Chapter 7
Shape Commonalization to Develop Common Platforms for Mass Customization

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Abstract To be a global leader in the current market, a company needs to keep on adapting to the changing requirements of its customers and also provide customization of its products to suit the customers' needs. A robust *product platform* can support a variety of products to satisfy different segments of the market with reduced manufacturing and product development cost. The common components for a set of similar products belonging to a family can be grouped into a common platform. However, development of product platform requires measuring similarity among a set of products. This chapter presents an approach to measure the *degree of similarity* among a set of products by extracting the information from their existing CAD models. The extraction process leads to a suitable development of *shape commonality indices* to identify the components and products that can be potentially arranged under a common platform. Two case studies are presented to demonstrate the steps of the approach.

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Abbreviations

CAD	Computer-aided design
MLD	Multiple levels of details
AAPCI	Average assembly platform commonality index
AC	Average commonality for a feature-set
ACPCI	Average component platform commonality index
API	Application programming interface
BBB	Basic building block
DC	Dimensional commonality
IGES	Initial graphics exchange specification
LRE	Lower reservoir extrusion
NOC	Number of component-sets in a given product-set
NOF	Number of feature-sets in a given component-set
PC	Positional commonality
S	Shell
STEP	Standard for the exchange of product model data
UOC	Upper opening cut
UoS	Union of spheres
WPC	Warming plate cut
WPE	Warming plate extrusion

7.1 Introduction and Background

The current market place is characterized by customers with a diverse set of requirements, with customers changing their demands frequently. In order to compete in the current global market, companies are now determined to treat customers as individuals with different needs rather than lump them into homogeneous groups. A well defined product platform is necessary to support *mass customization* or provide varieties.

With the development of technology, the use of *CAD in design* has increased significantly in recent decades. In such a design environment, establishing a common platform for a set of similar products or mass customization will require measuring the *commonality* among similar components used in a range of products. A technique to measure the similarity among the different 3D models would enable faster development of the product platform. Consequently, one of the challenges that need to be addressed for more efficient and effective use of 3D CAD to support mass customization and develop efficient product platforms will be to compare and identify 3D CAD models of components and products that are common or similar.

Existing *shape matching techniques* apply a *two stage* process, first transforming the shape and then measuring the resemblance with using similarity measures. During shape matching processes, the applied *transformations* often ignore the attributes of the CAD models, which have significant design information. However, there is a lack of research on measuring the *geometric* (*shape*) *commonality* of components, especially for 3D solid models. The shape commonality between a set of components could be used as a key factor in designing product platforms from an existing set of components, optimizing existing product platforms to increase component commonality, and searching component databases to identify similar components. Thus, it is becoming necessary for product designers to measure the shape commonality between a given set of components. This chapter addresses the following research question: how can we compare and measure *commonality of 3D CAD models* of products to develop common platforms?

7.2 Literature Review

7.2.1 Product Platform

There has been substantial research conducted in the areas of product family design. Duray and Milligan (1999) discussed the significance and effects of involving customers at various stages in the product development and manufacturing process. The authors present *common characteristics and practices* of mass customizers. Simpson *et al.* (2005) described two basic approaches to product family design – "*top-down*" (proactive platform) approach and "*bottom-up*" (reactive design) approach. In the top-down approach, the product family is derived, developed, and managed from a product platform. In the bottom-up approach, a group of distinct products are redesigned and standardized in order to improve economies of scale.

Shooter (2005) has described the top-down approach used by *Innovation Factory* in the development of the "IceDozer" product family of ice scrapers using the platform concept. The *top-down* approach used resulted in an increase in product variety in the existing product line, lower tooling costs, and shorter lead times for development. This was largely due to the use of standardized components, which made it easier to develop additional variants in the product line by simply introducing extensions to the existing products. The success achieved by Innovation Factory proved that product family concept is beneficial not only to large firms but also to small start-up firms.

Halman *et al.* (2003) investigated why companies are adopting product family and platform concepts, along with the methodologies used to develop, implement, sustain, and monitor these concepts. In the paper the authors concluded that even though the products offered by the companies differed substantially, all the companies under investigation used the product family concept for the same goals, anticipated *similar risks*, and expected *similar benefits*.

Fellini *et al.* (2003) presented a *strategy* to identify and select the product platform for a given product family, based on the individual optimization results of the variants in the family. Product variants in the family are obtained by incorporating the functions that they are required to perform. The *assumption* is that product variety in a product family can be achieved by making only *minor changes* in the design. The individual variant designs are used to formulate a metric, known as the performance deviation vector. Based on the values in the vector, commonality decisions are made and the product family is *optimized* and designed around the chosen platform. This technique is applied to redesign a product family of automotive body structures.

Alizon *et al.* (2008) discussed two development strategies to derive product families: (1) *a platform-driven strategy* and (2) *a product driven strategy*. In a platform-driven process, the platform is specified at the beginning and all the products in the family are developed and launched at the same time based on this platform. In the product-driven process, only one product goes through the process from design to manufacturing and is then launched in the market. So, the platform is not directly specified and the initial product is used as the basis for future variants.

Khire *et al.* (2008) presented a *product family commonality* selection method based on individual product optimization and interactive visualization by the designer. Sandborn *et al.* (2008) applied the product platform design concepts to determine the best *reuse* of the electronic components. The authors concluded that timing and supply chain disruptions should be taken into account in designing product platform. Alizon *et al.* (2008) proposed two novel *indices* emphasizing shape and functional similarity to achieve differentiation within a family of products.

It can be concluded from the literature summarized in this section that product platform development is a *multivariable problem*. Various similarity issues such as functions, costs, shape, manufacturing process, *etc*., should be considered for the successful development of product platforms. In order to support product platform development, especially for an existing set of components, measuring the *geometric similarity* is one of the challenging tasks that need to be performed. In this research, an approach to develop a *common platform* based on shape similarity for an existing set of products derived from their CAD models is presented. This approach can be used in parallel with the other available platform development techniques and can be extended taking other issues into account in the future.

7.2.2 Similarity Measurements

Many researchers have focused their attention on the problem of representing 3D models in a format useful for measuring similarity. Shen *et al.* (2003) proposed a *shape descriptor* based on 2D views (images rendered from uniformly sampled positions on the viewing spheres), called *light field descriptor*, to represent a 3D model useful for similarity measurement. Since it is based on *2D images*, it is unable to represent the internal features, which are important design information contained in CAD models.

Lu *et al.* (2007) proposed a *partial geometric feature* based approach, which is based on curve-skeleton histogram. Here, a curve skeleton is extracted from 3D models using the electrostatic field function. Extracted curves are divided into a number of segments based on electrostatic concentration. A thickness distribution histogram is generated from all segments of the curve skeleton that are grouped based on topological and curvature information. The histogram is used for similarity measurement. Since CAD models are modified during the process of measuring similarity, it is not possible to keep track of features which are dissimilar. The modification process often ignores some of the features which might be important to represent 3D CAD models.

Cornea *et al.* (2005) used a *curve skeleton* of a 3D object, which is capable of capturing the essential topology of an object in three dimensions for similarity measurement. It has the additional advantage of measuring the similarity of parts/components from an *assembly*.

Pu *et al.* (2006) proposed an MLD (*multiple levels of detailed*) representation of 3D CAD models. The approach uses three orthogonal views (front view, side view, and top view) to represent a 3D model. They extend their orthogonal view based 3D similarity approach by splitting the information into three distinct levels of detail (silhouette, contour, and drawing level).

