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DETECTOR: A knowledge-based system for injection molding diagnostics

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A knowledge-based system (KBS) for diagnosis of multiple defects in injection molding is presented. The general scheme for knowledge representation based on fuzzy set theory has been shown useful in representing inexact and incomplete information for developing the KBS. An optimality criterion is created for selecting a simple and 'best' cover to explain the given problem. An efficient search algorithm for finding such cover is also discussed.

Keywords: Injection molding, expert system, knowledge representation, fuzzy set, maximum priority cover

1. Introduction

Injection molding is one of the major processes of producing plastic parts, consisting of approximately one-third of all plastics production. The process can be fully automated, can be easily adapted to mass manufacturing and performs most efficiently for high-volume production.

The quality of a molded part must in general address geometric, aesthetic, structural and material properties considerations. A plastic part could thus exhibit defects such as warpage, shrinkage, sink marks, bubbles, weld lines, flashing, surface defects, etc. The final product quality is a function of the variables related to the molding conditions, mold design, raw material and machines. The task of the diagnostic system is to identify the sources that contribute to the observed product defects. In addition, remedy recommendations must also be provided.

The traditional approach to the diagnostic problem has relied heavily on human process operators. Developing an expert operator normally requires years of training. Many skilled operating personnel come up through the ranks learning through experience, their skills about the process often exceeding their technical understanding. Unfortunately, the knowledge gained by years of experience is often lost when that person leaves the job. In addition, the knowledge of an operator is often restricted to a subset of the processing environment in a particular company.

A computer-based system could help in addressing some of the above problems. Such a system could encode the expert information about the process, thus retaining much of the process knowledge that would have otherwise been lost. This is not a trivial task, since the expert thinking is often intuitive and hard to formalize into appropriate rules for an expert system. However, the resulting encoded knowledge could represent the accumulated experience of many experts, producing a 'super expert'. Much information that can be stored in databases as process-specific data can enhance the applicability of the system to a wide variety of products and conditions. As the use of engineering materials and the variety of the different materials and part geometries increases, such a need will become more pronounced. Such a system can also be used for educating and training operators, reducing the time required for them to reach a certain level of expertise.

There has been an extensive research effort to create expert systems capable of dealing with specific areas of expertise such as MYCIN (Shortliffe, 1976) in medical diagnostics, DENDRAL (Feigenbaum, 1971) in chemistry and PROSPECTOR (Phelps, 1978) in geology.

In general, the problem of development of an expert system can be broken down into the following interrelated subproblems. The first is the choice of the form for representing and constructing the expert knowledge base and is treated in Section 2. The second, of developing a mechanism of logic inference on the basis of the available knowledge database, is dealt with in Section 3. The third is to design facility programs for experts for their efforts to modify the knowledge database and improve the inference mechanism. These facilities and the overall system structure are discussed in Section 4. The diagnostic system is illustrated by an example in Section 4.2, and conclusions are presented in Section 5.

2. A general knowledge representation scheme

The representation and manipulation of qualitative and inexact knowledge are difficult to address by conventional means. One particularly encouraging method of dealing with imprecise concepts, such as those related to injection molding diagnostics, is based on fuzzy set theory (Kandel, 1986; Zadeh, 1979; Sugeno, 1985). The formulation of our problem in terms of this theory will be presented next.

2.1. *Mathematical tools for knowledge representation*

We call the universal set or universe of discourse **U**, and the others as follows.

Let $\mathbf{D} = \{d_j \mid j = 1, 2, \ldots, n\}$ represent all defects that can occur in injection molding, and where d_j is one of the possible defects.
Let $\mathbf{C} = \{c_i \mid i = 1, 2, \ldots, m\}$ represent all possible causes that may occur when one or more defects are present, and where c_i is one of the possible causes.

We proceed with the following definitions:

Definition: Let a, b be any two elements, then **<a, b>** is called the ordered pair a, b.
In our case $<c_i, d_j>$ represents "c_i can cause d_j". Note that $<c_i, d_j>$ does not imply that c_i always occurs when d_j is present, but only that c_i *may* occur. Also, let

$$\mathbf{E} = \{<c_i, d_j> \mid c_i \text{ can cause } d_j\}.$$

Definition: Let **C**(i) be a family of non-empty subsets of **C** and i∈I, where I is a finite set of integers. Then {**C**(i)|i∈I} is called a **partition** of **C** if

$$P_1: \bigcup_{i \in I} \mathbf{C}(i) = \mathbf{C}$$

$$P_2: \text{For any } i \neq j,\ \mathbf{C}(i) \cap \mathbf{C}(j) = \varnothing$$

Example: Let T = {a, b, c, d, e, f, g} and let U = {a, b, c}, V = {d, e}, W = {f, g}, then {U, V, W} is a partition of T. In our case, we partition the possible causes into the following four categories:

- category(1) : Molding condition problems
- category(2) : Material problems
- category(3) : Machine problems
- category(4) : Mold design problems.

Based on this partition $c_i(k)$ will be interpreted as "cause i" from "category k", where k = 1,2,3,4.

