	A, RA, RAA, WA, 9A, 32A, 8A, WRA WAA, 97A, GC, 8BW, 7BP, 8BP	WA, PA, HA, GC, C
Grain size	36, 46, 54, 60, 70, 80, 100, 120	36, 46, 60, 100
Bonding strength	F, G, H, I, J, K, L, M, N	G, H, I, J, K
Vickers hardness $HV$	115~2200	12~1900
Elongation $\varphi$ [%]	0.5~60	0.5~60
Tensile strength $\sigma$ [MPa]	314~3900	30~2400
Thermal conductivity $\varepsilon$ [W/(m·K)]	4~80	4~230
Work material	Carbon steel, Alloy steel, Tool steel, Martensitic stainless steel, Austenitic stainless steel, Aluminum alloy, Cemented carbide, Brass, Bronze casting, Ceramics	Carbon steel, Alloy steel, Tool steel, Malleable cast iron, Martensitic stainless steel, Austenitic stainless steel, Gray cast iron, Nodular graphite cast iron, Aluminum alloy, Permanent magnet material

The five factors concerning grinding wheels and type, outside diameter, inner diameter, maximum usable cutting speed, etc. of grinding wheels corresponding to each work material are summarized in the catalog of grinding wheels and JIS (B4051). In general, a grindstone is custom-made according to its targeted use; however, these factors are extracted by data mining that is considered to include at least tacit knowledge and know-how related to the five factors concerning grinding wheels recommended by the maker of grinding wheels and researchers as well as utilization speed, surface-grinding processes (at least for shape) and machine tools, and the characteristics of workpiece materials, etc. In inputting data, it is important to have target factors and explanatory factors as parameters for branching the conditions. In this study, as shown in Table 1, we selected abrasive grain type, grain size and bonding strength out of the three factors and five elements of straight grinding wheels (Type 1), and for the latter, as the workpiece material and grinding wheel conditions, we input the Vickers hardness  $HV$ , elongation  $\phi$  [%], tensile strength  $\sigma$  [N/mm<sup>2</sup>], thermal conductivity  $\epsilon$  [W/(m·K)], grinding wheel outer diameter  $D$  [mm]. In an example application of this data-mining process, we used straight surface grinding wheel as listed in the latest versions of the catalogs of wheel maker X. We also applied it to the combined target data of the JIS (B4051). For inputting the value of workpiece material characteristic, material data book edited by The Japan Institute of Metals and Materials was referenced. A decision tree was prepared for each of abrasive-grain type, grain size, and bonding strength (among the five factors of the grinding wheels described in the catalog) as target elements.

