Automated Process Planning and Cost Estimation under Material Quality Uncertainty

Guoxiang Huang

A Thesis Submitted in Fulfillment of the Requirements for the Degree of Master of Engineering in Industrial and Systems Engineering

Prince of Songkla University

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I hereby certify that this work has not already been accepted in substance for any degree, and is not being concurrently submitted in candidature for any degree.

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ABSTRACT

In a mass customization production system, a product quotation must be fed back to customers in no time after an order is placed. Estimation of a product cost can be performed upon finalization of process planning. In an initial cutting process of wooden product manufacturing, optimization of cutting parameters is complicated under the uncertainty of raw material quality. Manual arrangement of the process parameters always leads to non-optimality. In this study, an automated system was developed to shorten process lead time, ensure an optimal cutting process plan, as well as estimate an accurate material cost. An architectural structure of the system was composed of three modules: (1) a digital image processing module to accelerate product configuration, (2) a cutting plan generation module to evaluate raw materials for their applicability to produce the product and a set of feasible plans was thereafter established, and (3) an optimization module to quantify material loss. A process plan which satisfied a preferred objective function (either minimum cost or minimum loss) could then be revealed. The model proposed in this study exhibited a superior performance over the other reported models in predicting loss and estimating material cost.

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Guoxiang Huang

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CHAPTER 1

INTRODUCTION

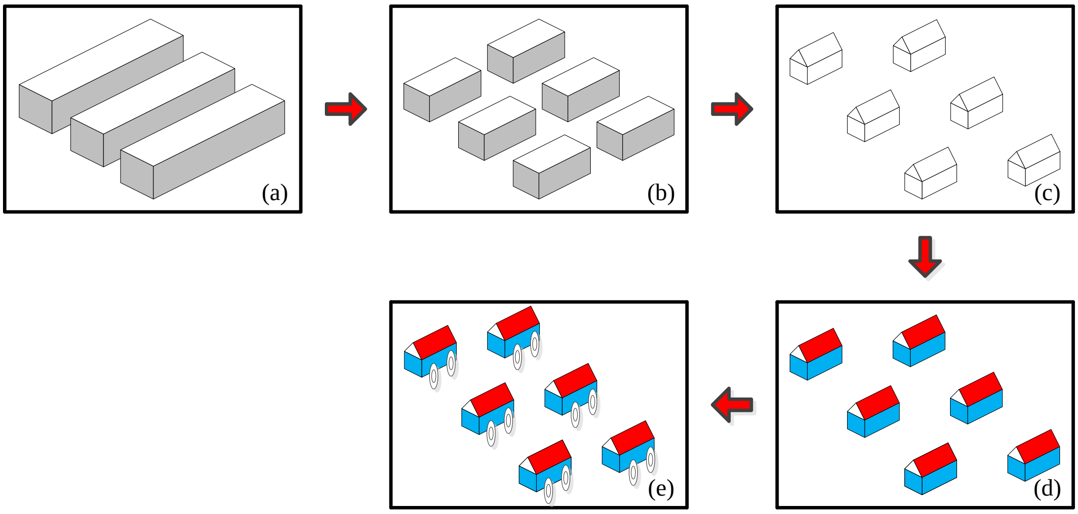
1.1 BACKGROUND

In an era of global marketing, customers have unlimited worldwide opportunities to search for products that fulfill their needs. In response to such phenomenon, manufacturers are struggling to offer various choices, expectedly to meet the individual needs. Standardized products from a mass production (MP) system will be eventually pushed off the markets. With rapid development of science and technology, as well as increasing demands of customers, manufacturing industry has a dramatic change, which mainly evolved from original craft production to more personalized production [1]. A new marketing paradigm called "mass customization" (MC) has emerged and would be a competitive strategy for future manufacturing business. The concept of MC was initially put forward by Davis [2]. It has been promoted as a production strategy to provide individually designed products and services to every customer through high process agility, flexibility and integration [3, 4] at a reasonably low cost [5]. MC's abilities to fulfill personal needs will soon outplay ordinarily standardized MP products. With the advancement in information technology and flexible manufacturing technologies, MC is now even more than realizable.

In MC, information technology systems play a crucial role in accelerating a product development chain. Customers can specify their needs through channels a company has provided especially for this purpose. These communication channels would be retail stores or web-based systems. Specifications of customer needs would be in a form of product images, blueprints, or physical prototypes, whichever the company allows. Throughout the cycle of MC, one of the critical upstream activities is cost estimation. It is of great importance to a concern because it helps the company to decide about manufacturing and selling policies

[6]. Since a company adopting an MC strategy produces a variety of products, the cost estimation process must be performed every time a new order is placed. To ensure the success of mass customization, a rapid, automatic yet accurate cost estimation is needed [7]. However, costs associated with the product can be estimated after production plans including material and labor consumption and descriptions of related processes are released. Finalization of such plans would take lengthy time and great effort to communicate with all related departments, especially when manually done. Delay in cost estimation gains the company no advantage and could be loss in product orders in some cases.

In this study, manufacturing of wooden toys was used as a case study. In production of the toys, rubberwood accounted for more than 51% of the total direct material cost [8]. Typically wood was received in a form of commercial standard wood planks available in different sizes and grades. Most planks came at a length of either 1.00 or 1.25 m. Some companies may further cut these planks lengthwise and keep them in store for producing smaller products. A production process using solid wood planks started from (a) receiving material, (b) initial cutting, (c) shaping, (d) painting, and (e) assembling before packing and shipping to customers as shown in Fig. 1.1. Once a production order was confirmed, a process planner would search through a database of available wood planks to find ones which were applicable, i.e., ones having dimensions suitable for a product. A plank was chosen by its cross-sectional area which was called "*area of cut*, a_c." Then in the initial cutting process, they were cut into pieces of the same "*length of cut*, l_c." As shown in Fig. 1.2, both "*area of cut*" and "*length of cut*" as known as cutting parameters in this study were constrained by product dimensions. Past records indicated that substantial loss of wood was found in the initial cutting and shaping processes. Unlike other industrial materials, wood has unpredictable defects, differing randomly from plank to plank, embedded in its mass. As illustrated in Fig. 1.3, by applying different "*length of cut*" and "*area of cut*" to a plank with the same defect pattern, they apparently arrived at different material losses. Such loss complicates calculation of material consumption, herein material cost.



NB: (a) receiving material, (b) initial cutting, (c) shaping, (d) painting, and (e) assembling

Fig. 1.1 Manufacturing process of a wooden product

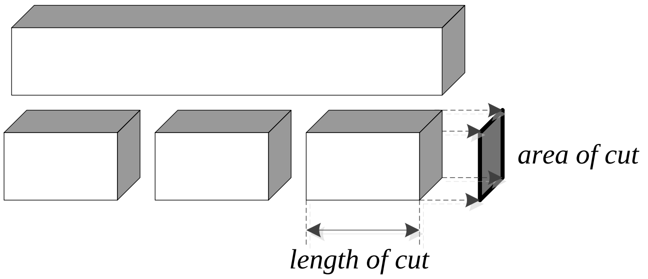


Fig. 1.2 Determination of "*length of cut*" and "*area of cut*"

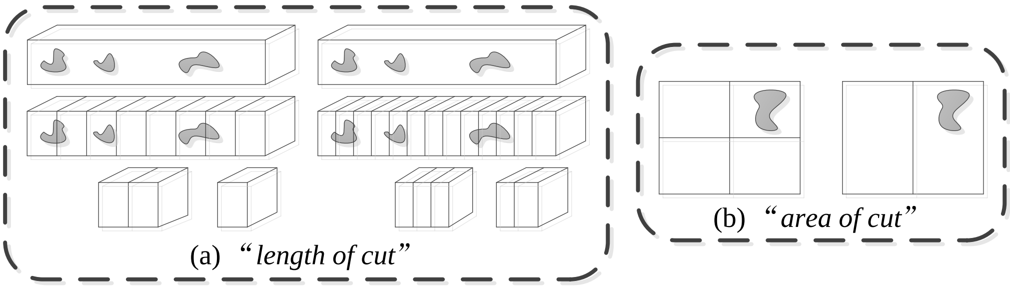


Fig. 1.3 Amount of material loss affected by "*length of cut*" and "*area of cut*" [8]

Efforts to quantify material loss in natural derivatives were evident in some researches [8, 9]. Recently, Chansaad et al. [8] proposed a fuzzy inference method to estimate loss of material used to produce wooden products when it was subject to defect uncertainty. Loss was conditionally explained by fuzzy rules on cutting parameters (length and area of cut). The system in [8] was built on the scenario that defects were assumed unpredictable and unavoidable. Although results from the fuzzy system were far superior to the existing method being used by a case study company, what forbade the system from practical use is that the number of fuzzy rules grew larger with the number of possible cutting parameters. Especially when complexity of characterization of the defects increases, fuzzy theory becomes more difficult to specify the correct set of rules and membership functions to describe the behavior of the defects appropriately.

Besides the fuzzy theory, probability theory has long been a major contender in dealing with uncontrollable, imprecision and inherently uncertain information. The probability theory concerns with the analysis of random phenomena by using statistics. The probability theory can capture the mathematical essence of quantification of the defect characterization, which is done abstractly by specifying what properties such the quantification should have [10]. In this study, a probability-based simulation model was developed to simulate the wood defects and loss they induced in association with certain cutting plans.

As mentioned, the cost can only be accurately estimated once a product development plan is ready [11]. Tremendous effort has been put into developing an automated process planner as documented in a number of past studies. Those works evolved around feature recognition [12-18], knowledge representation [19-25] and inference engine [26, 27], and integration of process planning, and upstream or downstream processes [28, 29]. Some researchers applied different methods/technologies such as OPPS-PRI 2.0 system [30], genetic algorithms (GA) [31-36], imperialist competitive algorithm [37], energy-efficient oriented method [38], neural network-based system [39-41], fuzzy set theory/fuzzy logic method [39, 42, 43], agent-based methodology [44, 45], Internet-based technology [46, 47], functional blocks [48, 49], Petri net model [50] and STEP-compliant method [51-54], just to name a few, for process planning optimization. In 2014, [55] presented a survey of CAPP of the last 12 years based on its approaches, methods/technologies. None has focused on the involvement of defects uncertainties. In this present study, a challenge lies behind randomly distributed defects embedded in the raw material. Because of a time constraint in product development and uncontrollable defects of the incoming wood planks, a material requirement plan for each batch of the wooden products is often overestimated to accommodate losses of any kinds. Therefore an optimal plan is not always achieved.

All of the above reasons have led to the development of an automated system proposed in this study. Its architectural structure is composed of three modules: (1) a digital image processing module to accelerate product configuration, (2) a cutting plan generation module to evaluate raw materials for their applicability to produce the product; a set of feasible plans are thereafter established, and (3) an optimization module to quantify material loss. A process plan which satisfies a preferred objective function (either minimum cost or minimum loss) will be chosen. Expectedly this system will shorten product development lead time, assure optimality of a chosen process plan, and more accurately estimate the material cost.

1.2 OBJECTIVES

The specific objectives of the research explained in this work are to:

1) Develop an automated system to achieve efficient utilization of material and minimum unit material cost and material loss in an initial cutting process.

2) Develop a probability-based simulation model to simulate wood defects and quantify loss from defects given length and area of cut.

1.3 BENEFITS

The benefits of the research include:

1) A rapid acquisition of wood cutting plan and an increase in more agility and accuracy of product cost estimation.

2) A simplification of product process planning and reduction of wood material loss.

1.4 SCOPES OF THE RESEARCH

The scopes of the research described in this work are:

1) Materials in this research are commercial standard AB Grade rubberwood planks with height, width and length of 25 mm, 60 mm and 1,250 mm.

2) Cutting parameters: "*length of cut*" and "*area of cut*" of this study are of the initial cutting process of wooden product manufacturing.

3) Defects in this research are apparently observable on the surface of a plank, exclusive of defects may hidden underneath the surface that will be revealed once the plank is cut.

4) The main hypothesis of this research is that using the image processing technique and statistical tool is valid to develop a cost estimation model for direct material (rubberwood) of the small and simple products in wooden product manufacturing processes. Definition of small and simple products are those ones that can be directly produced by existing wood planks (range of width, height and length (mm) of wood planks, respectively: [0, 101.60], [0, 600] and [0, 1,250].

1.5 OVERVIEW OF THE RESEARCH

This research is divided into five chapters, of which the first has been covered.

Chapter 2 presents an exhaustive theory and literature review with respect to the paradigms of manufacturing (from craft production to mass customization or personalized production), type of cost, process planning, image processing technology, definition of wood defects and its types, as well as the development of two-dimensional and three-dimensional Minimum Bounding Box (MBB) algorithm, and the general process of statistical model in simulation. Chapter 3 describes the methodology to be used in this research as well as the research framework. In this chapter, the image processing module is to acquire the three dimensions of the selected product through the two dimensions of MBB algorithm. The cutting plan generation module is to inspect suitability of planks in producing the product. The acquisition of production dimensions, evaluation of wood plank applicability are tested and validated. The integration of these two modules is discussed in detail. Chapter 4 presents a development of a cost model. The wood loss from shaping processes and loss from defects were analyzed. In addition, the simulation on defects is presented, followed by a proposed probabilistic model of wood defects that composes two phases: defect model creation and simulation of defects in an initial cutting process. The analysis of the data was collected from a Thai wooden product company. Chapter 4 also shows the results from the simulated model. The performances of the models (parametric and simulated models) are compared with actual data. Chapter 5 summarizes all the previous chapters. The discussions and recommendations are presented based on the results of analysis from Chapter 3 and Chapter 4. Suggestions for further research and limitations of this study are discussed.

The appendices contain two articles: A Probabilistic Model of Wood Defects (accepted for publication in *Applied Mechanics and Materials*) and Automated Process Planning and Cost Estimation under Material Quality Uncertainty (accepted for publication in *The International Journal of Advanced Manufacturing Technology*).

The overview of this research to the responses associated to each chapter is illustrated in Fig. 1.4 as explained follow.

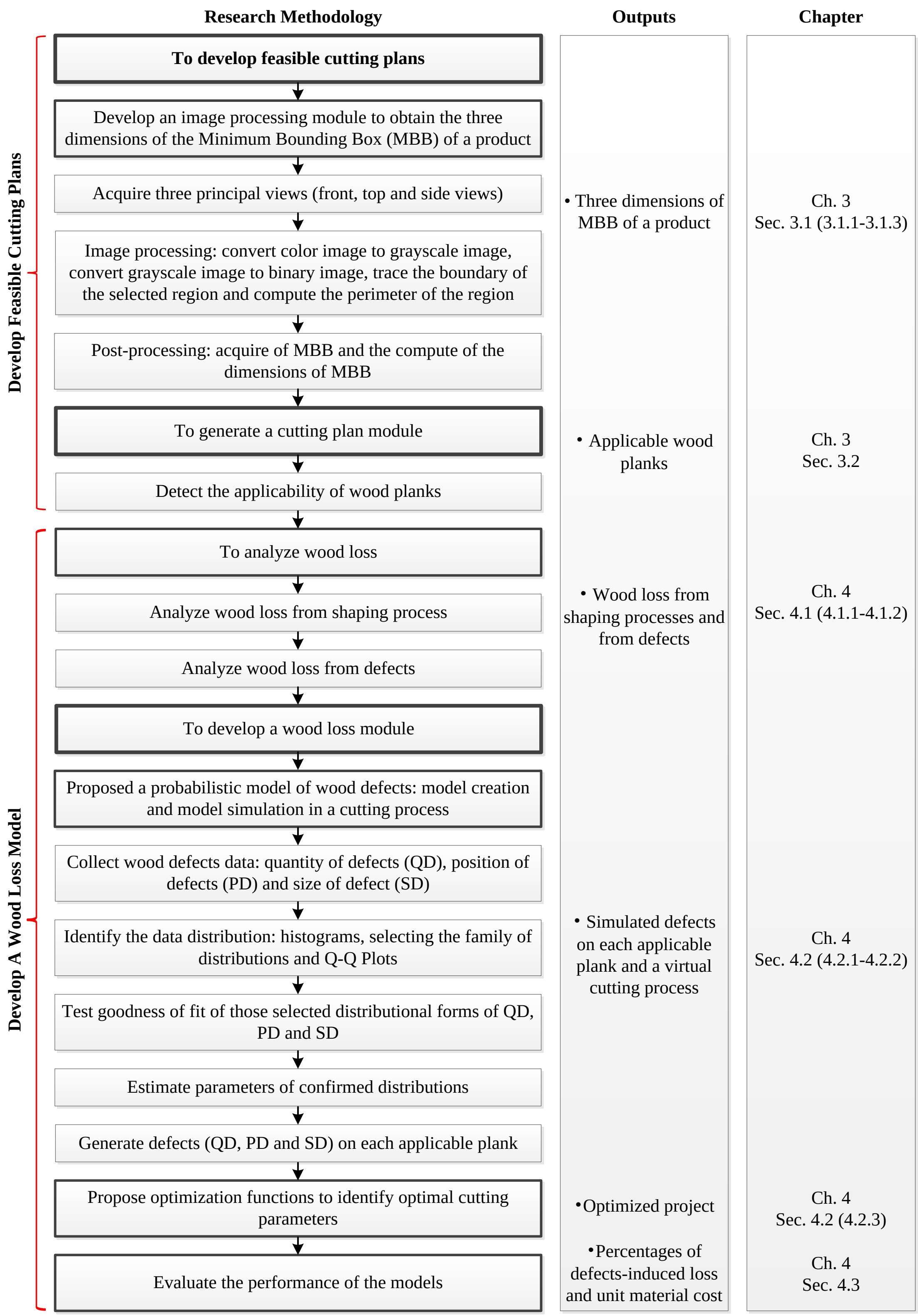


Fig. 1.4 The overview of this research to the outputs associated with corresponding chapter and section

CHAPTER 2

THEORY AND LITERATURE REVIEW

2.1 PARADIGMS OF MANUFACTURING

With rapid development of science and technology, the manufacturing industry has a dramatic change that mainly evolved from original craft production to current personalization [1]. The evolution of the paradigms of manufacturing is shown in Fig. 2.1 based on the relationship between volume and variety.

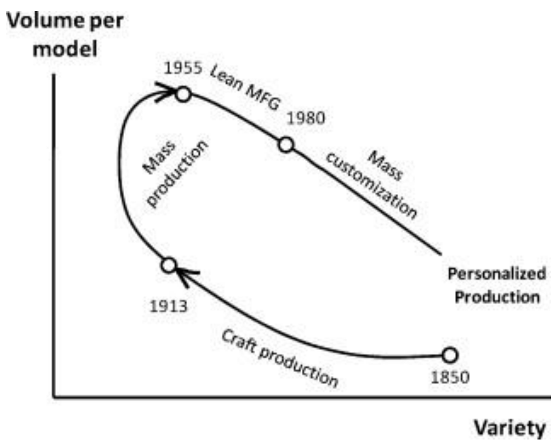


Fig. 2.1 The evolution of manufacturing paradigms [1]

“Craft Production” became the first paradigm, which is a method of creating goods by hand, often with a tool to provide the unique product for a customer but at high cost. “Mass Production” (MP) is a production strategy to provide standardized products and service in large quantities at low cost per unit enabled by the key science, technology and systems i.e., interchangeable ability, moving assembly lines and scientific management methods [1]. Workers are given precise and repetitive tasks to produce products or services of the same specifications. Standardized products will be eventually pushed off the markets. Therefore, a new marketing strategy called "Mass Customization" (MC) emerged to produce customized and high quality products and service at a reasonably low unit cost [5] through flexible computer-aided manufacturing systems. The theoretical knowledge of MP and MC and enabling technologies are described in sub-sections respectively.

2.1.1 MASS PRODUCTION

The conventional MP system is the system known for producing products in large quantities at low cost per unit. It involves making many copies of products rapidly, using assembly lines to send partially complete products to workers who work on an individual step [5]. Technology and strategy [56] such as computers and internets, flexible manufacturing system (FMS) and reconfigurable machining are enabler for MP. The common concept of MP is illustrated in Fig. 2.2. Some limitations are discussed subsequently.

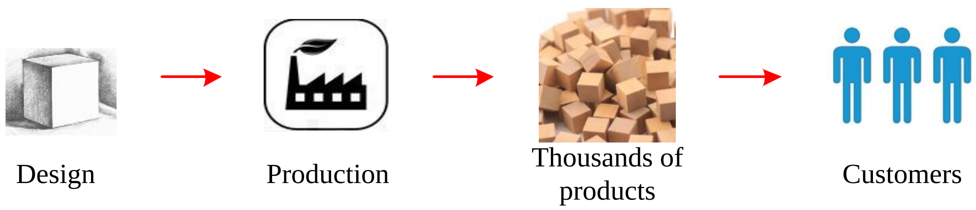


Fig. 2.2 The manufacturing process of mass production

The pursuit of productivity is the main goal of MP. After manufacturers designed products, they directly pushed the finished goods to the consumers. The economies of MP come from a variety of sources. To reduce nonproductive effort of all types is the primary cause. In craft production, craftsmen bustle about a shop and they use plenty of tools and times for varying tasks such as getting parts and assembling them. In MP, each worker uses the same tool to repeatedly perform identical or near-identical operations on a constant stream of products. The exact tool and parts at hand are always having been moved down the assembly line consecutively. The point, then, is to spend as little or no time as possible retrieving and or preparing tools and materials. Therefore, to manufacture a product using MP takes less time than when using traditional methods. For another, it can reduce the likelihood of human error and variation, as tasks are predominantly implemented by machinery. Using MP strategy has an advantage in reduction of labor costs, as well as an increased rate of production, which enables a company to produce a product in a larger quantity at a lower cost than using traditional, non-linear methods.

However, after a production line is implemented, mass production is difficult to alter a design or production process. All products produced on one production line will be identical or very similar, and introducing variety to satisfy individual wants is not easy as well. Some variety, however, can be achieved by applying different finishes and decorations at the end of the production line if necessary. The manufacturer must make sure that the product can be sold, otherwise, he would loss a great deal of money, more seriously, and lead the concern to utter failure because the starter cost for the machinery is fairly expensive.

2.1.2 MASS CUSTOMIZATION

The concept of mass customization (MC) was anticipated by Alvin Toffler in “Future Shock” in 1970 [57]. Davis [58] firstly delineated MC in “Future Perfect” in 1980s. It has been promoted as a production strategy to provide individually customized goods and services to every customer through high process agility, flexibility and integration [3, 4, 59] between supply chain members at a reasonably low cost [5]. The process of the development of customized products is illustrated in Fig. 2.3.

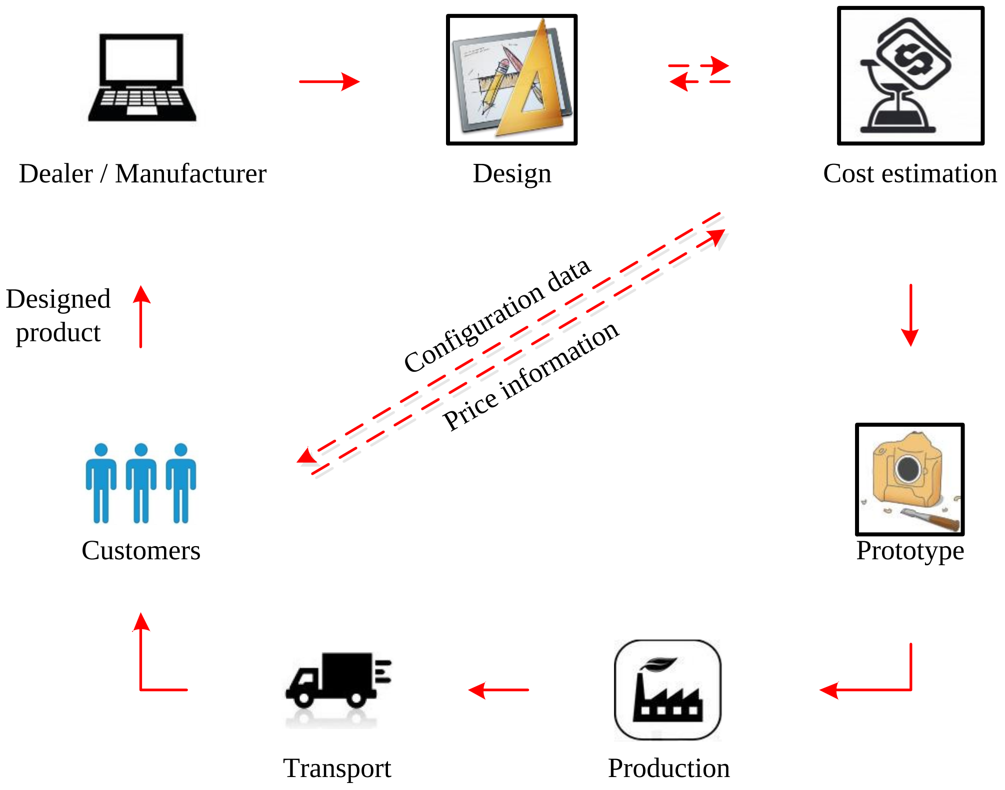


Fig. 2.3 The process of the development of customized products

The number of varieties of products which is offered by products manufacturers has been increased since 1980's. So far, the applications of MC in some sectors, e.g. food industry [60], electronics [61], large engineered products [62], mobile phones [63] and personalized nutrition [64] have been dominating their competition. Some special MC applications have been presented in homebuilding [65] and the production of foot orthoses [66].

Previous literature [67] indicated that MC can be made possible by six factors which are customer demand, markets, value chain, information technology, customizable offer and knowledge. Factor 1 and factor 2 are based on market factors. Factors: 3–6 are on the base of organization factors. The primary advantages and disadvantages of MP and MC are shown in Table 2.1. The primary difference between MP and MC is illustrated in Fig. 2.4.

Table 2.1 The advantages and disadvantages of MP and MC

Manufacturing paradigms	Main advantages	Main disadvantages
Mass production	- Decrease in probability of human error - Increase in quality of goods - Reduction in labor costs - Reduction of nonproductive effort	- A design of the product or production process is difficult to alter once production line is implemented.
Mass customization	- It provides a product or service to satisfy individual customer's needs. - The product or service offered to customers at a price is near mass production efficiency.	- A flexible production technology is needed [68]. - A complicated system for eliciting customers' wants and needs is required [68]. - A direct-to-customer logistics system is needed [68]. - Human beings might not want to pay everything customized [68].

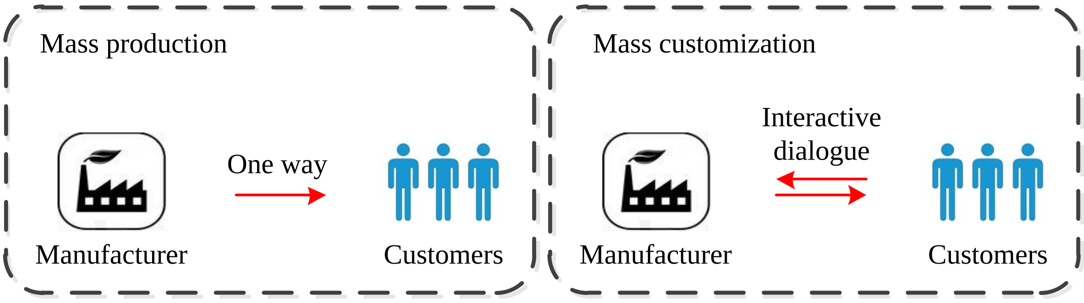


Fig. 2.4 The primary difference between MP and MC

In the process of product development and manufacturing of individually customized products, costing plays a crucial role. Costs are basically driven by material consumption and production. Manufacturers must be aware of various expenses incurred in such cost objects. The content of costs is described in Section 2.2.

2.2 COST

Cost can be defined as the expenditure that a company manufactures a product or a service. For the sellers, cost is the expenditure that is spent to produce goods. A seller would break even, if he sold his products at the production price. Apparently, he would neither lose money on his sales nor make a profit. For the buyers, the cost of a product can be called the price. It can be divided into the production cost and the mark-up cost, which is added by the seller to make a profit.

One of the most important considerations for successful industrial enterprises is to minimize cost of the product without affecting the quality helps to earn higher profits so that a company survives in today's competitive market place. Costs can be classified according to different criteria. If the criterion is how they vary with the quantity being manufactured, they would be classified as fixed costs and variable costs. Another criterion of classification is how they are allocated to a specific part, hence the name: direct and indirect costs. Therefore, in order to achieve the goal of cost reduction, the elements of total costs have to be well understood. The most familiar cost classification may make up of three main elements, i.e., material, labor, and burden cost as shown in Fig. 2.5 [6].

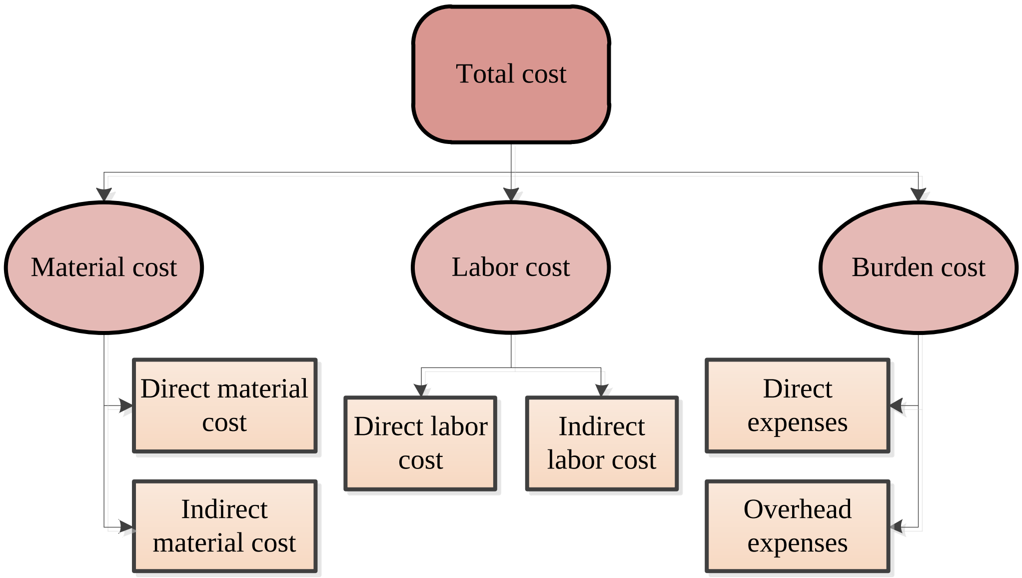


Fig. 2.5 Total cost of a product [6]

2.2.1 Material Cost

Material cost is the cost of material that goes into the manufacture of products. The material cost of a product excludes any indirect costs, such as overhead or wages. It is sub-divided into the following:

a) Direct material cost

Direct material cost is the cost of the raw materials and components directly used for the production processes and become a part of the final product. This expense can be directly and specifically associated with or assigned to the manufacture of a product or provision of a service. It also includes the scrap and waste that has been removed from a raw material stock. The raw material can be cost upon its volume or weight. The procedures of determination of direct material (solid material) cost can be summarized as follows [6].

