# A Case-based Decision Support Model for The Semiconductor Packaging Tasks

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## Abstract

*When a semiconductor package is assembled, various materials such as die attach adhesive, lead frame, EMC (Epoxy Molding Compound), and gold wire are used. For better preconditioning performance, the combination between the packaging materials by studying the compatibility of their properties as well as superior packaging material selection is important. But it is not an easy task to find proper packaging material sets, since a variety of factors like package design, substrate design, substrate size, substrate treatment, die size, die thickness, die passivation, and customer requirements should be considered.*

*This research applies case-based reasoning(CBR) technique to solve this problem, utilizing prior cases that have been experienced. Our particular interests lie in building decision support model to aid the selection of proper die attach adhesive. The preliminary results show that this approach is promising.*

***Keywords:***

Case-based Reasoning; Decision support system, Semiconductor Industry

## Introduction

Getting into the multimedia era, the needs of the semiconductor products continue to undoubtedly be increased in various market areas ranging from the latest personal computers to light weight portable consumer products. As next generation electronic systems require higher levels of performance, device functionality has rapidly increased. Accordingly technologies related to the semiconductor packaging have been improved rapidly to achieve light in weight, handy and personal use products. In order to meet the changes of demands of the market, the packaging technology having better performance, cost effectiveness and better reliability becomes more important.

This research is about making better reliability of semiconductor products. All products and packages are required to meet the minimum reliability level. Because reliability relates to the number of parts that may be expected to fail or deteriorate over a given period of time after placing into service. Therefore, after assembly completion of semiconductor packages, short term reliability is assessed and qualified through the MRT (Moisture Resistance Test) known as preconditioning and followed by long term reliability test like temperature cycling, thermal shock, and highly accelerated temperature & humidity stress test, etc.

When a semiconductor package is assembled, various materials such as die attach adhesive, lead frame, EMC (Epoxy Molding Compound), and gold wire are used. For better preconditioning performance, the combination between the packaging materials by studying the compatibility of their properties as well as superior packaging material selection is important. But it is not easy to find proper packaging material set, since a variety of factors like package design, substrate design, substrate size, substrate treatment, die size, die thickness, die passivation, and customer requirements should be considered. Therefore, lots of trial and error tests in reality are done and redone to meet the minimum reliability level, which cause time delay, high cost, and customer dissatisfaction.

Case-based Reasoning(CBR) is a knowledge-based problem solving technique that is based on reuse of previous experience [9,10,17,20]. Unlike traditional knowledge-based techniques, such as decision trees [16,6] or artificial neural network [14] which solve problems from scratch by reasoning with general knowledge, CBR focuses on specific problem-solving experience captured in cases that are collected in a case base. New problems are solved by retrieving cases that are dealt with previous similar problems [9,17,20]. The solutions recorded in those similar cases are then transferred to become a solution of the new problem [2] Numerous applications of CBR have been reported including finance and accounting domain [3,5,7,12], software effort estimation [13], applications to customer services [11], retail real estate [15], indirect bank lending [19].

In this research, we discuss the implementation of a case-based decision support model for semiconductor assembly domain. Our particular interests lie in building decision support model to aid the selection of proper die attach adhesive which is considered as a very important element to pass the MRT (Moisture Resistance Test).

This paper is organized as follows. Section 2 provides a description of semiconductor packaging process and the related reliability test procedure. Section 3 presents the case-based reasoning methodology. Section 4, 5 illustrates the model development process and the experiment design & results. The final section discusses the conclusion and future research issue.

## Semiconductor Assembly Process and Preconditioning Test Procedure

Semiconductor products find wide use in applications ranging from the latest personal computer to light portable and handheld devices like cell phone. With the consumers' needs for increasing functionality and performance, while decreasing size, weight and cost of these electronic devices, IC (Integrated Circuit) packaging technology is a driving force. The assembly is the process of transforming hundreds to thousands of ICs per wafer into individually packaged units. The packaging of IC is to protect delicate circuitry, to handle easily and to increase overall final yield. This section briefly describes the semiconductor assembly process and the preconditioning test flow.