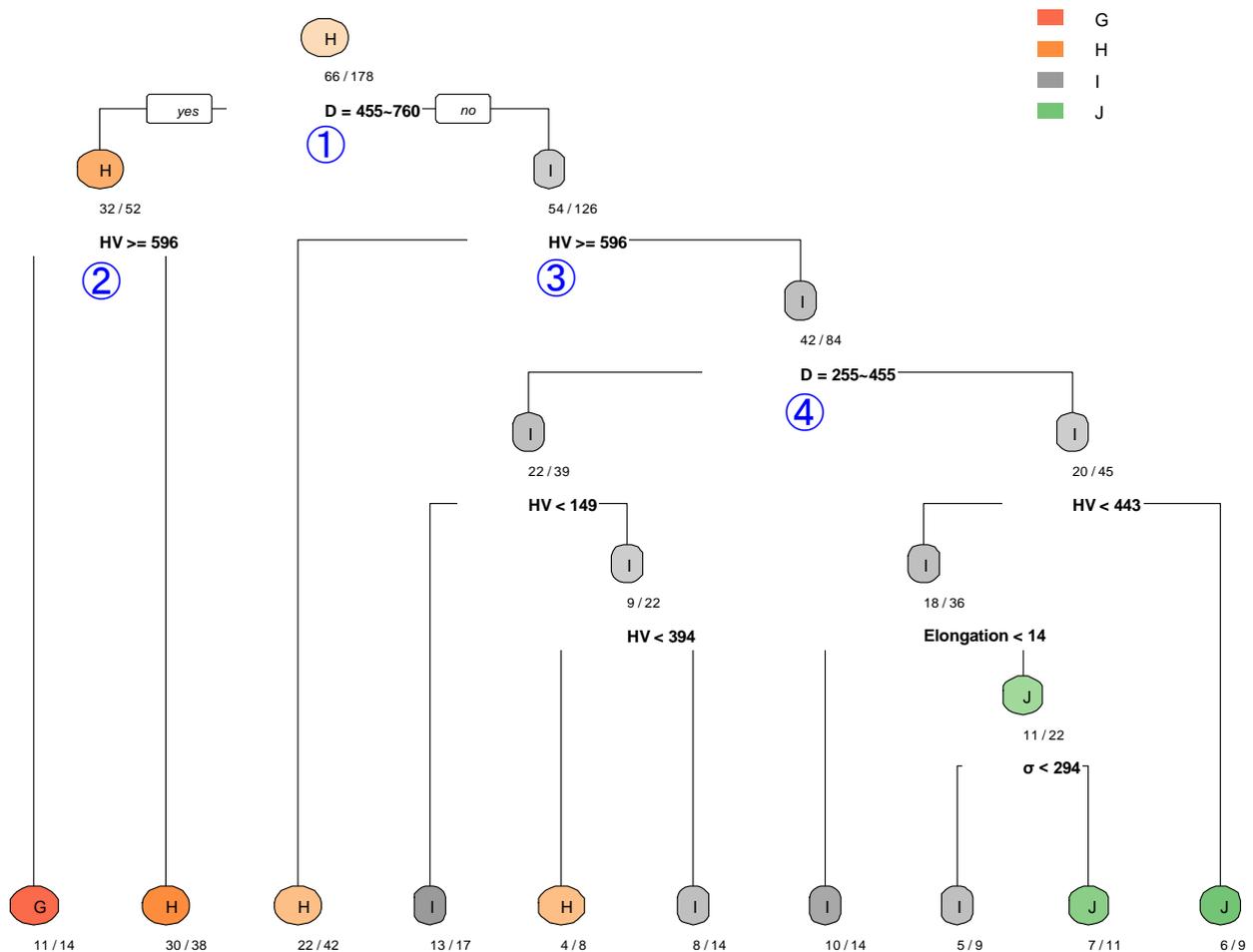


Fig. 1 Example result of decision tree for bonding strength decision.

## Visualization method of extracted knowledge

The main difficulty of deciding on a grinding wheel occurs when the workpiece has high hardness or viscosity. In either case, since it is always necessary to continue cutting with sharp edge, we should select a grinding wheel that promotes the inherent cutting action characteristic of grinding wheels. Figure 1 visualizes the extracted knowledge in conditions summarized from decision trees for bonding strength of JIS standard dataset derived from R (CART) in this study. The two elements that appeared most often in the decision tree are placed on the vertical and horizontal axes, and the branch order of the first branch (thermal conductivity) and second branch (hardness, outside diameter) are shown in Figure 2 (① to ④). When anything other than an element used on the axis appears, it is surrounded by a square in the figure as a branch in another dimension (⑤ and ⑥).

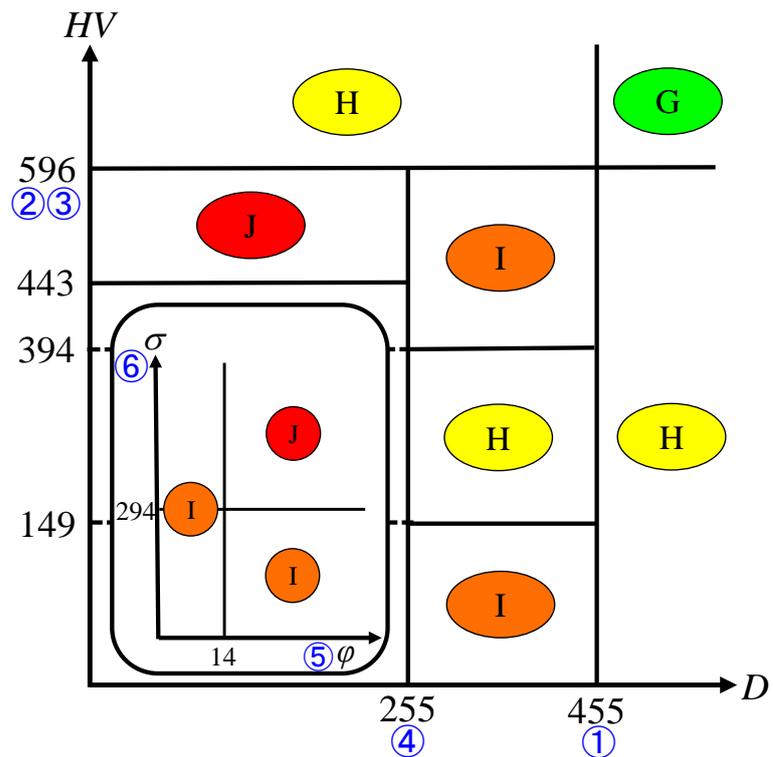


Fig. 2 Visualization map of bonding strength selection.

When anything other than an element used on the axis appears, it is surrounded by a square in the figure as a branch in another dimension (⑤ and ⑥).