- Through the product blueprint, a list of all the components that are required to the finished product is determined. If the blueprint is complex, study it carefully and partition it into simple geometrical shapes such as cylinders, cubes, etc.

- Determine the volume of each component by applying some simple formulae after adding the tooling allowances on all sides which are to be machined.
- Sum the volumes of each component to obtain total volume of the product.
- Figure out the cost of the direct material for the product by multiplying the total volume of each part by the unit cost of material used.

b) Indirect material cost

Apart from direct materials, a quantity of other material is necessary to assist direct material to be the final good. Although these materials are used in the production process, they cannot be linked to a specific product or job and they do not become the part of the final product. These materials are indirect materials such as oils, greases, sand papers, glue, tapes, general tools, cleaning supplies, coolants, cotton waste and other indirect material. The cost with these indirect materials is defined as indirect material cost.

2.2.2 LABOR COST

The labor cost is the expense made up of the salaries, wages, overtime, bonuses, benefit (if any), payroll taxes and other expenses which are paid to employees. It can be decomposed into direct and indirect costs as described in follows:

a) Direct labor cost

Direct labor costs are expenditures done by workers who actually convert raw materials into the finished product on the production line. For example, wages for the employees physically involving the manufacture of the product on the production line are direct labor cost. Direct labor costs are usually variable. Therefore, in order to calculate the labor cost accurately, estimator should have rich experience or knowledge of the operations which are implemented in production line.

b) Indirect labor cost

Indirect labor cost can be defined as all other labor costs out of the production processes. Indirect labor employees can include purchasing staffs, production supervisors, maintenance workers, materials handling staff, gatekeeper, crane driver, secretaries, marketing people etc. They contribute the manufacturing process but do not directly involve in the active conversion of materials into final goods.

It is really necessary for the estimator in the company to differentiate between direct and indirect labor cost, which can measure the productivity or efficiency of their workers. How long and on average for a worker to produce one unit should be measured. When the productivity is below target levels, these measures can provide valuable information to improve it.

2.2.3 BURDEN COST

Burden costs refer to any costs which are not directly involved in the production of a good or service. For example, special layouts and designs, hire of special tools and equipment, building rent, utilities etc. are considered burden cost because they are not directly tied to manufacturing processes. Therefore all costs other than direct material and direct labor costs are known as burden costs. Namely, the burden costs include indirect material cost and indirect labor cost and such other expenditures.

a) Direct expenses

Simply, direct expenses are any expenditure other than direct material or direct labor costs involved in a specific product or serve. For instance, the cost of hire of special equipment and tools, the cost of special fixtures and jigs, and such other expenses can be called direct expenses.

b) Overhead expenses

Overhead expenses are comprised of indirect material cost, indirect labor cost and other expenses which do not contribute to the actual creation of products or services. In some cases, the production expenses, administrative expenses, distribution expenses and selling expenses are classified as the indirect expenses.

2.3 PROCESS PLANNING

In order to carry out the cost estimation accurately and rapidly, and manufacture a product competitively and economically, process planning plays a vital role. Planning can be defined as the process to generate a set of integrated instructions to produce a component from a product drawing. In this process, the first step is to recognize the manufacturing features from an image representation such as a CAD image. Process planning concerns with the process which prepares the sequence of individual manufacturing operations prepares to produce workpieces or parts competitively and economically from initial stages to finished stages [69]. Process planning is a continuing effort to guide the best way to use the existing facilities, correct the errors of the past and hold serious misjudgments to a minimum so that it can lead to lower costs, higher efficiency, higher accuracy, higher productivity for essential business tasks [6, 70].

As shown in Fig. 2.6, the process planning techniques can be categorized into variant, generative, and macro-level techniques [71, 72]. The variant approach is to make the necessary modifications to the plan for the new part relying on existing standard plans developed from previously manufactured similar components [73]. The generative approach is resolved generatively for every new product configuration. It can be further divided into declarative and procedural process planning techniques [71]. Declarative systems are the expert systems which relied primarily on a data-base of matching related rules. While procedural systems are primarily based more on algorithmic analysis than analysis of direct rules. Macro-level process planning depends on the knowledge of declarative process including machine tools, geometry, fixtures, technological requirements and time that is represented by the features of the order would be produced [72].

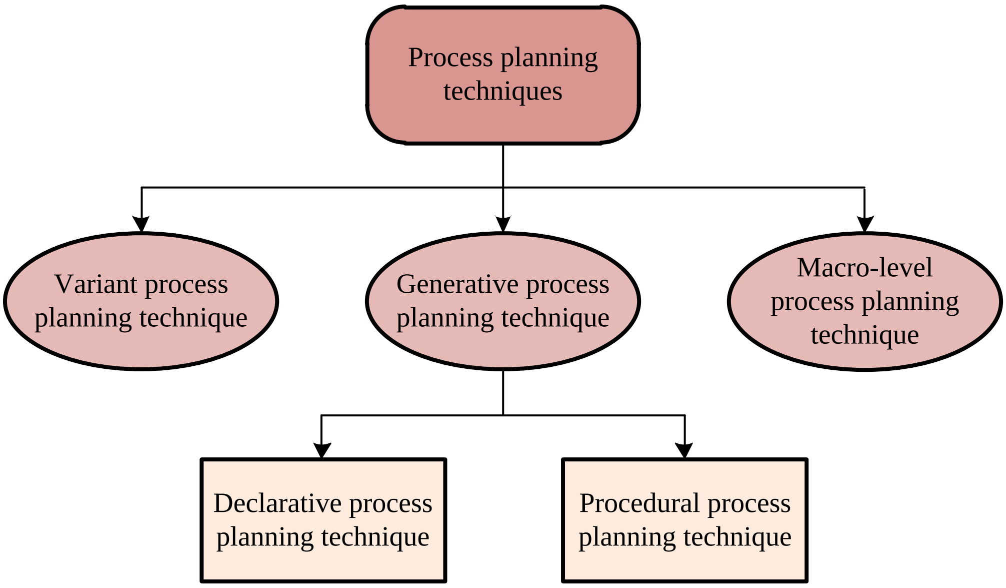


Fig. 2.6 Classification of process planning techniques [71, 72]

In the manufacturing, process planning is also defined as the development of the general sequence of steps required to convert a design into a final product. It may include some activities as shown in Table 2.2.

Table 2.2 Activities in process planning in manufacturing

1. Selection of raw material, machine tools and cutting tools.
2. Determination of machining methods, set-up and machining sequences.
3. Selection or design of machine tools.
4. Calculations or determination of cutting conditions.
5. Calculation and planning of tool paths.
6. Process the process plan.

The overall development of process planning primarily consists of three parts which are product design, processing planning and manufacturing in turn as shown in Fig. 2.7

[6]. The process planning is as an indispensable bridge between product design and manufacturing the product.

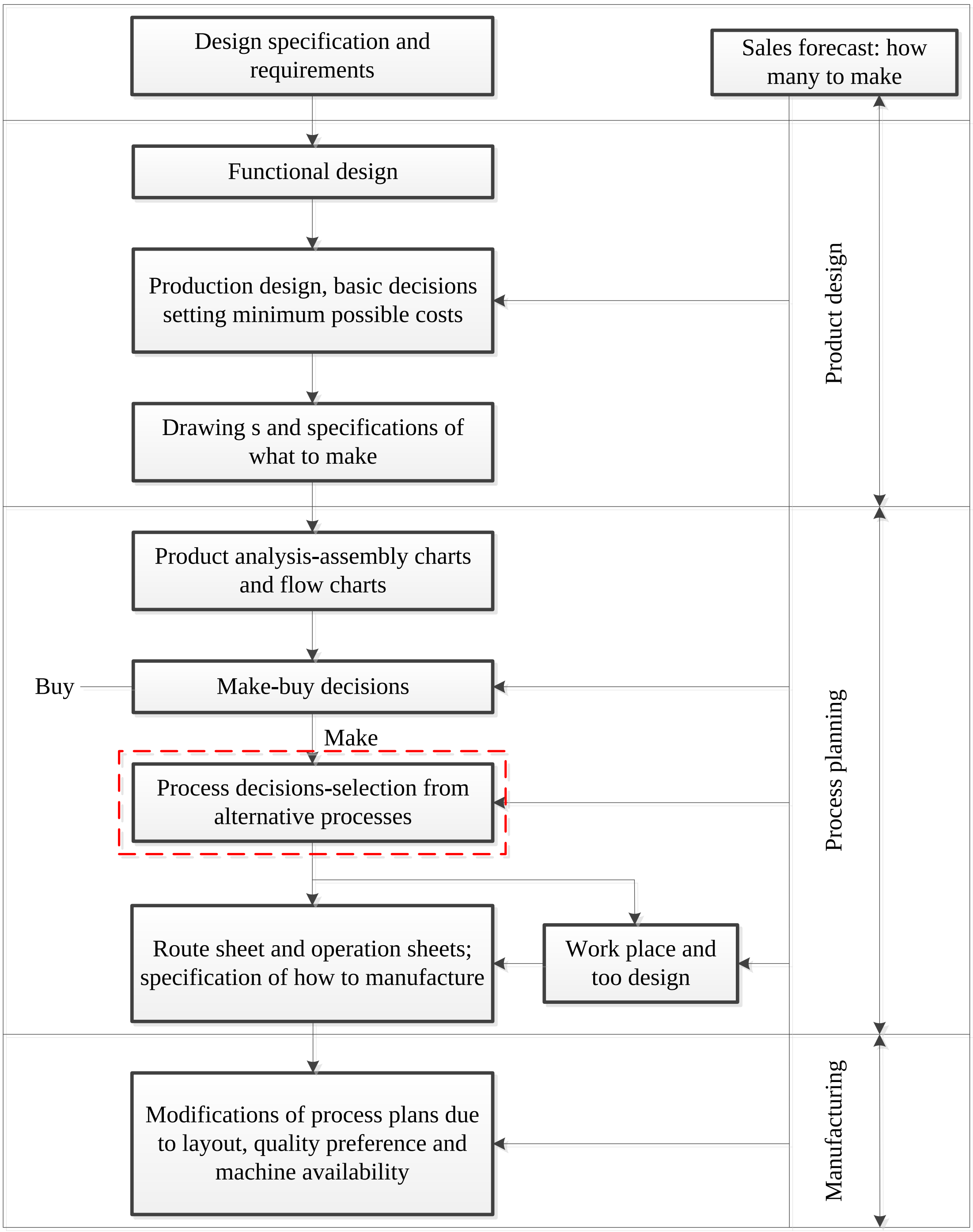


Fig. 2.7 The overall development of process planning [6]

Process planning mainly influences time to market and productions cost. Therefore, the planning activities play a crucial role in competitive advantage. In order to achieve such objectives, some studies associated with the system development have been proposed. Bhandarkar et al. [74] and Newman et al. [75] indicate that the manufacturing paradigm has been shifted from traditional manufacturing to the agile manufacturing, which meets customers' demands rapidly. Jiang et al. [76] described the development of an automatic process planning system (APPS), which enables generate process planning rapidly from a CAD image.

In this study, cutting parameters of the initial cutting process will be determined automatically upon the receipt of a product image through image processing. The process planning in manufacturing wooden products focuses on the red box shown in Fig. 2.7 e.g. to select the most suitable wood plank (s) and to determine the optimal cutting method.

2.4 IMAGE PROCESSING TECHNIQUES

As previously described in Chapter 1, a rapid, automatic and accurate cost estimation and control system can ensure the success of mass customization [7]. Digital image processing would be one of the solutions. Image processing is to apply computer algorithms to convert an image into a digital form so as to obtain an enhanced image or extract some useful information such as a sequence of characteristics or parameters associated with the image. Nowadays, with its growing technologies including image analysis technology, the image input and output technology, image recognition and extraction technology, and transformation pretreatment technology for relevant information of image feature, digital image processing has been applying widely in various domains [77] such as morphology, criminology, microscopy, remote sensing, photography, medical imaging, forensics, military and transportation but not limited to [78].

Image processing methods include many processes such as image acquisition, enhancement, segmentation, and image classification, recording and recalling. With the progress in image processing technology, the gradation and classification techniques in food researched have developed. The tomato classification [79], automated strawberry grading system [80], real-time color grading of stone fruit [81], the detection of apple defection [82] based on image processing was implemented. Not only image processing techniques applied in food research, but also its applications are industry, medicine and some other areas. In the fields of automation and computerization, the detection and assessment of physical and biological damage played an important role in the steel industry [83, 84], hardwood grading [85], forestry [86] and oil production [87]. Dimensions of workpieces [88], volume measurement of citrus fruits [89], size measurement of cereal grain [90] based on image processing technology have been proposed.

In conclusion, digital processing techniques apply computer algorithms to deal with the digital images. Because the raw data from imaging sensors has deficiencies, in order to obtain originality of information, various phases of processing e.g. image pre-processing, image enhancement and information extraction are executed as shown in Fig. 2.8 [91].

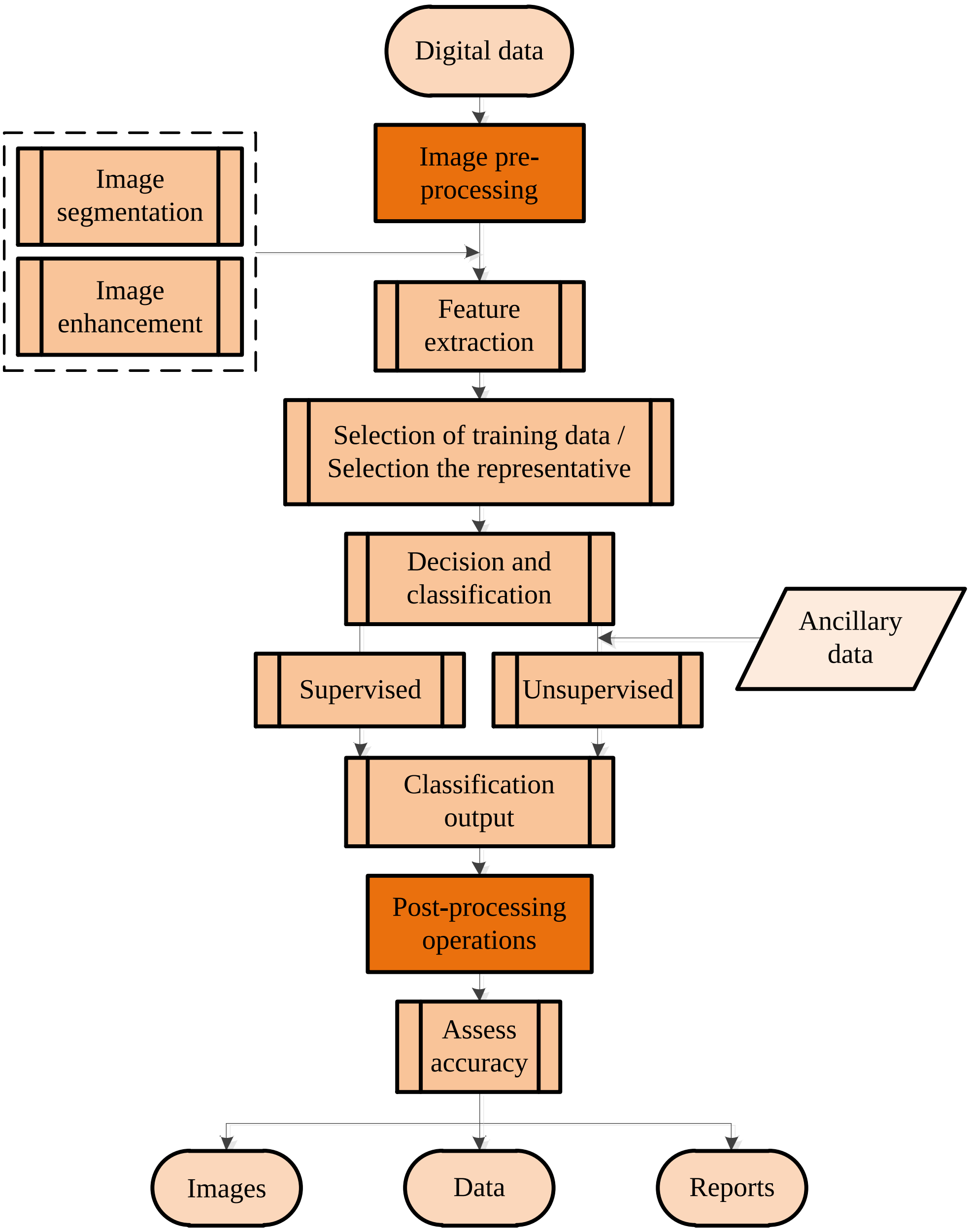


Fig. 2.8 The general phases: pre-processing, image enhancement and information extraction [91]

a) Image acquisition

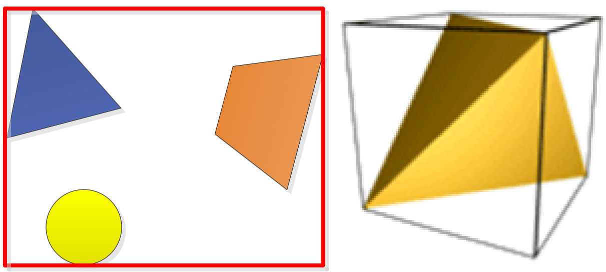
Image acquisition in image processing can be defined as the creation of digital images, typically from a physical scene, which is captured by a digital camera but other tools are also employed, and converted into a manageable entity [92]. Performing image acquisition in image processing is usually first phase of the whole integration process because, without an image, no processing is possible.

b) Image pre-processing

The purpose of image pre-processing is to provide images with higher quality to the image processing, which can reduce time to implement the image analysis. It commonly comprises of image enhancement, image registration and masking portions of images [93]. Image enhancement is to adjust digital images, such as noise removal, sharpening or brightening an image so that the results are more suitable for display or further image analysis [94]. Image registration aligns multiple scenes into a single integrated image [85]. Image mask is used to remove some part of the image. Some filtering operations in pre-processing can intensify or reduce certain image details so that it enables an easier or faster analysis.

c) A minimum bounding box

In this study, cutting parameters of the initial cutting process will be determined automatically upon the receipt of a product image. Product features will be recognized by an algorithm called a "Minimum Bounding Box, MBB." MBB also known as a smallest enclosing box is an expression used in geometry to find the oriented MBB enclosing a point set. It can be divided into two dimensions and three dimensions of MBB as shown in Fig. 2.9 [95-97]. Applications in two dimensions and three dimensions of MBB algorithms are shown in following.



(a) (b)

Fig. 2.9 The Minimum Bounding Box (MBB): (a) A series of geometric shapes enclosed by its two dimensions of MBB and (b) Three dimensions of MBB of a cone [95-97]

Two Dimensions of Minimum Bounding Box

In the two-dimensional case, it is called the minimum bounding box or rectangle (MBB/MBR). For the convex polygon, a linear time algorithm for the minimum-area enclosing rectangle is presented by Freeman et al. (see Fig. 2.10) [95]. It is based on the observation that a side of a minimum-area enclosing box must be collinear with a side of the convex polygon. It is possible to enumerate boxes of this kind in linear time with the approach called rotating calipers by Toussaint in 1983 [96]. The same approach can be applied to find the minimum-perimeter enclosing rectangle. Chaudhuri et al. [98] introduced a new approach for fitting of abounding rectangle to closed regions. The overview of this approach has five steps that are simply described as follows (See Fig. 2.11) The recursive minimum bounding rectangle (RMBR) applied to the building boundaries generated from LiDAR data which was able to make the LiDAR boundaries partition into a set of rectangles for future processing [99].

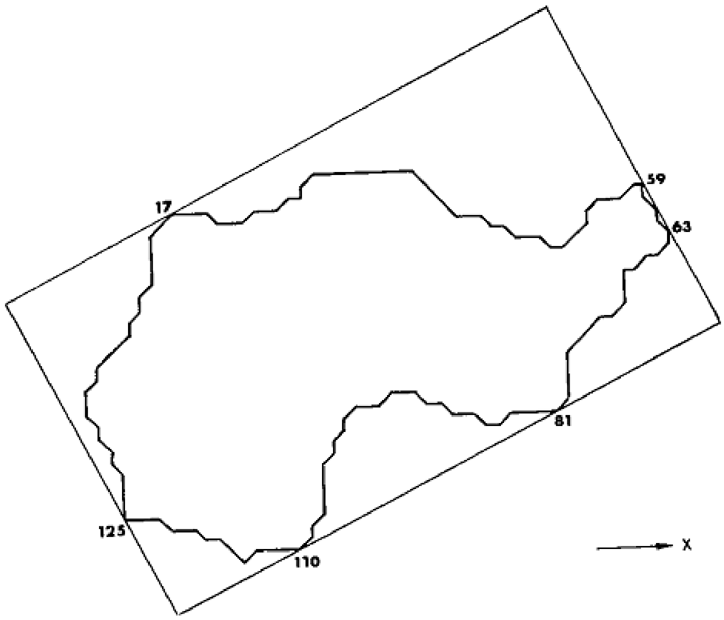


Fig. 2.10 The minimum-area rectangle by a linear time algorithm [95]

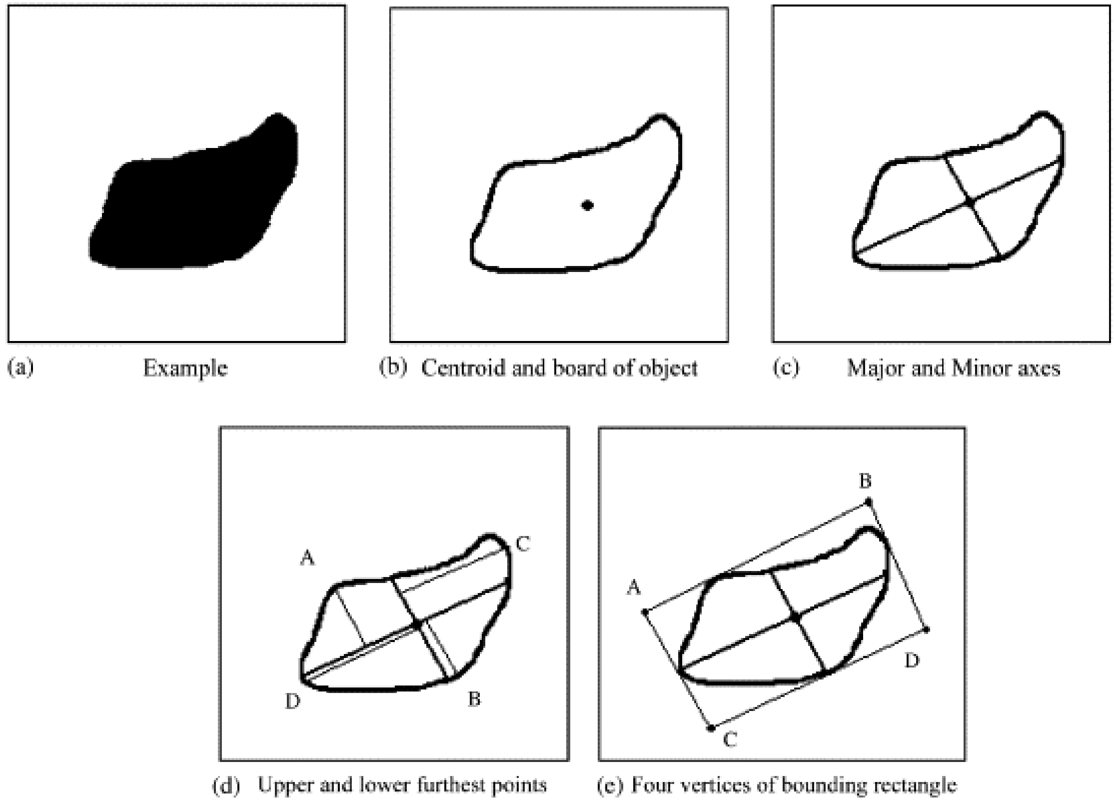


Fig. 2.11 Example for four steps of bounding fitting rectangle [98]

(1) To begin with, compute boundary (edge points) of the object and the centroid of the object through these edge points.

(2) Next, find the major and minor axes of the object through these edge points.

(3) And then, find the upper and lower furthest points with respect to both major (two points) and minor axes (two points).

(4) Finally, find the four vertices of bounding rectangle by using these four points.

Three Dimensions of Minimum Bounding Box

In 1985, J. O'Rourke presented a three-dimensional rotating calipers algorithm to find the minimum-volume enclosing box of a 3-dimensional point set in cubic time [97]. As of August 2008, this algorithm has not been improved although heuristic methods for tackling the same problem have been developed. A decade ago the algorithm of minimum volume bounding box computation (MVBB) proposed by Barequet et al. [100]. In 2008, Huebner et al. [101] envelops given 3D data points into primitive box shapes by a fit-and-split algorithm that is based on an efficient MVBB implementation (see Fig. 2.12).

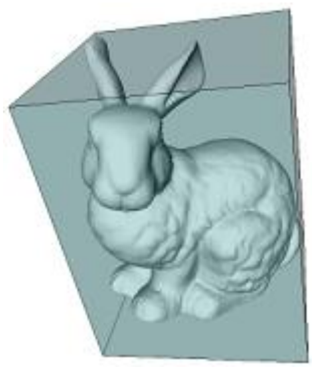


Fig. 2.12 The oriented MVBB of the Stanford bunny model by MVBB computation [101]

Chan et al. [102] proposed a simple iterative approach to determine the minimum oriented bounding box (OBB) of an arbitrary solid. This approach simplified the complicated three-dimensional problems by making use of the projected contours of the model and then used them to determine the minimum OBB (see Fig. 2.13).

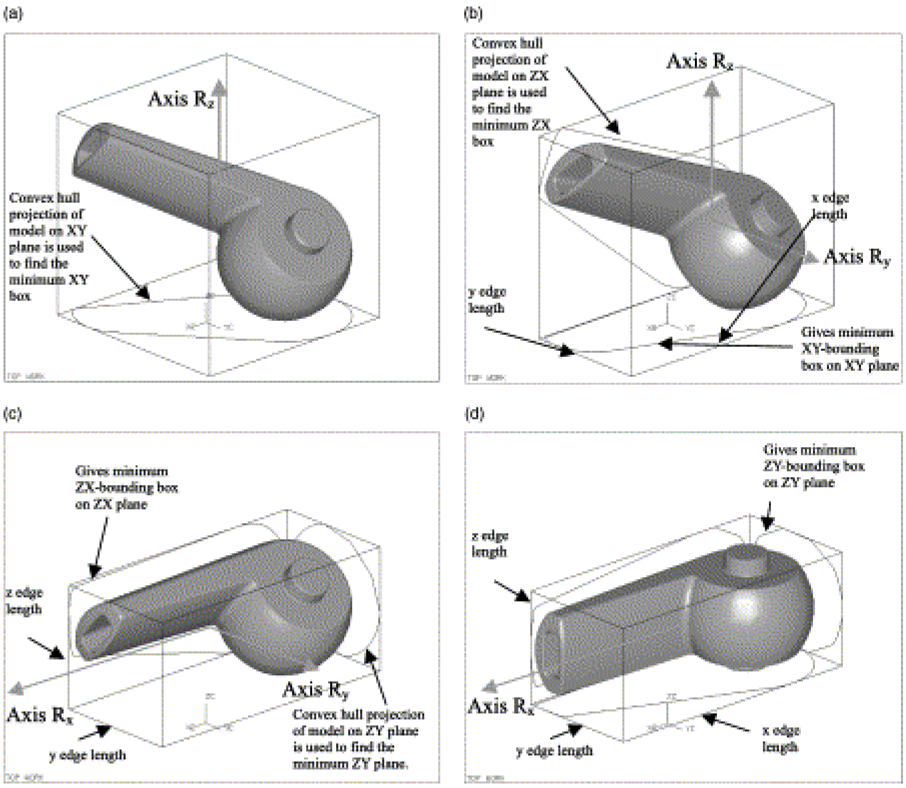


Fig. 2.13 A MBB algorithm: the procedures of determining the MBB of a simple model [102]

Minimum Bounding Box Algorithm in MATLAB

An algorithm of 2-dimensional minimal bounding box was developed by Diener [103] to compute quickly the minimal bounding box of a set of 2D points and it is similar to the “minimum bounding rectangle” proposed by D’Errico [104]. In this algorithm, input is a 2×n matrix that contains the (x, y) coordinates of n points and the output is a 2×4 matrix that contains the coordinates of the bounding box. The overview of this algorithm has six steps and is simply described as follows. The procedure of the algorithm is outlined in Algorithm 1.

(1) Compute the convex hull points of the object.

(2) Compute the angle to test which are the angles of the convex hull’s edges.

(3) Through rotating all angles, obtain all possible the bounding box.

(4) Compute border size and area of bounding box for all possible edges.

(5) Find minimal area.

(6) Compute the bound (min and max) on the rotated frame.

(7) Compute the corner of the bounding box.

