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A Diagnostic Expert System for Defects in Forged Parts

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This paper describes the development of a diagnostic expert system that identifies the cause of various manufacturing defects in hot forging and suggests remedies. The formation of defects is various and the defects are due to many possible causes. They depend on part designs, tool designs, and process conditions. This paper utilizes the theory of conditional probability to construct a diagnostic expert system that can adapt and learn its diagnostic mechanism through field data. The demonstration program, FORDIA, runs in HyperCard. FORDIA takes the part defect symptoms, uses conditional probability theory to identify possible causes, and suggests remedies. The FEM simulation is conducted to accumulate the graphical knowledge.

1. INTRODUCTION

1.1 Background

The past decade has seen the development of expert systems in various fields. There are a number of expert system applications in forging engineering, mainly on cold forging die design. However, there are few applications to diagnoses of forging defects.

Forging is a net shape manufacturing process in which a set of dies deforms a metal billet into desired shapes with high force and energy. There are two types of forging: cold forging and hot forging. The cold forging process deforms the billet at room temperature, while hot forging uses a heated billet at about 1200 degrees centigrade. Since cold forging normally applies only to simple shapes, it is easy to apply theoretical analysis to cold forging processes. On the other hand, hot forging can handle complex shapes and involves thermal problems making theoretical analysis difficult. Therefore, people rely on expert heuristic knowledge in designing the part, tool, and the process. This fact is the most important motivation of our research.

Forging engineers always strive to eliminate any defects on production parts. However, the mechanism of generation of hot-forging defects is not clearly known in most cases. The patterns of defect generation are various and due to many factors. They depend on shapes of parts, or the location in the parts. Some experts can intuitively explain how the defect may be generated. However, it is not easy to identify the mechanism of defect generation and to document the prescription. Consequently, a small number of experts have traditionally kept their heuristic knowledge of combating defects as private knowledge.

If the forging die design is perfectly compatible with the process, there should be no defect generated in any location of the parts. However, the conditions for defects are quite complicated. They depend not only on how good the die design is, but on other process conditions such as the state of lubrication, location of the preformed work piece on the die, and formability of materials. In other words, optimizing the die design does not solve all defects. This fact gives us the motivation to develop a diagnosis system to be used by production engineering for identifying the root cause of any processing defects and feeding the information back to design.

1.2 Previous Work

There have been numerous studies reported in the field of diagnostic expert systems. MYCIN is famous as the diagnostic system that uses Bayesian probability and addresses medical applications (Shortliffe and Buchanan, 1975). The medical field has a strong interest in applying expert systems, because the relationship between symptoms and causes are very complex requiring human experience to deduce remedies. There are many research reports in this field (e.g., Graham, 1989), most of which use Bayesian network.

In other engineering fields, there have been many applications that used Bayesian theory. Agogino used a Bayesian inference engine for milling machine monitoring and control (Agogino *et al,* 1988). Other applications include nuclear engineering (Kaplan, et al, 1990) and process management (Guarro, 1990).

In forging, there have been some applications of AI in part design. Ohio State developed a knowledge-based system for computer-aided part and processing-sequence design for cold forging processes (Sevenler, 1990). Osakada et al developed a cold forging expert system using neural networks (Osakada, Yang *et al,* 1988). Many other researchers have applied knowledge-based systems to the design of cold forging (e.g., Azushima, 1992). Motomura (1992) applied the fuzzy system approach to axisymmetric hot-forged parts. Their objectives of most of these studies are to determine the optimal process sequences.

Despite the popular use of expert system technology in forging design and in general diagnostic systems, there are few applications for diagnosis of forging defects in production parts. As stated before, engineers can benefit from a diagnostic system that relates defects to part and process design parameters. This information assists part and tool designers in improving the quality of the production parts.

1.3 Research Approach

The main objective of this research is to construct a diagnostic system for hot-forging defects. Before developing a computer program, one must establish a sound formulation that relates the defects to various causes. We accomplish this by collecting information based on the experiences and analyzing the mechanism of the forging defect generation using the finite element method.

The second objective is to construct an expert system for diagnosis. This task involves the application of Bayesian probability theory and is targeted to not only forging but other manufacturing quality problems. The system incorporates a common certainty factor formulation and a learning system for the identification of Bayesian probabilities.