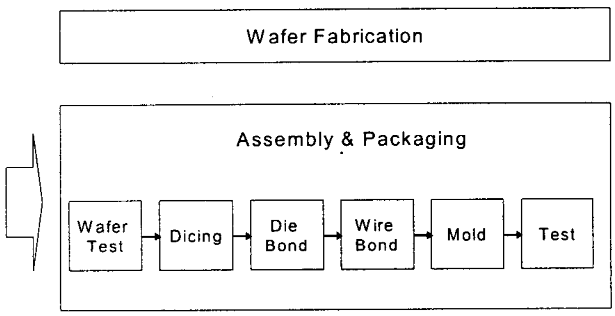


*Figure 1 - Assembly Process*

In plastic package technology, the chip is first bonded to the lead frame using an adhesive and the die is then electrically connected to the package by bonding a gold wire to the bonding pad on the die and the package leads. Finally the entire assembly is completely sealed using EMC (epoxy mold compound) to protect the device mechanically and environmentally from the outside environment. Figure 1 shows the assembly process.

After assembly completion, the preconditioning test is performed at various moisture and temperature condition for different lengths of times to simulate package environment from post mold cure through board mounting. The moisture soak conditions for preconditioning are dependant on the moisture sensitivity level as defined by the JEDEC (Joint Electronic Device Engineering Council) or EIAJ (Electronic Industries Association of Japan) standard.

SAT (Scanning Acoustic Tomograph) is used to detect some failure like delamination or cracking. Preconditioning test flow is summarized in Figure 2.

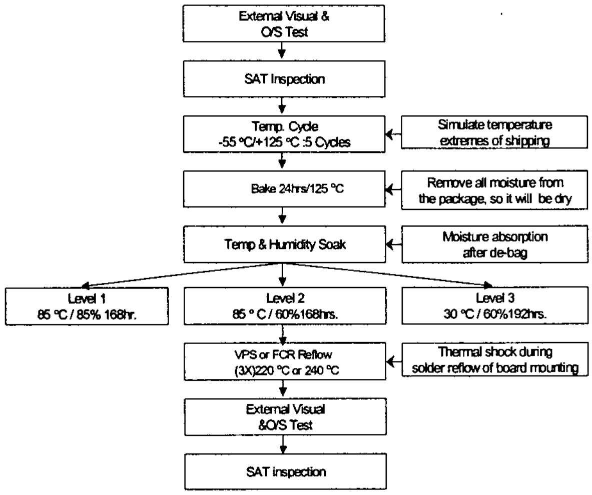


*Figure 2 - Preconditioning Flow for Surface Mount Package*

During the simulation, many problems can arise. The following attributes could affect the moisture sensitivity of device: die attach material/process, mold compound material/process, die pad area/shape, body size, die passivation, lead frame design/material/finish, die thickness/size, and interconnect. The defects can range mainly from poor bonding interface, voids, delamination to cracking.

Plastic semiconductor packages uptake moisture under ambient. Moisture inside a plastic package turns to steam and expands rapidly when the package is exposed to the high temperature of VPS (Vapor Phase Reflow) or FCR (Forced Convection Reflow) soldering process for board mounting. The pressure from this expanding moisture can cause internal delamination at various interfaces within the package. In the most severe case, the stress can result in external package cracks.

It is also accepted that the failure is caused by a combination of factors including the high stress resulting from the mismatch in the CTE (coefficient of thermal expansion) of the various materials and poor adhesion between dissimilar materials. Voids can be introduced during die attach and molding from out-gassing of the solvent-filled material or improper curing profiles, which affect the stress profiles.

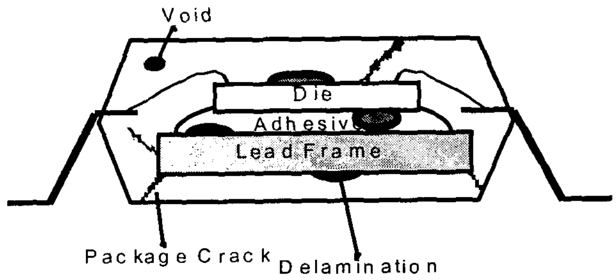


*Figure 3 - Failure Mode for Semiconductor Package*

Figure 3 shows some of the common mode of failure which may occur either through assembly conditions or precondition testing. Advancements and combination in mold compound, die attach material, and lead frame minimize the failures.