Algorithm 1 2-D Minimum Bounding Box

Input. 2×n matrix contains the [x, y] coordinates of n points of the selected object. (There must be at least 3 points which are not collinear.)

Output. 2×4 matrix contains the coordinates of the bounding box corners.

Step 1: Compute the convex hull. (CH is a 2*k matrix subset of x)

1. k = convhull (x(1, :), x(2, :));

2. CH = x(:, k);

Step 2: Compute the angle to test which are the angles of the CHs' edges. (Note that one side of the bounding box contains an edge of the convex hull)

3. E = diff (CH, 1, 2); (CH edges)

4. T = atan2 (E (2, :), E (1, :)); (angle of CH edges (used for rotation))

5. T = unique (mod (T, pi/2)); (reduced to the unique set of first quadrant angles)

Step 3: Create rotation matrix which contains the 2×2 rotation matrices for all angles in T. (R is a 2n*2 matrix)

6. R = cos (reshape (repmat (T, 2, 2), 2*length (T), 2), (duplicate angles in T) …… + repmat ([0 – pi; pi 0]/2, length (T), 1)); (shift angle to convert sine in cosine)

7. RCH = R*CH;

Step 4: Compute border size [w_1; h_1; w_2; h_2; …; w_n; h_n] and area of bounding box for all possible edges.

8. bsize = max (RCH, [ ], 2) – min (RCH, [ ], 2);

9. area = prod (reshape (bsize, 2, length (bsize)/2));

Step 5: Find minimal area, thus the index of the angle in T.

10. [a, i] = min (area);

Step 6: Compute the bound (min and max) on the rotated frame.

11. Rf = R (2*I + [–1 0], :); (rotated frame)

12. bound = Rf*CH; (project CH on the rotated frame)

13. bmin = min (bound, [], 2);

14. bmax = max (bound, [], 2);

Step 7: Compute the corner of the bounding box.

15. Rf = Rf';

16. bb(:,1) = bmin (1)*Rf (:, 1) + bmin (2)*Rf (:, 2);

17. bb(:,2) = bmin (1)*Rf (:, 1) + bmax (2)*Rf (:, 2);

18. bb(:,3) = bmax (1)*Rf (:, 1) + bmax (2)*Rf (:, 2);

19. bb(:,4) = bmax (1)*Rf (:, 1) + bmin (2)*Rf (:, 2);

For 3-dimensional minimal bounding box, an algorithm "minboundbox" was presented by Korsawe [105] that can easily compute the minimal box (with right angles) around a set of point in 3-d. The extremal property of the box is determined either in terms of volume, surface or sum of edge lengths. The calculation is based on heuristic method, but a great quantity of tests did not show any counterexamples yet. The algorithm behind the function can be subdivided into three levels of accuracy with differing runtimes.

The purposes of this chapter are to review some image processing methods, and to present some applications of image processing in different researches. Image processing technique can be one of the solutions to ensure the success of mass customization.

2.5 WOOD DEFECTS

Wood defects are irregularity or abnormality occurring on the surface of the wood or hidden underneath the surface that will be revealed once the wood is cut, which is responsible for its [106-109]:

(1) Strength reduction

(2) Lowering of durability

(3) Lowering of utility

(4) Poor appearance

(5) Decay

The wood defects can be classified into two categories which are as follows (see Table 2.3) [106-109]:

Natural defects: chemical stain, knots, shakes, twisted fibres, rind galls, upsets and burls.

Other than natural defects: these defects can be caused due to insects, fungi, conversion and seasoning.

Table 2.3 Classification of wood defects [106-111]

Wood defects		Definition	Figures
Common natural defects	Loose knots	These are the bases of branches or limbs which are broken or cut off from the tree.	
	Shakes	These are longitudinal separations in wood between the annual rings.	
	Pitch	An accumulation of resinous material on the surface or in pockets below the surface of wood.	
	Tight knot	A knot fixed by growth or position in the wood structure so that its place in the surrounding wood.	
	Resin pocket	Resin patches are found in wood is called resin pocket.	
Common other than natural defects	Insects	Wood defects are deteriorated by insects.	
	Fungi	Wood defects are deteriorated by fungi.	
	Seasoning	It is caused by faculty techniques of seasoning.	

As before, the defects, either on or beneath the surface, cause loss in material productivity. Chansaad et al. [8] developed a set of fuzzy rules to explain how loss in wooden material was dependent upon changes in cutting parameters, when defects were assumed to be distributed unsystematically and uncontrollably. To a given defective plank, by applying different "*length of cut*" and "*area of cut*," different material loss will result as illustrated in Fig. 1.3. However, by leaving aside the defect characterization, to give a full explanation of such dependency over the range of product lines, the number of fuzzy rules would be too large to handle. There was also an effort to identify defect position in a wooden beam [112], but this approach could not provide other information significant to manufacturing applications.

2.6 STATISTICAL MODELS IN SIMULATION

The actions of the entities in the real-world phenomenon can be predicted by an appropriate model. To begin with, the available data are collected. Then, the model builder would select a known distribution form by educated guesses. Next, it would make an estimation of the parameter(s) of the distribution selected. Finally, goodness-of-fit tests show how good a fit can be obtained. A hypothesized model will be accepted through unremitting efforts in selecting an appropriate distribution form. These steps are described in detail in Section 2.7.

2.6.1 DISCRETE RANDOM VARIABLES AND DISCRETE DISTRIBUTIONS

Discrete random variables can be defined as random phenomena in which only integer values can occur. Consider the experiment of slipping a coin twice. This experiment can have four possible outcomes: on the head and on the head (HH), on the head and on the tail (HT), on the tail and on the head (TH), and on the tail and on the tail (TT). Define the random variable X as the number of Heads. The random variable X can be as $R_X = \{0, 1, 2\}$. The discrete probability distribution for this experiment is given by Table 2.4.

Table 2.4 The probability distribution of the experiment of slipping a coin

x_i	0	1	2
$p\ (x_i)$	1/4	1/2	1/4

If a random variable is a discrete variable, the probability distribution is called a discrete probability distribution. Common distributions are described in following.

The possible values of X are given by the range space of X, which can be written as R_X. Here R_X = {0, 1, 2 …}. If X is a discrete random variable, with each possible outcome x_i in R_X, a number $p(x_i) = P(X = x_i)$ gives the probability that the random variable is equal to the value of x_i. The numbers $p(x_i)$, i = 1, 2, …, must satisfy two conditions as follows:

(1) $p(x_i) \geq 0,$ for all i ;

(2) $\sum_{i=1}^{\infty} p(x_i) = 1$.

The collection of pairs (x_i, $p(x_i)$), i = 1, 2,…is called the probability distribution of X, and $p(x_i)$ is called the probability mass function (pmf) of X.

The cumulative distribution function (cdf), denoted by $F(x)$, measures the probability that the random variable X assumes a value less than or equal to x, that is $F(x) = P(X \leq x)$. If X is discrete, therefore,

$$F(x) = \sum_{\substack{all \\ x_i \leq x}} p(x_i) \tag{2.1}$$

All probability questions about X can be answered in term of the cdf. For instance,

$$P(a < X \leq b) = F(b) - F(a) \quad \text{for all } a < b \tag{2.2}$$

a) Bernoulli trials and the Bernoulli distribution

Consider an experiment consisting of n trials, each of which can be a success or a failure. Let X_j = 1 if the jth experiment resulted in a success, and let X_j = 0 if the jth experiment resulted in a failure. It is called a Bernoulli process. A Bernoulli trial is a random experiment with two possible outcomes: success or failure, and the probability of a success remains constant from trial to trial. Therefore,

$$p(x_1, x_2, \ldots, x_n) = p_1(x_1) \cdot p_2(x_2) \cdots p_n(x_n)$$

and

$$p_j(x_j) = p(x_j) = \begin{cases} p, & x_j = 1, j = 1, 2, \ldots, n \\ 1 - p = q, & x_j = 0, j = 1, 2, \ldots, n \\ 0, & \text{otherwise} \end{cases} \tag{2.3}$$

For one trial, the distribution given in Eq. (2.3) is well known as the Bernoulli distribution. The mean and variance of X_j can be calculated as follows:

$$E(X_j) = p \tag{2.4}$$

and

$$V(X_j) = p(1 - p) \tag{2.5}$$

b) Binomial distribution

The random variable X that denotes the number of successes in n Bernoulli trials has a binomial distribution given by $p(x)$. Binomial distribution is used only when two conditions are satisfied. They are:

(1) Only two outcomes are possible;

(2) The sample must be random.

$$p(x) = \begin{cases} \binom{n}{x} p^x q^{n-x}, & x = 0,1,2,\ldots,n \\ 0, & \text{otherwise} \end{cases} \tag{2.6}$$

where

$$\binom{n}{x} = \frac{n!}{x!(n-x)!}$$

In the above Eq. (2.6), n represents the total number of possibilities, the term p is the frequency with which the desired number. Define the random variable X follows the binomial distribution with parameters n and p, we write $X \sim B(n, p)$. To calculate the mean and variance of binomial distribution is to consider X as a sum of n independent Bernoulli random variables, each with mean p and variance $p(1-p)$. Therefore,

$$X = X_1 + X_2 + \cdots + X_n$$

and the mean, $E(X)$, is given by

$$E(X) = p + p + \cdots + p = np \tag{2.7}$$

and the variance $V(X)$ is given by

$$V(X) = p(1-p) + p(1-p) + \cdots + p(1-p) = np(1-p) \tag{2.8}$$

And, the cdf is given by

$$F(x)=\sum_{i=0}^{x}\binom{n}{i}p^{i}(1-p)^{n-i} \tag{2.9}$$

The graphical interpretation of Eq. (2.6) and Eq. (2.9) is shown in Fig. 2.14. The pmf and cdf for a binomial distribution with n =20, p = 0.7, and n = 40, p = 0.5.

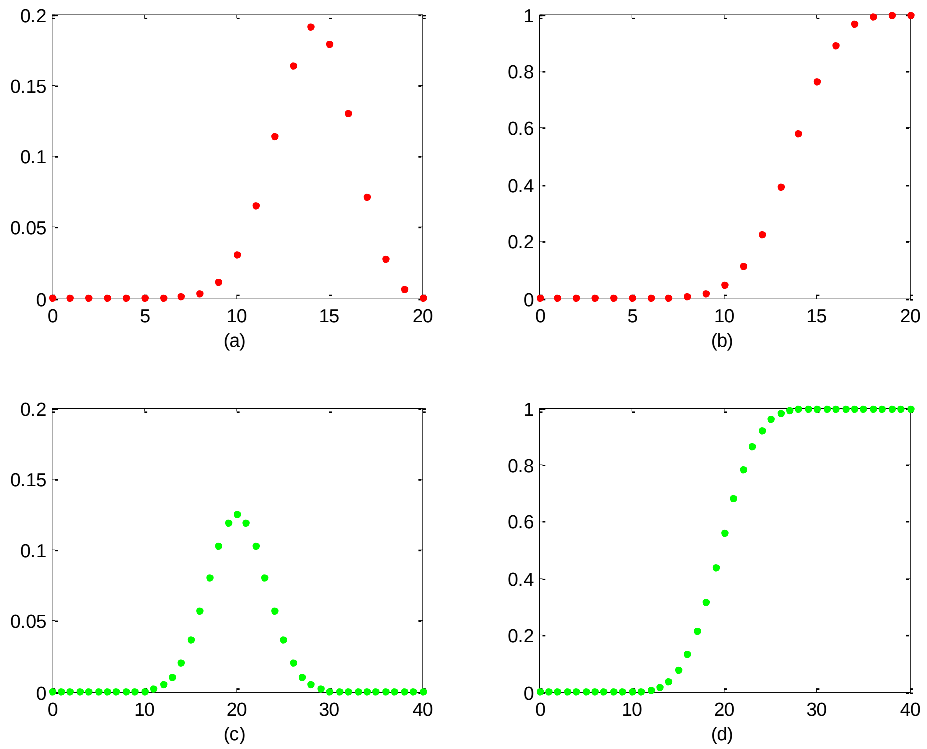


Fig. 2.14 The pmf and cdf for a binomial distribution

c) Hypergeometric distribution

In statistics, hypergeometric distribution is a discrete probability distribution used only when three conditions are satisfied. They are:

(1) The test has only two possible outcomes;

(2) The sample must be random;

(3) Selections are not replaced.

If a random variable X follows the hypergeometric distribution, its probability mass function (pmf) is given by:

$$P\left(X = k\right) = \frac{\binom{K}{k}\binom{N-K}{n-k}}{\binom{N}{n}} \tag{2.10}$$

where N is the population size; K is the number of success states in the population; n is the number of draws; and k is the number of successes.

d) Poisson distribution

Poisson distribution is defined the same way as seen above in the “Binomial distribution” section. It is essentially a derived limiting case of the binomial distribution. Poisson distribution has widely applied in the production and life. The Poisson probability mass function is given by

$$p(x) = \begin{cases} \dfrac{e^{-\alpha}\alpha^{x}}{x!}, & x = 0,1,... \\ 0, & \text{otherwise} \end{cases} \tag{2.11}$$

where e is the base of the natural logarithm (e = 2.71828…); x is the number of occurrences of an event; x! is the factorial of x; and α is a positive real number, equal to the expected number of occurrences that occur during the given interval.

One of the important properties of the Poisson distribution is that the mean and variance are both equal to α, that is,

$$E(X) = \alpha = V(X) \tag{2.12}$$

And, the cdf is given by

$$F(x) = \sum_{i=0}^{x} \frac{e^{-\alpha}\alpha^{i}}{i!} \tag{2.13}$$

The pmf and cdf for a Poisson distribution with α = 2 are illustrated in Fig. 2.15.

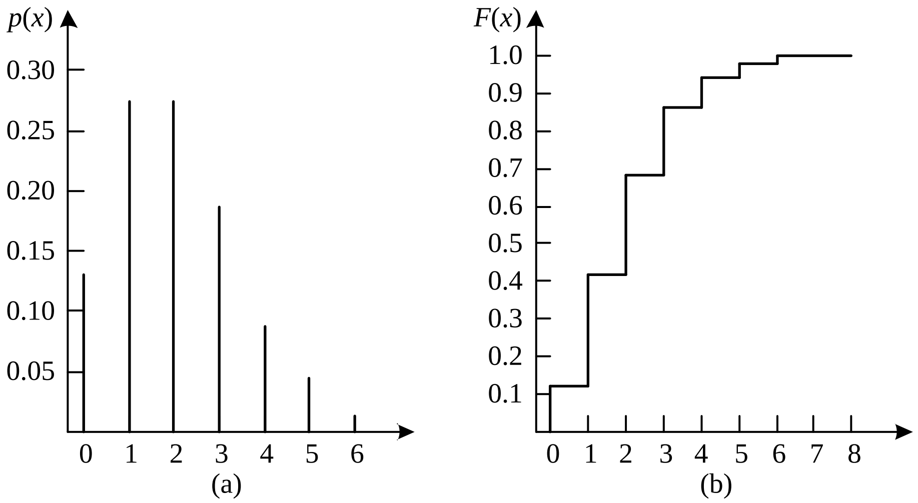


Fig. 2.15 The pmf (a) and cdf (b) for a Poisson distribution with α = 2

f) Summary

Table 2.5 summarizes the main characterizations of the key discrete distributions as follows.

Table 2.5 Summary of key discrete distributions

	Main distributions			
Characterization	Bernoulli	Binominal	Hypergeometric	Poisson
Notation	$X \sim \text{Bern}(p)$	$B(n, p)$	$X \sim H(n, M, N)$	$P \sim (\lambda)$
Parameters	$0 < p < 1$	$n \in N_0$ $P \in [0,1]$	$N \in \{0,1,2,...\}$ $m \in \{0,1,2,..., N\}$ $n \in \{0,1,2,..., N\}$	$\lambda > 0$
Support	$x_j \in \{0,1\}$	$k \in \{0,..., n\}$	$k \in \{\max(0, n + m - N),..., \min(m, n)\}$	$k \in \{0,1,2,3,...\}$
Mean	p	np	$n\frac{K}{N}$	λ
Variance	$p(1-p)$	$np(1-p)$	$n\frac{K}{N}\frac{N-K}{N}\frac{N-n}{N-1}$	λ
Requirements	- The trials are independent. - Each trial has only possible outcomes (success or failure)	- Only two outcomes are possible. - Sample is random.	Selections are not replaced.	- Success is independent of the interval. - The probability of two consecutive successes is small.

2.6.2 Continuous Random Variables and Continuous Distributions

A continuous random variable is a random variable where the data can take any value in an interval. If the range space R_X of the random variable X is an interval, X is a continuous variable, the probability that X lies in the interval $[a, b]$ is given by

$$P(a \le X \le b) = \int_a^b f(x)\, dx \tag{2.14}$$

The function $f(x)$ used to describe a continuous probability distribution is called the probability density function (pdf) of the random variable X. The pdf satisfies the following conditions:

(1) $f(x) \geq 0$ for all x in R_X ;

(2) $\int_{R_X} f(x)\, dx = 1$;

(3) $f(x) = 0$ if x is not in R_X .

As a results of Eq. (2.14), for any specified value x_0, $P(X = x_0) = 0$, because

$$\int_{x_0}^{x_0} f(x)\, dx = 0$$

Therefore,

$$P(a \leq X \leq b) = P(a < X \leq b) = P(a \leq X < b) = P(a < X < b) \qquad (2.15)$$

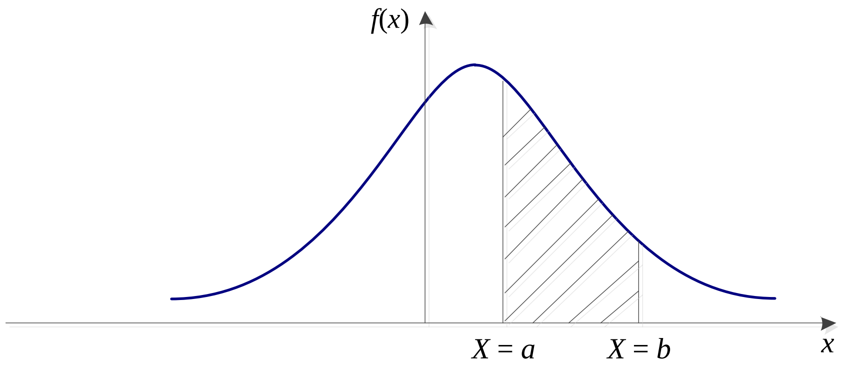


Fig. 2.16 Graphical interpretation of P ($a < X < b$)

The graphical interpretation of Eq. (2.14) is shown in Fig. 2.16. The shaded area in the graph represents the probability that random variable X lies in the interval [a, b].

In the Section 2.6.1, the cdf is described. If X is continuous, therefore,

$$F(x) = \int_{-\infty}^{x} f(t)\, dt \qquad (2.16)$$

For continuous distributions, not only does Eq. (2.2) hold, but also the probabilities in the Eq. (2.15) are equal to $F(b) - F(a)$.

Several familiar distributions are described in the following.

a) Uniform distribution

A uniform distribution, sometimes also called rectangular distribution, is the probability distribution of random number selection from the continuous interval between *a* and *b*. Its pdf and cdf are respectively given by Eq. (2.17) and Eq. (2.18).

$$f(x) = \begin{cases} \dfrac{1}{b-a}, & a \le x \le b \\ 0, & \text{otherwise} \end{cases} \tag{2.17}$$

$$F(x) = \begin{cases} 0, & x < a \\ \dfrac{x-a}{b-a}, & a \le x < b \\ 1, & x \ge b \end{cases} \tag{2.18}$$

Note that

$$P(x_1 < X < x_2) = F(x_2) - F(x_1) = \frac{x_2 - x_1}{b-a}$$

is proportional to the length of the interval, for all x_1 and x_2 satisfying $a \le x_1 < x_2 \le b$. Therefore, the mean and variance of the distribution are given by

$$E(X) = \frac{a+b}{2} \tag{2.19}$$

and

$$V(X) = \frac{(b-a)^2}{12} \tag{2.20}$$

When a = 1 and b = 6, the pdf and cdf are illustrated in Fig. 2.17.

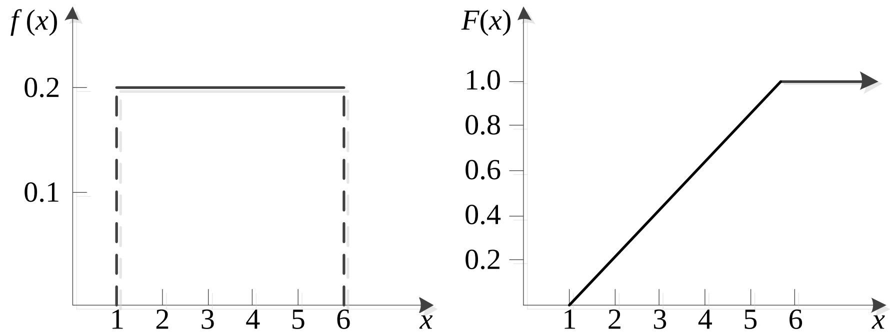


Fig. 2.17 pdf and cdf for uniform distribution

b) Normal distribution

The normal distribution i.e., Gaussian distribution is defined by the Normal equation $f(x)$.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right], \quad -\infty < x < \infty \tag{2.21}$$

where x is a normal random variable; μ is the mean; and σ is the standard deviation.

The normal distribution is used so often that the notation $X \sim N(\mu, \sigma^2)$ has been adopted by many authors to indicate that random variable X is normally distributed with mean μ and variance σ^2. The normal pdf is shown in Fig. 2.18.

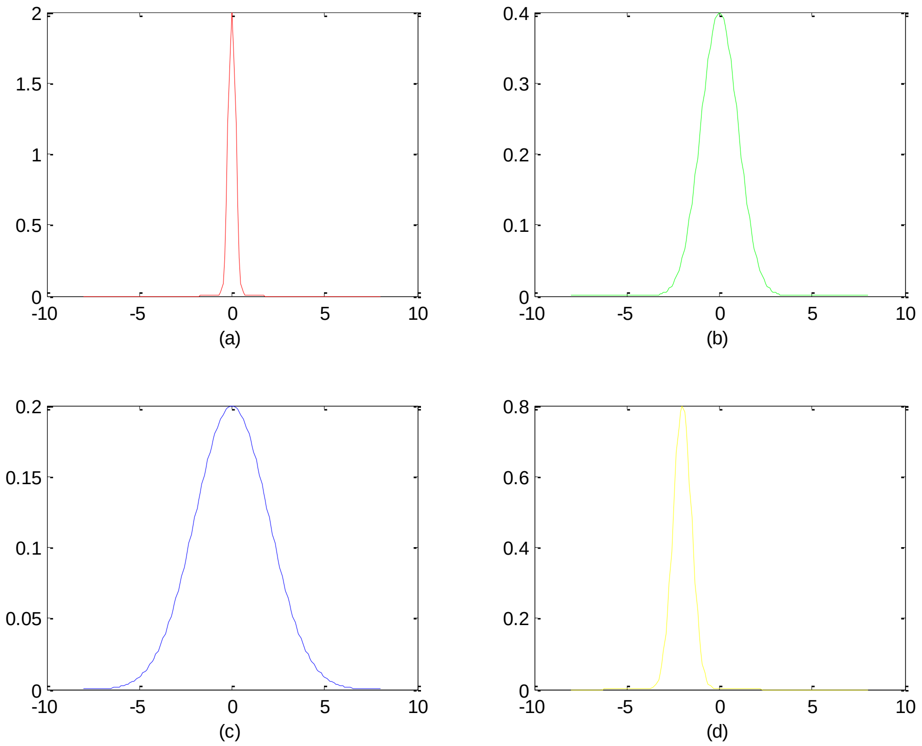


Fig. 2.18 The pdf for a normal distribution with differernt parameters: (a) μ = 0, σ^2 = 0.04, (b) μ = 0, σ^2 = 1, (c) μ = 0, σ^2 = 4, and (d) μ = -2, σ^2 = 0.25

The cdf for the normal distribution is given by

$$F(x) = P(X \le x) = \int_{-\infty}^{x} \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2\right] dt \qquad (2.22)$$

It is not possible to evaluate Eq. (2.22) in closed form. Numerical methods could be used, but it appears that it would be necessary to evaluate the integral for each pair (μ, σ^2). However, a transformation of variables, z = (t − μ) /σ, allows the evaluation to be independent of μ and σ. If X~N (μ, σ^2), let Z = (X − μ) /σ to obtain

$$\begin{aligned} F(x) &= P(X \le x) = P\left(Z \le \frac{x-\mu}{\sigma} \right) \\ &= \int_{-\infty}^{(x-\mu)/\sigma} \frac{1}{\sqrt{2\pi}} e^{-z^2/2}\ dz \\ &= \int_{-\infty}^{(x-\mu)/\sigma} \phi(z)\ dz = \Phi\left(\frac{x-\mu}{\sigma} \right) \end{aligned} \tag{2.23}$$

The pdf

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}, \quad -\infty < z < \infty \tag{2.24}$$

is the pdf of a normal distribution with mean 0 and variance 1. Therefore, Z~*N* (0, 1) and it is said that Z has a standard normal distribution. The cdf for the standard normal distribution can be exhibited by integrating Eq. (2.24) to obtain

$$\Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{-t^2/2}\ dt \tag{2.25}$$

Eq. (2.25) has been widely tabulated.

c) Exponential distribution

The exponential distribution is the probability distribution used to model the time between independent events that occur continuously at a constant average rate λ. Its pdf is given by Eq. (2.26). The pdf and cdf are shown in Fig. 2.19.

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, & x \ge 0 \\ 0, & \text{elsewhere} \end{cases} \tag{2.26}$$

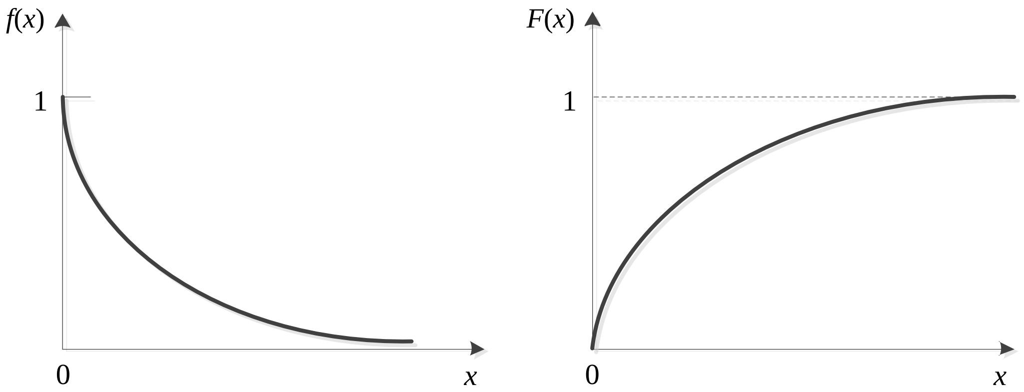


Fig. 2.19 pdf and cdf for exponential distribution

The exponential distribution has mean and variance given by

$$E(X) = \frac{1}{\lambda} \quad \text{and} \quad V(X) = \frac{1}{\lambda^2} \tag{2.27}$$

The cdf is given by

$$F(x) = \begin{cases} 0, & x < 0 \\ \int_0^x \lambda e^{-\lambda t}\, dt = 1 - e^{-\lambda t}, & x \geq 0 \end{cases} \tag{2.28}$$

d) Lognormal distribution

Lognormal distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed. Its pdf is given by Eq. (2.29)

$$f(x) = \begin{cases} \dfrac{1}{\sqrt{2\pi}\sigma x} \exp\left[-\dfrac{(\ln x - \mu)^2}{2\sigma^2} \right], & x > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.29}$$

where $\sigma^2 > 0$. The mean and variance of a lognormal distribution are

$$E(X) = e^{\mu + \sigma^2/2} \tag{2.30}$$

$$V(X) = e^{2\mu + \sigma^2}(e^{\sigma^2} - 1) \tag{2.31}$$

Note that the parameters μ and σ^2 are not the mean and variance of the lognormal distribution. The parameters μ and σ^2 come from the fact that when Y has a $N\,(\mu, \sigma^2)$ distribution then $X = e^Y$ has a lognormal distribution with parameter μ and σ^2. If the mean and variance of the lognormal are known to be μ_L and $\sigma_L{}^2$, respectively, therefore, the parameters μ and σ^2 can be given by

$$\mu = \ln\left(\frac{\mu_L^2}{\sqrt{\mu_L^2 + \sigma_L^2}}\right) \tag{2.32}$$

$$\sigma^2 = \ln\left(\frac{\mu_L^2 + \sigma_L^2}{\mu_L^2}\right) \tag{2.33}$$

e) Gamma distribution

A random X is gamma distributed with β and θ, its pdf is given by

$$f(x) = \begin{cases} \dfrac{\beta\theta}{\Gamma(\beta)}(\beta\theta x)^{\beta-1}e^{-\beta\theta x}, & x > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.34}$$

where β is the shape parameter; and θ is the scale parameter.

The mean and variance of the gamma distribution are given by

$$E(X) = \frac{1}{\theta} \quad \text{and} \quad V(X) = \frac{1}{\beta\theta^2} \tag{2.35}$$

The cdf of X is given by

$$F(x)=\begin{cases}1-\int_{x}^{\infty}\frac{\beta\theta}{\Gamma(\beta)}(\beta\theta t)^{\beta-1}e^{-\beta\theta t}\ dt, & x>0\\ 0, & x\le 0\end{cases} \tag{2.36}$$

f) Weibull distribution

The random variable X has a Weibull distribution, its pdf is given by

$$f(x)=\begin{cases}\frac{\beta}{\alpha}\left(\frac{x-\nu}{\alpha}\right)^{\beta-1}\exp\left[-\left(\frac{x-\nu}{\alpha}\right)^{\beta}\right], & x\ge\nu\\ 0, & \text{otherwise}\end{cases} \tag{2.37}$$

where υ ($-\infty<\upsilon<\infty$) is the location parameter; α (α > 0), is the scale parameter; and β ($\beta>0$) is the shape parameter.