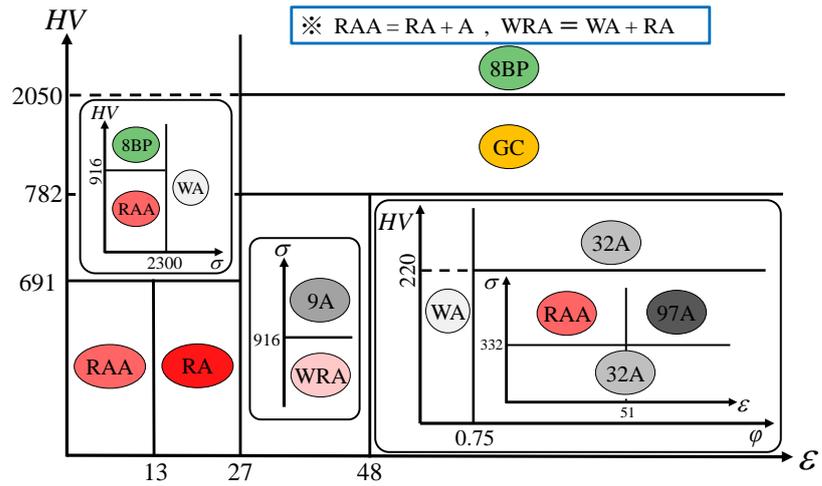
## Results and Discussion

### Grinding wheel selection tendency for maker X

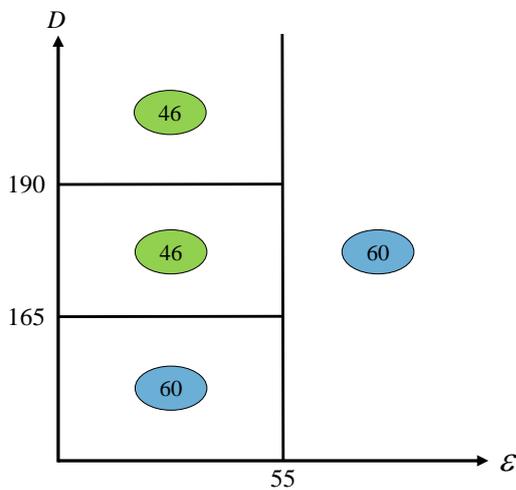
The grinding-wheel-selection guidelines for (a) abrasive-grain type, (b) grain size, and (c) bonding strength of maker X are visualized in Figure 3. According to the figure, as for selecting a grinding wheel for hard workpieces, maker X recommends 8BP (a blend of ceramic abrasive and RAA) or GC with high abrasive-grain hardness and superior grinding performance. As for bonding strength, relatively weak degrees of coupling (to stimulate self-sharpening blade action) are recommended for hard workpieces. If the number of revolutions is constant, as the outer diameter of the grinding wheel increases, its peripheral speed also increases. Therefore, the grinding-point temperature—which determines quality of the grinding surface and amount of wear of the grinding wheel—is likely to rise, so grinding burn is likely to occur. It is clear from Figure 3 that for hard workpieces, it is recommended to select a grinding wheel that facilitates the escape of heat by using a coarse grinding wheel having a small grain size and a weakened degree of bonding of abrasive grains. In addition, in the case that a workpiece with large  $\varepsilon$  surface is ground, the possibility of grinding burn is conceivably reduced because the heat is easily transferred to the workpiece. Accordingly, as shown in Figure 3, it is suggested that when  $\varepsilon$  exceeds 55 W/(m·K), fine-texture abrasive grains with large grain size and abrasive grains with high bonding strength (namely, high I and J) can be used.

### Grinding wheel selection tendency for mixing Maker X and JIS (B4051)

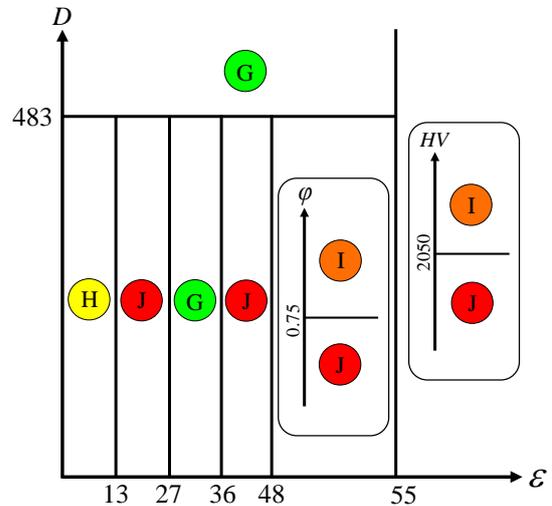
In previous research, which assumed JIS (B4051) as the target database, type, granularity, and organization of abrasive grains were visualized by using a decision-tree algorithm (i.e., C4.5) based