A simple and instructive way of illustrating the relationships between sets is in the use of Venn-Euler diagrams. These sets are depicted in Figure 1, which shows the relation of **C** to **D**. The defect (c_i) represents some defects caused by c_i. Clearly, if defect (c_i) is known for every element (cause) c_i, or if cause (d_j) is known for every element (defect) in **D**, then the causal relation **C** to **D** is completely determined. From a mathematical point of view, this is a many-to-many relation. When one or more defects are found on the part, it is not easy to distinguish which subset of causes best explains the observed defects. From expert knowledge, we know each element in **D** can be caused by some elements (causes) in **C**. Now, let

$$\text{cause}(d_j) = \{c_i \mid <c_i, d_j> \in \mathbf{E}\} \qquad \forall d_j \in \mathbf{D}$$

$$\text{defect}(c_i) = \{d_j \mid <c_i, d_j> \in \mathbf{E}\} \qquad \forall c_i \in \mathbf{C}$$

$$\text{cause}(\mathbf{D}) = \bigcup_{d_j \in \mathbf{D}} \text{cause}(d_j) = \mathbf{C} \qquad \text{where } \cup \text{ means union}$$

$$\text{defect}(\mathbf{C}) = \bigcup_{c_i \in \mathbf{C}} \text{defect}(c_i) = \mathbf{D}$$

A diagnosis problem may now be posed as a mathematical problem in which one is first given a subject of manifestations (symptoms, defects, abnormal test results). This subset of **D** will be called the floating defect subset $\mathbf{D}^+$. In injection molding, the set $\mathbf{D}^+$ represents the observed defects of the produced parts which the user inputs to the system. We also let the floating causes subset, $\mathbf{C}^+$, represent the subset of **C** which consists of all associated causes that explain at least one of the observed manifestations. Given the initial set $\mathbf{D}^+$, and associated degrees of severity of the observed defects, as well as information about the current status of the project, the system will select a subset of $\mathbf{C}^+$ that 'best' explains the observed defects. The method by which we can manipulate that information to arrive at the final diagnosis will use concepts from fuzzy set theory.

2.2. *Knowledge representation via fuzzy sets*

One of the underlying principles of knowledge engineering is that the methodology for solving a problem is based on some representation techniques that are independent of the application. This methodology should be well defined and should facilitate direct thinking and traceability. One

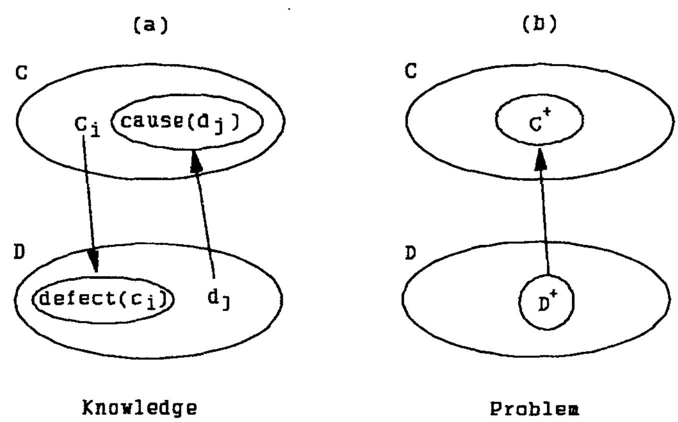

Fig. 1. Organization of diagnostic knowledge (a) and problem (b) with a Venn Diagram.

tool that lends itself well to this goal is a table or a diagram, without which misunderstandings, omissions and inconsistencies may occur in the design stage. When the knowledge can be represented in a table, the entries can be easily changed: they can also be easily maintained and manipulated.

In our system, we will deal with uncertain information which, based on fuzzy set theory, will require the use of tables to model the relations of causes to defects. The theory of fuzzy sets, 'a generalization of conventional set theory, provides an adequate conceptual framework as well as a mathematical tool to solve real physical world problems which are usually fuzzy. It can account for inexactness, like ambiguity and vagueness, and thus for nonstatistical uncertainty'. The theory was originally developed by L. A. Zadeh (1965). Many investigators are presently exploring the usefulness of fuzzy set theory in a wide variety of fields ranging from medical diagnosis to industrial control and man–machine communication problems.

A nonfuzzy finite set may be simply represented by the list of its elements as for example, $A = \{c_1, c_3\}$. In contrast, a finite fuzzy set is represented by its elements and their associated weights, for example, $B = \{0.6/c_1, 0.4/c_3\}$. The notation denotes that the grade of the membership for $c_1 \in B$ is 0.6 and for $c_1 \notin B$ is 0.4.

Definition: The fuzzy relation is considered to be a mapping from $\mathbf{C} \times \mathbf{D}$ into [0,1], such that $w_{ij} = f(c_i, d_j)$ for all pairs (c_i, d_j).

Clearly, we can associate with every relation a matrix to represent the relation of the fuzzy sets, giving rise to the notation of relation matrices. When the related sets **C** and **D** are finite, a fuzzy relation f on $\mathbf{C} \times \mathbf{D}$ can be represented as a matrix **[W]** whose entries are w_{ij}.