The mean and variance of the Weibull distribution are given by Eq. (2.38) and Eq. (2.39), respectively.

$$E(X)=\nu+\alpha\Gamma\left(\frac{1}{\beta}+1\right) \tag{2.38}$$

$$V(x)=\alpha^{2}\left[\Gamma\left(\frac{2}{\beta}+1\right)-\left[\Gamma\left(\frac{1}{\beta}+1\right)\right]^{2}\right] \tag{2.39}$$

The cdf of the Weibull distribution is given by

$$F(x)=\begin{cases}0, & x<\nu\\ 1-\exp\left[-\left(\frac{x-\nu}{\alpha}\right)^{\beta}\right], & x\ge\nu\end{cases} \tag{2.40}$$

g) Beta distribution

A random variable X is beta distributed with parameters $\beta_1>0$ and $\beta_{2,}$ its pdf is given by

$$f(x) = \begin{cases} \dfrac{x^{\beta_1 - 1}(1-x)^{\beta_2 - 1}}{B(\beta_1, \beta_2)}, & 0 < x < 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.41}$$

where $B(\beta_1, \beta_2) = \Gamma(\beta_1)\,\Gamma(\beta_2)/\,\Gamma(\beta_1+\beta_2)$.

In practice, the beta distribution is often defined on a different range. The finite range (0, 1) is replaced with (a, b), $a < b$. It can be accomplished by defining a new random variable

$$Y = a + (b-a)X$$

Therefore, the mean and variance of Y are given by

$$E(Y) = a + (b-a)\left(\frac{\beta_1}{\beta_1 + \beta_2}\right) \tag{2.42}$$

$$V(Y) = (b-a)^2\left(\frac{\beta_1\beta_2}{(\beta_1+\beta_2)^2(\beta_1+\beta_2+1)}\right) \tag{2.43}$$

h) Empirical distribution

The empirical distribution is a distribution whose parameters are obtained from the empirical measure of the sample. It is characterized by specifying a small number of parameters such as the mean and variance. When a random variable has any particular parametric distribution cannot be established, an empirical distribution will be used. However, a disadvantage of the empirical is that the sample might not cover the whole range of possible values.

i) Summary

The purposes of this chapter are to review some important probability distributions. These distributions can be applied in the simulation system as described in following sections. A primary assignment in simulation is to collect data and then analyze the input data. One of the first steps in this assignment is to hypothesize a distributional form for the input data through comparing the shape of the pmf or pdf to a histogram of the data. Actually, the computer software can assist in this effort.

2.7 SIMULATION MODEL DEVELOPMENT

Input modeling provides a driving force in a successful simulation application. In the simulation of a queuing system, the typical input data modeling includes the distribution of time between arrivals and of service times. The input modeling is the distribution of demand and of lead time in a supply chain simulation. From the standpoint of time and resource requirements, the main task is to choose appropriate distributions for input data in real-world simulation applications. Make no mistake: there is no true distribution for any stochastic input process i.e., it is just an approximation of reality. The development of a useful model of input data has four main steps.

(1) Collect data from the real system of interest. This process is supported by a substantial time and resource commitment. In some conditions, data collection is not possible (For example, when time is not limited, or when laws prohibit and other situations.) When data is not available to collect, expert opinion and knowledge of the process will be used to make some educated guesses.

(2) Identify a probability distribution with data to represent the input process. If the data collection is available, it will begin with the development of a histogram of the data. Analysis of the histogram and a structural knowledge of the process, a family of distributions described in Section 2.7.1 is chosen.

(3) Choose parameters that determine a specific instance of the distribution family. When the data is available, these parameters are estimated from these data.

(4) Evaluate the chosen distribution and the associated parameters of goodness of fit. Goodness of fit can be evaluated either informally by graphical methods or normally by statistical tests. The standard goodness-fit-tests are both chi-square test and the Kolmogorov-Smirnov test. If the chosen distribution is not good approximation of data, then the analyst will return to the step (2), and choose a different family of distributions, and repeat the procedure until the satisfied distribution is found. If several iterations of this procedure still cannot yield a fit between an assumed distributional form and the collected data, the empirical form of the distribution may be used.

2.7.1 DATA COLLECTION

Data collection is one of the largest tasks in solving a real problem and at the meanwhile it is also one of the most difficult and important problems in simulation. The input modeling focuses on the statistical aspects of fitting probability distributions to data. These distributions will provide the driving inputs to the simulation. The properties of the data need to be well understood and the accurate and relevant input data is available before “fitting” can occur.

Sometimes data can contain errors and be out of date. The effort to transform data into a usable form can be as significant as that required to obtain it. Input modeling always requires the analyst to use their judgment as well as to apply appropriate statistical tools. Understanding which input models are the most and least reliable is important for judging the reliability of the conclusions drawn from the simulation study. And since uncertainty about the correctness of the input models can never be entirely eliminated, it is sensible to run the simulation with several plausible input models to see if the conclusions are robust or highly sensitive to the choices.

2.7.2 IDENTIFYING THE DISTRIBUTION WITH DATA

In this section, the methodology for selecting families of probability distributions will be discussed when data are available and are believed to be distributed independently and identically. And then the specific distribution will be specified by estimating its parameters, as described in Section 2.7.3.

a) Histograms

In statistics, the histogram is a graphical representation of distribution of data and is useful for identifying the shape of a distribution. A histogram can be constructed as follows:

(1) To partition the range of the data into some intervals. There is no "best" number of class intervals. Different class interval sizes can reveal different features of the data. Hines et al. [113] indicated that choosing the number of class intervals approximately equal to the square root of the sample size often works well in practice.

(2) To label the horizontal axis to conform to the intervals.

(3) To work out the frequency of occurrences of each interval.

(4) To label the vertical axis to show the total occurrences of each interval.

(5) To plot the frequencies on the vertical axis.

The histogram for continuous data, a line drawn through the center point of each class interval frequency should result in a shape like a probability density function (pdf). While, the histogram for discrete data, if there is an amount of data points, each value should be as a cell in the range of the data. If few data points, it had better combine adjacent cells to eliminate the ragged appearance of the histogram. If the histogram is associated with discrete data, it looks like a probability mass function (pmf). The purpose of preparing a histogram of data collected is to infer a pdf or pmf.

b) Selecting the family of distributions

Several distributions that often arise in the simulation were described on

Section 2.6.1 and Section 2.6.2. A family of distributions is selected upon the shape of the histogram of investigated context. In general, the normal, uniform, Poisson and exponential distributions are often encountered and they are not difficult to analyze. So far, an amount of probability distributions have been created. Most frequently encountered distributions were discussed in Section 2.6.1 and Section 2.6.2.

2.7.3 PARAMETER ESTIMATION

After a family of distributions is selected, the next is to execute the parameters estimation of the selected distributions. The approaches of parameters estimation are described in the follows.

a) Preliminary statistics: sample mean and sample variance

In a number of instances, the sample mean and sample variance are to estimate the parameters of a hypothesized distribution. Two sets of equations Eq. (2.44), Eq. (2.45), Eq. (2.46) and Eq. (2.47) are often given for computing the sample mean and sample variance. Both Eq. (2.44) and Eq. (2.45) are used in continuous or discrete raw data. If the data are discrete and grouped in a frequency distribution, Eq. (2.46) and Eq. (2.47) are used and it can promote the much greater computational efficiency.

The sample mean denoted $\bar{X}$ is simply the average of the n data points X_1, X_2, ... , X_n. The sample variance denoted S^2 summarizes the variation of the data.

$$\bar{X} = \frac{X_1 + X_2 + \cdots + X_n}{n} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{2.44}$$

$$S^2 = \frac{\left(X_1 - \bar{X}\right)^2 + \left(X_2 - \bar{X}\right)^2 + \cdots \left(X_n - \bar{X}\right)^2}{n-1} = \frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2 \tag{2.45}$$

$$\bar{X} = \frac{\sum_{j=1}^{k} f_j X_j}{n} \tag{2.46}$$

$$S^2 = \frac{\sum_{j=1}^{k} f_j X_j^2 - n\bar{X}^2}{n-1} \tag{2.47}$$

where k is the number of distinct values of X; and f_j is the observed frequency of the value X_j of X.

When the data are discrete or continuous and have been placed in class intervals, the sample mean and sample variance are calculated by Eq. (2.48) and Eq. (2.49), respectively.

$$\bar{X} = \frac{\sum_{j=1}^{c} f_j m_j}{n} \tag{2.48}$$

$$S^2 = \frac{\sum_{j=1}^{c} f_j m_j^2 - n\bar{X}^2}{n-1} \tag{2.49}$$

where f_j is the observed frequency in the jth class interval; m_j is the midpoint of the jth interval; and c is the number of class intervals.

b) Suggested estimators

Suggested estimators for distributions often used in simulation are shown in the Table 2.6. The distributions were described in Section 2.6.1 and Section 2.6.2. A parameter is an unknown constant, but the estimator may be a statistic or random variable which depends on the sample values.

Table 2.6 Suggested estimators for distributions often used in simulation

Distribution	Parameter(s)	Suggested estimator(s)
Poisson	α	$\hat{\alpha} = \bar{X}$
Exponential	λ	$\hat{\lambda} = \frac{1}{\bar{X}}$
Normal	μ, σ^2	$\hat{\mu} = \bar{X}$ $\sigma^2 = S^2$ (unbiased)
Lognormal	μ, σ^2	$\hat{\mu} = \bar{X}$ $\sigma^2 = S^2$ (after taking ln of the data)
Weibull with $\nu = 0$	α, β	$\hat{\beta}_0 = \frac{\bar{X}}{S}$ $\hat{\beta}_j = \hat{\beta}_{j-1} - \frac{f(\hat{\beta}_{j-1})}{f'(\hat{\beta}_{j-1})}$ Iterate until convergence $\hat{\alpha} = \left(\frac{1}{n}\sum_{i=1}^{n} X_i^{\hat{\beta}}\right)^{1/\hat{\beta}}$
Beta	β_1, β_2	$\Psi(\hat{\beta}_1) + \Psi(\hat{\beta}_1 - \hat{\beta}_2) = \ln(G_1)$ $\Psi(\hat{\beta}_2) + \Psi(\hat{\beta}_1 - \hat{\beta}_2) = \ln(G_2)$ where Ψ is the digamma function, $G_1 = \left(\prod_{i=1}^{n} X_i\right)^{1/n}$ and $G_2 = \left(\prod_{i=1}^{n} (1 - X_i)\right)^{1/n}$
Gamma	β, θ	$\hat{\beta}$ $\hat{\theta} = \frac{1}{\bar{X}}$

2.7.4 GOODNESS-OF-FIT TESTS

The goodness of fit tests is to describe the degree of agreement between a known or hypothesized distribution and the sample distribution. The Chi-Square test is to compare the histogram of the data with the shape of the candidate density or mass function to determine whether there is a significant difference between them. And the Kolmogorov-Smirnov test is to test whether two samples are drawn from identical distributions.

When parameters are estimated by maximum likelihood, Chi-Square test is suitable for large sample sizes and both discrete and continuous distributional assumptions. Kolmogorov-Smirnov test is used when sample sizes are small and when no parameters have been estimated from the data.

To apply a goodness-of-fit test, a significance level must be chosen. Nowadays, many software packages compute a *p*-value for the test statistic. The *p*-value is the significance level at which one would just reject the probability of falsely rejecting (H_0) for the given value of the test statistic. A large *p*-value indicates a good fit, while a small one means a poor fit. Therefore, the *p*-value can be considered as a measure of fit with larger values being better. We could fit every distribution at our disposal, and compute a test statistic for each fit, eventually choose the distribution that yields the largest *p*-value. No software can implement this specific algorithm, but many software packages can recommend the suitable distribution(s) after evaluating all possible distributions. Measure of fit, such as the *p*-value, can be used to rank the distributions. Therefore, the user should make a final choice after inspecting the automatic recommended distribution(s).

Data collection and analysis in a discrete-event simulation project require plenty of time and resource commitments. Reliable inputs can lead to outputs whose subsequent interpretation could result in reliable and effective recommendations. This chapter mainly discussed that four steps in the development of input modeling were raw data collection, statistical distribution identification, parameters estimation and goodness of fit tests.

Some suggestions are given for facilitating the data-collection step. Once the data have been collected, a statistical model will be hypothesized. If the data are available, a histogram is useful for identifying the shape of a distribution. The parameter(s) of the hypothesized distribution can be estimated by the function of the sample mean and sample variance, and suggested estimators. Eventually, the goodness-of-fit tests evaluate the suitability of a potential input model. The familiar Chi-Square and Kolmogorov-Smirnov goodness-of-fit tests can be applied to many distributional assumptions. If a distributional assumption is rejected, another distribution will be tried. The empirical distribution could be used in the model when all else the distributions are rejected.

CHAPTER 3

GENERATION OF FEASIBLE CUTTING PLANS

Because of uncontrollable defects of raw materials, a material requirement plan for wooden products is often overestimated to accommodate losses from defects. An existing process planning model cannot efficiently capture the essence of a product and an optimal plan is not always achieved. The system proposed herein is aimed for more rapid product identification and more profitable cutting planning. It consists mainly of an image processing module, a cutting plan generation module and a cost estimation module. The image processing module is to acquire dimensions of the product through a minimum bounding box (MBB) algorithm. The dimensions are subsequently submitted to the cutting plan generation module. Within this module, a 'wood plank applicability detection' unit is to inspect suitability of planks in producing the product. The applicable planks will be put through a defect simulation, and defect-induced loss, as well as shaping-induced loss, associated with each plank is evaluated. Once the loss is quantified, material cost can be estimated accordingly.

The interoperable modules and information flow in the semi-automated process planner is illustrated in Fig. 3.1.

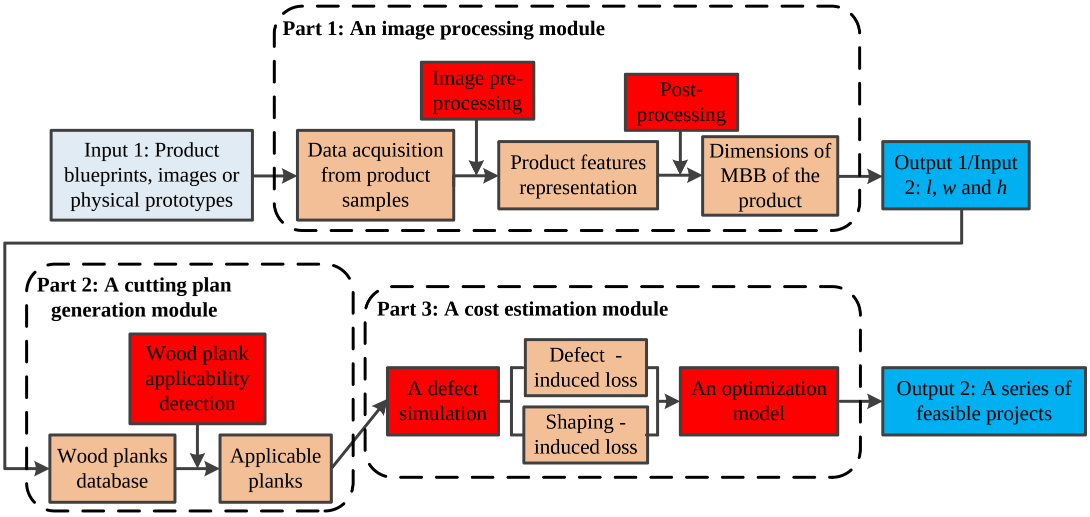


Fig. 3.1 Information flow within the proposed system

3.1 An Image Processing Module: Recognition of Product Dimensions

In mass customization production environment, products specifications submitted by a customer may be in a form of product images, product blueprints, or physical prototypes, whichever the company allows. Due to flexibility of digital image processing technologies, their applications are increasingly adopted in both research and industrial implementation. In this study, a semi-automated process planner was developed from a product digital image provided by a customer. Fig. 3.2 displays a sequential order of image processing operations used in MATLAB.

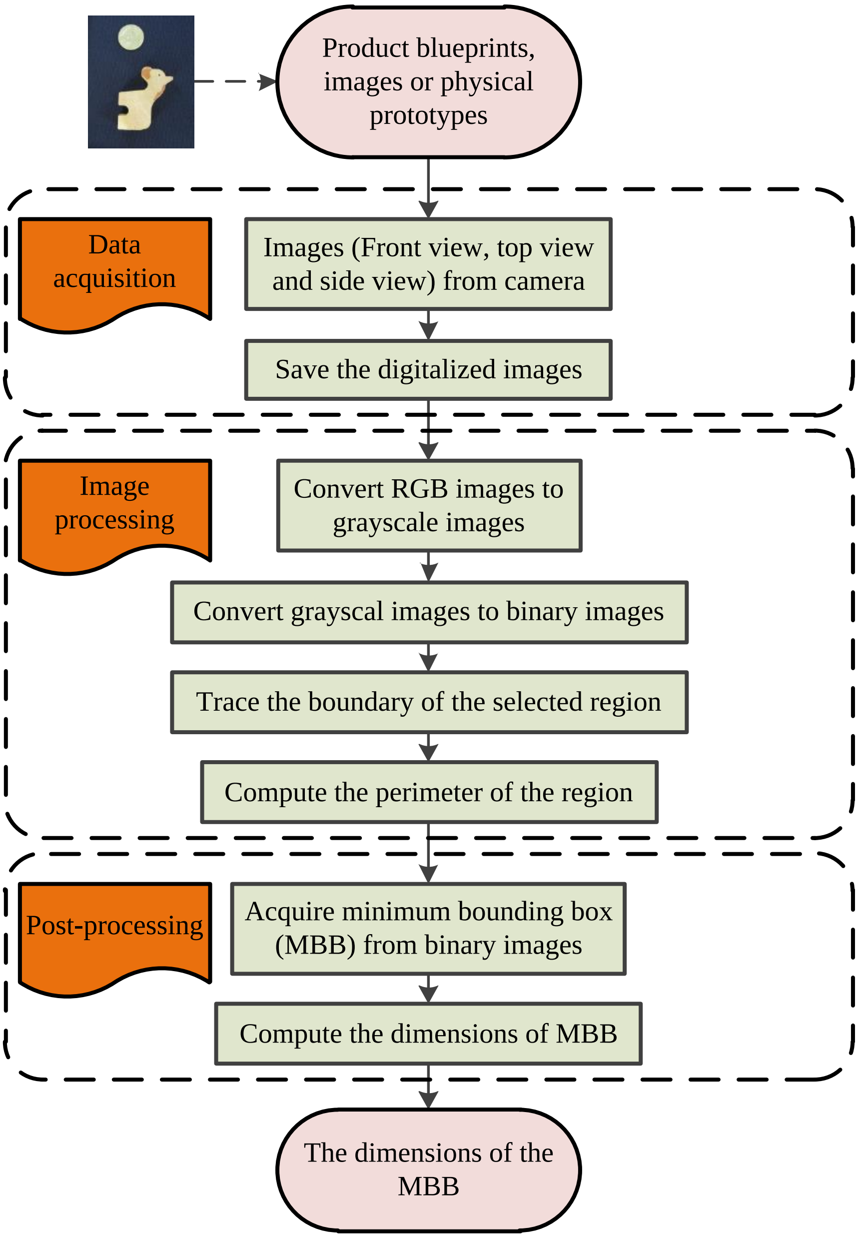


Fig. 3.2 The flowchart of image processing and post-processing procedures

3.1.1 Data Acquisition

In order to ensure that the product data can be recognized by a computer system with ease, it is essential that such data (product blueprints, images or physical prototypes which are provided by a customer or a designer) is converted into a digital format.

This conversion process is the first phase of the whole integration process; it is also of prime importance as it determined whether or not the overall objective can be achieved. Product digital information must contain three principal views (front, side and top) in clear and high contrast images with minimum noises.

An image acquisition system as shown in Fig. 3.3 is consisted of four basic components: an illuminator, a camera, hardware and software. RGB images of wooden products were illuminated using four fluorescents tubes (natural daylight). All four lamps were situated 300 mm around the sample. Images were captured using a camera (Canon, model IXUS 210) located vertically over the background at a distance of 300 mm. The angle between the camera lens and the sample axis was approximately 0^{o}. Images were taken on a matte black background using the following camera settings: no zoom, no flash, intermediate resolution of the video camera (640 x 480 pixels), before the images are stored in a JPG format. The white balance of the camera was set using the same white reference as the colorimeter. The video camera was connected to Gigabit Ethernet port of a PC provided with image capture software to visualize and acquire the digitalized images directly from the computer.

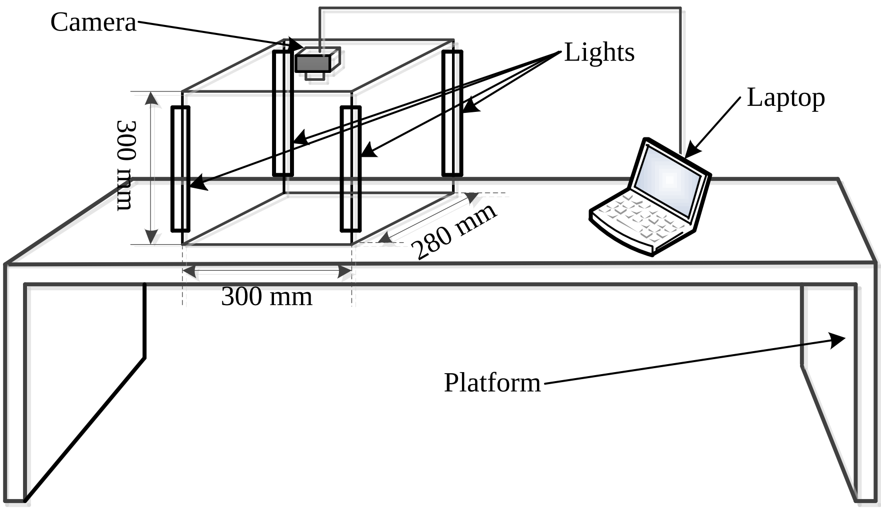
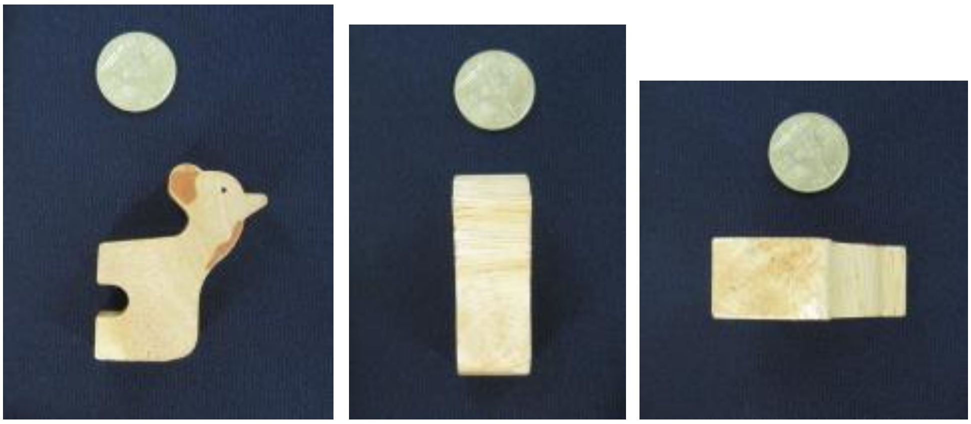


Fig. 3.3 An image acquisition system

Fig. 3.4 depicts a wooden product, which its dimensions to be measured, being placed on a dark background with a 50-Satang coin as a reference object. The image can be captured by a common digital camera. The camera must be held parallel to the plane on which the product is settled to avoid dimension distortion.

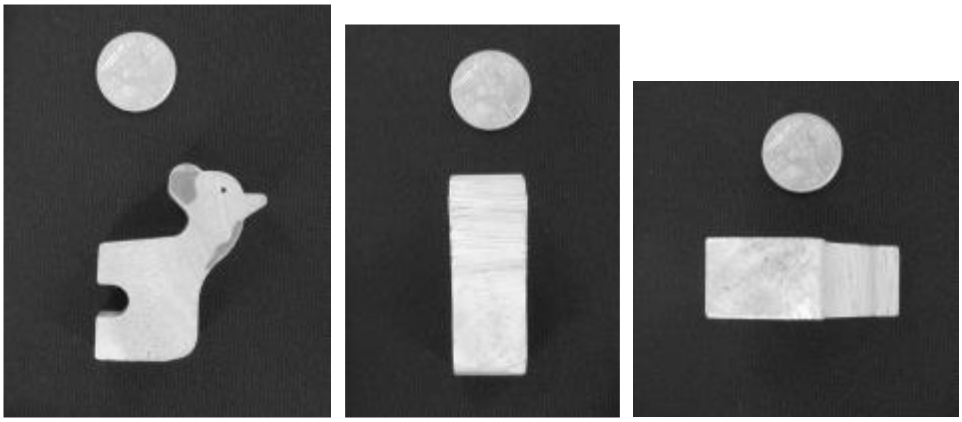


(a) (b) (c)

Fig. 3.4 The acquisition of the digitalized images (RGB) (Wooden product with a 50-Satang coin as a reference object) of three principal views: (a) top view, (b) side view, and (c) front view of a product by a camera

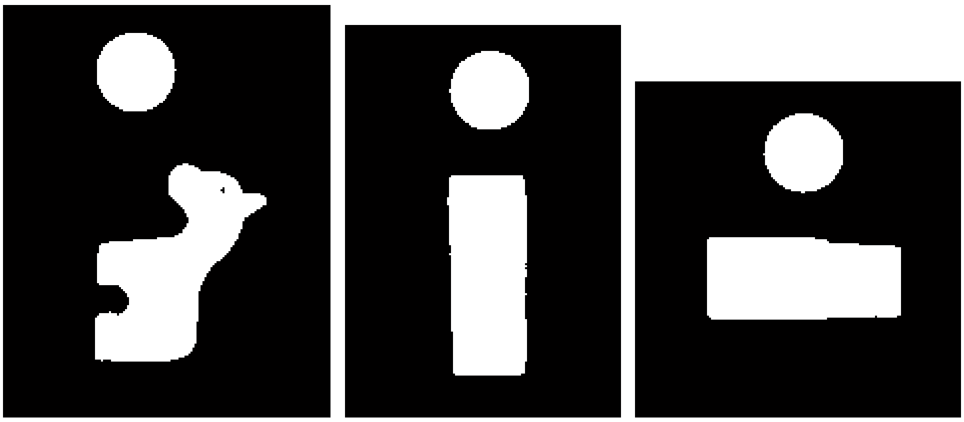
3.1.2 IMAGE PRE-PROCESSING

MATLAB is a high-level language for technical computing where problems and solutions are expressed in familiar mathematical notation. The MATLAB processing is a semi-automatic method used in this study to calculate dimensions of wooden products. The code is written in MATLAB version R2011b 7.13. This code will work in any higher version of the program. The original image is converted into grayscale images and then sub-converted into binary images as shown in Fig. 3.5 and Fig. 3.6, respectively. A function called "bwboundaries" in MATLAB is used to trace a boundary of a selected region in the image as shown in Fig. 3.7. After the boundary of the selected region is identified, properties such as perimeter and area can be determined using a function called "regionprops." Most properties returned from this function are in an actual number of pixel count.



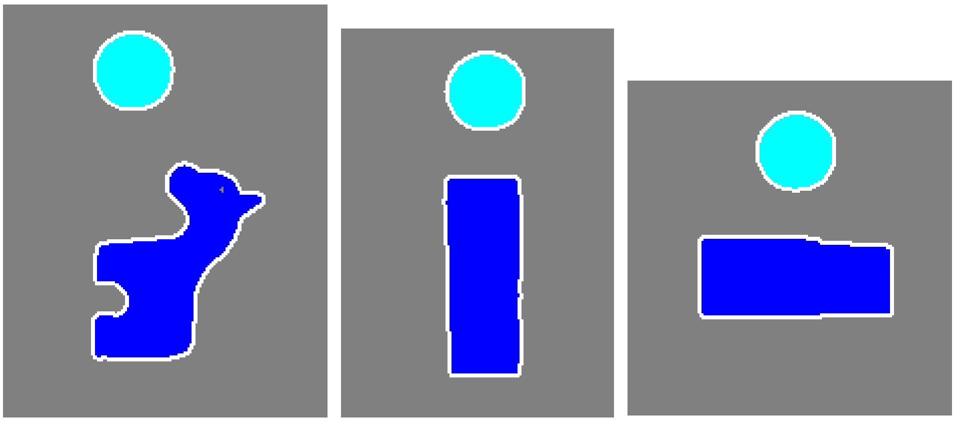
(a) (b) (c)

Fig. 3.5 Converting the color image to grayscale image: (a) top view, (b) front view, and (c) side view



(a) (b) (c)

Fig. 3.6 Converting the grayscale image to binary image: (a) top view, (b) front view, and (c) side view

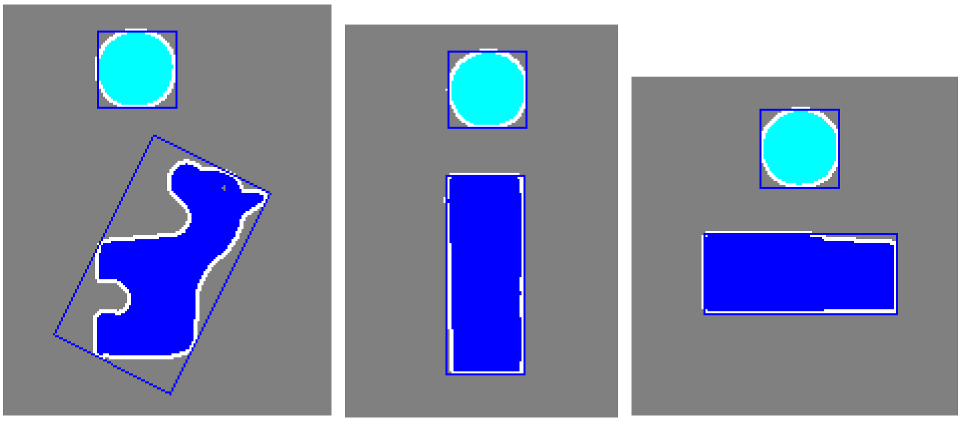


(a) (b) (c)

Fig. 3.7 Tracing the boundary of the selected region: (a) top view, (b) front view, and (c) side view

3.1.3 Post-Processing: Acquisition of Minimum Bounding Box

Since majority of products are of a free-form shape, a rectangle is virtually drawn to bound a region which is marked as the product image. Dimensions of the product in each view (top, front, and side) are therefore of the dimensions of the rectangle, so called a bounding box. To ensure the rectangle imposed on the product image reflects accurate product dimensions, a Minimum Bounding Box (MBB) algorithm is employed. The algorithm computes a minimal bounding rectangle of points in a plane as shown in Fig. 3.8. Dimensions of MBB of a wooden product are calculated through pixel number statistics. Pixel count of a processed image depends on a distance between a camera and an object when its image is taken. The smaller the distance, the larger the pixel counts and vice versa. Therefore, a reference object is needed to translate the pixel count to an actual measuring unit.