McWherter and Regli (2001) presented an approach for *indexing* solid models of mechanical components from boundary representations and engineering attributes, which are mapped into graphs known as "*model signature graphs*"; the graphs are projected into multi-dimensional metric spaces called "*model comparison spaces*". Three distance matrices are computed between the CAD models using vector spaces. Sharf *et al.* (2004) combined topology, geometry, feature characteristics, and positioning of 3D objects by approximating their volume using a UoS (*union of spheres*) representation. Spagnuolo *et al.* (2006) proposed *structural descriptors* to represent 3D objects based on differential topology. Akgül *et al.* (2007) used *density based shape descriptors* using kernel densities derived from the probability density functions of local surface features characterizing the 3D object geometry. The 3D object is represented by a collection of triangular mesh. The information of the entire triangular area is exploited using an integration scheme. By using the intermediate kernel, the local geometric information from the triangular mesh is accumulated to density points resulting in a global shape description.

Lele and Richtsmeier (1991) proposed a new method for comparing *biological shapes* based on the *Euclidean distance matrix* representation of the form of an object. Siegel and Benson (1982) used *resistant fitting* techniques to determine localized differences in the form of two related animal skeletons.

All the works presented in this section describe various approaches to transform 3D shapes for similarity measure, with focus on 3D graphical models (models used in medical imaging, movie industry, *etc.*), rather than CAD models, which have directed the research in *global shape matching*. When comparing 3D CAD models designers often want to identify and modify the features, which are dissimilar. Using global shape matching, identification of similar shapes/features is not allowed, which is the *first step* towards modifying 3D component geometry to increase commonality.

7.3 Method

The key challenge in measuring similarity is to represent CAD models of components to facilitate the identification of common geometrical shapes/features. As indicated in the Literature Review, researchers have proposed various approaches to turn a 3D shape usable for similarity measurement, focusing on 3D graphical models rather than CAD models. In CAD design shapes often have high genus and contain important features of various types. These can include holes, ribs, fillets, shells, *etc*. Their numbers, as well as relative positions are important factors when measuring similarities.

With the development of technology, the use of CAD in design has become commonplace. A relative advantage of 3D CAD models over other 3D graphics is that CAD models have to be created by using certain features and then specifying the dimensions. It is possible to retrieve the features used in a CAD model and the relative dimensions of the sketches drawn under the features.

The approach presented in this chapter identifies common platforms by extracting the geometric information directly from CAD models. The extracted features and parametric information are then used to determine the components' commonality. The proposed process also highlights commonality of features for components being compared, which facilitates increasing the commonality of platforms.

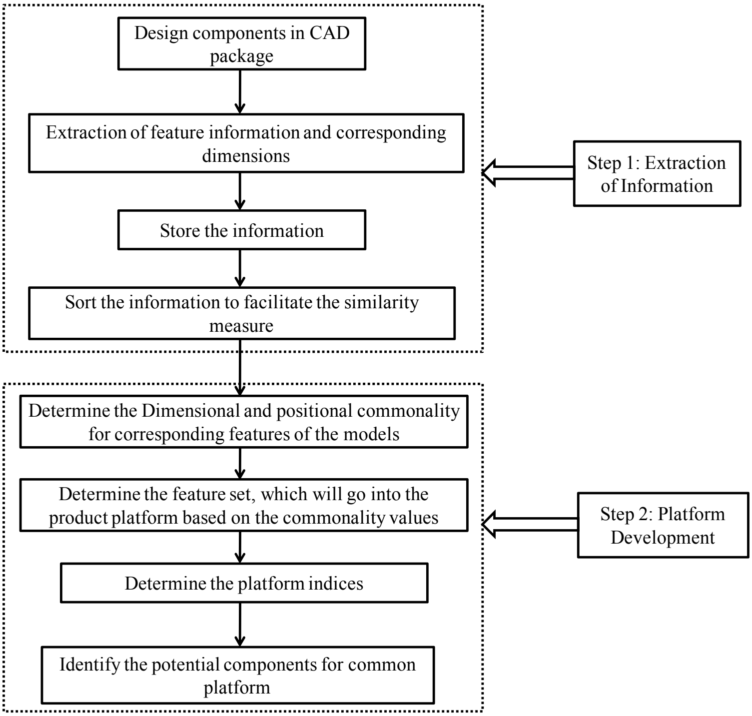

Figure 7.1 The overall approach to measure the common platform

Since there is no transformation of original models involved in the approach, all significant attributes of a model will be considered.

The overall process for identifying similarity among 3D CAD models can be divided into two steps (Figure 7.1):

Step 1: extraction of information from 3D models;
Step 2: common Platform development.

Detailed activities for the two steps are presented next.

7.3.1 Step 1: Extraction of Information from 3D Models

In Step 1, all the important information of the CAD model is extracted and stored in a sequential order to make the comparison process easier and correct. The information of the model is extracted using the CAD software capability to keep track of all information that is given as input during the development, as long as it remains on the same CAD platform. However, the exchange of models among different CAD systems through several neutral formats (such as IGES, STEP, *etc.*) no longer ensures the availability of parametric information. Information can only be extracted from the original model, which did not undergo any exchange among CAD systems. Activities related to Step 1 are described in this section.

7.3.1.1 Design Components in CAD

The process starts by designing the components in the CAD environment. Any CAD software available in the market can be used. In this research, SolidWorks was used to develop the CAD models. SolidWorks has built in applications and functions to facilitate automated extraction of feature and geometric information. In this research it is assumed that the designer will be consistent in the process of creating the 3D CAD models. To facilitate the development of consistent models, the following rules are proposed:

1. The designers will follow the same sequence to build the model regardless of what planes are being used to start the design.
2. The positional dimensions of a feature will be determined after the physical dimension (feature parameters).
3. The positional dimensions will be placed from the same reference for each model.
4. It is assumed that the designer will specify every dimension clearly.

7.3.1.2 Extraction of Feature Information and Corresponding Dimensions

During the development of the CAD model, the designer specifies all *feature information and dimensions* as input to the CAD software. The CAD software manages all information specified by the designer and creates the model accordingly. Model information, representing the CAD model, is extracted from the CAD software to compare different models. SolidWorks has a *feature manager design tree*, where all model information is stored sequentially. SolidWorks API (*application programming interface*) contains functions, routines, protocols, and tools to link with the feature manager design tree. Macros can be developed to extract the information of the models from the feature manager design tree.

In SolidWorks *macro programming* is also very strong. By writing appropriate macros using the API functions all the information from the feature manager design tree may be collected. Macro programming has another advantage: one single macro is sufficient to extract all the information from different models; there is no need to develop specific macros for different models. SolidWorks macros are written in Visual Basic. The challenge here is to determine how efficiently the API functions can be used through macro programming such that all the necessary information can be extracted from the model.

7.3.1.3 Storing and Sorting the Information

The extracted information is *stored* in a *text file*. After information storage, CAD models are not required to compare the models from the next step. The information needs to be sorted before storing, so that comparison can be easily automated. Every designer has his/her own *vision and style* in creating CAD models. A model can be created in different ways in terms of selecting the features and placing dimensions. Different designers, or even the same designer at different times, perform these tasks differently. As a result the same model may be represented by different file contents. The challenge is to organize the contents in such a way that the files can be recognized as representing the same model. An algorithm has been developed and implemented as a macro to load the information in a certain order and not in the way they are organized in the feature manager design tree. Steps for sorting the information are the following:

1. For every model (and corresponding text files), traverse through the feature information.
2. For every feature, traverse through the sketch information.
3. For every sketch, traverse through the dimension information.
4. Separate the positional dimensions [last two dimensions (x,y)] and physical dimensions (rest of the dimensions).
5. For the positional dimensions, sort them with the increasing value of x or y. Sort the sketch information under the feature according to the sorted set of positional dimensions.