Determination of the grades of membership w_{ij} which may range anywhere between 0 and 1, is based on expert knowledge. The value of 1 is assigned to w_{ij} when cause c_i will always result in defect d_j, while 0 is assigned to causes that are not related to the defects. The term w_{ij}/c_i signifies that w_{ij} is the grade of membership of c_i in $\mathbf{W}(d_j)$. Based on this notation, we interpret the fuzzy set

$$\mathbf{W}(d_j) = \{w_{ij}/c_i \mid w_{ij} > 0\}$$

as representing the relationship of defect j to the related causes in terms of grades of membership, e.g.

$$\mathbf{W}(d_1) = \{w_{11}/c_1, w_{21}/c_2, w_{31}/c_3, \ldots\ldots, w_{n1}/c_n\}$$

$$\mathbf{W}(c_1) = \{w_{11}/d_1, w_{12}/d_2, w_{13}/d_3, \ldots\ldots, w_{1m}/d_m\}$$

A typical cause-defect relation is represented in Table 1. The assigned initial confidence factors to each w_{ij} for injection molding, were based on expert domain knowledge (Rosato, 1986; Rubin, 1972; Mosanto, 1988; McCarthy, 1989).

Table 1. Knowledge organization based on fuzzy sets.

	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	....	d_n
$c_1(2)$	0.5	0.1		0.7		0.3	0.5	0.2		
$c_2(1)$		0.3			0.3			0.6		
$c_3(2)$	0.3			0.8						0.2
$c_4(3)$		0.4	1.0							
$c_5(4)$					0.5	0.7	0.3			0.9
$c_6(4)$						0.8				0.4
$c_7(2)$					0.6	0.5		0.5		
.										
.										
.										
$c_n(1)$					0.7		0.6	0.8		

From the above table, we may also deduce facts such as:

$c_1(2) \in \text{Category}(2)$
$c_5(4) \in \text{Category}(4)$
$\text{cause}(d_1) = \{c_1(2), c_3(2)\}$
$\text{defect}(c_1) = \{d_1, d_2, d_4, d_6, d_7, d_8\}$
$\mathbf{W}(d_2) = \{0.1/c_1, 0.3/c_2, 0.4/c_4\}$
$\mathbf{W}(c_1) = \{0.5/d_1, 0.1/d_2, 0.7/d_4, 0.3/d_6, 0.5/d_7, 0.2/d_8\}$

2.3. *Manipulation of knowledge via fuzzy matrices*

Once the knowledge is represented, our task is to discover an appropriate way to manipulate the weights associated with the elements in the fuzzy sets. The process of fuzzy matrix manipulation allows us to determine the grade membership for each associated cause in the floating cause model. Subsequent to the grade membership calculation, a set with elements in descending order of grade membership will be produced. This set will be input to the PFC algorithm presented in the next section to produce the proposed diagnosis.

The first step in the diagnostic process is to accept the set of observed defects from the user, and associate appropriate weights for their respective severity. The operator reads the defects from the rejected part and judges the degrees by his subjective estimate or by experience. He is given three choices of severity, namely 'slight', 'moderate' and 'serious'. He may associate for example, d_1 (bubbles) with 'serious', d_2 (short shot) with 'slight', and d_3 (black streaks) with 'serious'. These are internally normalized to reflect the relative importance of each defect with respect to the others. By associating 'slight' with weight 1, 'moderate' with 2 and 'serious' with 3, we assign appropriate weights as shown below for our example.

$P(d_1)$ = P(bubbles) = |'serious'|/Σ|degree| = 3/(3 + 1 + 3) = 3/7

$P(d_2)$ = P(short shot) = |'slight'|/Σ|degree| = 1/(3 + 1 + 3) = 1/7

$P(d_3)$ = P(black streaks) = |'serious'|/Σ|degree| = 3/(3 + 1 + 3) = 3/7

where $P(d_i)$ is the normalized severity of the *i*th defect.

In this example, bubbles, short shot, and black streaks have relative severity given by the vector $\mathbf{P}(\mathbf{D}^+)^T$ = [3/7, 1/7, 3/7]. These degrees will be later used to modify the elements of the fuzzy relational matrix.

The second step is to determine the associated set of possible causes, $\mathbf{C}^+$, to the observed defects $\mathbf{D}^+$. Let's take $\mathbf{D}^+ = \{d_i, d_2, d_3\}$ for example. First, d_1 is used to retrieve the causes, $c_1(2)$ and $c_3(2)$, with their initial associated weights. This step is repeated for d_2 and d_3. We thus obtain a submatrix $[\mathbf{W}^+]$ of $[\mathbf{W}]$, containing the necessary entries for diagnosis process, from the knowledge table as follows.

	d_1	d_2	d_3
$c_1(2)$	0.5	0.1	
$c_2(1)$		0.3	
$c_3(2)$	0.3		
$c_4(3)$		0.4	1.0

All subsequent diagnostic operations will deal with the submatrix $[\mathbf{W}^+]$. The elements of this submatrix will next be modified to give $[\mathbf{W}'^+]$ based on current status information. This information consists of data entered by the operator about the status affecting the causes of the four categories mentioned previously. For example, information as to whether a new material or mold is presently used by the operator, will alter the weights of $[\mathbf{W}^+]$ for the respective categories.