(a) (b) (c)

Fig. 3.8 MBB of three principal views: (a) top view, (b) front view, and (c) side view

In this study, a 50-satang coin with 18 mm in diameter is chosen as a reference object. For example, if the pixel count of a perimeter of the coin as returned from MATLAB is 129.87.

Hence, 1 pixel value = actual perimeter of the coin / perimeter in pixel count

$$1 \text{ pixel value} = \frac{\text{actual perimeter of the coin}}{\text{perimeter in pixel count}} = \frac{\pi(18)}{129.87} = 0.44 \text{ mm}$$

Using the MBB algorithm with this image, the pixel count of the length, width and height of the resultant MBB is 104.61, 67.47 and 35.45 pixels respectively. Therefore,

$$\text{Length of the MBB in mm} = \text{pixel} * 1 \text{ pixel value} = 104.61 * 0.44 \text{ mm} = 46.03 \text{ mm}$$

$$\text{Width of the MBB in mm} = 67.47 * 0.44 \text{ mm} = 29.69 \text{ mm}$$

$$\text{Height of the MBB in mm} = 35.45 * 0.44 \text{ mm} = 14.72 \text{ mm}$$

To test performance of the image processing module, images of wooden ox-head-shaped, horse-shaped, moon-shaped, hexagon-shaped and circle-shaped products were taken and input into the module. Table 3.1 lists their actual dimensions, resultant dimensions from the module and relative errors. The relative errors are evaluated using Eq. (3.1). It can be seen that the relative errors are as high as almost 10%. It was possibly caused by an angle between the camera lens and the sample axis. The angle must be kept at 0º to have a precise measurement on product dimensions. The error is magnified as the camera moves away from the nominal axis as shown in Fig. 3.9. Since the image is submitted from a customer who assumedly does not possess any imaging skills, errors due to camera-sample misalignment and poorly controlled environment can be expected. Although the proposed approach can accommodate some amount of errors, care must be taken to minimize the errors and prevent the approach to arrive at a non-optimal plan.

Table 3.1 Comparison of actual dimensions and the dimensions obtained from the image processing module

Product No.	AMV (mm)			MVIP (mm)			Error (%)		
	L*	W*	H*	L*	W*	H*	L*	W*	H*
Ox-head	45	45	22	49.34	46.16	23.79	+9.64	+2.58	+8.14
Horse	47	28	14.5	46.03	29.69	14.72	-2.06	+6.04	+1.52
Moon	47.5	39	15	47.87	38.34	16.18	+0.78	-1.69	+7.87
Hexagon	57	50	15	57.86	54.2	16.02	+1.51	+8.40	+6.80
Circle	50	50	15	51.91	51.53	16.37	+3.82	+3.06	+9.13

AMV = actual measured value, MVIP = measured value by image processing method, L* = length of MBB of an object, W* = width of MBB of an object, and H* = height of MBB of an object

$$E = \frac{M_v - M_t}{M_t} \quad (3.1)$$

where E is relative error; M_v is the measured value; and M_t is the true value.

Fig. 3.9 The magnified error

3.2 A CUTTING PLAN GENERATION MODULE

An objective of the cutting plan generation module is to find a set of feasible cutting plans before an optimal one will be selected under manufacturing conditions. Although only a few sizes of standard wood planks are available commercially, the case study often cut those planks into smaller different sizes before keeping them in storage for future use. Some wooden product companies may have a hundred different plank sizes in their database from which a process planner can choose from. In this section, a term "workpiece" is used to call a wood piece cut from a plank. To determine which wood planks are applicable to be used in the initial cutting process, the virtual dimensions of a product or the dimension of MBB (w, h and l) (see Fig. 3.10 (a)) and the dimensions of a wood plank (W_i, H_i and L_i) are compared (see Fig. 3.10 (b)). To justify the applicability of a wood plank and determine "*length of cut*", the following "if-then-else" rules are used. In general, a 3-D workpiece has six faces comprising two faces of "*w-l*," two faces of "*w-h*" and two faces of "*h-l*." By rotating the workpiece around its axes, six different cutting methods (C_m) can be applied as shown in Fig. 3.10 (c). For instance, if face *l-h* is chosen as the cross-section plane or the plane parallel to *area of cut*, *w* will be l_c. All of these scenarios are described in Table 3.2. It notes that the width, height and length of a MBB are w, h, and l, and W, H, and L are the width, height and length of a wood plank.

Table 3.2 Cutting methods associated by cross-section plane and "*length of cut*"

Cutting method (C_m)	Cross-section plane	"*length of cut*" (l_c)
132	l-h	w
231	l-w	h
321	h-w	l
123	h-l	w
213	w-l	h
312	w-h	l

"if-then-else" rules
1: **if** $\{(l < L_i)$ & $(w < W_i)$ & $(h < H_i)\}$
2: or **if** $\{(l < L_i)$ & $(h < W_i)$ & $(w < H_i)\}$
3: or **if** $\{(w < L_i)$ & $(h < W_i)$ & $(l < H_i)\}$
4: or **if** $\{(w < L_i)$ & $(l < W_i)$ & $(h < H_i)\}$
5: or **if** $\{(h < L_i)$ & $(w < W_i)$ & $(l < H_i)\}$
6: or **if** $\{(h < L_i)$ & $(l < W_i)$ & $(w < H_i)\}$
then "The plank i is applicable to produce the product."
else "It is not."

If at least one of these conditions is satisfied, it means that the wood plank can be used to produce the product.

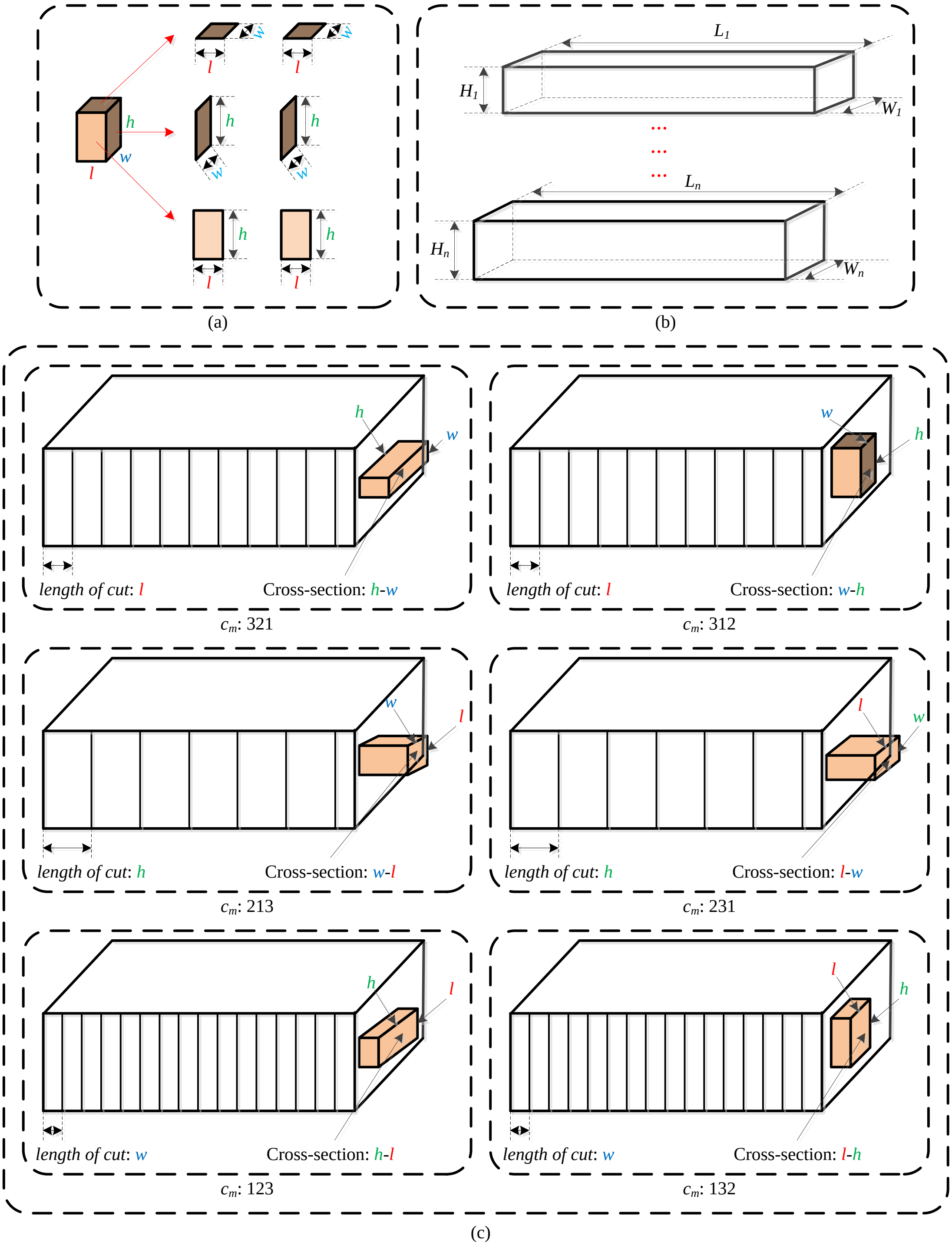


Fig. 3.10 (a) Six faces of MBB of a sample, (b) three dimensions of the wood planks (W, H and L), and (c) and a wood plank with varying cutting parameters

"Horse" as shown in Fig. 3.4 was used in an experiment to evaluate performance of the proposed system. It has a volume of 43643 mm^3 and its MMB has dimensions of 23 mm (w), 46 mm (h), and 55 mm (l) in width, height, and length respectively. By applying the "if-then-else" rules as described above, two hundred and seventy two out of the total of 733 wood planks were accounted applicable as shown in Table 3.3. Please note that some planks can be registered as applicable using more than one cutting method. If they are not applicable, N/A is shown.

Examples of applicability justification

Dimensions of MBB: 23 mm (w), 46 mm (h), and 55 mm (l).

(1) Plank No. 1: W_1 = 15.88, H_1 = 15.88 and L_1 = 1,000.00

When considering the cutting rules, it is found that no rules are satisfied. It means that no cutting method can be used to cut this plank in order to produce this product.

(2) Plank No. 391: W_{391} = 25.00, H_{391} = 48.00 and L_{391} = 1,000.00

When considering the cutting rules, it is found that the Rule 1 "if $\{(l < L_i)$ & $(w < W_i)$ & $(h < H_i)\}$" is satisfied. The rule can be translated to the cutting method 312 to cut the Plank No. 391 to product the product.

(3) Plank No. 395: W_{395} = 25.00, H_{395} = 60.00 and L_{395} = 1,000.00

When considering the cutting rules, it is found that the Rules 1 and 5 (1: if $\{(l < L_i)$ & $(w < W_i)$ & $(h < H_i)$, or 5: if $\{(h < L_i)$ & $(w < W_i)$ & $(l < H_i)\}$) are satisfied. The rules can be translated to the cutting method 213 and 312 to cut the Plank No. 395 to product the product.

(4) Plank No. 698: W_{698} = 55.00, H_{698} = 70.00 and L_{698} = 1,000.00

When considering the cutting rules, it is found that the Rules 1-3 and 5 (1: if $\{(l < L_i)$ & $(w < W_i)$ & $(h < H_i)$, or 2: if $\{(l < L_i)$ & $(h < W_i)$ & $(w < H_i)\}$, or 3: if $\{(w < L_i)$ & $(h < W_i)$ & $(l < H_i)\}$, or 5: if $\{(h < L_i)$ & $(w < W_i)$ & $(l < H_i)\}$) are satisfied. The rules can be translated to the cutting method 123, 213, 312 and 321 to cut the Plank No. 698 to product the product.

(5) Plank No. 733: W_{733} = 101.60, H_{733} = 101.60 and L_{733} = 1,000.00

When considering the cutting rules, it is found that all the Rules 1-6 (1: if {($l < L_i$) & ($w < W_i$) & ($h < H_i$), or 2: if {($l < L_i$) & ($h < W_i$) & ($w < H_i$)}, or 3: if {($w < L_i$) & ($h < W_i$) & ($l < H_i$)}, or 4: if {($w < L_i$) & ($l < W_i$) & ($h < H_i$)}, or 5: if {($h < L_i$) & ($w < W_i$) & ($l < H_i$)}, or 6: if {($h < L_i$) & ($l < W_i$) & ($w < H_i$)}) are satisfied. The rules can be translated to the cutting method 132, 123, 213, 231, 312 and 321 to cut the Plank No. 733 to produce the product.

Table 3.3 A list of applicable wood planks that could be used to produce "Horse"

Plank No.	Plank price	W (mm)	H (mm)	L (mm)	C_m
1	3.47	15.88	15.88	1,000.00	N/A
2	9.73	15.88	44.45	1,000.00	N/A
3	11.12	15.88	50.80	1,000.00	N/A
…	…	…	…	…	…
391	28.68	25.00	48.00	1,000.00	312
392	31.14	25.00	50.00	1,000.00	312
393	28.68	25.00	51.00	1,000.00	312
394	33	25.00	55.00	1,000.00	312
395	37.78	25.00	60.00	1,000.00	213, 312
…	…	…	…	…	…
412	16.77	25.40	57.15	1,000.00	213, 312
…	…	…	…	…	…
698	69.15	55.00	70.00	1,000.00	123, 213, 312, 321
…	…	…	…	…	…
733	136.80	101.60	101.60	1,000.00	132, 123, 213, 231,312, 321

Once a list of applicable planks is established, the planks will be brought into a virtual cutting process. Each cutting method is associated by different “*area of cut*” and “*length of cut,*” hence different material loss as shown in Fig. 3.10. Justification on the optimality of these cutting parameters will be described subsequently.

CHAPTER 4

DEVELOPMENT OF A COST MODEL

In the previous chapter, wooden product dimensions are acquired from the product image through the Minimum Bounding Box (MBB) algorithm. The dimensions are fed into the cutting plan generation module to generate a set of feasible cutting plans. However, among these plans, an optimal one exists but yet to be identified. In this study, the plan associated with a minimum cost is considered optimal.

As cost is directly related to loss, a wood loss model is to be developed in this chapter to calculate losses as results of shaping processes and wood defects. Actual losses collected from past records and losses obtained from the existing parametric model are to be compared with the losses calculated from the proposed loss model to indicate performance of the model. Once the losses are quantified, cost will be realized and suggestions on cutting planning can be made.

4.1 ANALYSIS OF WOOD LOSS

Existing establishment of a cutting plan, currently performed by human operations, may lead to some excessive wasteful material due to subjectivity and uncertainty of human perception. Cost can be unnecessarily added due to an operator's shortage of experience or lack of expertise. Furthermore, the plan is often inconsistent from one operator's to the other. An objective of the cutting plan generation module is then to find a set of feasible cutting plans before an optimal one will be selected under manufacturing conditions for the time being. As a matter of fact, loss is inevitable in manufacturing environment; keeping it as minimum as possible; however, will help reduce unreasonable production cost. To prevent excessive wood loss, cutting parameters must be deliberately chosen. In this study, the loss is decomposed into two parts explained in following sub-sections.

4.1.1 Loss from Shaping Processes

In general, wood loss from shaping processes is the material removed from a wooden workpiece to become a product as shown in Fig. 4.1. As a result, the loss is apparently the difference between the volume of the workpiece and that of the product. The larger the workpiece, the greater the loss, when the same product is applied. The loss from shaping processes ($LOSS_{sp}$) per workpiece can be obtained from Eq. (4.1):

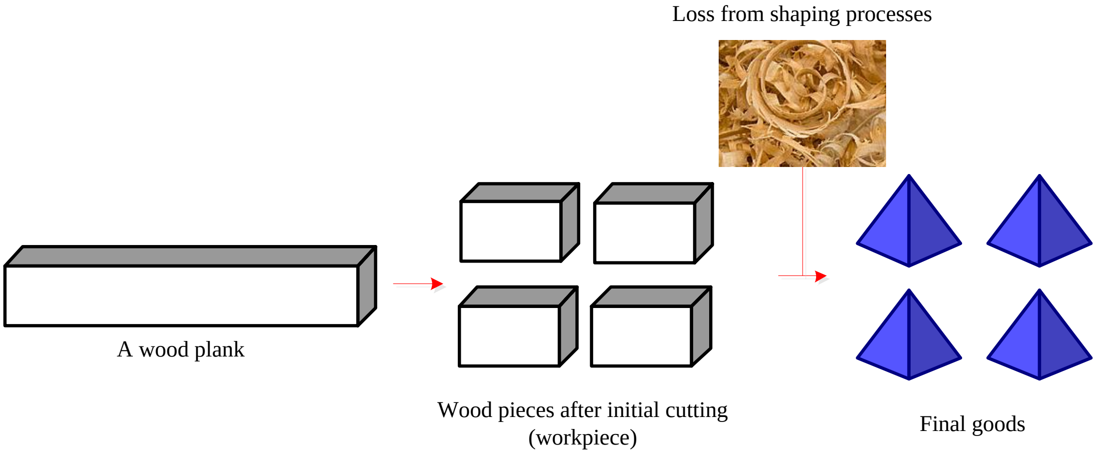


Fig. 4.1 Loss from shaping processes

$$LOSS_{sp} = q\left(V_w - V_p\right) \tag{4.1}$$

where $V_w = l_c * W * H$, is the volume of a wood piece; V_p is the volume of a product; and q is the number of non-defective wood pieces.

Examples of calculation of loss from shaping processes

(1) Considering Plank No. 394 of W_{394} = 25.00, H_{394} = 55.00 and L_{394} = 1,000.00, the Plank No. 394 can be just cut by the Method 312, the loss from shaping processes can be obtained by using Eq. (4.1),

$$LOSS_{sp_{394}} = 13*(55*25*55-43643) = 415,766.00 \text{ mm}^3$$

(2) Considering Plank No. 412 of W_{412} = 25.40, H_{412} = 57.15 and L_{412} = 1,000.00, the Plank No. 412 can be cut by the Method 213 and 312, the loss from shaping processes can be obtained by using Eq. (4.1),

$$LOSS_{sp_{412(C_m:\ 213)}} = 16*(46*25.40*57.15-43643) = 370,096.96 \text{ mm}^3$$

$$LOSS_{sp_{412(C_m:\ 312)}} = 13*(55*25.40*57.15-43643) = 470,542.15 \text{ mm}^3$$

(3) Considering Plank No. 733 of W_{733} = 101.60, H_{733} = 101.60 and L_{733} = 1,000.00, the Plank No. 733 can be cut by the Method 132, 123, 213, 231, 312 and 321, the loss from shaping processes can be obtained by using Eq. (4.1),

$$LOSS_{sp_{733(C_m:\ 132/123)}} = 31*(23*101.60*101.60-43643) = 6,007,052.28 \text{ mm}^3$$

$$LOSS_{sp_{733(C_m:\ 213/231)}} = 16*(46*101.60*101.60-43643) = 6,899,116.16 \text{ mm}^3$$

$$LOSS_{sp_{733(C_m:\ 312/321)}} = 13*(55*101.60*101.60-43643) = 6,813,271.40 \text{ mm}^3$$

Results of this loss from all the applicable planks are reported in Table 4.9.

4.1.2 LOSS FROM DEFECTS

Wood is a natural material which is prone to defects of different kinds. Defects, firmly embedded in wood mass, downgrade a plank commercial value. Industrial quality for wood planks is graded (A, B or AB grade) based on severity of wood defects. In grading the wood, a plank must have wood mass without any observable defects for at least 80% of its total length for A graded wood and 60% applies for B. AB grade which is a combination of 60% A and 40% B is widely used for producing industrial products. Defects can be found observable on surfaces of the plank or hidden beneath the surfaces that will be revealed once the plank is cut up. Defects of either type would cause material loss and unfortunately, they are distributed with random and uncertain pattern as shown in Fig. 4.2.

Fig. 4.2 Wood defects

In the initial cutting process, the plank is cut into pieces of the same length specified by a process planner. Pieces with defects if detected will be rejected inducing excessive loss in this process. The non-defective items will be collected and further conveyed to shaping processes. Cutting parameters reportedly contribute in determination of amount of material loss in an initial cutting process [8]. By applying different "*length of cut*" and "*area of cut*" to a given certain plank, different material loss is expected as illustrated in Fig. 1.3 and

Fig. 3.10. Loss is minimized with optimal cutting parameters that will eventually result in production cost reduction.

4.2 DEVELOPMENT OF A WOOD LOSS MODEL

In order to avoid complication of estimating loss from defects, the case study manufacturing company simply applies a fixed 5% as a compensation rate to wood defects which is referred as a parametric model (Eqs. (4.2–4.4)) [8]. Although defects can be found on all surfaces of a plank, chances are minimal that defects will be spotted on end surfaces or surfaces parallel to them.

$$q = round\left(\frac{L-2e}{l_c+t}(1-c)\right) \tag{4.2}$$

$$LOSS_d = \left(1-\frac{q*l_c}{L}\right)*\left(L*W*H\right) \tag{4.3}$$

$$C_u = \frac{C_w}{q} \tag{4.4}$$

where $LOSS_d$ is the wood loss from defects; e is the length of end cut, mm; t is the tooling allowance, mm; c is the fixed compensation rate for the parametric model; *round* (x) is a function to round the calculated result to the nearest lower integer; C_u is unit cost of a wood piece; and C_w is the price of a wood plank. It should be noted that the factory applies fixed values of e, t, and c of 50 mm, 3 mm, and 0.05, respectively.

<u>Examples of determination of loss from defects</u>

(1) Considering Plank No. 394 of W_{394} = 25.00, H_{394} = 55.00 and L_{394} = 1,000.00, the Plank No. 394 can be just cut by the Method 312, the loss from defects can be

obtained by using Eq. (4.3),

$$LOSS_{d_{394}} = \left(1 - \frac{13 * 55}{1,000.00}\right) * (25.00 * 55.00 * 1,000.00) = 391,875.00 \text{ mm}^3$$

(2) Considering Plank No. 412 of W_{412} = 25.40, H_{412} = 57.15 and L_{412} = 1,000.00, the Plank No. 412 can be cut by the Method 213 and 312, the loss from defects can be obtained by using Eq. (4.3),

$$LOSS_{d_{412(C_m:\ 213)}} = \left(1 - \frac{16 * 46}{1,000.00}\right) * (25.40 * 57.15 * 1,000.00) = 383,225.04 \text{ mm}^3$$

$$LOSS_{d_{412(C_m:\ 312)}} = \left(1 - \frac{13 * 55}{1,000.00}\right) * (25.40 * 57.15 * 1,000.00) = 413,708.85 \text{ mm}^3$$

(3) Considering Plank No. 733 of W_{733} = 101.60, H_{733} = 101.60 and L_{733} = 1,000.00, the Plank No. 733 can be cut by the Method 132, 123, 213, 231, 312 and 321, the loss from defects can be obtained by using Eq. (4.3),

$$LOSS_{sp_{733(C_m:\ 132/123)}} = \left(1 - \frac{31 * 23}{1,000}\right) * (101.60 * 101.60 * 1,000) = 2,962,574.72 \text{ mm}^3$$

$$LOSS_{sp_{733(C_m:\ 213/231)}} = \left(1 - \frac{16 * 46}{1,000}\right) * (101.60 * 101.60 * 1,000) = 2,725,155.84 \text{ mm}^3$$

$$LOSS_{sp_{733(C_m:\ 312/321)}} = \left(1 - \frac{13 * 55}{1,000}\right) * (101.60 * 101.60 * 1,000) = 2,941,929.60 \text{ mm}^3$$

Results of this loss from all the applicable planks are reported in Table 4.9.

In this study, a defect model is constructed to simulate material loss as affected from defects in the cutting process (see Fig. 4.3). There are three variables in the model, i.e., quantity of defects (QD), position of defects (PD) and size of defects (SD) essential in expressing a pattern of defects on a plank. The simulation was developed as according to Banks et al. [114]. Model development is composed of two phases: defect model creation and simulation of the defects in a cutting process (see Fig. 4.4).

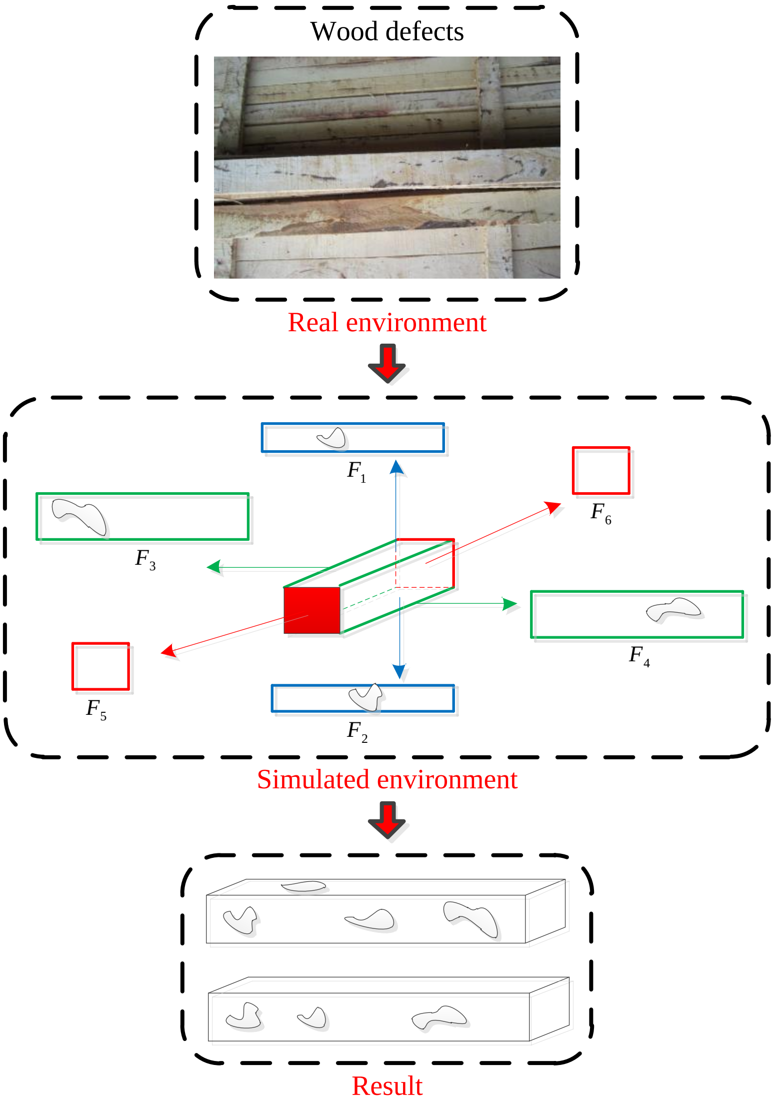


Fig. 4.3 Simulation architecture

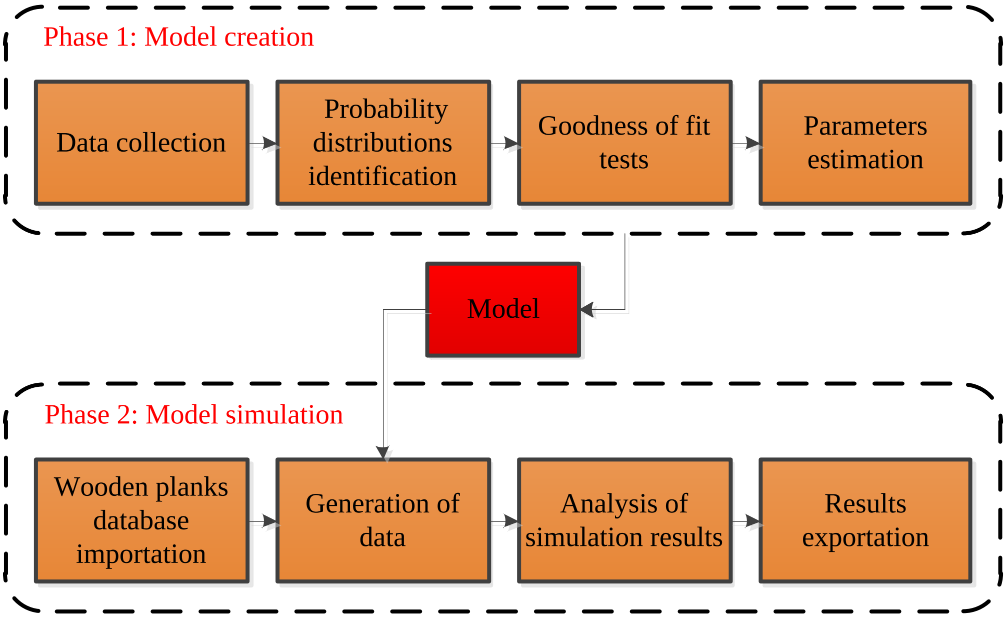


Fig. 4.4 Main scenarios that appear at the simulation process

4.2.1 Defect Model Creation

The model was created in 4 steps: (1) collecting data from a wooden product company, (2) identifying their probability distributions to represent the input process, (3) evaluating the chosen distributions and parameters associated with them for goodness of fit, and (4) determining parameters of the selected distributions.

a) Data collection

Data collection is a critical step in model simulation development. It must be handled in a random manner without biasness. Defects can be found in any faces of the plank, the data therefore were collected on all four faces (F_1, F_2, F_3 and F_4) as shown in Fig. 4.5. Faces at both ends, F_5 and F_6 were slightly cut off as a standard cutting operation. Defects found on these faces had no effect on material loss. One hundred and two wooden planks of 25mm * 60 mm * 1250 mm were collected in a wooden products company. Details of collection of each variable are discussed as follows.