Follow Steps from 1 to 5 for the rest of the models.

7.3.2 Step 2: Common Platform Development

In Step 2, different models developed using *SolidWorks CAD system* are compared to calculate commonality indices using the information extracted in Step 1. The commonality indices are then used to develop common platforms for products. Activities in Step 2 focus on the comparison of models to identify features (in a set of components) and components (in a set of assemblies) that are (1) common and (2) similar but with potential to be common, for inclusion in the platform.

The sorted text files are used for similarity comparison. All feature information is rearranged sequentially for the models by going through the information contained in the files and identifying corresponding feature sets taken for comparison. The positional and physical dimensions (feature parameters) of the sketches under the feature set will be used to determine the positional and dimensional commonality indices for a feature set.

7.3.2.1 Indices for Component Shape Comparison

Shape commonality can be considered as the degree to which a given mechanical component is similar to another component from a purely *geometrical viewpoint*. In other words, it is the extent of commonality of their topological constructions. A common way to express the shape commonality among components is by using *commonality indices*. These indices express the commonality as a quantitative value, which makes it easier for designers to get a clear idea about the commonality of a component set.

In this research, to compare components and express the shape commonality quantitatively, commonality indices have been formulated. Components are compared *feature-wise* (a set of similar features at a time) in this study. The fundamental entity of any component is the basic building block (BBB). BBB is the main underlying shape upon which sub-features are constructed by performing geometrical operations. The shape commonality that exists among components is commonality of dimensions and positions of the BBB and the sub-features. Indices to compute the positional or dimensional commonality are presented next.

Dimensional Commonality Indices

Features are the fundamental entities of 3D CAD models in SolidWorks that contain all the required geometries and related parameters. Hence, components are compared feature wise in this study. When all features of a component in the feature-set are of the same type, the dimensional commonality measure for each feature-set is computed using (7.1):

$$(DC)_F = \frac{1}{t}\left(d_1 + d_2 + d_3 + \ldots\ldots + d_t\right) \tag{7.1}$$

where

$(DC)_F$	=	dimensional commonality measure for any given feature-set;
n	=	number of component models to be compared feature wise;
$1, 2, 3, \ldots, t$	=	various types of dimensions (length, width, height, depth, or radius) used to represent the feature;
t	=	total number of dimensions for the feature in question;
$d_{j1}, d_{j2}, d_{j3}, \ldots, d_{jn}$	=	the dimensional values of type j in corresponding features;
d_{jm}	=	maximum dimension value of type j in the entire feature-set;
$deld_1, deld_2, \ldots, deldt$	=	normalized difference among the dimensions for different types in the feature-set:

$$deld_1 = \frac{1}{(n-1)}\left(\frac{d_{1m}-d_{11}}{d_{1m}} + \frac{d_{1m}-d_{12}}{d_{1m}} + \frac{d_{1m}-d_{13}}{d_{1m}} + \ldots\ldots.. + \frac{d_{1m}-d_{1n}}{d_{1m}}\right)$$

$$deld_2 = \frac{1}{(n-1)}\left(\frac{d_{2m}-d_{21}}{d_{2m}} + \frac{d_{2m}-d_{22}}{d_{2m}} + \frac{d_{2m}-d_{23}}{d_{2m}} + \ldots\ldots + \frac{d_{2m}-d_{2n}}{d_{2m}}\right)$$

$$\ldots.. \quad \ldots.. \quad \ldots.. \quad \ldots.. \quad \ldots.. \quad \ldots\ldots$$

$$deld_t = \frac{1}{(n-1)}\left(\frac{d_{tm}-d_{t1}}{d_{tm}} + \frac{d_{tm}-d_{t2}}{d_{tm}} + \frac{d_{tm}-d_{t3}}{d_{tm}} + \ldots.. + \frac{d_{tm}-d_{tn}}{d_{tm}}\right)$$

$$d_1 = 1 - deld_1,\ d_2 = 1 - deld_2,\ d_3 = 1 - deld_3, \ldots.. d_t = 1 - deld_t\,.$$

If the features in a feature-set are not of the same type, *i.e.*, if both are not rectangular, the dimensional commonality measure for that feature-set is considered as zero.

Two simple blocks are shown in Figure 7.2. Each block has a through hole with different dimension and center position. The dimensions (radius, depth) of holes for the two blocks are (7.5, 10 mm) and (10 12 mm). The dimensional commonality of the hole-pair is calculated using equation (1). Parameters are: $n = 2$ (two blocks are compared) and $t = 2$ (number of dimensions). Radius (1) and depth (2) are the two dimensions for the hole-pair. The dimensional commonality calculations are shown in Table 7.1.

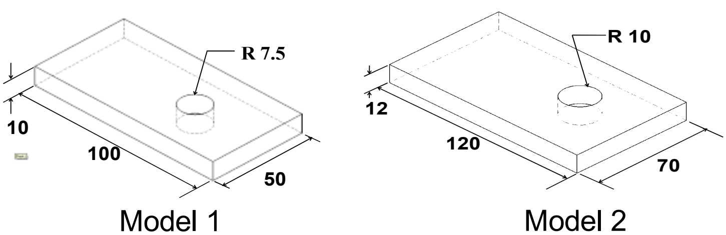

Figure 7.2 Physical dimensions (parameters) shown in the illustrative example

Table 7.1 Dimensional commonality calculation for the hole feature

Radius	Depth
d11 = 7.5; d12 = 10; d1m = 10	d21 = 10; d22 = 12; d2m = 12
$deld_1 = \frac{1}{(2-1)}\left(\frac{10-7.5}{10}+\frac{10-10}{10}\right)=\frac{1}{4}$	$deld_2 = \frac{1}{(2-1)}\left(\frac{12-10}{12}+\frac{12-12}{12}\right)=\frac{1}{6}$
$d_1 = 1-\frac{1}{4}=\frac{3}{4}$	$d_2 = 1-\frac{1}{6}=\frac{5}{6}$
$(DC)_H = \frac{1}{2}\left(\frac{3}{4}+\frac{5}{6}\right)=0.79$	

Positional Commonality Indices

When features in the feature-set are of the same type and they are on the same corresponding faces in the respective models, the positional commonality measure for the feature-set in the models is computed using (7.2):

$$(PC)_F = 1 - del \tag{7.2}$$

where:

$(PC)_F$ = positional commonality measure for any given feature-set in the models

CX_i, CY_i, CZ_i = x, y, and z coordinate of geometric center of the feature in model i

n = Number of component models to be compared feature wise.

