Prediction of Abnormal Grain Growth in Carburized Components Using Bayesian Networks

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Abstract

Abnormal grain growth, which leads to a decrease in the strength of carburized drivetrain components, is a complex phenomenon that is difficult to predict. In this study, we developed a method for predicting the occurrence of abnormal grain growth by constructing a Bayesian network, which was trained using test piece data to simulate cold forging based on the material properties and manufacturing conditions.[1]

1. Introduction

In recent years, the automotive industry is facing a strong demand for a stable supply of high-quality components with short development time to address CASE (Connected, Autonomous, Shared & Services, Electric). With a decrease in the number of skilled engineers and the ongoing digital transformation (DX) at manufacturing sites, efficient methods are urgently required to optimize manufacturing conditions.

Against this industrial background, the optimization of manufacturing processes and conditions using artificial intelligence (AI) has been attracting attention as an effective approach to simultaneously shorten the development time and stabilize product quality.[2] Based on these technological trends, our company has begun developing AI-based technologies to optimize manufacturing processes.

2. Themes and issues

Because drivetrain components are mainly associated with power transmission, they are carburized and tempered at high temperatures to ensure high strength. One of the concerns in this process is the grain growth (G.G.) of the steel crystals, which causes a reduction in component strength (Figs. 1 and 2). This phenomenon is caused by a combination of factors such as the metal microstructure, carburizing temperature, and plastic strain.[3]

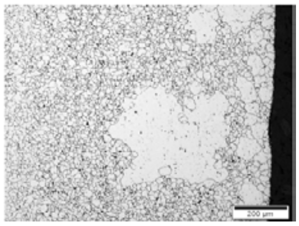

Fig. 1 Example of G.G.

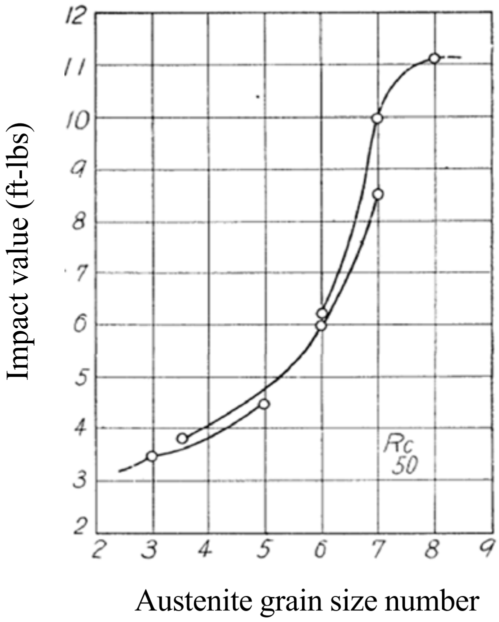

Fig. 2 Strength reduction due to G.G. [4]

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This makes prediction using a simple regression of the parameters difficult, making it necessary to predict by considering the variations in sensitivity that depend on a combination of parameters (Fig. 3).

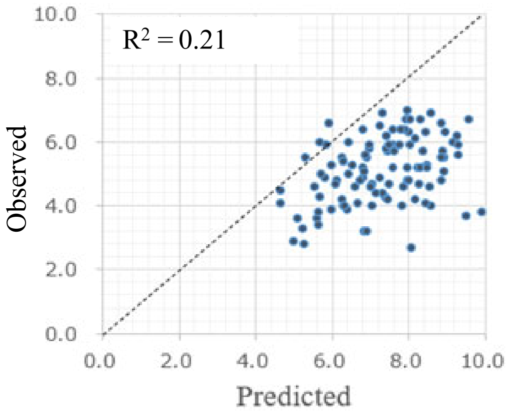

Fig. 3 Multiple regression analysis of post-carburization grain size number based on in-house evaluation test results

In a previous study, the quantitative effects of these parameters on the occurrence of G.G. were reported by varying only certain parameters.[5] However, because other parameters also vary in actual component manufacturing, configuring the component manufacturing conditions based on this previous study is difficult.

Therefore, we aimed to predict the G.G. occurrence using various combinations of multiple parameters that are varied simultaneously.

3. Methodology

In this study, AI was used to predict G.G. occurrence using various combinations of multiple parameters that were varied simultaneously.

The prediction of material properties using AI has been widely applied, mainly for polymeric materials whose properties are determined in a single process.[6] However, few examples of applications exist for predicting the properties of steel components that undergo complex microstructural changes during multiple processes.[7]

In conventional prediction models with simple AI usage, AI tends to learn the relationships between explanatory and objective variables without considering the relationships among explanatory variables. Hence, the prediction cannot adequately consider the effects of a combination of explanatory variables.