1) Quantity of defects, QD, was collected by counting the number of

observable defects on each face. Some defects may have an irregular shape and justification from an experienced operator was needed. These defects are shown in Fig. 4.6.

2) Position of defects, PD, was collected by measuring the distance from one plank end to the defect center.

3) Size of defects, SD, was collected by measuring a difference in position of both defect extreme points lengthwise.

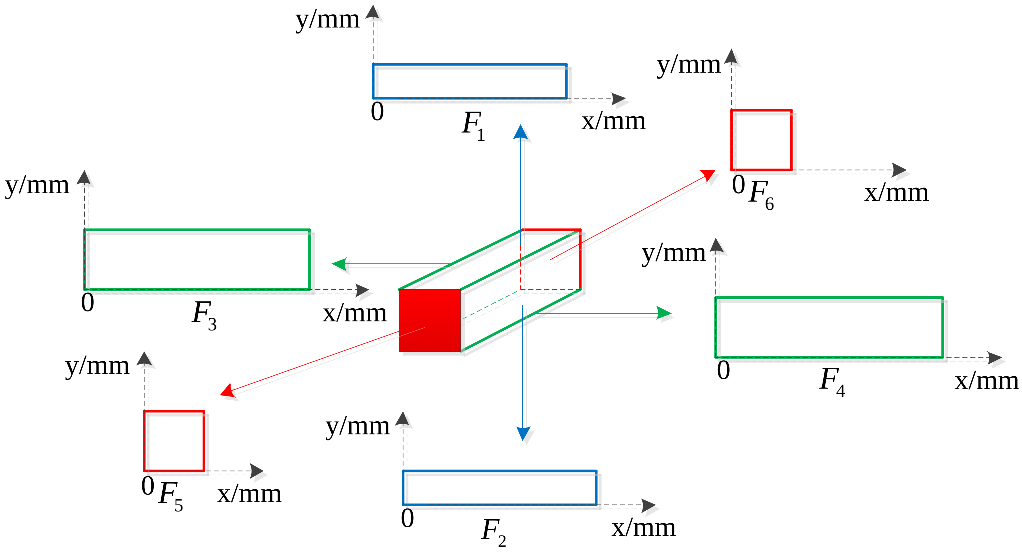


Fig. 4.5 QD, PD, and SD express in a 2-d coordinate system on each face

Fig. 4.6 Defects with irregular shape(s)

To illustrate the collection of each variable, Fig. 4.7 shows faces of one plank with defects on them. In this figure, QD is 5. SDs from F_1 to F_4 are $|SD_1|$, $|SD_2|$, $|SD_3|$, $|SD_4|$ and $|SD_5|$, respectively. PDs from F_1 to F_4 are (a_1, b_1), (a_2, b_2), (a_3, b_3), (a_4, b_4) and (a_5, b_5). One hundred and two wood planks (AB Grade) were collected from a wooden product company. Repeatedly, the QD, PD and SD of these planks were recorded.

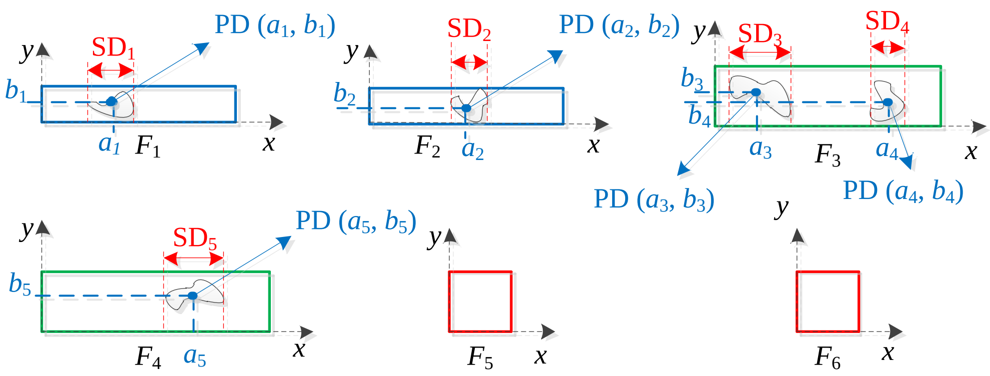


Fig. 4.7 Determination of QD, PD, and SD

b) Identifying data distributions

After all the data were collected from randomly selected plank samples, distributions of the variables (QD, PD, and SD) must be assumed. The details are described as followed.

Table 4.1 Distribution of quantity of defects on 4 faces of 102 wood planks (AB Grade)

Quantity of defects (piece)	Frequency	Probability (%)	Cumulative (%)
0	285	69.85	69.85
1	85	20.83	90.69
2	25	6.13	96.81
3	12	2.94	99.75
More	1	0.25	100

Table 4.2 Distribution of position of defects

Position of defects (mm)	Frequency	Probability (%)	Cumulative (%)
$0 < PD \leq 400$	68	38.86	38.86
$400 < PD \leq 800$	49	28.00	66.86
$800 < PD \leq 1200$	58	33.14	100.00
$PD > 1200$	0	0.00	100.00

Table 4.3 Distribution of size of defects

Size of defects (mm)	Frequency	Probability (%)	Cumulative (%)
$0 < SD \leq 20$	126	72.00	72.00
$20 < SD \leq 40$	31	17.71	89.71
$40 < SD \leq 60$	8	4.57	94.28
$60 < SD \leq 80$	5	2.86	97.14
$SD > 80$	5	2.86	100.00

Histograms

A frequency distribution or histogram is useful to preliminarily identify a shape of the data distribution. Relative frequencies in QD, PD, and SD appear in Table 4.1–4.3, respectively.

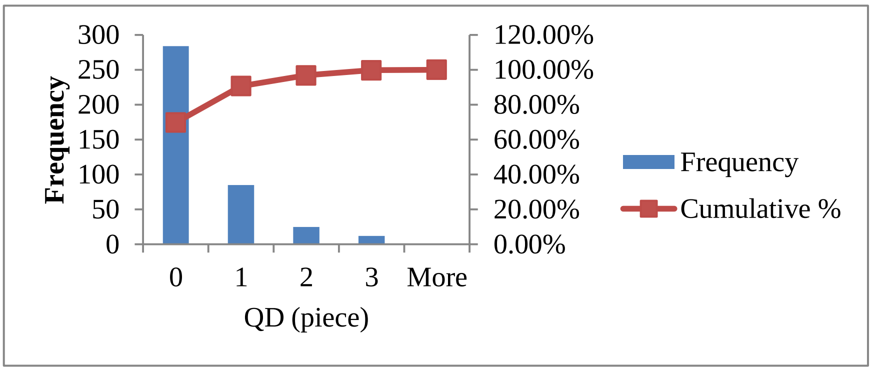


Fig. 4.8 Histogram of defect quantity (QD)

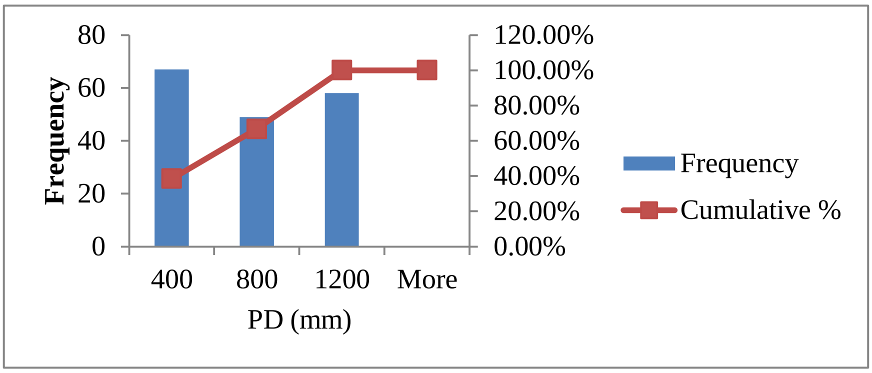


Fig. 4.9 Histogram of defect position (PD)

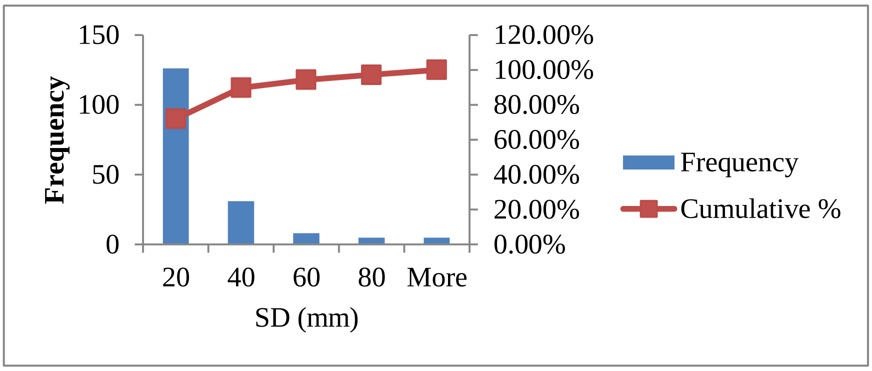


Fig. 4.10 Histogram of defect size (SD)

It is worth mentioning that QD, PD and SD are discretized by intervals of 1, 400, and 20, respectively and the resulting histograms are shown in Fig. 4.8–4.10, respectively.

Selecting a family of distributions

The purpose of preparing a histogram is to infer a known pdf or pmf [114]. The distribution of QD is a discrete distribution. Based on the shape of the histogram in Fig. 4.8, it is similar to the pmf of binominal distribution [115] or Poisson distribution [116]. According to the definition of binominal distribution that is used when there are two possible outcomes, the binominal distribution is rejected. Therefore, Poisson distribution is selected. From Fig. 4.9, the all outcomes are equally likely and the histogram has a shape similar to the pdf of the uniform distribution [117], the assumption of an uniform distribution will be warranted. The histogram in Fig. 4.10 has a shape similar to the pdf of the Gamma [118], or lognormal [119], or Weibull [120], or exponential distribution [121], the assumption of these distributions are selected. Using SPSS Statistics Version 22, a quantile-quantile (Q-Q) plot was constructed for evaluating fitness of such distributions.

Q-Q Plots

The construction of histograms as described, and the recognition of a distributional shape as discussed as above, plays a crucial role in selecting a family of distributions to represent the sample of data. In order to evaluate the fit of the chosen distributions, the Q-Q plot is applied.

The hypothesis of QD is Poisson distribution that is a discrete distribution, herein Q-Q Plot of QD is not considered. The plotted values are shown in Fig. 4.11 (a)–(e). From Fig. 4.11, most points fall approximately along a 45-degree reference line. The plotted values in Fig. 4.11 (c) show that the greatest points from lognormal Q-Q plot fall along the reference line. Therefore, the assumptions of a uniform distribution in PD and a lognormal distribution in SD are warranted.

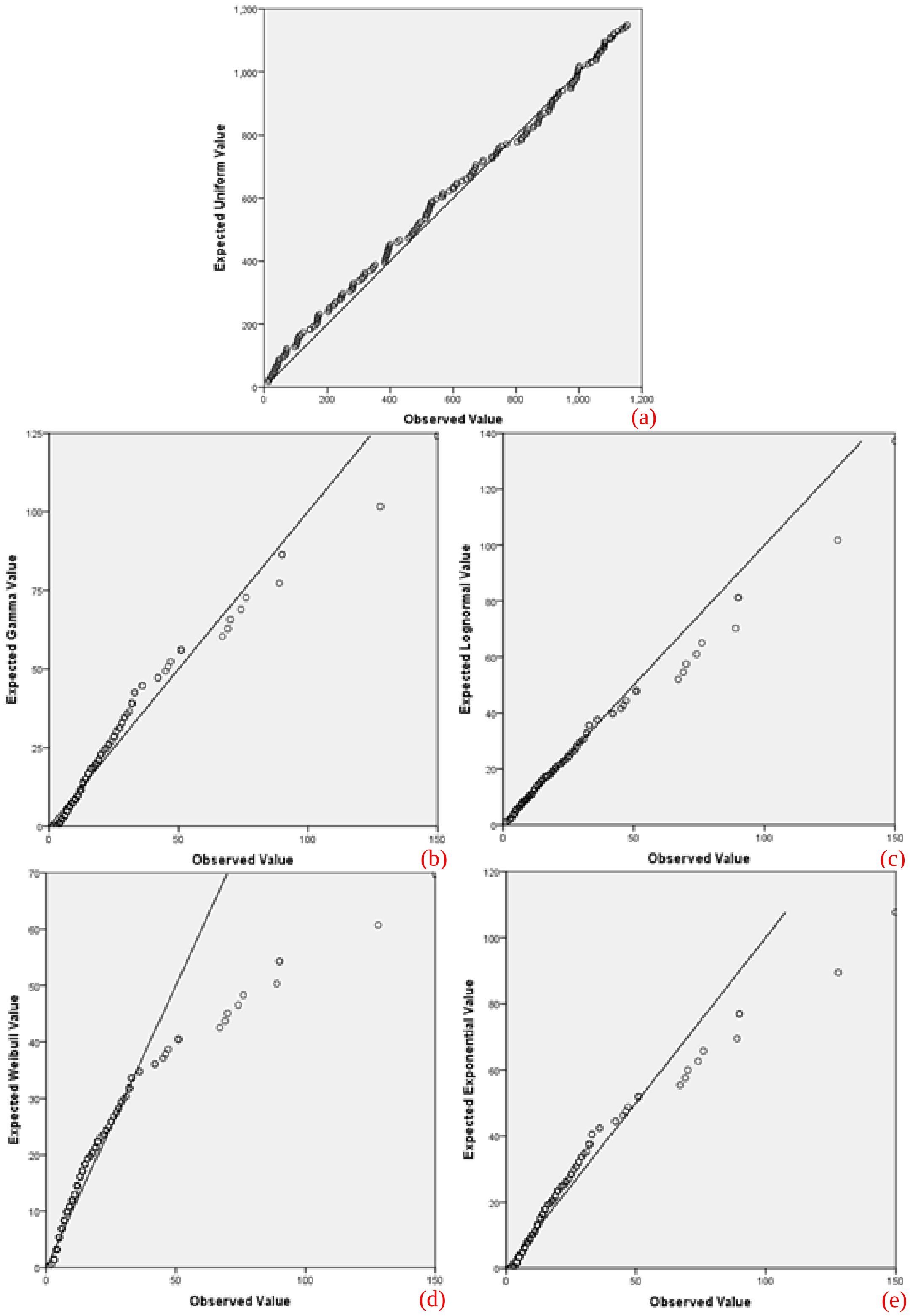


Fig. 4.11 (a) Uniform Q-Q Plot of PD and Q-Q Plot of SD: (b) Gamma Q-Q Plot, (c) Lognormal Q-Q Plot, (d) Weibull Q-Q Plot, and (e) Exponential Q-Q Plot

c) Goodness-of-fit tests

In this section, the Kolmogorov-Smirnov test is applied to the hypotheses about distributional forms of quantity of defects (QD), position of defects (PD) and size of defects (SD) by SPSS Statistics Version 22. Results are shown in Table 4.4–4.6, respectively. It must be noted that raw data of SD were transformed to the logarithm scale.

Table 4.4 One-Sample Kolmogorov-Smirnov Goodness-of-Fit Test for Poisson distribution

		QD
N		408
Poisson Parameter[a,b]	Mean	0.4289
Most Extreme Differences	Absolute	0.07
	Positive	0.47
	Negative	-0.24
Kolmogorov-Smirnov Z		0.956
Asymp. Sig. (2-tailed)		0.320

a. Test distribution is Poisson.

b. Calculated from data.

Table 4.5 One-Sample Kolmogorov-Smirnov Goodness-of-Fit Test for uniform distribution

		PD
N		175
Uniform Parameters[a,b]	Minimum	13.50
	Maximum	1152.5
Most Extreme Differences	Absolute	0.52
	Positive	0.52
	Negative	-0.31
Kolmogorov-Smirnov Z		0.694
Asymp. Sig. (2-tailed)		0.721

a. Test distribution is Uniform.

b. Calculated from data.

Table 4.6 One-Sample Kolmogorov-Smirnov Goodness-of-Fit Test normal distribution

		Transformed data of SD to Lg_{10}
N		175
Normal Parameters[a,b]	Mean	1.1005
	Std. Deviation	0.38527
Most Extreme Differences	Absolute	0.066
	Positive	0.066
	Negative	-0.052
Test Statistic		0.877
Asymp. Sig. (2-tailed)		0.425

a. Test distribution is Normal.
b. Calculated from data.

Through the Table 4.4–4.6, the *p*-value of QD, PD, and SD by K-S test are 0.320, 0.721 and 0.425, respectively, of which are equal or greater than the critical value 0.05. Therefore, it is reasonable to assume that QD, PD, and SD are sampled from Poisson, uniform and lognormal distributions, respectively.

d) Parameters estimation

For QD, applying Eq. (2.44), $\bar{X}$ = 0.4289. From Table 2.6, the suggested estimator $\lambda = \hat{\alpha} = \bar{X}$, $\lambda = 0.4289$. For PD, parameters *a* and *b* are equal to the minimum value of the data and maximum one, respectively, therefore, *a* = 13.50 and *b* = 1152.50. For SD, using Eq. (2.44) and Eq. (2.45), mean (μ) = 19.1086 and Std. Deviation (σ) = 21.6186, therefore,

$$\mu = \ln\left(e^{\mu+\sigma^2/2}\right) - \frac{1}{2}\ln\left(1+\frac{\left(e^{\sigma^2}-1\right)e^{2\mu+\sigma^2}}{\left(e^{\mu+\sigma^2/2}\right)^2}\right) = 2.92, \text{ and } \sigma = \sqrt{\ln\left(1+\frac{\left(e^{\sigma^2}-1\right)e^{2\mu+\sigma^2}}{\left(e^{\mu+\sigma^2/2}\right)}\right)} = 0.24$$

The parameters of hypothesized distributions are estimated as shown in Table

4.7. The distribution graphs plotted by MATLAB version R2011b 7.13 are as shown in Fig. 4.12. Please also note that defects collected from planks of different sources and sizes may differ from ones reported herein.

Table 4.7 The determined distributions of QD, PD, and SD

Each variable	Determined distributions	Abbreviation
QD	Poisson distribution	$q \sim P\,(0.43)$
PD	Uniform distribution	$p_x \sim U\,(13.50, 1152.50)$
SD	Lognormal distribution	$s \sim LN\,(2.92, 0.24)$

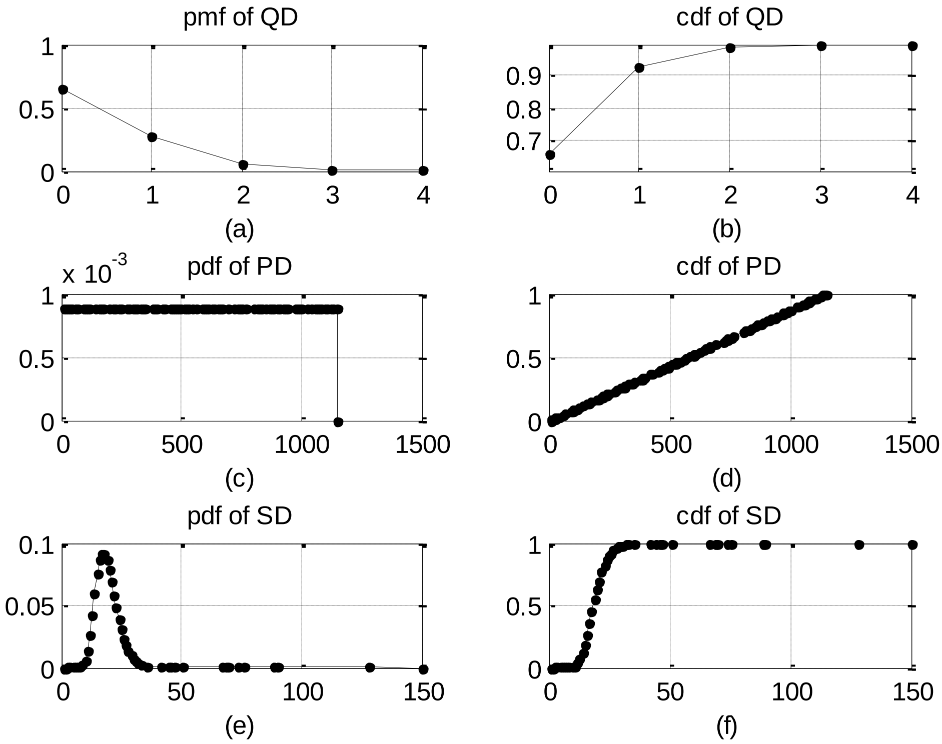


Fig. 4.12 The pmf or pdf of QD, PD, and SD and the cdf of QD, PD, and SD: (a) pmf of QD, (b) cdf of QD, (c) pdf of PD, (d) cdf of PD, (e) pdf of SD, and (f) cdf of SD

4.2.2 SIMULATION OF THE DEFECT IN A CUTTING PROCESS

Defect data randomly generated according to the model created and verified in the Defect Model Creation (Phase 1) are used as the input to the simulation (Phase 2). This process is implemented in MATLAB R2011b 7.13 environment.

The cutting process is assumed to automatically cut a plank into pieces of the same l_c. Cutting positions along the plank are marked and defects are virtually laid down on the plank. Usability of each wood workpiece is determined by comparing cutting positions and defect boundaries. The piece will be considered defect-free if any part of any defect is not found within. Defect-free wood pieces are collected to compute a percentage of material loss. For instance, x_1, x_3, x_5 and x_2, x_4, x_6 are the left-most points and right-most points of the simulated defects (Fig. 4.13). Cutting positions are of this order:

$e, l + t, 2l + t, \ldots\ldots, (n\text{-}1) * l + t, n * l + t$

and

$$n = floor\left(\frac{L-2e}{l_c+t}\right) \tag{4.5}$$

where n is the number of total wood pieces obtained from the initial cutting process; and *floor* (x) is a function to round the calculated result to the nearest integer less than or equal to x.

Therefore, the left and right boundaries of wood pieces are

$[e, e + l_c + t], [e + l_c + t, e + 2\, l_c + t], \ldots\ldots, [e + (n - 2) * l_c + t, e + (n - 1) * l_c + t], [(n - 1) * l_c + t, n * l_c + t]$

If one or more simulated defects fall within the range of any wood piece, it indicates that this piece had defect(s). Defect-free wood pieces (q) are collected to compute the material loss from defects in Eq. (4.3). This process is carried out in MATLAB as well.

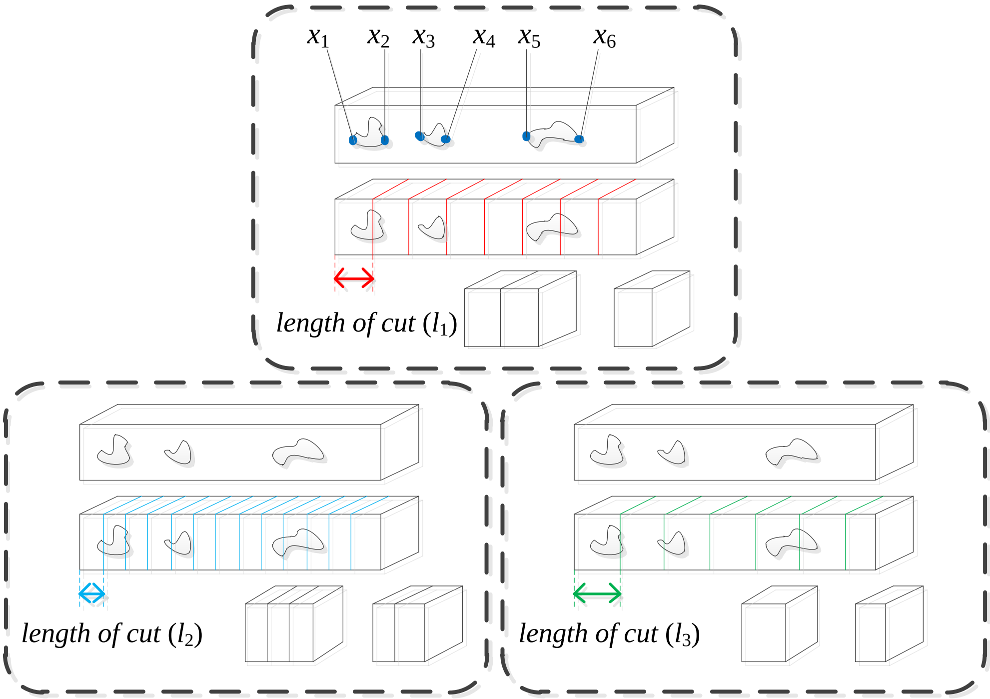


Fig. 4.13 The pattern of simulated defects and applying different cutting methods to obtain different good pieces

<u>Examples of determination of defective pieces</u>

Considering Plank No. 412 of W_{412} = 25.40, H_{412} = 57.15 and L_{412} = 1,000.00.

Random numbers according to the distributions in Table 4.7 are generated as follows:

QD = 2,

PD = 843.34, 859.89, 377.49 and 391.92,

and SD = 16.55 and 14.43.

These generated numbers is illustrated in Fig. 4.14 (a).

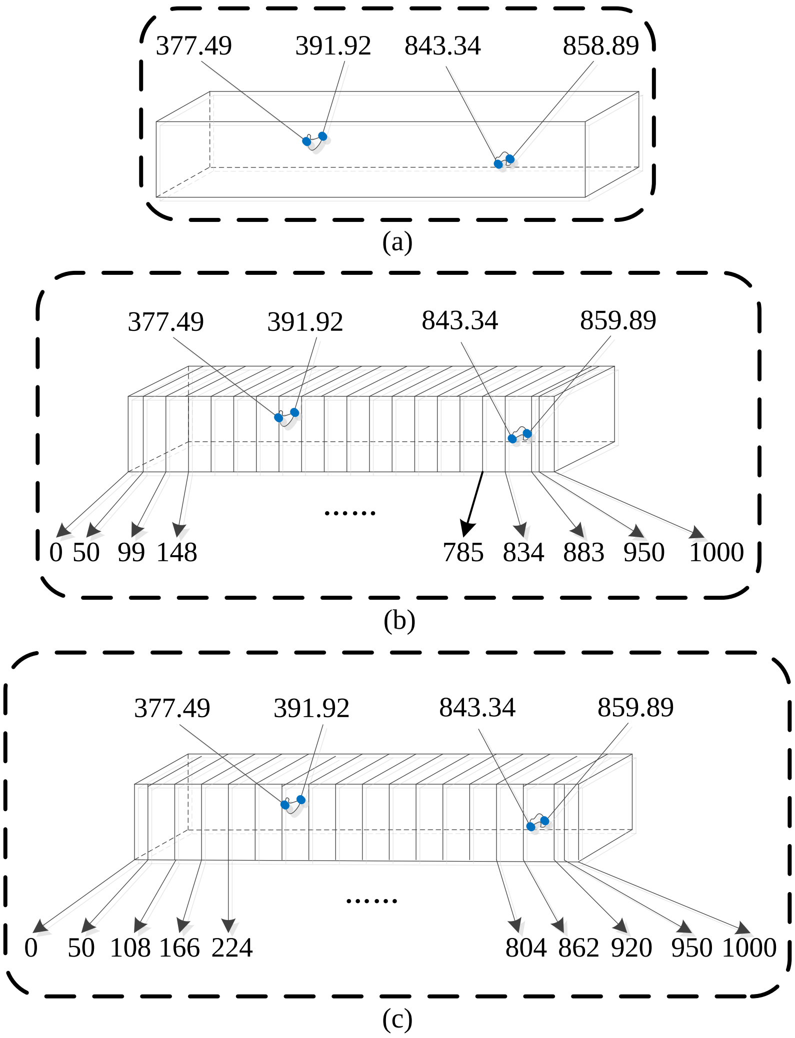


Fig. 4.14 The pattern of simulated defects and applying cutting methods 213 and 312 to the Plank No. 412 to obtain different good pieces

The Plank No. 412 can be cut by the Method 213 and 312. Therefore, the left and right boundaries of wood pieces are described in Fig. 4.14 (b) and (c), respectively.

From Fig. 4.14 (b), left-most point of 377.49, right-most point of 391.92, and other left-most one of 843.34, right-most one of 859.89 fall within the range of [344, 393] and [834, 883], respectively. For Fig. 4.14 (c), the defective pieces are the ranges of [340, 398] and [804, 862].

Therefore, it indicates that these pieces in the range of [344, 393] and [834, 883], and of [340, 398] and [804, 862] have defects when the Plank No. 412 is cut by the Method 213 and Method 312, respectively. Namely, by applying both Method 213 and 312 to Plank No. 412, the plank has two defective pieces through the defect model.

4.2.3 OPTIMIZATION FUNCTIONS

The optimization functions are formulated to identify optimal cutting parameters leading to a minimum wood loss and minimum cost.