CX_m, CY_m, CZ_m = the maximum dimension along the x, y, and z direction respectively

$delX$, $delY$, $delZ$ = normalized difference between the x, y, and z coordinates of the geometric centers of feature set

$$delX = \frac{1}{(n-1)}\left(\frac{CX_m - CX_1}{CX_m}+\frac{CX_m - CX_2}{CX_m}+\ldots\ldots+\frac{CX_m - CX_n}{CX_m}\right)$$

$$delY = \frac{1}{(n-1)}\left(\frac{CY_m - CY_1}{CY_m}+\frac{CY_m - CY_2}{CY_m}+\ldots\ldots+\frac{CY_m - CY_n}{CY_m}\right)$$

$$delZ = \frac{1}{(n-1)}\left(\frac{CZ_m - CZ_1}{CZ_m}+\frac{CZ_m - CZ_2}{CZ_m}+\ldots\ldots+\frac{CZ_m - CZ_n}{CZ_m}\right)$$

del = Average normalized difference between the coordinates of geometric centers of feature-set.
$del = Avg(delX + delY + delZ)$

If the same type of feature is not on the same corresponding faces in each model, or when the same type of features are not present in each model, then $(PC)_F = 0$.

The rectangular blocks of Figure 7.2 are reused to calculate the positional commonality of the hole-pair using (7.2). The geometric center (Figure 7.3) of holes in the two blocks are (65,25,5) and (80,40,6). The positional commonality index calculation for the hole pair ($n = 2$) is shown in Table 7.2.

The feature in question may be the BBB of the components or a sub-feature. The comparison is performed only between corresponding features of the same type, for example, a circular hole in a model is compared only with a circular hole in other models, a rectangular pocket in a model is compared only with rectangular pockets in other models and the BBB of a model is compared with the those of other models. The type of dimensions differs depending on the type of features being compared. For a rectangular BBB, the dimensions to be compared are the length, width, and height; hence the total number of dimensions (t) is 3. For a circular hole, the dimensions to be compared are the radius and the depth of the hole and hence the total number of dimensions is 2. For any dimension, say the length of a rectangular pocket, the component that has a largest value of length is used to assign the value to "d_{1m}" [if the length is considered as the dimension type 1, hence $j = 1$ using (1)]. For example, if the length of the rectangular pocket in model 1 is 30 units and that in model 2 is 50 units, $d_{11} = 30$, $d_{12} = 50$ and $d_{1m} = 50$. The same rule is applied for all feature dimensions in the model. The total dimensional commonality measure DC for a feature-pair will be equal to 1 if each and every dimension in model 1 is equal in magnitude to the corresponding dimension in model 2.

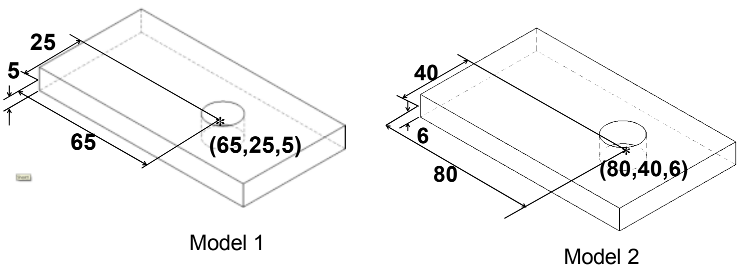

Figure 7.3 Positional dimensions shown in the illustrative example

Table 7.2 Positional commonality calculation for the hole feature

X	Y	Z
$CX_1 = 65$; $CX_2 = 80$; $CX_m = 80$	$CY_1 = 25$; $CY_2 = 40$; $CY_m = 40$	$CZ_1 = 5$; $CZ_2 = 6$; $CZ_m = 6$
$delX = \frac{1}{(2-1)}\left(\frac{80-50}{80} + \frac{80-80}{80}\right)$	$delY = \frac{1}{(2-1)}\left(\frac{40-25}{40} + \frac{40-40}{40}\right)$	$delZ = \frac{1}{(2-1)}\left(\frac{6-5}{6} + \frac{6-6}{6}\right)$
$= \frac{3}{8}$	$= \frac{15}{40}$	$= \frac{1}{6}$
	$(del)_H = Avg(\frac{3}{8} + \frac{15}{40} + \frac{1}{6}) = 0.31$	
	Positional commonality of the hole pair $(PC)_H = 1–0.31 = 0.69$	

Two coffeemaker lower housing component models are shown in Figure 7.4. Each of them possesses five features:

1. basic building block;
2. lower reservoir extrusion;
3. warming plate cut;
4. upper opening cut;
5. shell.

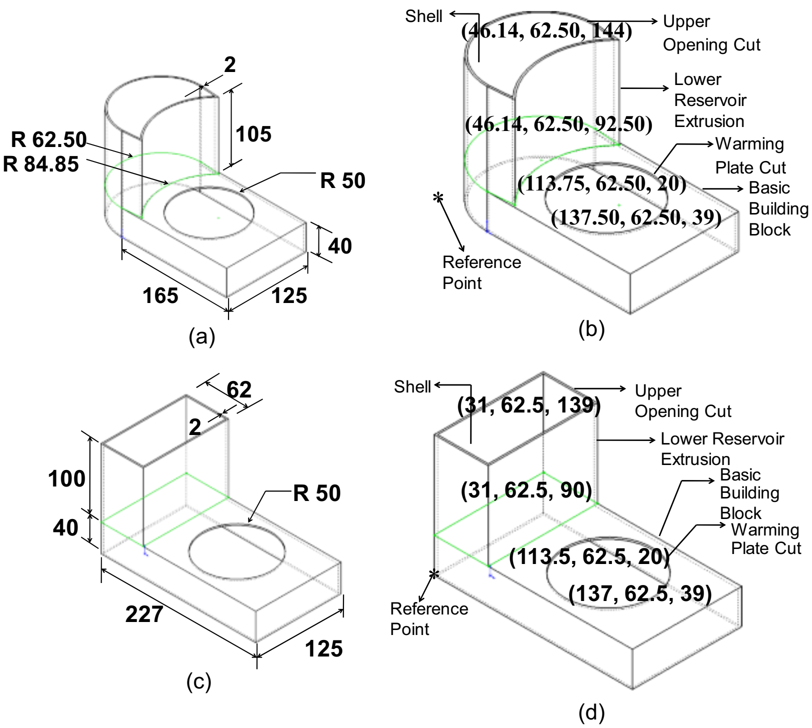

Figure 7.4 Two coffeemaker lower housing component models showing physical dimensions of lower housing 1 and 2 (a, c) and geometric center positions of the lower housing 1 and 2 (b, d)

The components are compared feature wise to calculate the dimensional and positional commonality between them using (7.1) and (7.2). Since the BBB, lower reservoir extrusion (LRE) and upper opening cut features of the two component models are not of the same type from the geometric point of view, the dimensional commonality of the feature-pairs are considered as 0. The dimensional and positional commonality index values of all the feature pairs of the models are shown in Tables 7.3 and 7.4.