2. PROBLEM DEFINITION IN FORGING DEFECT DIAGNOSIS

On the manufacturing floor, forging operators or engineers sometimes find defects during or after the processes and try to guess when, how, or why they appeared. They can only estimate, because they do not really witness the process in which the defects were formed. Usually they need some information to estimate the causes, such as the type of parts, location of the defects on the surface of parts, its depth, its profile, the ratio of parts that show the defects, etc. The more information they have, the more accurately they can estimate the correct cause. This computational inference requires the same type of information as needed by human experts. Figure 1-1 shows the schematics of the proposed diagnostic system.

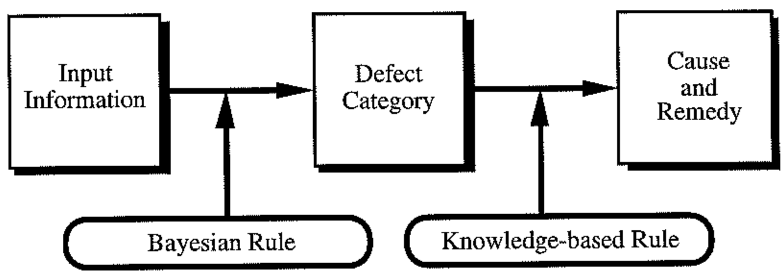

Figure 1-1. Schematic Flow of the Diagnostic System

This system (FORDIA) requires the following input:

1) Type of parts
2) The location of the defect
3) Type of processes (the combination of processes; the stage in which defects are found)
4) Properties of defects (depth, open or closed, decarburized or not)
5) Ratio of products including defects
6) Lot size of products including defects

The proposed system uses two-step diagnosis. The first step is the categorization of the defects. There are several types of defects. Figure 1-2 shows some of them on the surface of a crank shaft which is a typical hot-forged product. One can categorize hot forging defects into the following eight types:

1) Material defects: occurs because of imperfect materials in the billet.
2) Rolling defects: flaws that are caused by the material rolling process before forging.
3) Forging defects due to die design: flaws caused by undesirable geometry in the die.
4) Forging defects due to die fabrication: manufacturing errors and flaws.
5) Forging defects due to operator error: misuse of lubricants, inappropriate die setting.
6) Trimming defects: flaws during the after-forging trimming and deburring process.
7) Heat-treatment defects: flaws that occurs during heat treatment after forging.
8) Simple crack: defects due to mishandling of the part during transportation, etc.

At this stage, we must calculate the probabilities of each category regarding the symptoms in terms of Bayesian probability rules. First we collect the conditional probability of each outcome for each symptom and call it the "basic" probability. Some of these numbers can be determined theoretically, while others must be obtained from empirical information. The uncertain empirical probabilities can be modified by an adaptive learning procedure, which is discussed in section 3.2.

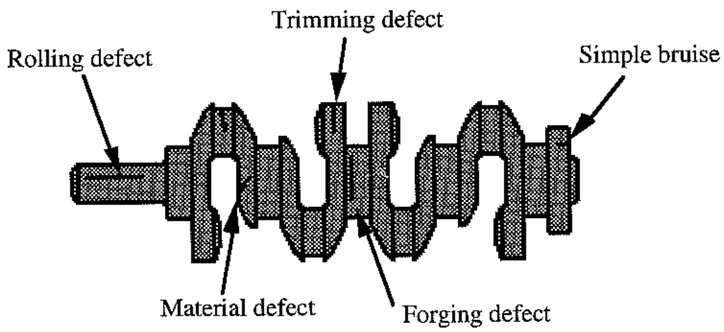

Figure 1-2. Crank Shaft and Typical Defects

The second step inference is for the cause and treatment of the defects. This step calls for expert knowledge of the forging engineers. Depending on the input information, the system triggers appropriate suggestions from the knowledge base. The knowledge base comprises the empirical data derived mainly from the forging engineer's experience (e.g.; Altan *et al*, 1973) and analytical data obtained by the FEM simulation studies. The proposed system incorporates visual information (animation) for the cause and treatment. This form of output proves to be much more effective than textual or quantitative description in explaining the diagnosis results.

3. MATHEMATICAL FOUNDATION

3.1 Diagnostics Using Bayesian Rules

This study uses an established technique in the use of Bayesian probability. This section summarizes the basic mathematics used in developing the FORging Defect DIAgnosis system, called FORDIA.

The certainty of a conjecture is determined by several facts and their properties. Each fact provides the category of conclusions with a probability. The probabilities could be determined by theoretical examination or from a statistical analysis of empirical data. For instance, suppose two conclusions and one fact are as follows:

Conclusion 1 : The person is a man.
Conclusion 2 : The person is a woman.
Fact 1: His/her hair is long.