Minimum wood loss: In a scarcity of material supplies or increasing environmental concerns, this objective function may gain attention. Impacts of loss or waste disposed from manufacturing processes is widely acknowledged, and more sustainable process planning is needed [122]. A total of loss is a combination of loss from defects and loss from shaping, thus an objective function can be formulated as in Eq. (4.6):

$$Min\ LOSS_{ij} = LOSS_d + LOSS_{sp} \tag{4.6}$$

$$Min\ LOSS_{ij} = \left(1 - \left(\frac{q_{ij} * l_{cij}}{L_j}\right)\right)\left(W_j * H_j * L_j\right) + q_{ij}\left(V_{wij} - V_p\right) \tag{4.7}$$

Minimum cost: Cost is always a key determinant of production efficiency in a business manufacturing company. Without any irregular situations, manufacturers are willing to adopt every solution to keep their production cost down. Cost herein means a cost per workpiece or a unit cost. In our model, it was simply derived from cost per wood plank divided by the number of usable (defect-free) pieces.

$$Min\ C_{uij} = \frac{C_{wj}}{q_{ij}} \tag{4.8}$$

where i is cutting method index, $i \in \{1, 2, \ldots 6\}$; j is wood plank index, $j \in \{1, 2, \ldots m\}$, m is the number of applicable planks; and *Loss* is the total wood loss.

Examples of calculation of minimum wood loss and minimum unit cost

(1) Through the wood defect simulation model, the number of defective pieces by applying different cutting methods to applicable wood planks could be determined. When it was subtracted from the total number of wood pieces (n), the non-defective wood pieces can be obtained from a cutting method on a plank using Eq. (4.2). It should be noted that Table 4.8 shows an average number of usable wood pieces gained from 250 simulation runs.

As shown in Section 4.2.1 and Section 4.2.2, the loss from shaping processes and from defects were calculated, then using the Eq. (4.7), the minimum wood loss can be obtained.

(2) Using the Eq. (4.4), unit cost can be calculated.

Considering Plank No. 391, 395 and 698.

$$\text{Plank No. 391:}\ C_{u(312,\ 391)} = \frac{C_{w391}}{n_{(312,391)}} = \frac{28.68}{13} = 2.21$$

$$\text{Plank No. 395,}\ C_m\text{: 213:}\ C_{u(213,\ 395)} = \frac{C_{w395}}{n_{(213,395)}} = \frac{37.78}{16} = 2.36$$

$$C_m\text{: 312:}\ C_{u(312,\ 395)} = \frac{C_{w395}}{n_{(312,395)}} = \frac{37.78}{13} = 2.91$$

$$\text{Plank No. 698,}\ C_m\text{: 123:}\ C_{u(123,\ 698)} = \frac{C_{w698}}{n_{(123,698)}} = \frac{69.15}{31} = 2.23$$

$$C_m\text{: } 213\text{: } C_{u(213,\ 698)} = \frac{C_{w698}}{n_{(213,698)}} = \frac{69.15}{16} = 4.32$$

$$C_m\text{: } 312\text{: } C_{u(312,\ 698)} = \frac{C_{w698}}{n_{(312,698)}} = \frac{69.15}{13} = 5.32$$

$$C_m\text{: } 321\text{: } C_{u(321,\ 698)} = \frac{C_{w698}}{n_{(321,698)}} = \frac{69.15}{13} = 5.32$$

Therefore, using Eq. (4.8), the minimum unit cost can be obtained.

From Table 4.8, a cutting plan satisfying the first objective function (minimum wood loss) is the plank 391 cut by the 312 cutting method i.e., the plank with a_c of 1058 mm^2 and l_c of 55 mm. But if cost is more of a concern than the loss of material, the plank 412 with the 213 cutting method (a_c of 1265 mm^2 and l_c of 46 mm) must be chosen. This cutting method allows the plank 412 to be cut into more number of wood pieces (18). Once this number is deducted by the number of defective pieces, the number of usable pieces (16) resulted. Its price is less expensive than the plank 391, with more number of pieces obtained, this plank is even more fitted to the second objective function. It can be seen that a cutting plan satisfying the first objective function (minimum wood loss) is not necessarily the same as one satisfying the second function (minimum cost). The second function is sensitive to market prices of the planks when the first one is less dynamic. The plans from both functions could be coincident but if not, one of them must be chosen depending on various circumstances of the factory.

Table 4.8 Results of defect simulation model

Planks No.	C_m	l_c (mm)	n (piece)	q (piece)	$Loss_{sp}$ (mm^3)	$Loss_d$ (mm^3)	Total Loss (mm^3)	Unit Cost
…	…	…	…	…	…	…	…	…
391[a, b, c]	312	55	15	13	290,641.00	342,000.00	632,641.00	2.21
392	312	55	15	13	326,391.00	356,250.00	682,641.00	2.40
393	312	55	15	13	344,266.00	363,375.00	707,641.00	2.21
394	312	55	15	13	415,766.00	391,875.00	807,641.00	2.54
395	213	46	18	16	405,712.00	396,000.00	801,712.00	2.36
	312	55	15	13	505,141.00	427,500.00	932,641.00	2.91
…	…	…	…	…	…	…	…	…
412[d]	213	46	18	16	370,096.96	383,225.04	753,322.00	1.04
	312	55	15	13	470,542.15	413,708.85	884,251.00	1.28
…	…	…	…	…	…	…	…	…
698	123	23	34	31	1,392,117.00	1,104,950.00	2,497,067.00	2.23
	213	46	18	16	2,135,312.00	1,016,400.00	3,151,712.00	4.32
	312	55	15	13	2,185,391.00	1,097,250.00	3,282,641.00	5.32
	321	55	15	13	2,185,391.00	1,097,250.00	3,282,641.00	5.32
…	…	…	…	…	…	…	…	…
733	132	23	34	31	6,007,052.28	2,962,574.72	8,969,627.00	4.41
	123	23	34	31	6,007,052.28	2,962,574.72	8,969,627.00	4.41
	213	46	18	16	6,899,116.16	2,725,155.84	9,624,272.00	8.55

Table 4.8 Results of defect simulation model (cont.)

Planks No.	C_m	l_c (mm)	n (piece)	q (piece)	$Loss_{sp}$ (mm^3)	$Loss_d$ (mm^3)	Total Loss (mm^3)	Unit Cost
	231	46	18	16	6,899,116.16	2,725,155.84	9,624,272.00	8.55
733	312	55	15	13	6,813,271.40	2,941,929.60	9,755,201.00	10.52
	321	55	15	13	6,813,271.40	2,941,929.60	9,755,201.00	10.52

[a] A plan with minimum wood loss from shaping processes

[b] Minimum wood loss from defects

[c] Minimum total wood loss

[d] A plan with minimum unit cost

4.3 PERFORMANCE OF THE MODELS

Performance of the proposed model is evaluated against its contender, i.e., the parametric model. Percentages of defect-induced loss (obtained from Eq. (4.3) and unit material cost (obtained from Eq. (4.4)) from both models are compared with the actual data. The comparison is made on only loss from defects because derivation of the loss from shaping processes seemed straightforward and it is likely that all models would share the same amount. Results of the comparison are tabulated in Table 4.9.

It can be seen that resultant wood loss and costs estimated from the simulation and parametric model are fluctuated around the actual values. However, the results from the simulation model indicate much less variation. They swing within less than 8.71% and 3.04% around the actual wood loss and costs. While compared with those from the parametric model, the maximum difference is 38.60% in wood loss and 13.57% in unit cost, respectively. The + and – indicate overestimation and underestimation of costs. Although overestimation may sound less catastrophic, it imperils business competitiveness. Prices will be unreasonably set high above the inaccurate cost. From another aspect, impacts of cost underestimation will lead the business toward financial losses. Accurate product cost estimation will certainly play a crucial role in maintaining enterprise competitiveness.

In this study, it should be noted that the defect model was developed from planks of a certain size and source. Data collected from planks of different sizes and sources may have dissimilar distributions. In Table 4.9, however, the comparison was made across a variety of plank size to offer a rough estimation of costs incurred. The researcher is aware that the most accurate estimation would lie around planks of similar sizes with ones collected in this study. Reevaluation of defect distributions should be considered when implementing this approach with planks out of the scope of this study. Commercial statistics packages are widely available and can analyze probabilistic patterns of the data in a very short time. Once distributions of the defect data are realized, they can be fed into a cutting plan generation module for determination of plank optimality. However, distribution analysis on plank of each size would be very tedious as some companies may have a large number of plank sizes stored in their databases. One challenge in a future study is to develop a model that is more general to be able to explain variation of defects collected from all plank sizes, and concise enough to allow rapid calculations through the automated cost estimation system. It is also worth noting that number of the input data in the simulation i.e., the QD, PD and SD of a plank is limited (102 planks). By increasing the number of wood planks in the data collection process, the model will be closer to explain the true pattern of the defects. Accuracy of the predictive data can be improved by increasing the number of planks collected, however, in exchange of longer collection task.

Table 4.9 Comparison between defect-induced losses and unit costs from two models and actual data

Plank No.	C_m	l_c	Wood loss (mm^3)			Unit cost			% difference in wood loss from Act. Data		% difference in unit cost from Act. data	
			Act.	Simu.	Para.	Act.	Simu.	Para.	Simu.	Para.	Simu.	Para.
…	…	…	…	…	…	…	…	…	…	…	…	…
391	312	55	342,000.00	342,000.00	210,000.00	2.21	2.21	1.91	0	-38.60	0	-13.57
392	312	55	356,250.00	356,250.00	218,750.00	2.40	2.40	2.08	0	-38.60	0	-13.33
393	312	55	363,375.00	363,375.00	223,125.00	2.21	2.21	1.91	0	-38.60	0	-13.57
394	312	55	391,875.00	391,875.00	240,625.00	2.54	2.54	2.20	0	-38.60	0	-13.39
395	213	46	396,000.00	396,000.00	327,000.00	2.36	2.36	2.22	0	-17.42	0	-5.93
	312	55	427,500.00	427,500.00	262,500.00	2.91	2.91	2.52	0	-38.60	0	-13.40
…	…	…	…	…	…	…	…	…	…	…	…	…
412	213	46	383,225.04	383,225.04	316,450.98	1.04	1.04	0.98	0	-17.42	0	-5.77
	312	55	413,708.85	413,708.85	254,031.75	1.28	1.28	1.11	0	-38.60	0	-13.28
…	…	…	…	…	…	…	…	…	…	…	…	…
698	123	23	1,016,400.00	1,104,950.00	927,850.00	2.16	2.23	2.1	8.71	-8.71	3.24	-2.78
	213	46	1,016,400.00	1,016,400.00	839,300.00	4.32	4.32	4.07	0	-17.42	0	-5.79
	312	55	1,097,250.00	1,097,250.00	673,750.00	5.32	5.32	4.61	0	-38.60	0	-13.35
	321	55	1,097,250.00	1,097,250.00	673,750.00	5.32	5.32	4.61	0	-38.60	0	-13.35
…	…	…	…	…	…	…	…	…	…	…	…	…
733	132	23	2,725,155.84	2,962,574.72	2,487,736.96	4.28	4.41	4.15	8.71	-8.71	3.04	-3.04
	123	23	2,725,155.84	2,962,574.72	2,487,736.96	4.28	4.41	4.15	8.71	-8.71	3.04	-3.04

Table 4.9 Comparison between defect-induced losses and unit costs from two models and actual data (cont.)

Plank No.	C_m	l_c	Wood loss (mm^3)			Unit cost			% difference in wood loss from Act. Data		% difference in unit cost from Act. data	
			Act.	Simu.	Para.	Act.	Simu.	Para.	Simu.	Para.	Simu.	Para.
733	213	46	2,725,155.84	2,725,155.84	2,250,318.08	8.55	8.55	8.05	0	-17.42	0	-5.85
	231	46	2,725,155.84	2,725,155.84	2,250,318.08	8.55	8.55	8.05	0	-17.42	0	-5.85
	312	55	2,941,929.60	2,941,929.60	1,806,448.00	10.52	10.52	9.12	0	-38.60	0	-13.31
	321	55	2,941,929.60	2,941,929.60	1,806,448.00	10.52	10.52	9.12	0	-38.60	0	-13.31

Act. = actual data (wood loss and unit cost), Simu. = simulation model, Para. = parametric model

CHAPTER 5

GENERAL CONCLUSION

5.1 CONCLUSIONS

In a new era of globalized commerce, a target customer group may no longer be in vicinity but it can be an unimaginable number of customers worldwide. Those customers come with a variety of needs and expectations. Manufacturers who can promptly response to those needs will gain an edge in business competition. With advancement in information and manufacturing technologies, a mass customization production system is now more than realizable. It is an integration of all constructive structures i.e., communication, design and manufacturing, logistics and inventory management altogether to become an efficient, flexible, and agile production system.

To survive today's fierce business competition in a mass customization environment, transition of information and materials among departments must be in a rapid and accurate manner. Planning is therefore a vital activity in leading the enterprise to achieve its goal. In this study, an approach for automated product configuration identification and profitable cutting planning was proposed. The approach was constituted of three modules: an image processing module, a cutting plan generation module and a cost estimation module. In the image processing module, three dimensions of the Minimum Bounding Box (MBB) of the product were acquired. They were subsequently submitted to the cutting plan generation module. Within this module, a 'wood plank applicability detection' unit inspected suitability of planks in producing the product by comparing sizes of the planks and the MBB through six different cutting methods. A list of applicable planks was generated; however, the optimal plank was yet to be identified. Optimality of the plank was later assessed in the cost estimation module.

In the last module, shaping-induced material loss and defect-induced loss were quantified. Derivation of the former was simply difference in volume of the product and its MBB. Estimation of the latter was rather complicated due to involvement of defect uncertainty. A probability theory was used to explain uncertain occurrence of the defect variables. Distributional functions were statistically formulated and tested for their validity to represent each variable. Defects were simulated as according to the functions, and loss associated to the defects therefore was evaluated. Once such loss was quantified, material cost was then estimated accordingly. Two optimization objectives were proposed for optimality assessment. The first one was to locate a cutting plan with minimum total material loss, when the other was more concerned with cost minimization.

A product specimen was used to illustrate how the approach operated to arrive at an optimal cutting plan. The plans from both objective functions were not necessarily coincident depending upon market prices of the wood planks. Performance of the proposed approach in estimating material loss was tested against the parametric estimation model currently employed in a case study wood factory. Results from both models were compared with losses actually collected from the factory. It was found that superiority of the proposed approach to the existing parametric model was clearly observed. Determinant of model accuracy is a deviation from the actual loss; results from the proposed approach were in the range of +/–, much less than those of the parametric model.

In conclusion, establishment of a cutting plan, currently performed by human operations, can arrive at non-optimality due to subjectivity of human perception, especially with involvement of material quality uncertainty. The automated approach proposed here will help accelerate and facilitate communication and production, as well as assure cutting plan optimality in a mass customization environment.

5.2 SUGGESTIONS AND FUTURE WORK

1) In this study, it should be noted that the number of the input data in the simulation were definite (102 planks). By increasing the number of wood planks in data collection, the model will be closer to explain the true pattern of the defects. Accuracy of the predictive data can be improved by increasing the number of planks collected, however, in exchange of longer collection task. This study implemented a concept of a probability theory by using statistics to tackle uncertainty found in cost management. Although the results shown are far superior to the pure parametric method, its application requires numerous data to assure validity of the developed model.

2) The study assumes the same defect distributions across all plank sizes. In reality, dissimilarity of the distributions of defects collected from plank of different sizes and sources may be detected. When implementing the proposed approach with planks out of the scope of this study, reevaluation of defect distributions must be considered. A more general model that can be explain uncertainty nature of the defects collected from all applicable plank sizes should be developed in a future study.

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APPENDIX A

A Probabilistic Model of Wood Defects (accepted for publication in *Applied Mechanics and Materials*)

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A Probabilistic Model of Wood Defects

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Abstract. Although widely used in construction and industrial applications, wood is more prone to defects of different kinds than other materials. These defects are unpredictable and differing randomly from plank to plank. This uncertain nature of the defects complicates establishment of manufacturing plans. In this study, a probabilistic model of wood defects was constructed as a function of three variables which were quantity of defects, position of defects and size of defects. The Kolmogorov-Smirnov hypotheses testing on distributional forms of these variables were carried out. Results showed that Poisson, uniform, and log-normal distributions were suitable to represent the variables statistically. Being knowledgeable of how the defects are distributed on the plank will be of benefit in profitability justification of a cutting plan.

Introduction

Despite of its versatility and sustainability, wood is prone to defects of different kinds [1, 2]. These defects are unpredictable and differing randomly from plank to plank. Besides defects apparently observable on the surface of the planks, there may be defects hidden underneath the surface that will be revealed once the plank is cut. The defects, either on or beneath the surface, cause loss in material productivity. Chansaad [3] developed a set of fuzzy rules to explain how loss in wooden material was dependent upon changes in cutting parameters, when defects were assumed to be distributed unsystematically and uncontrollably. To a given defective plank, by applying different length of cut, different material loss will result as illustrated in Fig. 1. However, by leaving aside the defect characterization, to give a full explanation of such dependency over the range of product lines, the number of fuzzy rules would be too large to handle. There was also an effort to identify defect position in a wooden beam [4], but this approach could not provide other information significant to manufacturing applications. In this study, a probabilistic model of wood defects is proposed. Being knowledgeable of how the defects are likely to appear on the plank surfaces will be of benefit to a process planner in profitability justification of a cutting plan.

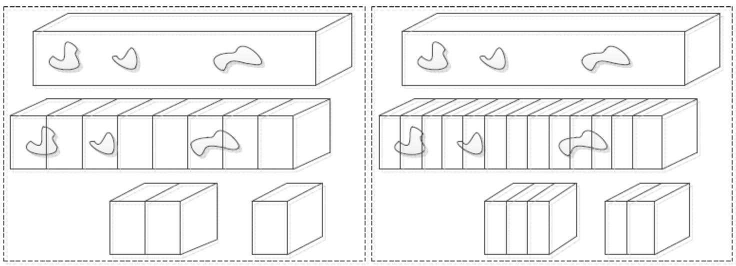


Fig. 1 Material loss as affected by different length of cut [3]

Methodology

The probabilistic model of wood defects is constructed by three variables which are quantity of defects (QD), position of defects (PD) and size of defects (SD). The model was developed as according to Jerry Banks [5]. It was created in 4 steps: (a) collecting data from a wooden product company, (b) identifying their probability distributions, (c) determining parameters of the distribution family, and (d) evaluating the chosen distributions and the parameters associated with them.

Data Collection. Data collection is a critical step in model simulation development. It must be handled in a random manner without biasness. Defects can be found in any faces of the plank, the data were collected on all four elongated faces (F_1, F_2, F_3 and F_4) as shown in Fig. 2. Faces at both ends, F_5 and F_6 were slightly cut off as a standard cutting operation. Defects found on these faces therefore had no effect on material loss. One hundred and two wooden planks were collected in a wooden products company. Details of collection of each variable are discussed as follow.

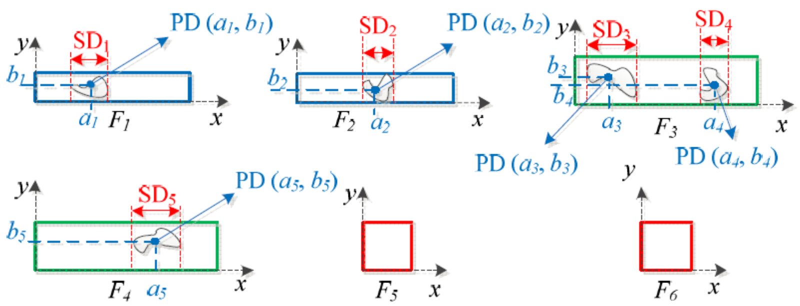


Fig. 2 Determination of QD, PD and SD

Quantity of Defects (QD). QD was collected by counting the number of observable defects on each face. Relative frequencies in QD appear in Table 1. Some defects may have an irregular shape and justification from an experienced operator was needed.

Table 1 Distribution of quantity of defects on 4 faces of 102 wood planks (AB Grade)

Quantity of defects (piece)	Frequency	Probability (%)	Cumulative (%)
0	285	69.85	69.85
1	85	20.83	90.68
2	25	6.13	96.81
3	12	2.94	99.75
More	1	0.25	100.00

Position of Defects (PD). PD was collected by measuring the distance from one end to the center of defects (Fig. 2). Relative frequencies in PD appear in Table 2.

Table 2 Distribution of position of defects

Position of defects (mm)	Frequency	Probability (%)	Cumulative (%)
$0 < PD \leq 400$	68	38.86	38.86
$400 < PD \leq 800$	49	28.00	66.86
$800 < PD \leq 1200$	58	33.14	100.00
$PD > 1200$	0	0.00	100.00

Table 3 Distribution of size of defects

Size of defects (mm)	Frequency	Probability (%)	Cumulative (%)
$0 < SD \leq 20$	126	72.00	72.00
$20 < SD \leq 40$	31	17.71	89.71
$40 < SD \leq 60$	8	4.57	94.28
$60 < SD \leq 80$	5	2.86	97.14
$SD > 80$	5	2.86	100.00

Size of Defects (SD). SD was collected by measuring a difference in position of both defect extreme points lengthwise. Relative frequencies in SD appear in Table 3.To illustrate the collection of each variable, Fig. 2 shows faces of one plank with defects on them. In this figure, QD is 5. SDs from F_1 to F_4 are $|SD_1|$, $|SD_2|$, $|SD_3|$, $|SD_4|$ and $|SD_5|$, respectively. PDs from F_1 to F_4 are (a_1, b_1), (a_2, b_2), (a_3, b_3), (a_4, b_4), and (a_5, b_5).

Identifying Data Distribution. After all the data were collected from randomly selected plank samples, distributions of the variables (QD, PD, and SD) were analyzed.

Histogram. A frequency distribution or histogram is useful to preliminarily identify a shape of the data distribution. Relative frequencies in QD, PD, and SD appear in Table 1, Table 2, and Table 3, respectively. It is worth mentioning that QD, PD and SD are discretized by intervals of 1, 400, and 20, respectively and the resulting histograms are shown in Fig. 3, Fig. 4 and Fig. 5.

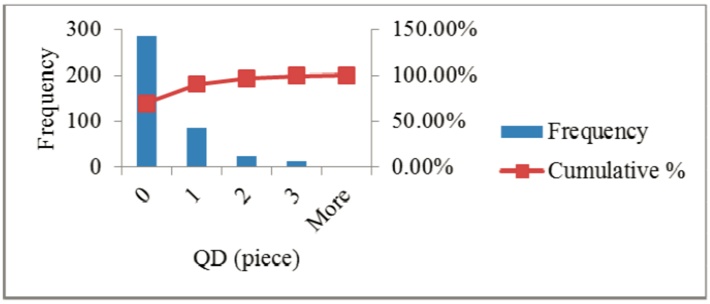


Fig. 3 Histogram of defect quantity (QD)

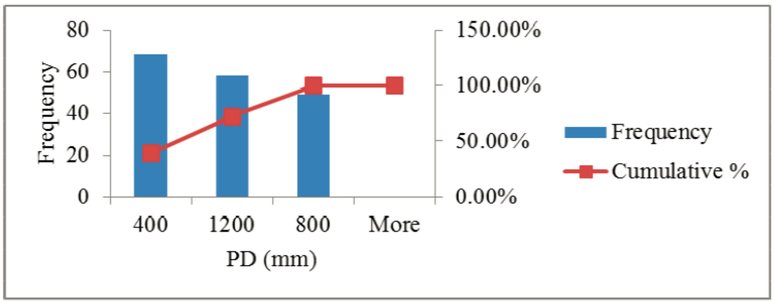


Fig. 4 Histogram of defect position (PD)

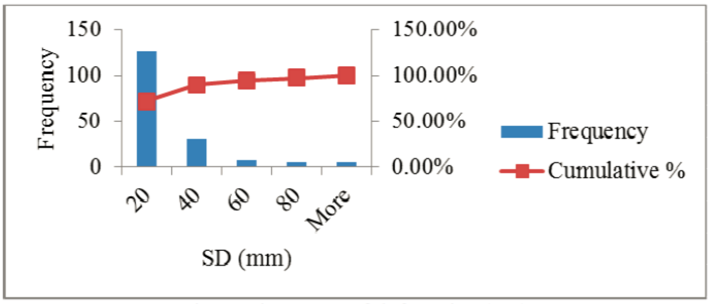
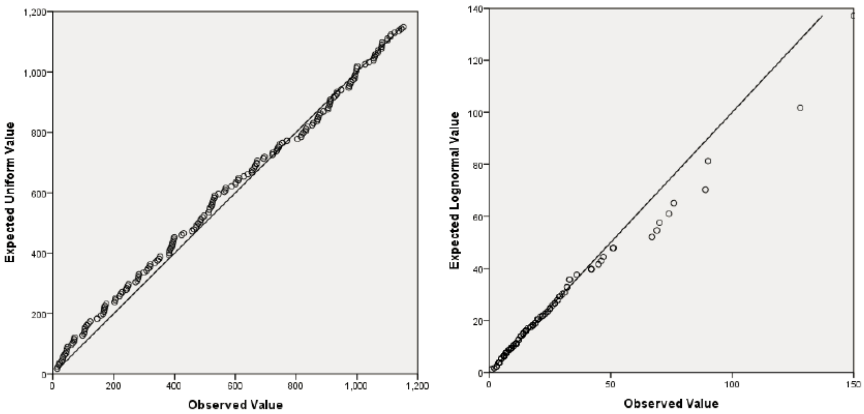


Fig. 5 Histogram of defect size (SD)

Selecting A Family of Distributions. The purpose of preparing a histogram is to infer a known pdf or pmf [5]. Based on the shape of the histograms (Fig. 3-5), QD, PD, and SD were assumed to distributed as Poisson, uniform, and lognormal distributions, respectively. Please note that transformation to a logarithmic scale for SD was required. Using SPSS Statistics Version 22, quantile-quantile (Q-Q) plots for PD and SD were constructed for evaluating fitness of such continuous distributions as shown in Fig. 6.



(a) (b)

Fig. 6 The Q-Q plots: (a) a plot of uniformly distributed PD, (b) a plot of log-normally distributed SD

Table 4 One-Sample Kolmogorov-Smirnov Goodness-of-Fit Test for Poisson distribution

		QD
N		408
Poisson Parameter[a,b]	Mean	0.4289
Most Extreme Differences	Absolute	0.047
	Positive	0.047
	Negative	-0.024
Kolmogorov-Smirnov Z		0.956
Asymp. Sig. (2-tailed)		0.320

a. Test distribution is Poisson.
b. Calculated from data.

Table 5 One-Sample Kolmogorov-Smirnov Goodness-of-Fit Test for uniform distribution

		PD
N		175
Uniform Parameters[a,b]	Minimum	13.50
	Maximum	1152.50
Most Extreme Differences	Absolute	0.052
	Positive	0.052
	Negative	-0.031
Kolmogorov-Smirnov Z		0.694
Asymp. Sig. (2-tailed)		0.721

a. Test distribution is Uniform.
b. Calculated from data.

Table 6 One-Sample Kolmogorov-Smirnov Goodness-of-Fit Test for normal distribution

		Transformed data of SD to Lg_{10}
N		175
Normal Parameters[a,b]	Mean	1.1005
	Std. Deviation	0.38527
Most Extreme Differences	Absolute	0.066
	Positive	0.066
	Negative	-0.052
Test Statistic		0.877
Asymp. Sig. (2-tailed)		0.425

a. Test distribution is Normal.
b. Calculated from data.

Parameters Estimation. After a family of distributions has been selected, the next step is to estimate the parameters of these distributions. For QD, the maximum likelihood estimator of λ is the mean of the sample (μ) [6], therefore, $\lambda = \mu = 0.4289$. For PD, parameters: a and b are equal to the minimum value of the data and maximum one, respectively, therefore, $a = 13.50$ and $b = 1152.50$. For SD, by using equations [7], the mean (μ) = 2.92, and variance (σ) = 0.24.

Goodness-of-Fit Tests. Goodness-of-fit test provides helpful guidance for evaluating the suitability of a potential input model. The Kolmogorov-Smirnov hypotheses testing on distributional forms of QD, PD and SD was carried out by SPSS Statistics Version 22. The results are shown in Table 4, Table 5, and Table 6, respectively.

Results

Through the Table 4, Table 5 and Table 6, the P value of the K-S tests on QD, PD, and SD are 0.320, 0.721 and 0.425, respectively, of which are equal or greater than the critical value 0.05. Therefore it is statistically valid to conclude that distributions of the variables are Poisson, uniform, log-normal distributions, respectively as shown in Table 7.These defect distributions can be applied to all faces except faces at both ends.

Table 7 The distributions of QD, PD, and SD

Variables	Distributions	Abbreviation
QD	Poisson distribution	$q \sim P\,(0.43)$
PD	Uniform distribution	$p \sim U\,(13.50, 1152.50)$
SD	Log-normal distribution	$s \sim LN\,(2.92, 0.24)$

Conclusion

This study mainly discussed four steps in the development of the probabilistic model of wood defects: data collection, statistical distribution identification, parameters estimation and goodness of fit tests. Once the parameters were determined, probabilistic models of defect variables were hypothesized. The hypotheses were tested to confirm validity of the models in representing those variables. These probabilistic defect models provided all information needed in justification of material loss probably incurred on a certain wood plank. A process plan, as well as a material requirement plan, can then be established accordingly to sustain business competitiveness.

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APPENDIX B

Automated Process Planning and Cost Estimation under Material Quality Uncertainty

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ORIGINAL ARTICLE

Automated process planning and cost estimation under material quality uncertainty

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Abstract In mass customization production environment, once an order is placed, a product quotation must be fed back to the customer in a relatively short time. Estimation of the product cost, however, can only be performed upon finalization of process planning. In wooden product manufacturing, optimization of process planning is complicated due to the uncertainty of raw material quality. Manual arrangement of process parameters always leads to non-optimality. In this study, an automated system was developed to shorten the process lead time, to ensure an optimal cutting process plan, and to estimate accurate material costs. The architectural structure of the proposed system is composed of three modules: (1) a digital image processing module to accelerate product recognition; (2) a cutting plan generation module to evaluate raw materials for their applicability, allowing a set of feasible plans to establish; and (3) an optimization module to quantify the amount of material loss. A process plan which satisfies a preferred objective function (either minimum cost or minimum loss) could subsequently be derived. The model developed in this study exhibits superior performance in predicting loss and estimating material cost over the other reported models.