Table 7.3 Dimensional commonality calculation for the coffeemaker lower housing

Component name	Dimensional commonality	
BBB feature-pair	$(DC)_{BBB} = 0$; the feature-pair are not of same type in terms of geometry	
LRE feature-pair	$(DC)_{LRE} = 0$; the feature-pair are not of same type in terms of geometry	
Warming plate extrusion (WPC) feature-pair Number of features to be compared, $n=2$ Number of different dimensions, $t=2$	Radius $d_{11} = 50; d_{12} = 50; d_{1m} = 50$ $deld_1 = \frac{1}{(2-1)}\left(\frac{50-50}{50} + \frac{50-50}{50}\right) = 0$ $d_1 = 1 - 0 = 1$ $(DC)_{WPC} = \frac{1}{2}(1+1) = 1$	Depth $d_{21} = 2; d_{22} = 2; d_{2m} = 2$ $deld_2 = \frac{1}{(2-1)}\left(\frac{2-2}{2} + \frac{2-2}{2}\right) = 0$ $d_2 = 1 - 0 = 1$
Upper opening cut (UOC) feature-pair	$(DC)_{UOC} = 0$; the feature-pair are not of same type in terms of geometry	
Shell (S) feature-pair Number of features to be compared, $n=2$ Number of different dimensions, $t=1$	Shell thickness $d_{11} = 2; d_{12} = 2; d_{1m} = 2$ $deld_1 = \frac{1}{(2-1)}\left(\frac{2-2}{2} + \frac{2-2}{2}\right) = 0$ $d_1 = 1 - 0 = 1$ $(DC)_S = \frac{1}{1}(1) = 1$	

Table 7.4 Positional commonality calculation for the coffeemaker lower housing

Component	Commonality in X	Commonality in Y	Commonality in Z
Basic building block (BBB) feature-pair Number of features to be compared, $n=2$	$CX_1 = 113.75$ $CX_2 = 113.50$ $CX_m = 113.75$ $delX = \frac{1}{(2-1)}\left(\frac{0+0.25}{113.75}\right) = \frac{0.25}{113.75}$	$CY_1 = 62.50$ $CY_2 = 62.50$ $CY_m = 62.50$ $delY = \frac{1}{(2\text{-}1)}\left(\frac{0+0}{62.5}\right) = 0$	$CZ_1 = 20$ $CZ_2 = 20$ $CZ_m = 20$ $delY = \frac{1}{(2\text{-}1)}\left(\frac{0+0}{20}\right) = 0$
	$(del)_{BBB} = Avg\left(\frac{0.25}{113.75} + 0 + 0\right) = 0.00073 \quad (PC)_{BBB} = 1 - 0.00073 = 0.99$		
Lower reservoir extrusion (LRE) feature-pair Number of features to be compared, $n=2$;	$CX_1 = 46.14$ $CX_2 = 31$ $CX_m = 46.14$ $delX = \frac{1}{(2\text{-}1)}\left(\frac{15.14+0}{46.14}\right) = \frac{15.14}{46.14}$		
	$(del)_{LRE} = Avg\left(\frac{15.14}{46.14} + 0 + \frac{0.50}{92.50}\right) = 0.11 \quad (PC)_{LRE} = 1\text{-}0.11 = 0.89$		

Table 7.4 Continued

Component	Commonality in X	Commonality in Y	Commonality in Z
Warming plate cut (WPC) feature-pair Number of features to be compared, $n = 2$	$CX_1 = 137.50$ $CX_2 = 137$ $CX_m = 137.50$ $delX = \frac{1}{(2-1)}\left(\frac{0+0.50}{137.50}\right) = \frac{0.50}{137.50}$ $(del)_{WPC} = Avg\left(\frac{0.50}{137.50}+0+0\right) = 0.0012$		$(PC)_{WPC} = 1-0.0012 = 0.99$
Upper opening cut (UOC) feature-pair Number of features to be compared, $n = 2$	$CX_1 = 46.14$ $CX_2 = 31$ $CX_m = 46.14$ $delX = \frac{1}{(2-1)}\left(\frac{15.14+0}{46.14}\right) = \frac{15.14}{46.14}$ $(del)_{UOC} = Avg\left(\frac{15.14}{46.14}+0+\frac{5}{144}\right) = 0.12$		$(PC)_{UOC} = 1-0.12 = 0.88$
Shell (S) feature-pair Number of features to be compared, $n = 2$	$(PC)_S = 0.99$; Shells and basic building block have same geometric centers.		

7.3.2.2 Platform Indices

All individual DC and PC values for each feature-set need to be combined to determine the platform indices and to help designers with platform decisions. Since there are no established platform indices or measures to calculate commonality for a set of products, in this chapter a simple hierarchical index has been proposed.

The proposed platform index starts with the calculated dimensional and positional commonality values. First, the designer decides on the set of components (other than identical components) that have the potential to be part of the common platform. This decision is a two step process: (1) since all features of a component set may not be identical, but can be very similar in terms of manufacturing process, rather than looking for the perfectly identical components for a common platform, a suitable platform index can be developed to accommodate the differences. Similarly the platform index values for different sets of components can be used to develop assembly platform indices for a set of products; and (2) components that may be slightly different in terms of geometry and dimension, can be made similar with minor changes in design to accommodate them into a common platform. The platform index developed here can be used to identify components, which have the potential to be in a common platform at present, or in the future. In this research, a hierarchical approach (Figure 7.5) is used to develop the average component platform commonality index (ACPCI) and average assembly platform commonality index (AAPCI). Using CAD software, the models have to be created following a specified sequence (Figure 7.6) of operations. A final product is an assembly of a number of components. Hence, the components have to be modeled before creating the final assembly. Components are accumulation of various features (basic building block, extrusion, cut, revolve, *etc.*), which have certain geometry with specific dimensions. The feature geometries are created using sketches.

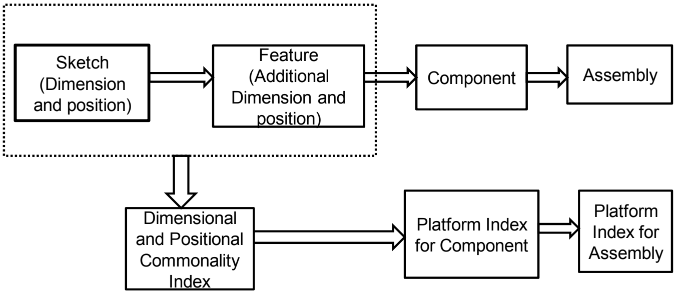

Figure 7.5 Hierarchical approach to develop the platform commonality index

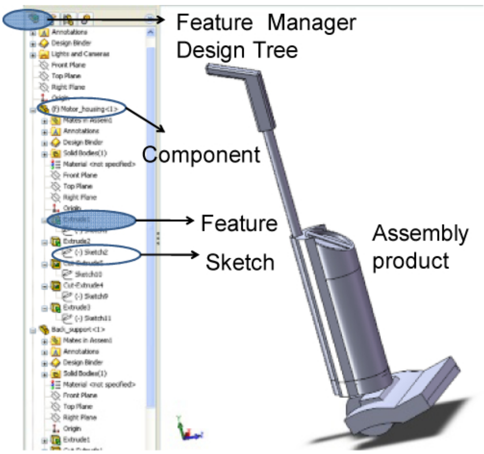

Figure 7.6 Sequential set of operations in the SolidWorks environment

The dimensional and positional commonality values, derived from a feature-set, are used to develop the ACPCI which will be then used to develop the AAPCI. Higher dimensional and positional commonality values for feature sets will result in higher ACPCI for a set of components. A higher ACPCI value for the component sets results in higher probability for the components to be in the common platform. Here the dimensional and positional commonality indices for each feature are averaged to calculate ACPCI. The maximum possible value of ACPCI is 1, when all elements in the feature set are identical. Similarly the maximum possible AAPCI is 1, when all components in the assemblies are identical. The ACPCI is determined based on how much the average commonality values for the individual feature set are offset from the maximum possible value, which is 1. The summation of all the offset values gives the total offset values for all the feature-sets among a given component-set. The average of the total offset values can be calculated dividing the summation by the total number of feature-sets used in the given component-set. The ACPCI will be the difference between the maximum possible average platform index and the total average platform index.

$$ACPCI = \left\{1 - \frac{1}{NOF}\sum\left(1 - AC\right)\right\} \times 100\% \tag{7.3}$$

where:
NOF = number of feature-sets in a given component-set
AC = average commonality for a feature-set.