## Case-based Reasoning

Case-based reasoning is a problem solving technique in which past cases and experiences are re-used to find a solution to particular problems [8]. The central tasks involved in CBR methods are to identify the current problem situation, find a past case similar to the new one, use that case to suggest a solution to the current problem, evaluate the proposed solution and update the system by learning from this experience [10,17,20]. Figure 4 illustrates the processes involved in CBR represented by a schematic cycle.

### Case Representation

A case is a contextualized piece of knowledge representing an experience. It contains a past lesson that is the content of the case and a context in which the lesson can be used. Typically a case comprises of: (1) the problem that describes the state of the world when the case occurred, (2) the solution which states the derived solution to that problem and (3) the outcome which describes the state of the world after the case occurred [9].

Cases can be represented in a variety of forms using the full range of AI representational formalisms, including frames, objects, predicates, semantic nets and rules [10,17].

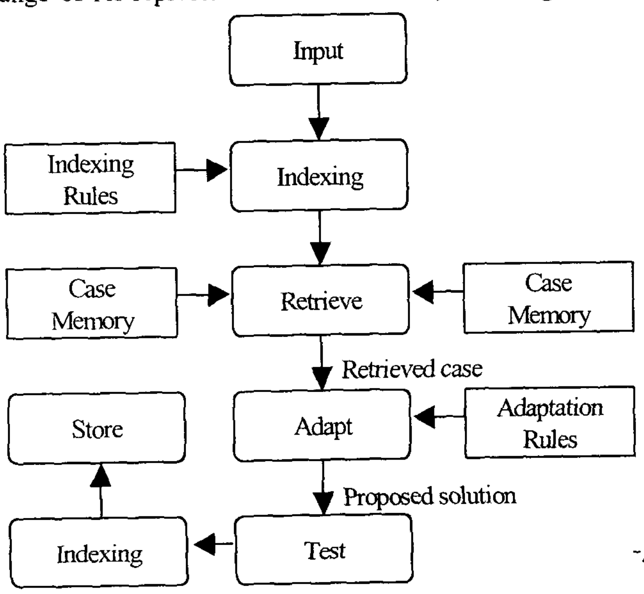


*Figure 4 - Overview of The Case-based Reasoning Process [17]*

### Case Indexing and Retrieving

Case indexing involves assigning indexes to cases to facilitate their retrieval. The Indexes organize and label cases so that appropriate cases can be found when needed. In building case-based reasoning systems, the CBR community proposes several guidelines for choosing indexes for particular cases: (1) indexes should be predictive, (2) indexes should be abstract enough to make a case useful in a variety of future situations, (3) indexes should be concrete enough to be recognizable in future cases, and (4) prediction should be useful [9,10]. Both manual and automated methods have been used to select indexes. Choosing indexes manually involves deciding the purpose of the case with respect to the aims of the reasoner and deciding under what circumstances the case may be useful.

The second issue of indexing cases is how to structure the indexes so that the search through case library can be done efficiently and accurately. Given a description of a problem, a retrieval algorithm which uses the indexes in a case-memory should retrieve the most similar cases to the current problem or situation. The retrieval algorithm relies on the organization of the memory to direct the search to potentially useful cases.