The introduction of new material increases the likelihood of problems associated with that category. Thus based on these current status conditions, the elements associated with category (2) will be multiplied by the factor 1.5, altering the entries $w_{11}$and w_{31} to 0.75 and 0.45 from 0.5 and 0.3 respectively. Manipulation based on other available current data, such as the present barrel temperature compared with normal ranges for that material, serves to modify the submatrix as shown below.

	d_1	d_2	d_3
$c_1(2)$	0.75	0.15	
$c_2(1)$		0.5	
$c_3(2)$	0.45		
$c_4(3)$		0.4	1.0

The observed relative severity of the defects will now be taken into account. This is done by multiplying the respective weighting vector $\mathbf{P}(\mathbf{D}^+)$ associated with $\mathbf{D}^+$ with the submatrix $[\mathbf{W}'^+]$ to give the likely importance vector $\mathbf{P}(\mathbf{C}^+)$ of the fuzzy set $\mathbf{C}^+$, so that

$$\mathbf{P}(\mathbf{C}^+) = [\mathbf{W}'^+]\mathbf{P}(\mathbf{D}^+).$$

In this case we have

$$\begin{bmatrix} P(c_1) \\ P(c_2) \\ P(c_3) \\ P(c_4) \end{bmatrix} = \begin{bmatrix} 0.75 & 0.15 & 0 \\ 0 & 0.5 & 0 \\ 0.45 & 0 & 0 \\ 0 & 0.4 & 1.0 \end{bmatrix} \begin{bmatrix} P(d_1) \\ P(d_2) \\ P(d_3) \end{bmatrix}$$

The normalized weights of the defects were found to be

$$\mathbf{P}(\mathbf{D}^+)^T = [1/7, 3/7, 3/7].$$

By matrix multiplication, we get

$$\mathbf{P}(\mathbf{C}^+)^T = [2.75/7, 0.5/7, 1.35/7, 3.4/7].$$

Based on the above, the list of causes in descending order for the above example is $\{P(c_4), P(c_3), P(c_2)\}$. This ordering will be an important step in the search algorithm described in the next section.

3. Maximum priority set covering

For a specified weighted list of observed defects, the resulting list of possible causes is arranged in descending order based on fuzzy set manipulations as shown in the previous section. The problem that must now be addressed is the appropriate selection of an adequate subset of this list as the 'best explanation' of the observed defects. One approach is to base the selection on a 'minimum cover' criterion, where the smallest possible set of causes explaining the defects is chosen as the 'best' explanation.

The set covering model was proposed and studied by other researchers (Reggia, 1982, 1983) as a general model for medical diagnostic problem-solving. Reggia and colleagues (1985) developed the Generalized Set Covering model (GSC), capturing intuitively plausible features of diagnostic inference and handling multiple simultaneous disorders. The most obvious advantage is to narrow the search space in the specified domain and to produce the sequential problem-solving paradigm to seek further information for the human diagnostician. The GSC is not directly suitable for our problem for two reasons. First, it ignores the fact that disorders usually occur with different degrees for the given set of manifestations. Second, although this model can generate a small set that can cover the occurring manifestations, it is still not sufficient for decision making because it requires additional responses from the user before it arrives at a conclusion.

3.1. *Maximum priority cover* (Pandelidis and Lin, 1988)

Our goal is to reduce the search space and determine the smallest set that can explain all of the defects present. An optimality criterion is set for selecting a subset of causes that explains the defects. This criterion is called 'Maximum Priority Cover'. An associated algorithm of how to find such a subset is also given.

Definition: $|E|$ denotes the cardinality of set E, i.e., the number of elements in E.

Definition: The sigma count, Σcount

$$A = \sum_{i=1}^{m} u_i,$$

is the arithmetic sum of the grades of membership in $A = \{u_1/u_1, u_2/u_2, \ldots, u_m/u_m\}$.

Definition: For any diagnostic problem, with a floating model $\mathbf{D}^+$, $\mathbf{D}^+ \subset \mathbf{D}$, and $\mathbf{E} \subset \mathbf{C}$,

(1) **E** is a **cover** of $\mathbf{D}^+$, if $\mathbf{D}^+ \subseteq \text{defect}(E)$.
(2) **E** is a **minimum cover** if $|\mathbf{E}| \leq |\mathbf{E}'|$ for any other cover $\mathbf{E}'$ of $\mathbf{D}^+$.

This definition captures the concept that the proposed causes in a set explains or 'covers' the presence of all the observed defects $\mathbf{D}^+$. Definition (1) specifies the reasonable constraint that a set of causes E must be able to cause all known $\mathbf{D}^+$, while (2) reflects the notion that the shortest explanation is the preferable one (Reggia, 1985).

Definition: The **solution**, Sol($\mathbf{D}^+$), is the set that contains all covers for the floating model $\mathbf{D}^+$.
$\text{Sol}(\mathbf{D}^+) = \{E_k \mid E_k \text{ is a cover of } \mathbf{D}^+\}$.

Definition: The **simplest solution** to the flaoting model $\mathbf{D}^+$, SS($\mathbf{D}^+$), is the set that contains all minimum covers of $\mathbf{D}^+$.
$\text{SS}(\mathbf{D}^+)=\{E_k \mid E_k \text{ is a minimum cover } \mathbf{D}^+\}$.
Definition: For two fuzzy sets A and B, A has higher **priority**, if

$$\frac{\Sigma\,\text{count A}}{|A|} > \frac{\Sigma\,\text{count B}}{|B|}, \text{ or if} \qquad (1)$$

$$\frac{\Sigma\,\text{count A}}{|A|} = \frac{\Sigma\,\text{count B}}{|B|} \;\&\; |A|<|B|. \qquad (2)$$

From this definition, we can see that a set has higher priority as the cardinality is deceased reflecting the need for simplicity that may represent a specific explanation. The significance of association, quantified in the sigma count, also reflects a higher priority.

Definition: A **Maximum Priority Cover** (MPC) is a cover with maximum priority from **C** to set $\mathbf{D}^+$.