The maximum possible value of ACPCI is 100%, when all components in a given component-set are identical and the minimum possible value will be zero, when the components are totally different.

The AAPCI for a set of products is calculated similarly, using the ACPCI values of component-sets in the given product-set.

$$AAPCI = \left\{1 - \frac{1}{NOC}\sum\left(1 - ACPCI\right)\right\} \times 100\% \tag{7.4}$$

where:
NOC = number of component-sets in a given product-set.

The maximum possible value of AAPCI will be 100%, when all the products in a given product-set are identical in respect to all characteristics measured and the minimum possible value will be zero, when the products are totally different.

7.4 Case Studies

Two case studies are presented in this section to illustrate the proposed method for common component and platform identification from 3D CAD models of components.

7.4.1 Case Study 1 – Cell Phone Casings Product Platform

The first case study focuses only on the component commonality measurement. The capability of the method and algorithms to compare 3D solid models is demonstrated by comparing cell phone covers. The calculated commonality indices are then used to determine the potential of the cell phone covers, used in the component-set, to be in a common component platform.

The case study analyses two cellular phone top casings. For simplicity, the number of casings in the component-set is restricted to two. The cell phone top casings are selected for this case study as they have a number of features for the buttons, the display screen, the speaker, and snap fits. The dimensions of the slots and the basic building blocks are different for the two casings.

Casing model 1 (Figure 7.7) has a shell thickness of 2 mm. All slots except for the snap fit slots, are through holes (depth = 2 mm). The depths of all the snap-fit slots are 5 mm. The snap fits are located symmetrically at the center locations of their respective faces. Casing model 2 (Figure 7.8) has a shell thickness of 2 mm. Dimensions of the features in the second casing are similar to the ones in the first casing.

The list of features in model 1 is (Figure 7.7):

1. Snap fit grooves 4 and 5 have the same dimensions;
2. Buttons 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, and 18 have the same dimensions;
3. Buttons 21 and 22 have the same dimensions;
4. Buttons 23 and 24 have the same dimensions.

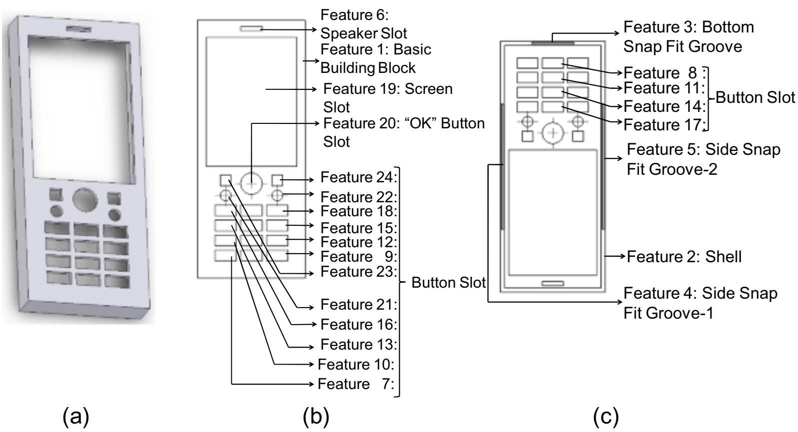

Figure 7.7 Cell phone casing model 1: (a) isometric view, (b) top view, and (c) bottom view

The list of features in model 2 is (Figure 7.8):

1. Snap fit grooves 4 and 5 have the same dimensions;
2. Buttons 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, and 18 have the same dimensions;
3. Buttons 21 and 22 have the same dimensions;
4. Buttons 23 and 24 have the same dimensions.

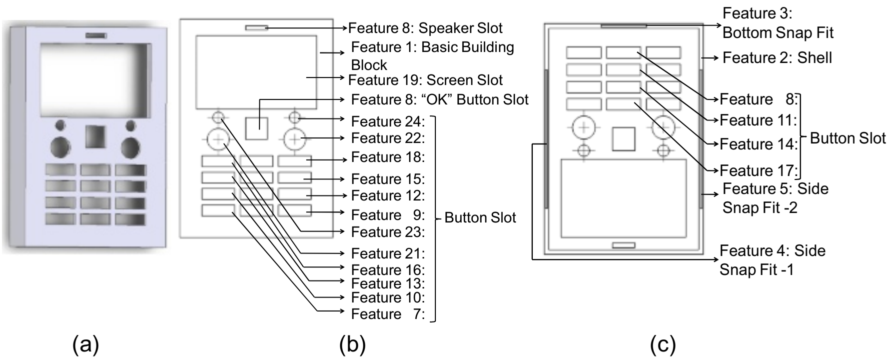

Figure 7.8 Cell phone casing model 2: (a) isometric view, (b) top view, and (c) bottom view

The features in each model are numbered as given in the feature lists and each feature in casing model 1 is compared with its corresponding feature in casing model 2. In other words, feature 1 in casing model 1 is compared with feature 1 in casing model 2; feature 2 in casing model 1 is compared with feature 2 in casing model 2, and so on. In this chapter it is assumed that the designer/user will provide this information.

The cell phone casings are modeled using SolidWorks. A SolidWorks macro, written in Visual Basic, is utilized to extract the entire feature, dimension, and position information from the models. Information from the models is stored in separate TEXT files. The information in the TEXT files is used to calculate the dimensional and positional commonality of the feature pairs. The screen shots of the TEXT files for the Cell phone casings are shown in Figure 7.9.

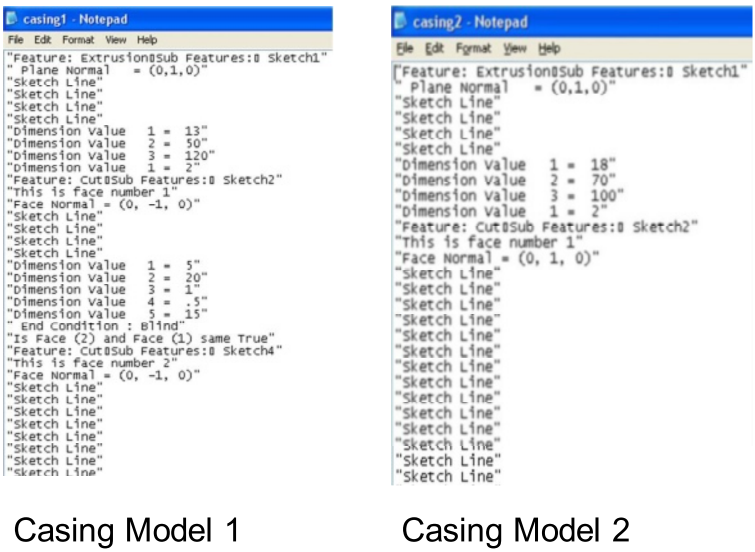

Figure 7.9 Partial text file screen shot extracted for cell phone casing models

Positional and dimensional commonality indices for all features in the two casings are shown in Table 7.5. The ACPCI (using (7.3)) for the model pair is 78.02%. The result obtained is quite high since most of features in the casing pair are similar.