Therefore, we decided to use a probabilistic model (hereinafter referred to as a “Bayesian network”) that directly represents the causal structure and reflects existing knowledge (Fig. 4).

We believe that this will enable us to conduct complex and diverse combinatorial studies and ultimately predict the occurrence of G.G.

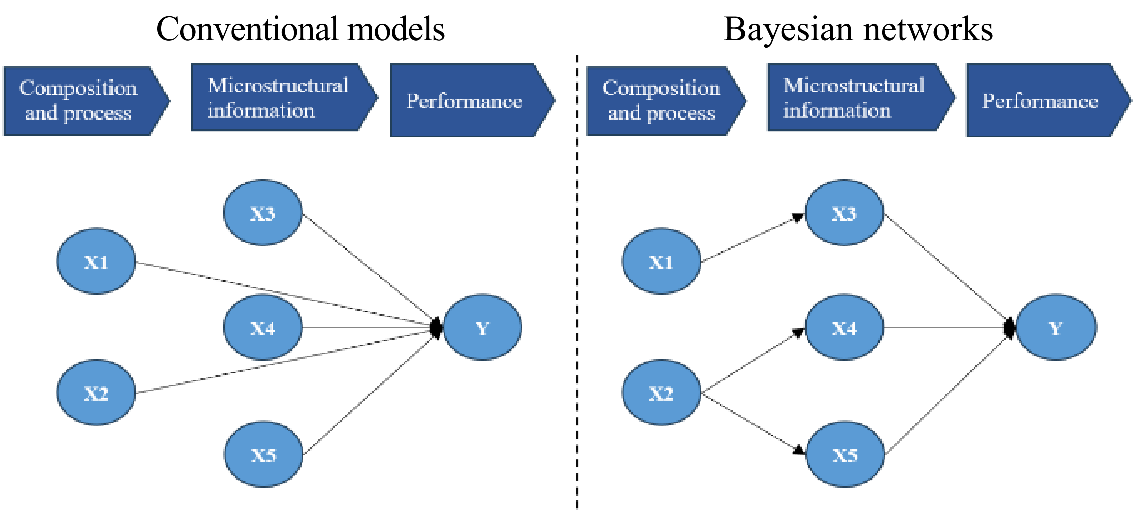

Fig. 4 Comparison between conventional prediction models and Bayesian networks

Generally, Bayesian networks assume a specific distribution, such as a normal distribution, when dealing with continuous values. Therefore, if the actual data deviate from this assumption, prediction accuracy may decrease. However, in this study, the problem was defined as a binary (discrete) classification problem of "whether or not G.G. occurs," thus obviating the need to deal directly with continuous-value data such as grain size. The largest grain size after carburizing was measured according to JIS G 0551, and G.G. occurrence was defined as a largest grain size of 5 or less after carburization.

With such discrete-value data, conditional probabilities can be modeled directly and computation can be performed efficiently without the risk of errors associated with distributional assumptions.

For this reason, we decided to use a Bayesian network based on classification.

4. Analytical procedure

Combination analysis and predictability evaluation utilizing AI were conducted using the results of test piece (TP) evaluations conducted in advance, by varying the parameters, thereby confirming the occurrence of G.G. The TP evaluation was performed by simulating actual component manufacturing, and each parameter was set considering the manufacturing range of the actual components.

In this study, using real data was expected to improve the prediction accuracy of G.G. occurrence without any supplemental AI learning.

To reflect the results of this study on actual component manufacturing, a model was developed to predict the occurrence or absence of G.G. using materials and process parameters that could be controlled during manufacturing.

4.1 Selection of influential parameters

Among the parameters identified as affecting G.G. in the preliminary TP evaluation, we selected those that correlated well with the largest grain size after carburizing.

Among the selected parameters, those that were collinear with the largest grain size after carburization were excluded (Table 1).

Table 1 Parameters affecting G.G.

Orange hatching: selected parameters

Material and forging parameters	Grain size number ave.
	Grain size number σ
	Width of pearlite bands σ
	Width of pearlite bands ave.-σ
	Spacing of pearlite bands σ
	Spacing of pearlite bands ave.-σ
	Shear strain
	Effective strain
Post-cold forming and carburization parameters	Grain size number in carbon segregation ave.
	Grain size number ave.
	Grain size number σ
	Aspect raito
	Angle between pearlite and gerrite
	L×Θ
	τ×migration distance
	Hardness×migration distance of carbon segregation
	Spacing of carbon segregation ave.
	Spacing of carbon segregation σ
	Spacing of carbon segregation ave.-σ
	Width of carbon segregation σ
	Width of carbon segregation ave.-σ
	Carburizing temperature
Post-carburization parameters	Grain size number ave.
	Grain size number σ
	Area fraction of grains with grain size number 5 or less
	Grain size number around the largest grain ave.
	Grain size number around the largest grain σ
	Distance from the largest grain to pearlite bands
	Spacing of pearlite bands ave.
	Width of pearlite bands ave.