The concept of maximum priority cover not only contains the concept of minimum cover in set theory but also takes the association of a set into account.

Example 1:

Given set $\mathbf{D}^+$ of defects $[d_1, d_2, d_c]$, assume the following relations as shown in Fig. 2:

$\text{cause}(d_1) = \{c_1, c_3\}$; $\text{cause}(d_2) = \{c_1, c_2, c_4\}$;
$\text{cause}(d_3) = \{c_4\}$. $\text{defect}(C_2) = \{d_1, d_2\}$
$\text{defect}(c_2) = \{d_2\}$ $\text{defect}(c_3) = \{d_1\}$
$\text{defect}(c_4) = \{d_2, d_3\}$ $\text{cause}(\mathbf{D}^+) = \bigcup_{d_j \in \mathbf{D}^+} \text{cause}(d_j)$
$= \{c_1, c_2, c_3, c_4\}$

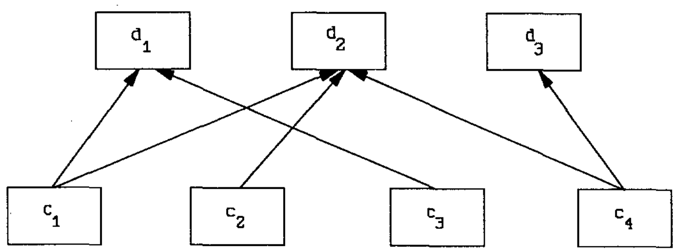

Fig. 2. Relations of causes to defects.

The above relations are also represented in Fig. 2:
We can see from Fig. 2 that a cover from **C** to $\mathbf{D}^+$ is either $\{c_1, c_4\}$, or $\{c_3, c_4\}$ or $\{c_1, c_2, c_4\}$, or $\{c_1, c_3, c_4\}$, or $\{c_2, c_3, c_4\}$, or $\{c_1, c_2, c_3, c_4\}$.
The set of all solutions is given by:

$\text{Sol}(\mathbf{D}^+) = \{\{c_1, c_4\}, \{c_3, c_4\}, \{c_1, c_2, c_4\}, \{c_1, c_3, c_4\}, \{c_2, c_3, c_4\}, \{c_1, c_2, c_3, c_4\}\}$.

The simplest solution, which is based on the minimum cover criterion, is

$\text{SS}(\mathbf{D}^+) = \{\{c_1, c_4\}, \{c_3, c_4\}\}$.

The fuzzy set of possible causes is $\mathbf{C}^+ = \{0.39/c_1, 0.07/c_2, 0.19/c_3, 0.49/c_4\}$ obtained from the previous section. The following describes the maximum priority cover criterion:

$(\Sigma\,\text{count}\,\{c_1, c_4\})/2 = (0.39+0.49)/2 = 0.44$

$(\Sigma\,\text{count}\,\{c_3, c_4\})/2 = (0.19+0.49)/2 = 0.34$

$\therefore\; (\Sigma\,\text{count}\,\{c_1, c_4\})/2 \geq (\Sigma\,\text{count}\,\{c_3, c_4\})/2$

The best choice for an explanation of the defects $\{d_1, d_2, d_3\}$ based on the maximum priority cover criterion is $E = \{c_1, c_4\}$. In general, the maximum priority cover will not necessarily be one of the simplest solutions, as it occurs in this particular example.

3.2. *Algorithm to find a maximum priority cover (MPC)*

The floating model containing the observed defects $\mathbf{D}^+ = \{d_1, d_2, d_3, \ldots, d_n\}$ will be used to identify the MPC of causes following the algorithm below:

(1) Get the defect d_i and the corresponding degree $P(d_i)$ for all $d_i \in \mathbf{D}^+$.
(2) Retrieve cause(d_j) and w_{ij} from the knowledge database for all $d_j \in \mathbf{D}^+$.
(3) Manipulate the fuzzy matrix and vectors as in Section 2.
(4) Find a cover based on the MPC criterion.

Finding an MPC from an unordered weighted list would normally require an exhaustive search which is very inefficient, particularly when the list is not small. It is useful, therefore, to find an algorithm for this purpose.

3.3. *Priority first cover (PFC)*

PFC has been developed as an alternative method to an exhaustive search. Such an algorithm which finds a sub-optimal subset based on the criterion of Priority is presented next. This algorithm depends on first creating an ordered weighted list and thus it is called the Priority First Cover (PFC) algorithm. One desirable feature of the algorithm is that it will always obtain a cover. Preliminary results show that the cover found by PFC algorithm is also the MPC. However we have not yet generated either a counterexample or a proof of this statement.

The Priority First Cover (PFC) Algorithm:

(1) Arrange the grades of membership in $\mathbf{C}^+$ in descending order.
The resulting ordered list will be denoted by

$\mathbf{O} = \{c^1, c^2, c^3, \ldots\}$ where c^i is the *ith* element in the list.

(Quicksort (Bratko, 1986) is a good method for this step.)
(2) Let $\mathbf{P}$ be the PFC set we wish to determine and $\mathbf{P}_i$ be the tentative cover in the *ith* step. The cause with the highest weight is selected first, so

$$\mathbf{P}_1 = \{c^1\}.$$

(3) At stage i, the element c^i is added to the list of $\mathbf{P}$ if it covers a new defect other than those previously covered. Otherwise, the next element is taken into account.
(4) The algorithm terminates when a cover has been found.