Table 7.5 Commonality results for the cell phone cover case study

Feature no.	Description	Dimensional commonality	Positional commonality	Average commonality	Offset from maximum	ACPCI (%)
1	Basic building block	0.76	0.88	0.82	0.18	–
2	Shell	0.74	0.89	0.815	0.185	–
3	Bottom snap fit groove	1	0.93	0.965	0.035	–
4	Side snap fit - 1 groove	1	0.95	0.975	0.025	–
5	Side snap fit - 2 groove	1	0.81	0.905	0.095	–
6	Speaker slot	1	0.84	0.92	0.08	–
7	Button slot	0.89	0.96	0.925	0.075	–
8	Button slot	0.89	0.92	0.905	0.095	–
9	Button slot	0.89	0.88	0.885	0.115	78.02
10	Button slot	0.89	0.96	0.925	0.075	–
11	Button slot	0.89	0.92	0.905	0.095	–
12	Button slot	0.89	0.88	0.885	0.115	–
13	Button slot	0.89	0.95	0.92	0.08	–
14	Button slot	0.89	0.92	0.905	0.095	–
15	Button slot	0.89	0.88	0.885	0.115	–
16	Button slot	0.89	0.95	0.92	0.08	–
17	Button slot	0.89	0.91	0.9	0.1	–
18	Button slot	0.89	0.87	0.88	0.12	–
19	Screen slot	0.77	0.9	0.835	0.165	–
20	"OK" button slot	0	0	0	1	–
21	Button slot	0.75	0.94	0.845	0.155	–
22	Button slot	0.75	0.86	0.805	0.195	–
23	Button slot	0	0	0	1	–
24	Button slot	0	0	0	1	–

7.4.2 Case Study 2 – Coffeemaker Product Platform

The second case study focuses on identifying the common platforms for a set of coffeemakers. The Average AAPCI is calculated to decide whether the assembly can be considered for the common platform. Components of the coffeemakers, which have the potential to be accommodated in the common platform, will be determined through the ACPCI calculation.

Two coffee makers are analyzed in the case study. The number is restricted to two for simplicity. During the modeling, insignificant aesthetic features (such as fillets, chamfers, *etc*.) are not considered. It is assumed that the designer will follow the same sequence of feature creation when making the component models. Both models (Figures 7.10 and 7.11) are comprised of: (1) lower housing, (2) upper housing, (3) upper end cover, (4) lower end cover, (5) heater, (6) heating tube, (7) warming plate, (8) filter, (9) electric circuit, and (10) condensing tube.

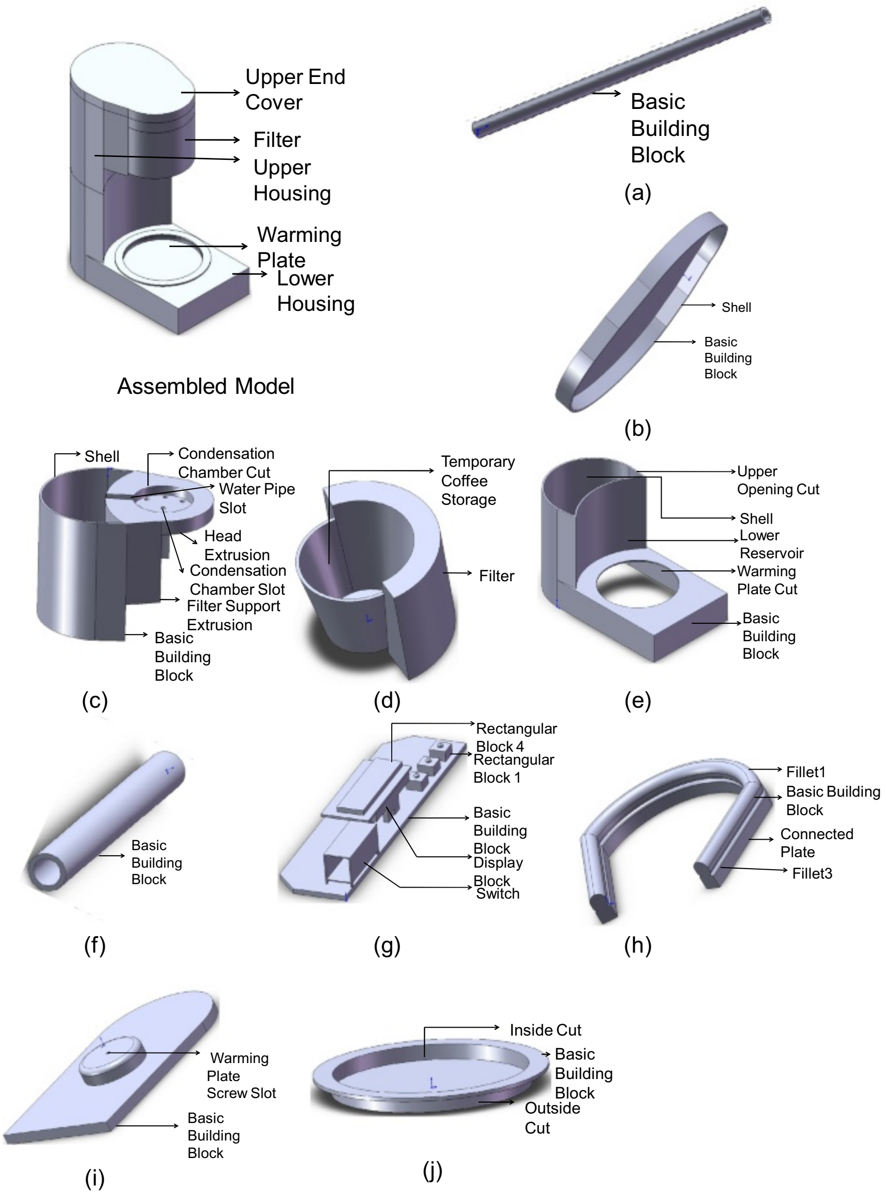

Figure 7.10 Coffeemaker 1 assembly and component: condensing tube (a), upper end cover (b), upper housing (c) , filter (d), lower housing (e), heating tube (f), electric circuit (g), heater (h), lower end cover (i), and warming plate (j)