4.2 Construction of a directed acyclic graph

Construction of a Bayesian network, requires that the relationships among the variables be represented.

A directed acyclic graph (DAG), which is the basis of the Bayesian network, was constructed based on the principles and relationships between the parameters obtained from the model. Because G.G. is caused by changes in the meta-microstructure during component manufacturing, the model was constructed step by step considering the changes in the microstructure (Fig. 5).

4.3 Discretization of variables

When dealing with Bayesian networks using classification, continuous values should be converted into discrete values.

Therefore, the data for the set of parameters were discretized and classified. Specifically, the parameter values after cold forming and those of carburizing conditions were used to obtain the values (thresholds) that would allow to roughly categorize whether the size of the largest grain was less than 5 after carburizing.

Similarly, threshold values were determined for the parameters of the material and cold forming conditions, to broadly classify them with respect to carburization (Fig. 6).

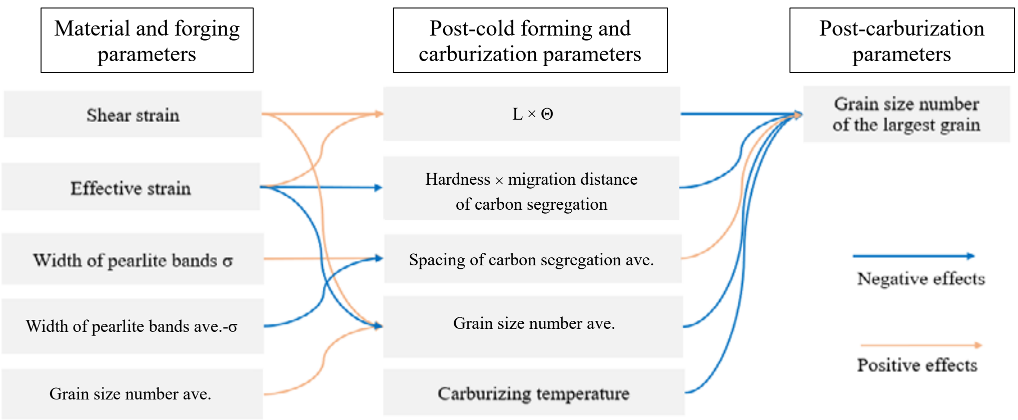

Fig. 5 The DAG in this study

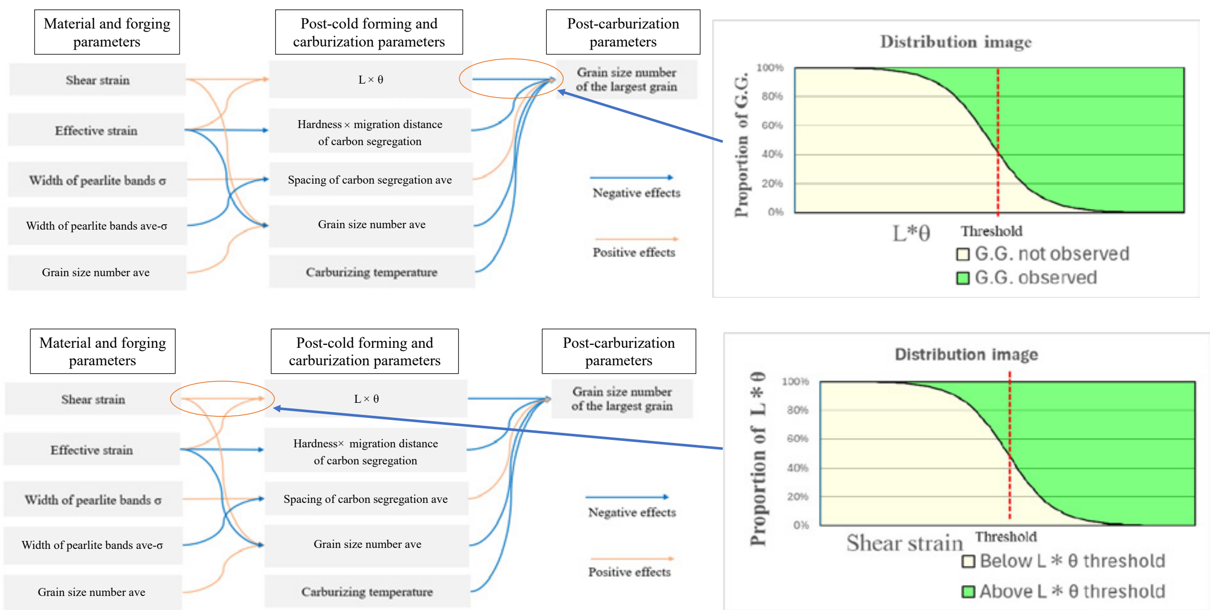

Fig. 6 Setting of threshold values

4.4 Construction of Bayesian networks

The results from Sections 4.1 to 4.3 were integrated to construct a Bayesian network. In a Bayesian network, when an explanatory variable (e.g., one of the material parameters) is varied, its effect is propagated through the network, and the probability distribution of the other related explanatory variables (post-cold-forming parameters) is updated. This update is ultimately reflected in the predicted probability of the objective variable (presence or absence of G.G. occurrence).

Using this characteristic, the material and process parameters can be varied to indicate the range of conditions under which G.G. may occur.

5. Method to validate the prediction and its results