We illustrate the PFC algorithm by way of Example 1.
Step 1:
Sort from $\{c_1, c_2, c_3, c_4\}$:
The resulting ordered list is $\{c_4, c_1, c_2, c_3\}$

Step 2:
Put c_4 into the set $\mathbf{P}_1$ and record defect(c_4):

$$\mathbf{P}_1 = \{c_4\}$$

defect(c_4) = $\{d_2, d_3\}$
Step 3:
Check whether defect(c_1) = $\{d_1, d_2\}$ can cover a new defect or not. The element c_1 is added to $\mathbf{P}_1$ because d_1 is a new defect.

$$\mathbf{P}_2 = \{c_4, c_1\}$$

defect($\{c_4, c_1\}$) = $\{d_1, d_2, d_3\}$.
The algorithm stops here and the cover is $\{c_4, c_1\}$. This set is the same as the one obtained in Section 3.1.
We shall now prove with the help of the following theorem and corollary a certain optimality property of the PFC algorithm.

Theorem: If a list $\{w_1, w_2, \ldots\}$ such that $w_i \geq w_{i+1}$ for $i \in N$, then

$$\frac{\sum_{i=1}^{n} w_i}{n} \geq \frac{\sum_{i=1}^{n+1} w_i}{n+1} \quad \text{for all } n \in N$$

Proof:

$$\text{Let } S(k) = \sum_{i=1}^{n} w_i$$

Since $w_i \geq w_{i+1}$, thus $S(n) \geq n\, w_{n+1}$
Adding $n \times S(n)$ to both sides of the inequality results in $(n+1) \times S(n) \geq n \times (w_{n+1} + S(n)) = n \times S(n+1)$

Therefore

$$\frac{S(n)}{n} \geq \frac{S(n+1)}{n+1}$$

which is the desired result.

Corollary: Given a decreasing list $w_1 \geq w_2 \geq w_3 \geq w_4 \geq \ldots \geq \ldots$, then

$$\frac{\sum_{i=1}^{n} w_i}{n} \geq \frac{\sum_{i=1}^{m} w_i}{m}, \text{ if } n < m.$$

The proof is easy to construct.
Given a list with descending order, we can always find a cover by using the PFC algorithm. This is guaranteed by construction. Assume $\mathbf{A} = \{w_1, w_2, w_3, w_4, \ldots, w_n\}$ is a

cover obtained from PFC. If we add another element to **A**, that element by construction will have an associated weight $w_{n+1} \leq w_n$ so we will have $\mathbf{B} = \{w_1, w_2, w_3, w_4, \ldots, w_n, w_{n+1}\}$. Based on the above-stated corollary, the priority of **A** is greater than that of **B**. This indicated that whenever a cover is found from a descending list, it is not necessary to consider the remaining elements of that list.

A comparison of the above method with the following two exhaustive searches will show its usefulness.

Exhaustive Search 1:

(1) Calculate the values of Σcount $\mathbf{E}_k/|\mathbf{E}_k|$ for all the combinations of the list $\{w_1, w_2, w_3, w_4, \ldots, w_n\}$. (If n is not small, this requires much computation.)

(2) Perform a or b.

a. Sort in a descending order for all $\mathbf{E}_k$, then pick the element sequentially from the list until a cover is found. (Much execution time is needed to sort the list to an ordered form because its length is much larger than the one used by the PFC algorithm.)

b. Find the maximum value of association (highest priority), then check whether it is a cover. If not, try the next maximum until a cover is found. (This step selects the combination with the largest number from an unordered list. Sometimes with luck it is possible to find a cover quickly. Otherwise, this step will require repetition.)

Exhaustive Search 2:

(1) Find all covers for $\mathbf{D}^+$, i.e., $\mathrm{Sol}(\mathbf{D}^+) = \{\mathbf{E}_k | \mathbf{E}_k$ is a cover$\}$. (This takes a lot of execution time and storage if the list is not small.)

(2) Calculate the value of Σcount $\mathbf{E}_k/|\mathbf{E}_k|$ for all $\mathbf{E}_k \in \mathrm{Sol}(\mathbf{D}^+)$.

(3) Search from $\mathrm{Sol}(\mathbf{D}^+)$ to find the set $\mathbf{E}_k$ with highest priority (maximum value of association).

Exhaustive search 2 is better than exhaustive search 1, but it is still not efficient. By using the PFC algorithm, we only sort $\{w_1, w_2, w_3, w_4, \ldots, w_n\}$, a subject of $\mathrm{sol}(\mathbf{D}^+)$, to an ordered list. Then we pick up each element from the beginning to check whether the set is a cover or not. Thus, the PFC algorithm is faster than exhaustive search methods.

4. System organization

The system is organized in such a way that it is centered by a knowledge base which consists of stored experiential data, theoretical rules for diagnosis, logic inference rules, technical data of plastic materials and injection machines, as well as rules monitoring the activity of the system itself. Around the knowledge base, three interactive functional components are built to provide facilities for diagnosis, explanation and discussion. On-line help is also implemented. An overview of the system architecture may be seen in Fig. 3.