The indexes can either index case features independently for strictly associative retrieval or arrange cases from the most general to the most specific for hierarchical retrieval. There are three approaches to case indexing: nearest-neighbor, inductive, and knowledge-guided [3,4,18]. The nearest-neighbor approach let the user retrieve cases based on a weighted sum of features in the input cases that match the cases in memory [1]. Every feature in the input cases is matched to its corresponding feature in the stored or old cases and the degree of match of each pair is computed. One of the most obvious measures of similarity between two cases is the distance. A matching function of the nearest-neighbor method is as follows:

$$DIS_{ab} = \sqrt{\sum_{i=1}^{n} w_i \times (f_{ai} - f_{bi})^2}$$

where DIS is the matching function using Euclidean distance between cases, n is the number of features, and $w_i$ is the importance weighting of a feature i. Basic steps of nearest-neighbor retrieval algorithms are quite simple and straightforward. Every feature in the input case is matched to its corresponding feature in the stored case, and the degree of match of each pair is computed using the matching function. Based on the importance assigned to each dimension, an aggregate match score is then computed. Ranking procedures order cases according to their scores where higher scoring cases are used before lower scoring ones.

Inductive indexing methods generally look for similarities over a series of instances and then form categories based on those similarities. Induction algorithms, such as ID3 [16] and CART, determine which features best discriminate cases, and generate a tree type structure to organize the cases in memory. An induction tree is then built upon a database of training cases. This approach is useful when a single case feature is required as a solution and where that case feature is dependent upon others.

Knowledge-guided indexing applies existing domain and experimental knowledge to locate relevant cases. Although this method is conceptually superior to the other two, knowledge-guided indexing is difficult to carry out since such knowledge often cannot be successfully and exhaustively captured and represented. Therefore, many systems use knowledge-guided indexing in conjunction with other indexing techniques [3].

### Adaptation

Adaptation is the process of adjusting the retrieved cases to fit the current case. Once a matching case is retrieved, a CBR system should adapt the solution stored in the retrieved case to the needs of the current case. Adaptation looks for prominent differences between the retrieved case and the current case and then applies formulae or rules that take those differences into account when suggesting a solution.

In general, there are two kinds of adaptation in CBR: (1) substitution method and (2) transformation methods. The substitution method substitutes values appropriate for the new situation for values in the old solution. The transformation methods are used to transform an old solution into one that will work in a new situation [10].

## Model Development

### Data and Variables

Research data contains 1,106 success cases (cases that have passed the MRT successfully) which were consist of 5 package types including QFP (Quad Flat Package), TQFP (Thin Quad Flat Package), LQFP (Low Profile Quad Flat, TSOP (Thin Small Outline Package), TSSOP (Thin Shrink Small Outline Package), and EPTQFP (Exposed Pad Thin Quad Flat Package). The sample data consists of the important features in selecting proper die attach adhesive derived from experts' opinion (input variables) and the corresponding types of die attach adhesives (output variables), which were collected from a semiconductor assembly company over 4 years. Table 1 and 2 shows the organization of the data set, and the selected input variables for the experiments, respectively.

Each data is split into two subsets, a reference set and a validation set of 85% and 15%, respectively. The reference data are used as case base for retrieval. The validation data are used to verify how well the indexing of CBR system works with the data which were not used to develop the system.

*Table 1 - The Number of Cases for Experiment*

| ypes of die ttach adhesive | Package Types | | | | |
|---|---|---|---|---|---|
| | QFP | TQFP | LQFP | TSOP | EPTQ FP/TS SOP |
| 84-1LMISR | 102 | 261 | 110 | 80 | 28 |
| 8361J | 222 | 44 | 58 | 42 | 70 |
| 84-1LMIS | 29 | 5 | 4 | 0 | 0 |
| 8390A | 5 | 0 | 0 | 0 | 0 |
| 8360 | 0 | 0 | 0 | 13 | 0 |
| 8290 | 0 | 0 | 0 | 0 | 33 |
| Sum | 358 | 310 | 172 | 135 | 131 |

*Table 2 - Input Variables for Experiment 2*

| Variables | Definition |
|---|---|
| X1 | Package type |
| X2 | Die size 1 |
| X3 | Die size 2 |
| X4 | Die thickness |
| X5 | Die passivation |
| X6 | Lead frame size 1 |
| X7 | Lead frame size 2 |
| X8 | Lead frame surface |
| X9 | Epoxy Molding Compound |
| X10 | Preconditioning level |
| X11 | Reflow temperature |

### Results and Analysis

We apply two types of case indexing/retrieving approach for this experiment; the pure nearest neighbor retrieving (CBR-Pure) and the integrated approach using the nearest neighbor retrieving and inductive learning (also called inductive indexing method). The CBR-Pure model uses nearest neighbor algorithm that has equal weight among the attributes for retrieval. The integrated approach using induction enables cases to be organized hierarchically so that only a small subset needs to be considered during retrieval. Induction algorithms determine which features do the best job in discriminating cases and generate a tree type structure to organize the cases in memory.