To verify the accuracy of the created model, leave-one-out cross-validation was conducted using all combinations (108 combinations) (Table 2). First, the AI was trained using the data for all combinations, except for one. Subsequently, the actual data for the material and process parameters of the excluded combination were input into the trained prediction model to predict the occurrence of G.G. The results were verified to determine if they aligned with the actual data.

The verification revealed that the prediction results of G.G. occurrence with material and process parameters as input agreed with the actual data for 79 combinations (Table 3).

Table 2 Leave-one-out cross-validation method

	Validation pattern						
	1	2	3	4	･･･	107	108
Data No. 1	×	○	○	○	･･･	○	○
No. 2	○	○	○	○	･･･	○	○
No. 3	○	○	○	○	･･･	○	○
No. 4	○	○	○	○	･･･	○	○
No. 107	○	○	○	○	･･･	○	○
No. 108	○	○	○	○	･･･	○	○

○ : Training data

× : Validation data

Table 3 Prediction results of G.G.

	Result
Occurrence	96% (22/23)
Non-occurrence	67% (57/85)
Total	73% (79/108)

6. Improving the accuracy of the prediction model

Although the prediction results were highly accurate in terms of predicting complex phenomena, the accuracy was 67% for G.G. non-occurrence in actual component manufacturing, which is lower than expected (Table 3). To improve the accuracy of the conditions required to avoid G.G. in component manufacturing, we reviewed the decision criteria within the range of conditions appropriate for actual manufacturing. As a result, prediction accuracy improved to 88%, as shown in Fig. 7. Consequently, the manufacturing conditions that do not cause G.G. can be predicted with high accuracy.

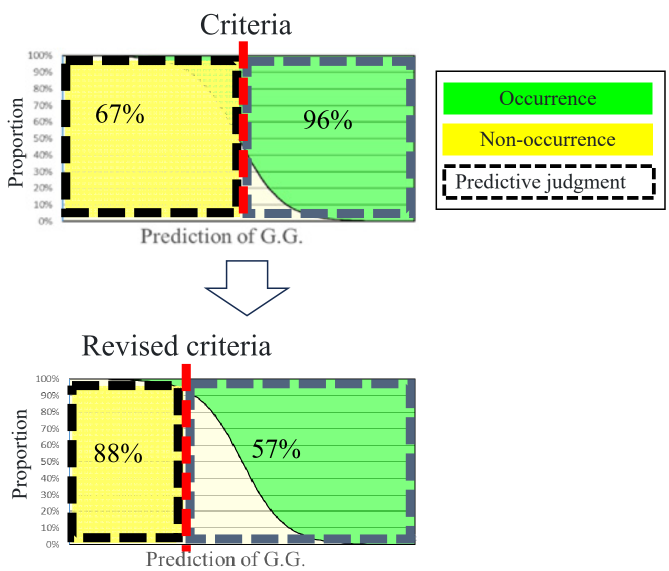

Fig. 7 Modified decision criteria improved non-G.G. precision to 88%

7. Conclusion

A technology was developed to optimize manufacturing processes using AI, to predict abnormal grain growth (G.G.) in steel crystals, which has been difficult to predict in previous studies. The following findings were obtained:

[1] The occurrence of G.G. can be predicted by constructing a Bayesian network that considers the causal relationships among the parameters.

[2] As a result of [1], the manufacturing conditions that do not cause G.G. were predicted with an accuracy of as high as 88%.

8. References

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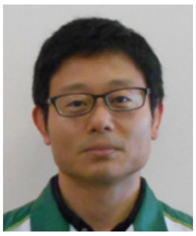
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