In this case, we cannot pinpoint a conclusion, because even though the hair is long, the person might be a man. However, we can expect that the person is probably a woman.

Now let $P(E_i)$ be the probability of sexes ($i = 1 - n, n = 2$), then F_j be Fact No. j. ($j = 1 - m$, in this case $m = 1$). F_1 represents the fact that his/her hair is long. $P(E_i|F_j)$ means the probability of E_i in the case that Fj is evident. This is called a conditional probability.

Similarly, $P(F_j|E_i)$ means the probability of Fj on condition of E_i. Using Bayesian formula, $P(E_i|Fj)$ can be expressed as follows;

$$P(E_i \mid F_j) = \frac{P(E_i) \cdot P(F_j \mid E_i)}{\sum_{i=1}^{n} P(E_i) \cdot P(F_j \mid E_i)} \tag{1}$$

How about the case in which we have two facts? We will add the next fact as the second one.

Fact 2 : The person is wearing a skirt.

This fact also supports the assumption that the person may be a woman.
Here we can get,

$$P(F_1, F_2 \mid E_i) = P(F_1 \mid F_2, E_i) \cdot P(F_2 \mid E_i) \tag{2}$$

If F_1 is independent of F_2,

$$P(F_1 \mid F_2, E_i) = P(F_1 \mid E_i) \tag{3}$$

$$P(F_1, F_2 \mid E_i) = P(F_1 \mid E_i) \cdot P(F_2 \mid E_i) \tag{4}$$

Consequently, using Equation (1), on the condition that F_1 and F_2 are independent of each other,

$$P(E_i \mid F_1, F_2) = \frac{P(E_i) \cdot P(F_1 \mid E_i) \cdot P(F_2 \mid E_i)}{\sum_{i=1}^{n} P(E_i) \cdot P(F_1 \mid E_i) \cdot P(F_2 \mid E_i)} \tag{5}$$

We can extend this equation for general numbers of facts all of which are independent of each other and events. Let m be the number of facts and n be the number of events. Then,

$$P(E_i \mid F_1, F_2, \cdots, F_m) = \frac{P(E_i) \cdot P(F_1 \mid E_i) \cdots P(F_m \mid E_i)}{\sum_{i=1}^{n} P(E_i) \cdot P(F_1 \mid E_i) \cdots P(F_m \mid E_i)}$$

$$= \frac{P(E_i) \cdot \prod_{j=1}^{m} P(F_j \mid E_i)}{\sum_{i=1}^{n} P(E_i) \cdot \prod_{j=1}^{m} P(F_j \mid E_i)} \tag{6}$$

Now, we obtain the certainty of Fj using Equation (6). If we know all the conditional probabilities for Event i, we seek the probability for Event i based on Fact j. In other words, if we want the certainty, all the probabilities are necessary.

3.2. Adaptive Learning of the System

As more field data become available, we should revise the empirical probabilities. If the user knows the true conclusion for a particular case, we may update the probability data. One of the parameters the user must define is how much weight he/she would like to place on the new data point. We call the weight β. Suppose the correct conclusion is E and the chosen fact number is k_{1i}. The system should examine the chosen facts and modify the apparent probabilities according to the next equations.

If $k = k_1$,

$$P(F_j(k) \mid E_i) = \frac{P_p(F_j(k) \mid E_i) + \beta}{1+\beta} \tag{7}$$

If $k \neq k_1$,

$$P(F_j(k) \mid E_i) = \frac{P_p(F_j(k) \mid E_i)}{1+\beta} \tag{8}$$

If $k_1 = 0$,

$$P(F_j(k) \mid E_i) = P_p(F_j(k) \mid E_i) \tag{9}$$

β=learning update parameter, P_p=previous data

Summing these equations,

$$P(F_j(k) \mid E_i) = \frac{P_p(F_j(k) \mid E_i) + \beta \cdot \delta_{k,k_1} \cdot (1-\delta_{2k_1,k_1})}{1+\beta \cdot (1-\delta_{2k_1,k_1})} \tag{10}$$

Similarly, using another changing weight γ, average probabilities can be also corrected. That is;

$$P(E_i) = \frac{P_p(E_i) + \gamma \cdot \delta_{k,k_1}}{1+\gamma} \tag{11}$$

Now that we have new apparent data and new average probabilities, we can obtain the updated probabilities using Equation (6). Equations (10) and (11) essentially define our probability learning algorithm.