(a) Visualization map of abrasive grain type selection



(b) Visualization map of grain size selection



(c) Visualization map of bonding strength selection

Fig. 3 Grinding wheel factors tendency for maker X

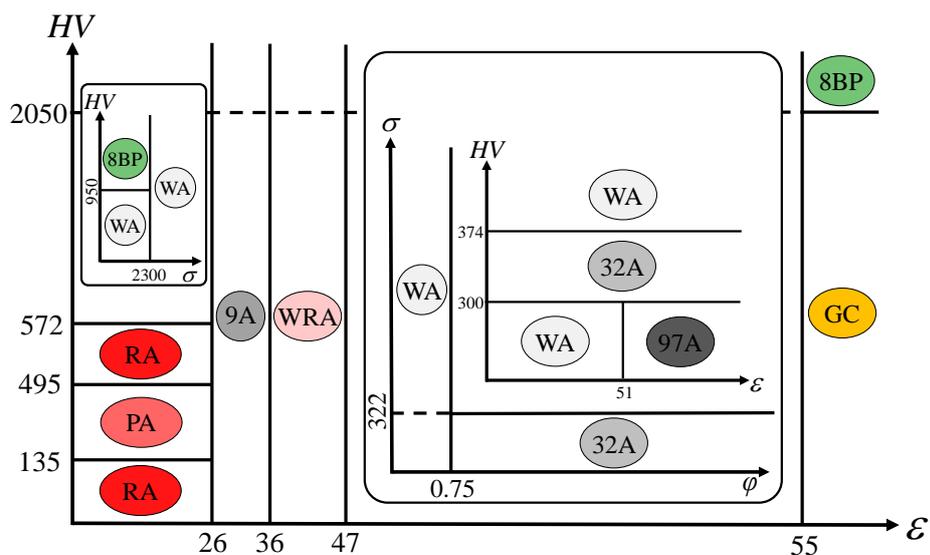


Fig. 4 Grain type selection map and tendency for mixing maker X and JIS(B4051)

on a method of calculating gain value. As a result of applying analysis using JIS (B4051) as a database, it was possible to extract and visualize knowledge that is generally well known to a grinding engineer.

In this study, we aimed to generalize the database by mixing data from the maker's catalog and the JIS database, and we tried to extract meaningful information for determining grinding-wheel factors from a more complicated database. As an example, the guidelines for grinding-wheel selection concerning abrasive-grain type from mixed data of maker X and JIS (B4051) are shown in Figure 4. No significant change in the decision tendency due to mixing the databases can be seen. As shown in the figure, as for selecting a grinding wheel, 8BP or WA, which both have high abrasive-grain hardness and superior grinding performance, is recommended for hard workpieces. Moreover, as for the range of  $HV > 572$  and  $\varepsilon < 26$ , RA abrasive grains and PA abrasive grains, which are suitable for grinding difficult-to-cut materials with low thermal conductivity and high hardness, are recommended. And as for selecting particle size and bonding strength, coarse grain size of 46 at  $\varepsilon < 59$  and bonding strengths G and H at  $D < 455$  are recommended. As for both of these recommended factors, similar to the trend in Figure 3, since the possibility of grinding burn tends to be high in the case of a material with low thermal conductivity, it is considered that the above tendency is recommended so that grinding heat is not concentrated on the processing point. In this way, it was revealed that the trend in determination factors concerning performance of a grinding wheel can be read quickly by applying the decision-tree method to a more-complicated database. As for an original method of data mining, it is desirable to improve extraction accuracy of predictions and knowledge by combined use of multivariate analysis and clustering methods. Accordingly, in the future, it is necessary to propose a data mining system that combines the decision-tree method and cluster analysis and to experimentally evaluate the effectiveness of the system and the accuracy of the derived trends by actually performing surface-grinding processing.

## Conclusion

With the objective of constructing the support system for determining the grinding wheel principal factors, we used decision tree method as data-mining technic to visualize the decision tendency of each factors from makers catalog data and JIS (B4051). The effects of decision tendency from these decision trees are summarized below.

- (1) By applying the decision-tree method for comparing the material properties of a workpiece to databases describing factors of a grinding wheel, it was possible to extract and visualize the knowledge necessary for determining important factors concerning the grinding wheel.
- (2) As for a maker catalog database, it was found that a variety of options for selecting abrasive grains according to the type of workpiece are available.
- (3) It was found that decision guidelines considering the influence of hardness and thermal conductivity of the workpiece are seen as a trend in determining type, grain size, and bonding strength of the abrasive grains.

## References

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