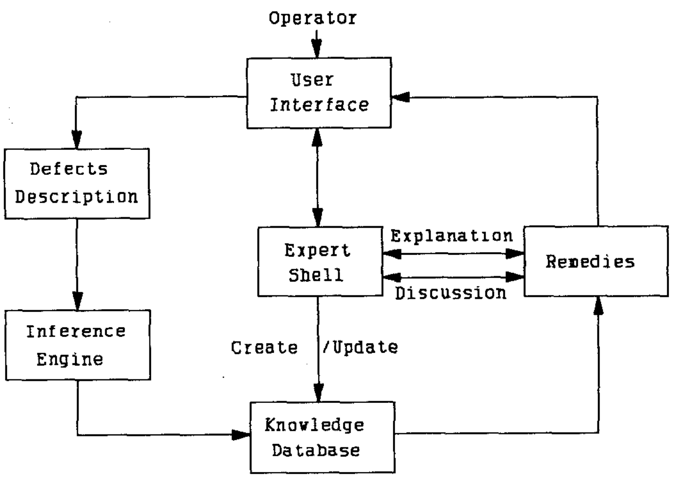

Fig. 3. System configuration.

4.1. *System development and requirements*

This program was written in the Prolog programming language primarily for three reasons: first, the knowledge is expressed in a context familiar to the human expert; second, it is efficient, both in speed and memory, which enables it to run on small computers; third, it is compatible on a variety of computers such as Vax or Sun using a C-prolog interpreter allowing sharing of the same database. Additional advantages which improve the performance and the acceptance of this system may be found in the menu-driven interface, learning capabilities (although limited) and explanation facilitation.

Knowledge about the relations of causes and defects are organized into well-defined categories of attributes and other factors. A few of the important characteristics of objects can be represented in a qualitative classification scheme. For example, a low mold temperature causing short shot with the relative weight 0.5 can be represented as:

cause_of([short, shot], molding, [mold,temperature], low, 0.5).
Defect: short shot
Category: molding
Causes: mold temperature
Description: low
Initial weight: 0.5

There are over 400 rules covering 25 types of molded part defects, as shown in Defects Menu in Section 4.3. The methodology has been thoroughly developed for Detector. The material database has been created for the plastics of the Monsanto Co. Presently, data for several kinds of machines are also stored. We still need further technical support from the parts manufacturers and the material producers to create a complete expert database.

System requirement for personal computers is that they be

- IBM PS/2 or IBM PC, XT, AT (or compatible)
- 640 K RAM
- One 5.25 or 3.5 inch disk drive or a hard disk
- DOS 2.0 or higher

4.2. *Functional components*

4.2.1. *Knowledge base:*

There are five functionally independent parts of this knowledge base.

(1) Trouble-shooting guide

This is the kernel of the knowledge database as we mentioned in Table 1. It records all of the relations of causes and defects with associated initial weights containing the necessary data for further diagnosis.

(2) Reference rules

This part contains general rules about the properties and relationships of plastic materials. These rules link to the trouble-shooting guide to help identification in the problem.

(3) Connection of plastic variables and machine variables

Remedies of the defects are given after the diagnosis is achieved. Suggested remedies are in terms of the adjustable variables or machine variables, while causes are in most cases in terms of plastic variables.

(4) Materials Data Base

The properties of the material and their general processing conditions are stored in a materials processing database. They form an independent area of the database where important information such as suggested melt temperature, mold temperature, screw speed, injection pressure, etc., is available for the diagnosis process.

The materials database is stored as a hierarchical frame structure with generic material such as ABS (Acrylonitrile Butydiene Styrene) being stored at the top and specific grades from a given company such as ABS–448 being stored at the bottom of the hierarchy. This arrangement allows for robust behavior of the expert system, since default values can be obtained through property inheritance from the parent category. The diagnostic system is thus capable of responding to inquiries about a general material as well as for a specific grade.

(5) Machine Data Base

The machine database consists of information about the process capabilities of the particular injection molding machine under consideration. Information such as maximum clamping force, plasticizing capacity and maximum injection pressures is stored for each machine. This information is stored under a system with default values, so that recommendations can still be given when this information is not available.

One of the important links of the processing capabilities to the quality of the part is the machine plasticizing capacity. Generally speaking, the shot weight in ounces should fall within 40–80 per cent of the plasticizing capacity of the barrel, which holds and heats the plastic before it is injected into the mold. A shot size much less than 40 per cent will have an extended barrel residence time. This exposes the plastic melt to heat, pressure and screw shear beyond its limits of endurance and degradation of the polymer will begin. On the other hand, residence times that are too short due to shot size beyond 80 per cent of the capacity of the barrel risk insufficent plasticizing of the resin. Comparison of the barrel capacity stored as machine data with the presently used shot size, is useful diagnostic information.

4.2.2. *Explanation program*

One of the advantages in writing a program using an artificial intelligence language is the ability to provide explanations of the steps taken by the program to arrive at a conclusion. The program can trace and review the rules invoked during the diagnostic process. It can produce a reasonable explanation of its conclusions by tracing the applicable rules for the given problem. It also gives the human expert a chance to change the rules to improve the performance. Whenever the users need the explanation of terminology, it also has the capability to explain the meaning of most injection molding terms. This feature gives the users the opportunity to understand plastic terminology or behavior associated with precise information from machines or material data from the database.

4.2.3. Discussion program

This program displays the list of the possible causes with a corresponding number. The user selects the number to deny or confirm it until no further discussion. Detector changes the weights associated with those items then invokes the diagnostic program again after knowing that some of the causes given by the previous diagnosis are denied or confirmed. The new information is supported for decision-making to yield another diagnosis. We can naturally expect to obtain a more reliable conclusion when more condition are known.