4. CONCEPT OF FORDIA

The name of this system is "FORDIA," which stands for the forging defect diagnostic system. Figure 4-1 shows the structure of the program. The Bayesian inference determines the certainties of each defect category according to the input information. This part should be a called Bayesian reasoning system with adaptive learning. The second part is the cause and treatment reasoning, which uses the knowledge-based approach. The cause and treatment inferred depend on the combination of input information. The output of the system is mainly graphics with animation obtained by the FEM simulation using a plastic deformation code "DEFORM" (Oh, 1991). Finally, if the operator knows the actual result, he/she can use the learning system to update the basic probability.

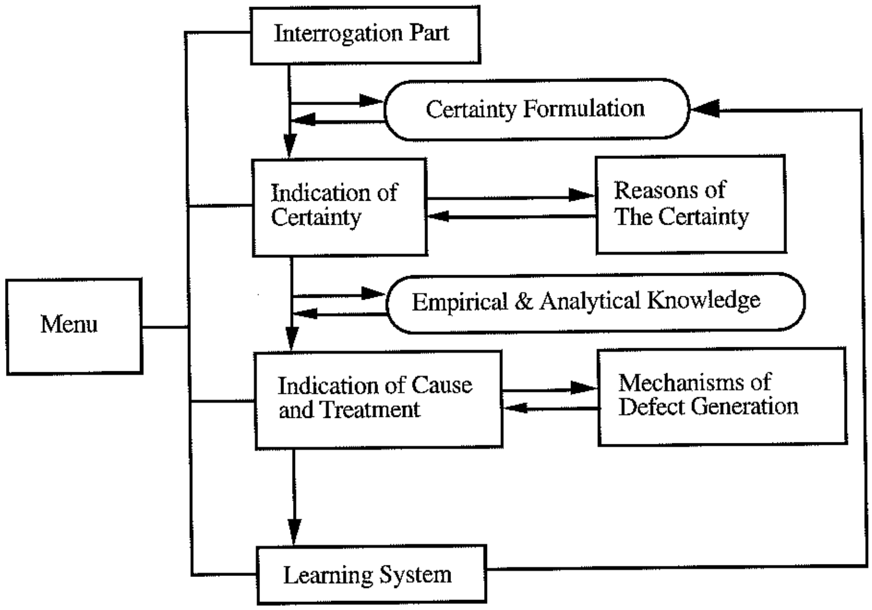

Figure 4-1. Structure of the System

5. NUMERICAL KNOWLEDGE

The procedure showing the corresponding cause and treatment is based on the knowledge-based expert system that can handle analytical and empirical knowledge. The authors used the commercial code for metal forming analyses, "DEFORM," to accumulate analytical knowledge. The authors finally got more than fifty examples of simulation. They show some of the FEM simulations for defect analyses by using DEFORM. The common simulation conditions are as follows;

Computer	VAX Station (ISE Dept. at The Ohio State University)
Software	DEFORM (Design Environment for FORMing)
Dimension	2-D (Plane strain or axisymmetric condition)
Temperature	1200 degrees C, Isothermal condition
Die property	Rigid
Flow stress curve	Stress = 200 * Strain-rate ** 0.25 (MPa)
Press speed	100 mm/Second (linear stroke)

(1) Crank shaft journal defect

Figure 5-1 shows the lap defect occurring on the surface of journals. Excessive volume of blocker is moved to the root of counter weight by edges of finishing dies. During this deformation, if we have a small root radius, this radius is folded into the surface of journals. In order to avoid this defect, we need the larger radius here.

(2) Connecting rod I-section defect (lap)

Figure 5-2 shows the mechanism of the lap defect generation of a connecting rod. Basically, a sharp corner at the root of the rib and over-lubrication make these defects occur. If we have a radius on the corner, or the lubrication is not good, we don't have any defects at the same location.

(3) Suck-in defect

The defect is called suck-in defects because the center point of outside flange is suck in the material long the center line of the shaft. This is mainly due to the length/diameter ratio of the upset billet. If the ratios are the same, the friction coefficient can affect the results. When the length/diameter ratio is very low, the very thin vertical suck-in defect is generated as shown in Figure 5-3. The length of the defect becomes over 4 mm during deformation. If the higher L/D ratio is chosen, this type of defect can be avoided. If the friction coefficient is changed to the higher value, the defect will not be generated.