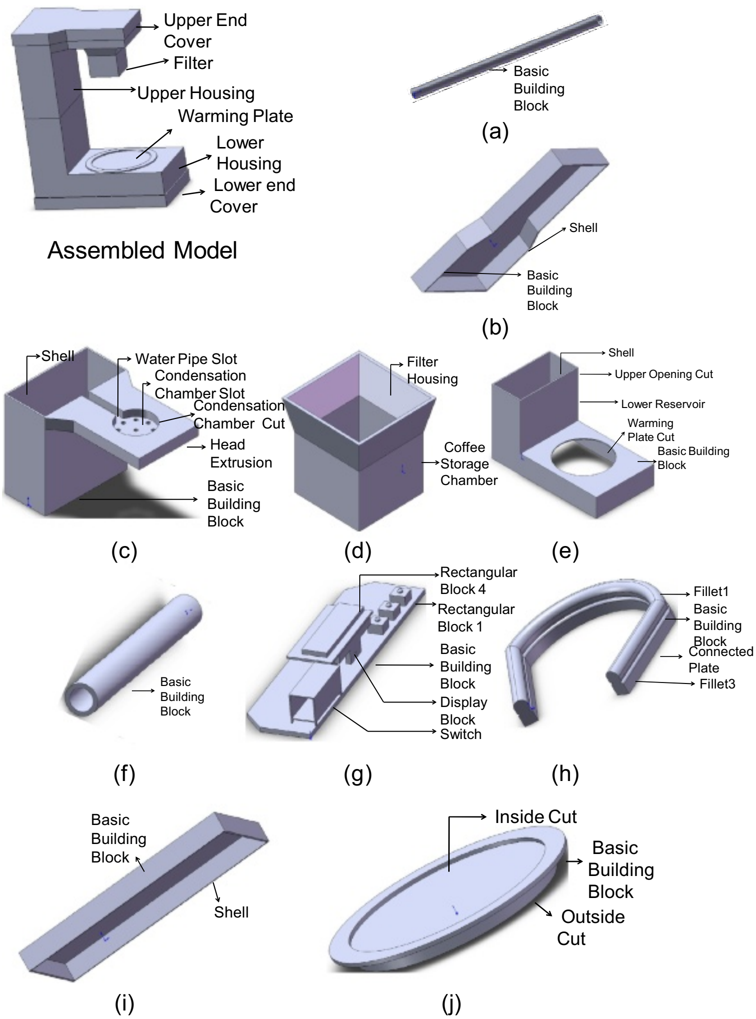

Figure 7.11 Coffeemaker 2 assembly and components: condensing tube (a), upper end cover (b), upper housing (c), filter (d), lower housing (e), heating tube (f), electric circuit (g), heater (h), lower end cover (i), and warming plate (j)

All components are modeled using SolidWorks and then assembled to complete the 3D model of the coffeemaker. The corresponding CAD models of the components are compared and the ACPCI is calculated for each component set. The information needed to calculate the positional and dimensional commonality, are extracted from the models using the macro mentioned in Case Study 1. As an example, consider the warming plate component (Figures 7.10j and 7.11j) with the following features: (1) basic building block, (2) inside cut, and (3) outside cut. The calculated ACPCI is 89.33% (Table 7.6).

The upper housing components (Figures 7.10c and 7.11c) of the coffeemakers have a total of 16 features. Although the outer geometry of the component varies significantly, some of the inner features have high positional and dimensional commonality. The ACPCI (using (7.3)) for the component set is 75.19% (Table 7.7).

Table 7.6 Commonality results for the warming plate component set

Feature no.	Description	Dimensional commonality	Positional commonality	Average commonality	Offset from maximum	ACPCI (%)
1	Basic building block	1	1	1	0	–
2	Inside cut	0.42	0.94	0.68	0.32	89.33
3	Outside cut	1	1	1	0	–

Table 7.7 Commonality results for upper housing components set

Feature No.	Description	Dimensional commonality	Positional commonality	Average commonality	Offset from maximum	ACPCI (%)
1	Basic building block	0	0.89	0.445	0.555	–
2	Shell	1	0.84	0.92	0.08	–
3	Head extrusion	0	0.98	0.49	0.51	–
4	Filter support extrusion	0	0	0	1	–
5	Water pipe slot	0	0.97	0.485	0.515	–
6	Condensation chamber cut	0.92	0.96	0.94	0.06	75.19
7	Condensation chamber slot1	1	0.94	0.97	0.03	–
8	Condensation chamber slot2	1	0.93	0.965	0.035	–
9	Condensation chamber slot3	1	0.94	0.97	0.03	–
10	Condensation chamber slot4	1	0.96	0.98	0.02	–
11	Condensation chamber slot5	1	0.96	0.98	0.02	–
12	Condensation chamber slot6	1	0.95	0.975	0.025	–
13	Condensation chamber slot7	1	0.92	0.96	0.04	–
14	Condensation chamber slot8	1	0.92	0.96	0.04	–
15	Condensation chamber slot9	1	0.98	0.99	0.01	–
16	Lower filter slot	0	0	0	1	–

Table 7.8 Average assembly platform commonality index (AAPCI) for the coffeemaker family

Name	Average component platform commonality index (ACPCI)	c	Average assembly platform commonality index (AAPCI), (%)
Upper housing	0.75	0.25	–
Lower housing	0.67	0.33	–
Upper end cover	0.69	0.31	–
Lower end cover	0.46	0.54	74.6
Warming plate	0.89	0.11	–
Heater	1	0	–
Electric circuit	1	0	–
Condensation tube	1	0	–
Heater tube	1	0	–
Filter	0	1	–

All ACPCI values for the entire component-sets are shown in Table 7.8. The ACPCI values are then used to determine the AAPCI (using (7.4)), which is 74.6%. Both coffeemaker assemblies are compared without the coffeepots.

From the calculated ACPCI, it can be observed that four components are identical for both coffeemakers; consequently the resulting AAPCI value of 74.6% (Table 7.8) is very high. The result obtained in the case study is reasonable. However, two of the components [filter, Figures 7.10 and 7.11d, and lower end cover, Figures 7.10i and 7.11i) have very low values of ACPCI. If ACPCI of 65% is considered as the threshold for the components to have the potential to be modified to be common, then eight components out of ten will be accommodated in the common platform. The designer will decide the threshold value of the ACPCI depending on his or her preference.

From Table 7.8 it can be observed that four components (upper housing, Figures 7.10c and 7.11c, lower housing, Figures 7.10e and 7.11e, upper end cover, Figures 7.10b and 7.11b, and warming plate, Figures 7.10j and 7.11j) have ACPCI values between 0.65 and 1. The components can be made identical with minor design changes and the ACPCI values can be improved to 1. Eventually, the AAPCI value for the Coffeemaker models can be improved to 84.6%. This increase in commonality will make the two coffeemakers almost the same product, which is not desired. Out of the four component sets upper housing, lower housing and upper end cover cannot be changed because they provide varieties among the coffeemaker models. Since warming plates do not provide any kind of variety among models, they can be made identical. The AAPCI value with the identical warming plates can be improved as high as 75.7%.

7.5 Concluding Remarks

In this chapter, a *shape commonality* comparison between mechanical components is presented to facilitate the development of common platform. An approach is proposed by which the dimension and position of every feature in the component models are compared and the commonality is expressed quantitatively. This process is repeated for all dimensions of the particular feature and all commonality measures are combined to yield the ACPCI and the AAPCI for a particular set of components and assemblies respectively. A Hierarchical approach for CAD models is proposed to calculate ACPCI and AAPCI.

Two case studies are presented to demonstrate the capability of the algorithms and equations developed. In order to determine component commonality, a macro has been written to extract all the information from the CAD models. Visual Basic is used to write the macro, which utilized the API functions of SolidWorks to communicate with various features of the CAD software.

However, there are some *limitations* to the proposed approach. Designers are assumed to give all the information needed to calculate the dimensional and positional commonality for a set of features. The designers have to follow same sequence in creating the features for all the components in the set. All positional dimensions for every feature in a component need to be specified from the same reference. This is not always possible, especially for complex CAD models. The information in the text files extracted from the model is very difficult to sort for models that have very complex geometry. The number of API available in the SolidWorks library is not enough to extract all detailed information from the CAD models. It cannot extract information for some of the features of SolidWorks. This also limits the independence of the designer.

The comparison process is currently being automated to lessen the manual effort, which will aid in the development of a 3D CAD search engine. An algorithm may be developed to search for similar components from the web by checking the similarity among the components. With the advent of outsourcing, industries are now located in different regions and designers around the world are working on the same product. One way to achieve fast and efficient design process is through collaboration among designers working in a common field. Interactions among them can prevent redesign of similar components or sub-systems. Designers need to be able to share their design to ensure a faster design process. Large databases of 3D CAD models are already being developed by many companies. An efficient and faster search process to identify common models will ensure the best utilization of such databases. The proposed method may be extended to incorporate a search algorithm for CAD models.

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