4.3. *Example of a consultation*

In this section we show a typical example of a consultation with the diagnostics program. A typical session involves a few minutes of interactive dialogue with the user. When the user types *diagnosis.* to run a consultation, Dector displays some options in the help menu. After selecting the defect by a corresponding number for the current problem to be solved, the user is guided to answer the degree of the defect then to answer whether other defects are found or not until there are no defects. Questions are about material, machines, molds, processing conditions, etc. The responses by Detector are different for the problems depending on what is needed. The following output is what is displayed after the initial interaction, where the operator enters the observed defects and information about the current status of the manufacturing process. The result contains the most possible causes and recommended remedies. It also lists all of the possible causes that can solve the problem.

DEFECTS MENU SCREEN

1. black specks	2. black spots
3. black streaks	4. brittleness
5. brown streaks	6. bubbles
7. charred area	8. cracking
9. delamination	10. dimensional variation
11. discoloration	12. drooling
13. erratic cycle	14. flashing
15. low heat distortion temperature	16. jetting
17. poor ejection	18. sink marks
19. shrinkage	20. short shot
21. sprue sticking	22. voids
23. warpage	24. weld lines
25. tearing	26. Why?

Please Enter the defect by choosing the corresponding number →

Please Enter the number to describe the degree of the defect:
1. means Slight
2. means Obvious
3. means Serious

Current operating environment:
Mold has not been changed recently.
Mold in good condition.
/* A new mold could contribute to the problem. */
The material in use is ABS–448 that is a general purpose grade.
The machine in use is machine 1 which is in good condition.
The melt temperature of the current processing conditions is 540°F.

Defects description:
Black streaks with slight evidence
Flashing with moderate evidence
My diagnosis is:

(1) high melt temperature with relative weight 1.46 which causes defect flashing of weight 1.46.
(2) insufficient mold venting with relative weight 0.4 which causes defect black streaks of weight 0.4.
Other possible causes are:
(3) excessive plastic feed with relative weight 0.79
(4) insufficient clamping with relative weight 0.79
(5) high injection pressure with relative weight 0.79
(6) low plasticizing capacity with relative weight 0.67
(7) high injection speed with relative weight 0.67
(8) non parallel mold plate with relative weight 0.5
(9) poor alignment of mold plate with relative weight 0.5
(10) high injection forward time with relative weight 0.34
(11) unequalized filling rate in cavities with relative weight 0.34
(12) non parallel machine platens with relative weight 0.3
(13) not maintained clamping pressure with relative weight 0.3
(14) plunger off center causes friction burning with relative weight 0.23
(15) inconsistent cycle in mold operation with relative weight 0.07

The following action can be taken to eliminate the identified causes:

REMEDY:
You can decrease the barrel temperature or nozzle temperature to decrease the melt temperature.

Note:
You should check and maintain that the melt temperature is actually between 475 to 525°F for Monsanto's ABS–448.
A common method is to insert the needle probe of a hand pyrometer into shot taken after the cylinder is up to operating temperature, and after the machine has been operating on cycles for 10 to 12 shots.

REMEDY:
You can increase mold venting.

Note:
The recommended mold venting for ABS–448 is 0.002 inch deep 0.002 to 0.5 inch wide.

INSTRUCTION SCREEN
Diagnosis finished and the prescription is given in the file "result". You can see that file by typing *view(result)*.
If you do not agree with this result, you can discuss it with me by typing discuss.
If you need the reasoning, please type *explain.*, then choose the item from the shown menu.

Press Esc to exit

Note:
In this particular case, the flashing is explained entirely by the high melt temperature and the black streaks are caused by insufficient mold venting, so the weights for each defect match the weights for each cause. This will not be true in

general. Note also that excessive plastic feed may have a higher weight than insufficient mold venting, but it does not explain black streaks, so it is not chosen in the maximum priority cover.
/* Several other simulated cases have been tested with positive results. However, no field data is available yet.*/

5. Conclusions

The diagnostic knowledge-based system, Detector, has been developed in order to attain the high level of performance that a human expert achieves in the trouble-shooting of injection molding. Three important parts of the solution process, problem representation, alternative generation and alternative evaluation, have been discussed and the requirements of the expert system judgment have been identified. By means of fuzzy set theory, initial confidence factors are assigned. This has made it possible to deal with intangible factors for the prenumerated set of possible solutions with which we have been concerned. Expert rules are retrieved only when they are related, avoiding unnecessary computation, and thereby increasing the efficiency of this program.

A list of possible causes generated by fuzzy matrix manipulations is obtained in descending order of weights. The inference solver then selects an appropriate subset of causes based on the Maximum Priority Cover (MPC). An alternative algorithm without exhaustive search for the MPC has been developed to find an optimal subset from the list of causes.

This system provides a new inference method, which is attractive because it supports a descriptive representation rather than a procedural representation. It also supports approximate reasoning for multiple simultaneous disorders and produces several possible alternatives, which are ordered in terms of priorities. If the corrective action for the most-likely causes fails to solve the problem, the *Discussion* program can be invoked to modify the original inference based on the newly acquired information. Remedies and suggestions of how to implement the recommendations associated with material properties are also given, and material specific information is provided through a materials processing database.

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