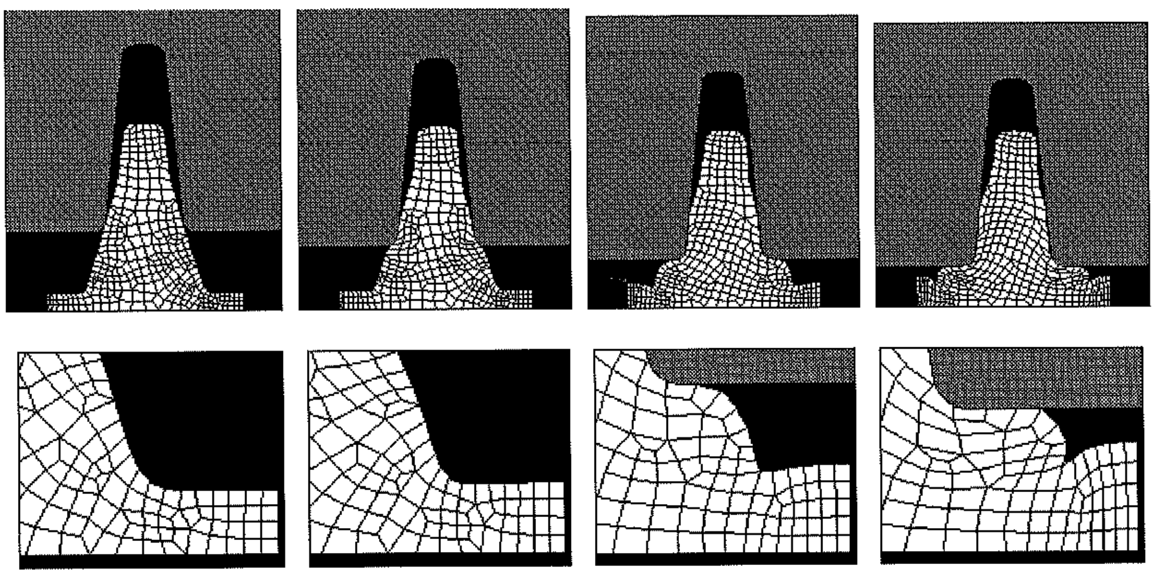

Figure 5-1. Crank Shaft Journal Defect (Root radius = 3)

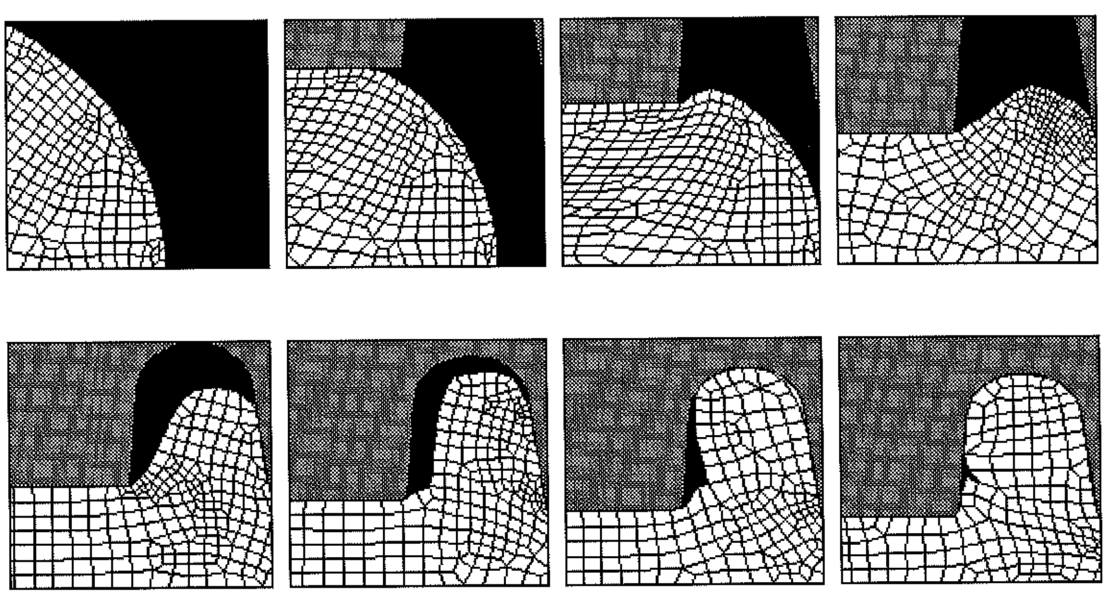

Figure 5-2. Connecting Rod Forging (Corner radius = 0.0, m = 0.0)