Integrated approach using induction technique and nearest neighbor retrieval reaps the benefit of both systems. First, we can retrieve more relevant cases through generalized domain knowledge. This is driven by the induction technique which extracts explicit knowledge from the data. Second, the integrated approach can enhance the efficiency of the system because only a small subset of data needs to be considered during retrieval. We use the software package, KATE™ for CBR, induction, and the integrated model.

Fig 5 presents one example of induction tree which is built upon a database of training cases for an effective and efficient retrieval in CBR, and Table 3 shows the figures of the tree. The nearest neighbor algorithm is applied at the end of the induction tree.

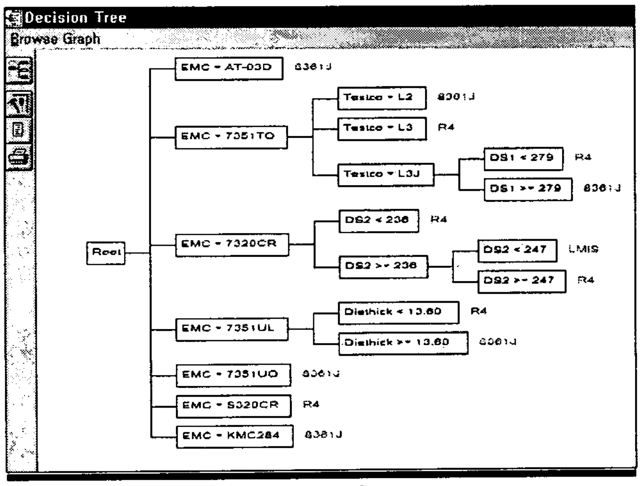


*Figure 5 - Decision Tree Example*

*Table 3 - Figures for The Induction Tree*

| Package type | Number of nodes | Number of leaves | Avg. depth | No. of cases per leaf | No. of quest-ions |
|---|---|---|---|---|---|
| QFP | 139 | 81 | 5.1 | 3.7 | 4.2 |
| TQFP | 67 | 44 | 3.2 | 5.8 | 2.8 |
| LQFP | 19 | 33 | 2 | 10.3 | 1.8 |
| TSOP | 44 | 29 | 3 | 3.8 | 2.9 |
| EPTQFP/ TSSOP | 34 | 21 | 3.1 | 5.3 | 3.1 |

Table 4 shows the comparison results of applied for each method in this study. The data shows the accuracy of the prediction by applying each method. As shown in Table 4, the results of both methods are very positive, showing 82 to 97 percent of accuracies.

*Table 4 - Result Accuracy (%)*

| | QFP | TQFP | LQFP | TSOP | EPTQFP/ TSSOP |
|---|---|---|---|---|---|
| CBR-Pure | 91.2 | 84.0 | 97.0 | 80.1 | 94.5 |
| Integrated | 82.0 | 84.0 | 94.5 | 84.3 | 94.5 |

## Concluding Remarks

In this paper, we have applied CBR using nearest neighbor algorithm and CBR using the induction in an attempt to select the proper die attach adhesive for semiconductor assembly domain. Our preliminary results show that CBR is a promising methodology for the applied domain.

This paper has several limitations. We selected the input variables for the model building process according to the experts' opinion. However, more important variables may have been excluded, and correlational structure among the variables does not considered. The sound procedure including statistical test to determine optimal variables are needed.

Secondly, further research is necessary to determine whether it is possible to improve the effectiveness of indexing in case-based reasoning using induction technique. One extension would involve identifying an optimal structure of induction tree for case-based reasoning.

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