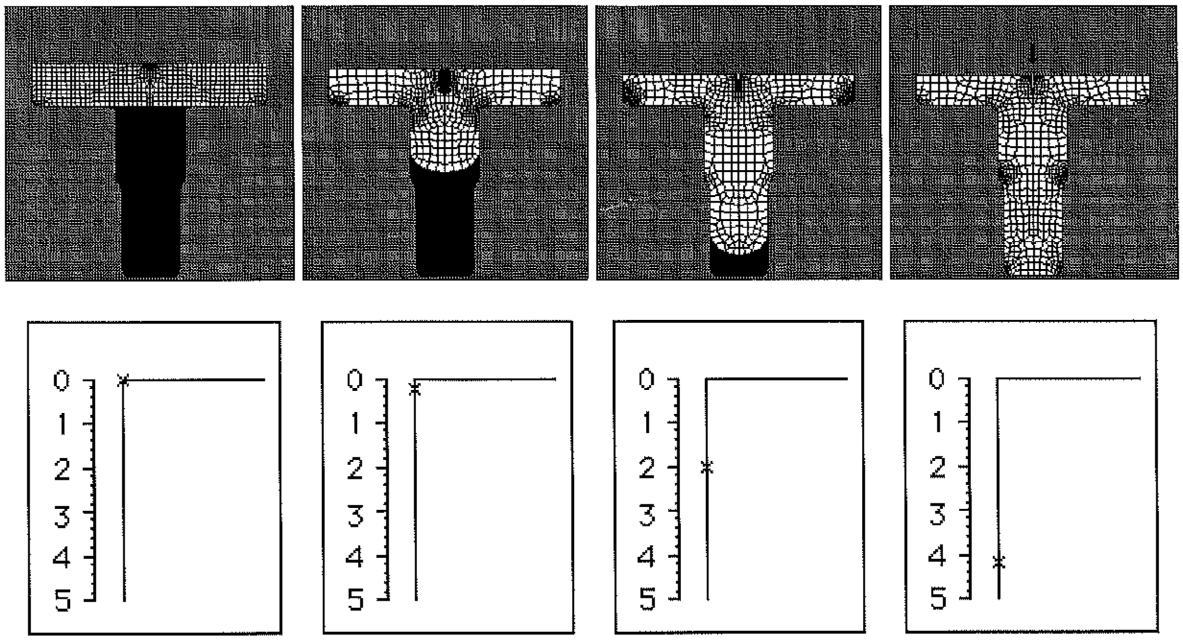

Figure 5-3. Suck-in Defect and Center Point Tracking
(Initial thickness = 15.7, m = 0.0)

6. CONCLUSION

This paper described a diagnostic expert system for forging defects that uses Bayesian inference. Specifically, the author developed an inference formulation based on Bayesian theory. This formulation led to a HyperCard Expert system called FORDIA. The basic formulation is useful for general manufacturing diagnostic systems, if one can collect enough facts that are independent of each other. The formulation has the following advantages:

(1) **Simplicity:** Because of its simplicity, we can avoid the complex conditional programming. The simplicity also makes the program adaptable to other applications with minimal code changes.
(2) **Accuracy:** The Bayesian approach allows a single fact to deny the final possibility for a certain category by using zero as the basic probability, no matter how much the other facts support the possibility. This is one advantage over an evaluation system based on weighted sum and closely matches the diagnostic concepts used by expert engineers.
(3) **Attribution of Symptoms to Causes:** The method identifies the contribution of each factor that leads the diagnostics to any indicated cause.
(4) **Adaptability:** The learning procedure is quite simple because all the system needs to do is to update the basic probabilities according to field data that are processed.

The field of hot forging is a very suitable area for AI applications since the current practice heavily relies on human experts. This project combined the use of empirical knowledge with theoretical and FEM results to construct a useful tool that links the manufacturing field data and engineering design. The most significant feature of the system is the Graphical

Output. The output is graphical and with animation that clearly communicates to the users the mechanisms of the defect generation.

The current system only accommodates input information that is statistically independent. In many cases, the factors interact and are not independent. The authors are developing methods to simplify the certainty formulation by using correlation coefficients. If the correlation coefficient between two facts is zero, which means that they are independent of each other, we do not need to modify the formulation. If the coefficient is 1 or -1, one can easily modify the relations. The challenge is in incorporating varying degrees of interactions. A systematic approach to these interactions will enable us to construct a truly adaptive diagnostic system. On the application front, we intend to further validate the system by using more field data. Of particular interest is the effectiveness of the learning system and the feedback from the manufacturing floor on the usefulness of the program.

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