Keywords Mass customization · Cost estimation · Uncertainty · Wood loss · Process planning

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Nomenclature

i	Cutting method index, $i \in \{1, 2, \ldots, 6\}$
j	Wood plank index, $j \in \{1, 2, \ldots, m\}$
m	Number of applicable planks
n	Number of total wood pieces obtained from the initial cutting process
q	Number of non-defective wood pieces
L, W, and H	Length, width, and height of a wood plank
l, w, and h	Virtual length, width, and height of a product
l_c	Length of cut
C_u	Unit cost of a wood piece
C_w	Cost of a wood plank
e	Length of end cut
t	Tooling allowance
c	Fixed compensation rate for the parametric model
V_w	Volume of a wood piece
V_p	Volume of a product
LOSS	Total wood loss
LOSS_d	Loss from defects
LOSS_{sp}	Loss from shaping processes

1 Mass customization manufacturing

In an era of global marketing, customers have unlimited worldwide opportunities to search for products that fulfil their needs. In response to such phenomenon, manufacturers are struggling to offer various product choices where one would expectedly meet all individual needs. Manufacturing industry is now confronting a dramatic shift from standardized production to a rather personalized one [1]. Standardized products will eventually be pushed off the markets as a new marketing strategy called “mass customization” (MC) has emerged with a distinct competitive edge. MC concept was first introduced

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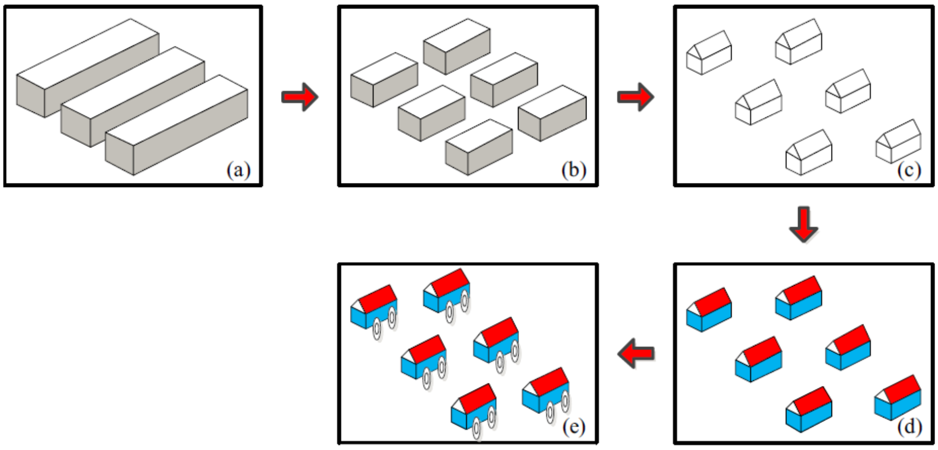

Fig. 1 Manufacturing processes of a wooden product. NB **a** material procurement, **b** initial cutting, **c** shaping, **d** painting, and **e** assembling

by Davis [2] in 1989. This production strategy can provide individually designed products and services to every customer through high process agility and flexibility [3, 4] at a reasonably low costs [5]. Though unlikely, with the advancement in information technology and flexible manufacturing technologies, MC is now more than ever realizable.

Throughout the cycle of MC, one of the critical upstream processes is cost estimation. It is of great importance that a company's decision on manufacturing and marketing policies depends upon [6]. Once a company adopts MC strategy, cost estimation process must be performed each time a new order is placed. To ensure success of mass customization, a rapid, automatic yet accurate cost estimation is needed [7]. However, costs associated with a product can be accurately estimated only when the product development plan is ready [8]. Finalization of such plan would take much time, and great effort to communicate with all related departments within the company, especially when such is conducted manually.

Tremendous effort had been put into developing an automated process planner as documented in a number of past studies. Those works evolved around feature recognition [9–15], knowledge representation [16–22] and inference engine [23, 24], integration of process planning, and upstream/downstream processes [25, 26]. Some researchers applied different methods/technologies such as OPPS-PRI 2.0 system [27], genetic algorithms (GAs) [28–33], imperialist competitive algorithm [34], energy-efficient oriented method [35], neural network-based system [36–38], fuzzy set theory/fuzzy logic method [36, 39, 40], agent-based methodology [41, 42], Internet-based technology [43, 44], functional blocks [45, 46], Petri net model [47], and STEP-compliant method [48–51], just to name a few, for process planning optimization. In 2014, Yusof and Latif [52] presented a comprehensive survey of researches on computer-aided process planning (CAPP) in the last 12 years (2002–2013) based on its approaches and methods/technologies. None however had focused on the involvement of uncertainties.

In this study, manufacturing of wooden toys is used as a case study. A challenge lies in randomly distributed defects embedded in raw materials. Due to rapid cycle change of the wooden products and uncontrollable defects of incoming wood raw materials, a material requirement plan for each batch of the wooden products is often overestimated to accommodate losses of any kinds. An existing process planning model does not account for such uncertainty, and an optimal plan is not always achieved. Thus, application of an automated system is proposed in this study to shorten lead time, assure optimality of a chosen process plan, and accurately estimate the material costs.

2 Research background

In a production of the toys, wood is accounted for more than 51 % of the total direct material cost [53]. Typically, wood is received in a form of commercial standard wood planks available in different sizes and grades. Most planks come at a length of either 1.00 or 1.25 m. Some companies further cut these planks lengthwise and keep them in store for producing smaller

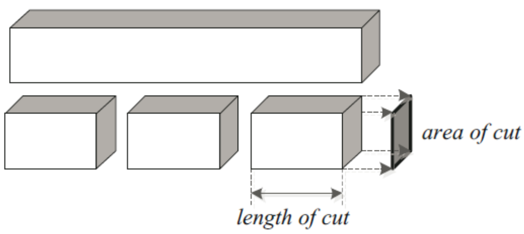

Fig. 2 Definitions of "*length of cut*" and "*area of cut*"

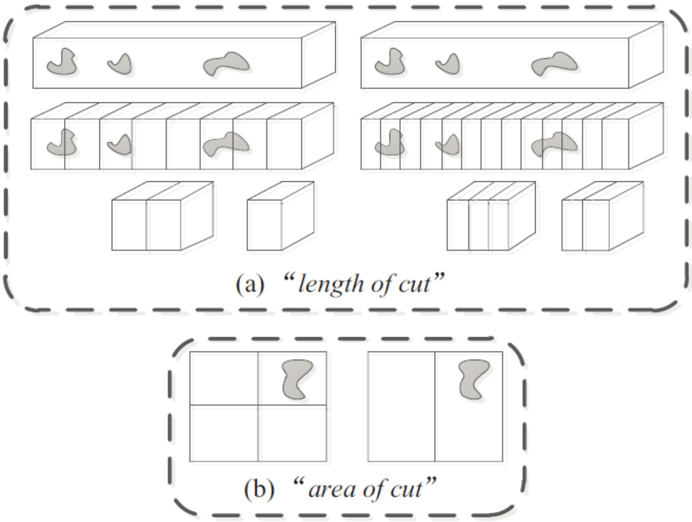

Fig. 3 Amount of material loss affected by "*length of cut*" and "*area of cut*" [53]

products. A production process using solid wood planks starts from (a) material procurement, (b) initial cutting, (c) shaping, (d) painting, and (e) assembling before packing and shipping to customers as shown in Fig. 1. Once a production order is confirmed, a process planner will search through a database of available wood planks to find ones which are applicable, i.e., ones having dimensions suitable for producing the product. The planks are chosen by their cross-sectional area which is called "*area of cut*." In the initial cutting process, they are cut into pieces of the same "*length of cut*." In Fig. 2, both area of cut and length of cut, known as cutting parameters in this study, are constrained by product dimensions. As illustrated in Fig. 3, applying different cutting parameters to the planks having same defect patterns will end in different material losses.

Defects, either on or beneath plank surfaces, cause losses in material productivity. Such defects found on the plank are random; material loss is uncertain from plank to plank. In order to avoid complication of estimating loss from defects, one manufacturing company simply assumes a fixed rate of 5 % as a compensation rate to wood defects which is referred as a parametric model (Eqs. (1)–(3)) [53] to calculate a material unit cost. Although defects can be found on all surfaces of a plank, chances are minimal that defects will be spotted on end surfaces or surfaces parallel to them.

$$q = \mathrm{round}\left(\frac{L-2e}{l_c+t}(1-c)\right) \quad (1)$$

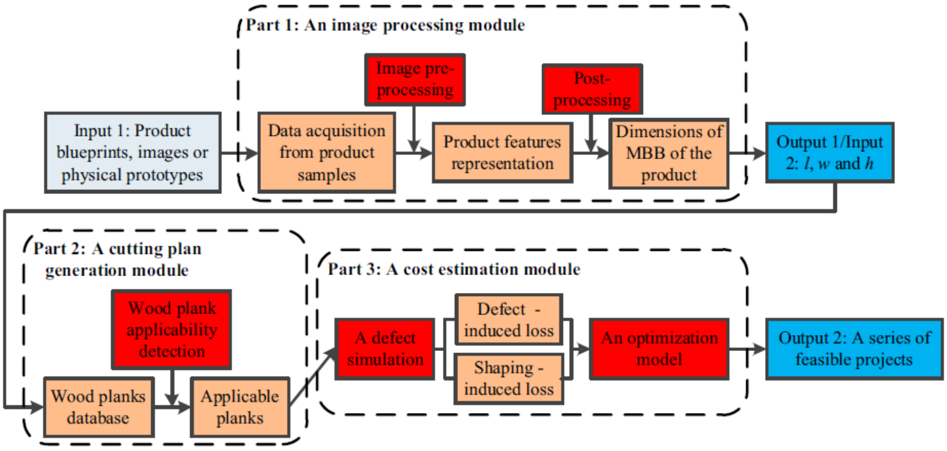

Fig. 4 Information flow within the proposed system

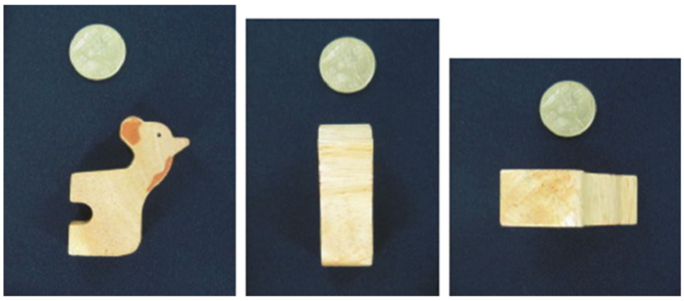

Fig. 5 Acquisition of digitalized images of the product in different views (RGB) (wooden product with a coin as the reference object)

$$\mathrm{LOSS}_d = \left(1 - \frac{q^* l_c}{L}\right) * (L^* W^* H) \tag{2}$$

$$C_u = \frac{C_w}{q} \tag{3}$$

It should be noted that the company applies fixed values of e, t, and c of 50, 3, and 0.05 mm, respectively.

Efforts to quantify material loss in natural derivatives have been undertaken in some earlier works. In 2014, Chansaad et al. [53] proposed a fuzzy inference method to estimate the loss of material used in wooden product manufacturing subject to defect uncertainty. Loss was conditionally explained by fuzzy rules on length of cut and area of cut. The system in [53] was built on the scenario that defects were assumed uncontrollable and unavoidable. Although results from the fuzzy system were far superior to the parametric method, an important issue of defects' characteristics was left undiscussed.

Besides the fuzzy theory, a probability theory has long been a major contender in dealing with uncontrollable, imprecision, and inherently uncertain information. Probability theory meanwhile concerns with an analysis of random phenomena using statistics. As complexity of defect characterization increases, the fuzzy theory becomes more difficult to specify a correct set of rules and membership functions and in some cases fails to describe the true behavior of the defects accurately. On the other hand, the probability theory can capture mathematical essence of a quantification of defect characterization by specifying what properties such quantification should have [54]. In this study, a simulation model based on probability theory is used to simulate wood defects and then predict material loss and unit cost of the material in wooden product manufacturing. Using loss information from the simulation in combination of product digital images, the optimal cutting solutions—area of cut and length of cut—can be identified.

3 System architecture

The system proposed herein is aimed for faster product configuration identification and more profitable cutting planning. It consists mainly of an image processing module, a cutting plan generation module, and a cost estimation module. The image processing module is designed to acquire virtual dimensions of the product through a minimum bounding box (MBB) algorithm. Dimensions are submitted to the cutting plan generation module. Within this module, a "wood plank applicability detection" unit inspects suitability of the planks for the product. Applicable planks will subsequently be put through a defect simulation. Losses associated with each plank are evaluated. Once they are quantified, material cost can be estimated accordingly. The interoperable modules and information flow in this system are illustrated in Fig. 4.

3.1 Image processing module

Due to flexibility of digital image processing technologies, their applications are increasingly adopted in both research

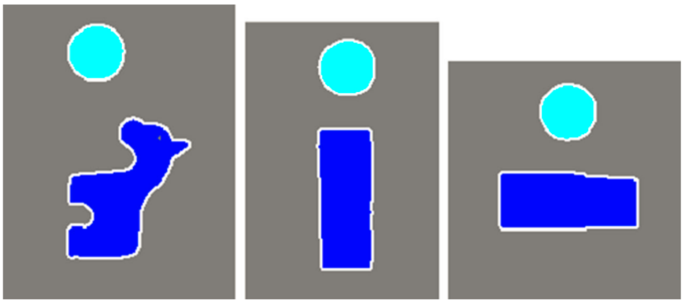

Fig. 6 Tracing a boundary of the selected region

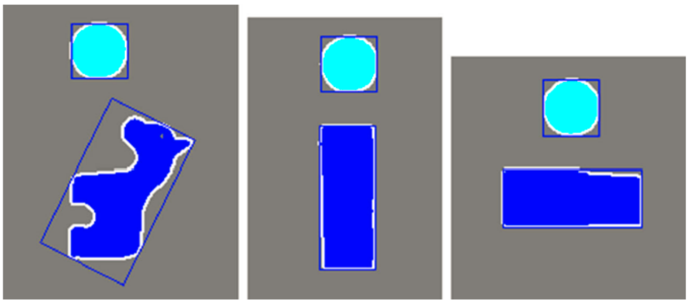

Fig. 7 MBB of the product images in different views

and industrial implementation. Downstream processes, e.g., process planning, tooling design, and manufacturing, can be automatized with digitally formatted product specifications.

3.1.1 Data acquisition

In order to ensure that product data such as product blueprints, images, or physical prototypes which are provided by a customer or a designer can be recognized by a computer system with ease, it is essential that they are converted into digital format. Product digital information must contain three principal views (front, side, and top) in clear and high-contrast images with minimum noises.

Figure 5 depicts a wooden product, which its dimensions to be measured, being placed on a dark background with a known size coin as a reference object. The image was captured by a common digital camera. It is important that the camera must be held parallel to the plane on which the product is settled to avoid dimension distortion.

3.1.2 Image pre-processing

The code was written in MATLAB version R2011b 7.13, compatible with higher version of the program. The original images are converted into grayscale images and further converted into binary images. A function called "bwboundaries" in MATLAB is used to trace a boundary of a selected region in the image as shown in Fig. 6. After the boundary of the selected region is identified, properties such as perimeter and area are determined using a function called "regionprops." Most of the properties returned from this function are in the unit of pixel count.

3.1.3 Post-processing

Since a majority of the products are in free-form shape, a rectangle is virtually drawn to enclose a region which is labeled as the product image. Dimensions of the rectangle or the bounding box are regarded herein as product's virtual dimensions. To ensure that the rectangle imposed on the product image reflects accurate product dimensions, a MBB algorithm is employed. The algorithm computes a minimal bounding rectangle of points in a plane as shown in Fig. 7.

Since the images are to be submitted from a customer who assumedly does not possess any imaging skills, errors due to camera-sample misalignment and poorly controlled environment are expected. Extra care must be taken while capturing product image in order to minimize such errors.

3.2 Cutting plan generation module

The objective of the cutting plan generation module is to find a set of feasible cutting plans before an optimal one can be identified. Although there are only a few sizes of standard wood planks available commercially, a company often cut those planks into smaller different sizes and keeping them in storage for future use. Some companies have up to a hundred different plank sizes in their database for a process planner to choose from. In this section, a term "workpiece" is used to call a wood piece cut from a plank. To determine which wood planks are applicable to be used in the initial cutting process, virtual dimensions of a product, i.e., the dimensions of MBB (w, h, and l) and the dimensions of the wood planks (W_i, H_i, and L_i) are compared. In justification of the applicability of a wood plank and determination of length of cut (l_c), the following "if-then-else" rules are used. In general, a 3-D workpiece has six faces comprising two faces of "w-l," two faces of "w-h," and two faces of "h-l." By rotating the workpiece around its principal axes, six different cutting methods (C_m) can be applied as shown in Fig. 8. For instance, if face l-h is chosen as the cross-section plane or the plane parallel to area of cut, w will be l_c. All of these scenarios are described in Table 1.

"if-then-else" rules

```
if{ (l< L_i) & (w< W_i) & (h< H_i)}
or if{ (l< L_i) & (h< W_i) & (w< H_i)}
or if{ (w< L_i) & (h< W_i) & (l< H_i)}
or if{ (w< L_i) & (l< W_i) & (h< H_i)}
or if{ (h< L_i) & (w< W_i) & (l< H_i)}
or if{ (h< L_i) & (l< W_i) & (w< H_i)}
then "The plank i is applicable to produce
the product."
else "It is not."
```

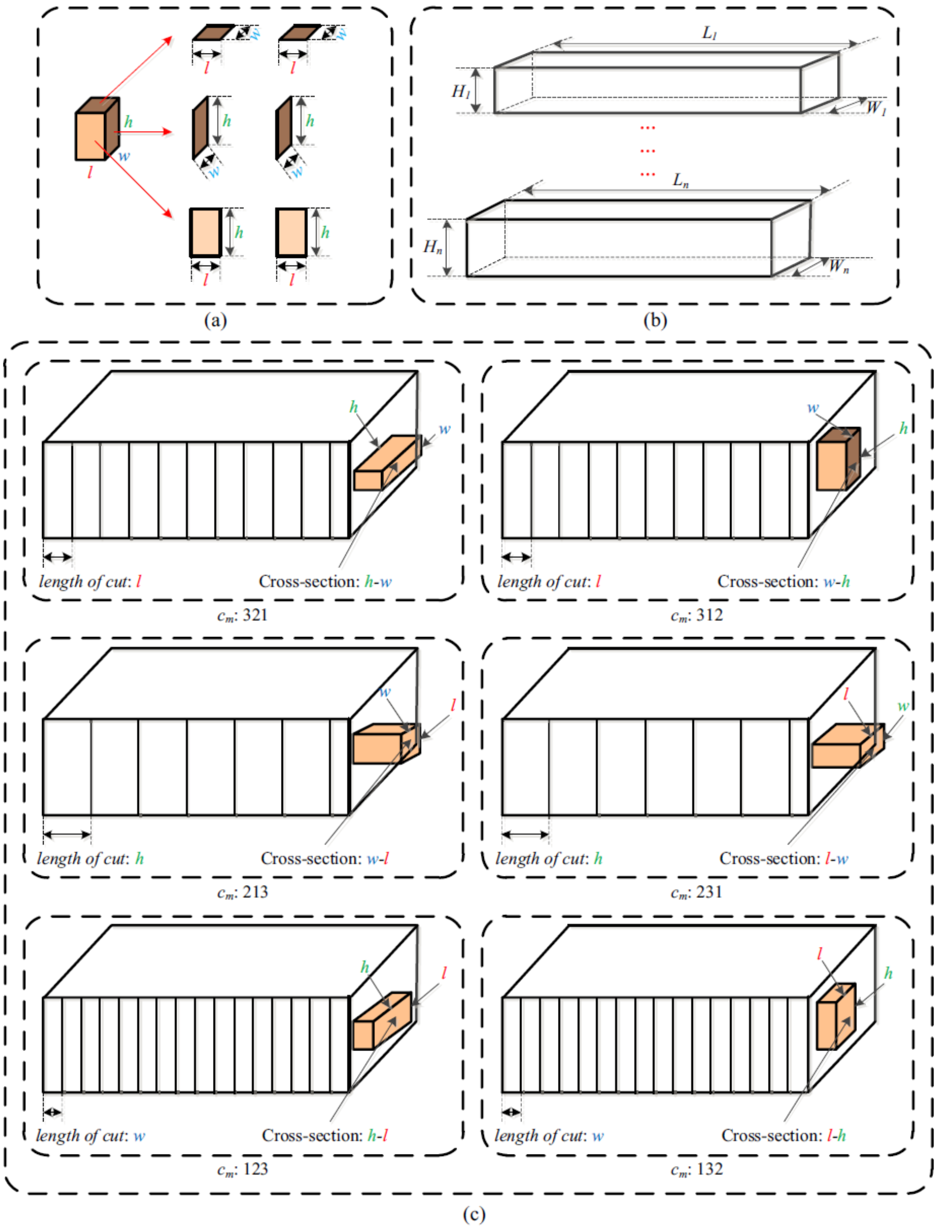

Fig. 8 **a** Six faces of MBB of the sample, **b** three dimensions of the wood planks (*W*, *H*, and *L*), and **c** a wood plank with varying cutting parameters

If at least one of these conditions is satisfied, the wood plank can be used to manufacture the product.

Once a list of applicable planks is established, the planks are brought into a virtual cutting process. Each cutting method is associated by different area of cut and length of cut, hence different material losses as shown in Fig. 8. Evaluation on the optimality of these cutting solutions will be described in the later section.

Table 1 Relationship between cross section and "*length of cut*"

Cutting method (C_m)	Cross-section plane	*Length of cut* (l_c)
132	*l-h*	*w*
231	*l-w*	*h*
321	*h-w*	*l*
123	*h-l*	*w*
213	*w-l*	*h*
312	*w-h*	*l*

3.3 An optimization module

3.3.1 Wood loss analysis

Loss is typically inevitable in manufacturing processes. Keeping it as minimum as possible will help reduce unreasonable production cost. To prevent excessive wood loss, cutting parameters must be deliberately chosen. Past company's records indicated that substantial loss of wood was found in the initial cutting and shaping processes as explained in the following sub-sections.

(a) Loss from shaping processes

In general, wood loss from shaping processes is the material removed from a wooden workpiece to become a product as shown in Fig. 9. As a result, the loss is apparently a difference between the volume of the workpiece and that of the product. The larger the workpiece, the greater the loss, when the same product is applied. The loss from shaping process ($LOSS_{sp}$) per workpiece can be obtained by Eq. (4):

$$\mathrm{LOSS}_{sp} = q\left(V_w - V_p\right) \tag{4}$$

(b) Loss from defects

Wood is natural material prone to defects of different kinds. Commercial quality of wood planks is graded (A, B, or AB grade) based on severity of wood defects. An "A" grade plank must have wood mass without any observable defects for at least 80 % of its total length and 60 % applied for "B" grade. "AB" grade, a combination of 60 % A and 40 % B grades, is widely used for producing industrial products (see Fig. 10).

In the initial cutting process, the plank is cut into pieces of the same length specified by a process planner. Pieces with defects if detected will be rejected causing excessive loss in this process. The non-defective items will be collected and further conveyed to shaping processes.

In this study, only defects on elongated surfaces are modeled to simulate material loss in the cutting process. There are three variables in the model, quantity of defects (QDs), position of defects (PDs), and size of defects (SDs) that are essential in expressing a pattern of defects on a plank. The simulation was developed according to Banks et al. [55]. Details of the defect model development can be found in [56]. Distribution functions of the random variables are plotted by MATLAB as shown in Fig. 11. Distribution parameters are listed in Table 2. Distributions reported herein were analyzed from 102 randomly collected planks of $25 \times 60 \times 1250$ mm in dimensions. It should be reminded that the distribution patterns may be deviated from what are shown here when planks of different grades and sources are in consideration.

3.3.2 A virtual cutting process

In the initial cutting process, the plank is assumed to be cut into pieces of the same l_c. Cutting positions are evenly marked along the plank. A randomly generated defect with the size of SD is virtually laid down at the PD. This simulation is repeated until the number of defects on the plank is equal to QD. Usability of a wood workpiece is determined by comparing cutting positions and defect boundaries. In Fig. 12, x_1, x_3, and

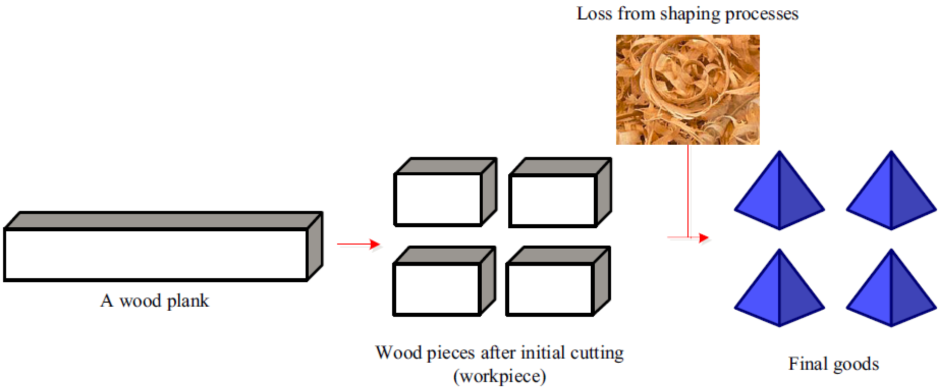

Fig. 9 Loss from shaping processes

Fig. 10 Wood defects

x_5 and x_2, x_4, and x_6 are the leftmost points and rightmost points of the simulated defects. Cutting positions are of this order:

$$e, l + t, 2l + t, \ldots\ldots, (n-1)*l + t, n*l + t$$

and

$$n = \text{floor}\left(\frac{L-2e}{l_c+t}\right) \tag{5}$$

Therefore, the left and right boundaries of wood pieces are

$$[e, e + l_c + t], [e + l_c + t, e + 2l_c + t], \ldots\ldots,$$
$$[e + (n-2)*l_c + t, e + (n-1)*l_c + t],$$
$$[(n-1)*l_c + t, n*l_c + t]$$

The piece will be considered defect-free if any parts of any defects are not found within. Defect-free wood pieces (q) are collected to compute the material loss from defects in Eq. (2).

3.3.3 Optimization functions

The optimization functions are formulated to identify cutting solutions leading to a minimum wood loss and minimum cost.

Minimum wood loss: If a scarcity of material supplies or environmental impact is a major concern, this objective function will gain attention. Impacts of loss or waste disposed from manufacturing processes are widely acknowledged, and more sustainable process planning is needed [57]. A total loss is a combination of loss from defects and loss from shaping; thus, the objective function can be formulated as in Eq. (6):

$$\text{Min LOSS}_{ij} = \text{LOSS}_d + \text{LOSS}_{sp} \tag{6}$$

$$\text{Min LOSS}_{ij} = \left(1-\left(\frac{q_{ij}*l_{cij}}{L_j}\right)\right)(W_j*H_j*L_j) + q_{ij}(V_{wij}-V_p) \tag{7}$$

where $V_{wij}=l_{cij}*W_j*H_j$, that is the volume of a workpiece obtained from cutting method i on the plank j.

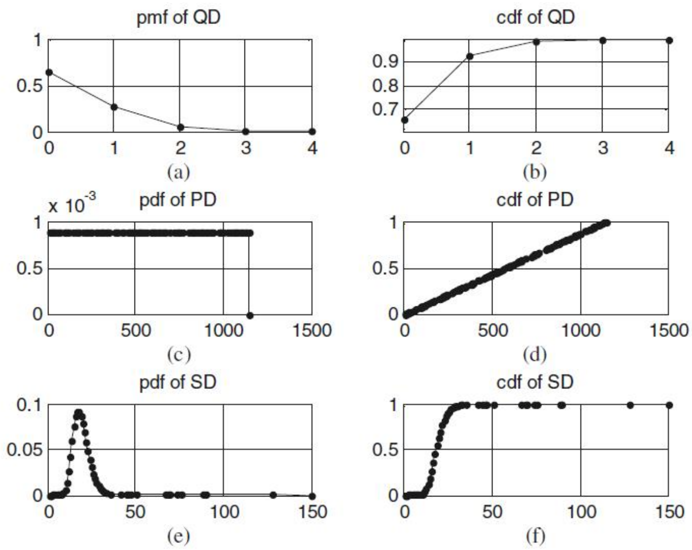

Fig. 11 Probability mass function (pmf) or probability density function (pdf) of QD, PD, and SD and cumulative distribution function (cdf) of QD, PD, and SD: **a** pmf of QD, **b** cdf of QD, **c** pdf of PD, **d** cdf of PD, **e** pdf of SD, and **f** cdf of SD

Table 2 Distributions of quantity of defects (QDs), position of defects (PDs), and size of defects (SDs) [56]

Variable	Distribution	Abbreviation
QD	Poisson distribution	$q \sim P$ (0.43)
PD	Uniform distribution	$p_x \sim U$ (13.50, 1152.50)
SD	Lognormal distribution	$s \sim LN$ (2.92, 0.24)

Minimum cost: Cost is always a key determinant of production efficiency in a business manufacturing company. Under normal circumstances, manufacturers are willing to adopt every solution to keep their production cost down. Cost herein means a cost per workpiece or a unit cost. In our model, it is simply derived from cost per wood plank divided by the number of usable (defect-free) pieces.

$$\text{Min } C_{uij} = \frac{C_{wj}}{q_{ij}} \tag{8}$$

4 Results and discussions

The wood product "horse" as shown in Fig. 5 was used in this experiment to evaluate performance of the proposed system. It had a volume of 43,643 mm^3, and its MMB had dimensions of 23, 46, and 55 mm in width, length, and height, respectively. Two hundred and seventy two out of the total of 733 wood planks were accounted as applicable (Table 3). Note that some planks can be registered as applicable with more than one cutting method. If they are not applicable, NA is shown.

4.1 An optimal plan

Defects were simulated on all 272 applicable planks according to the procedure explained in Sect. 3.3.2. The number of defective pieces could be determined from the simulation. When it was subtracted from the total number of wood pieces (n), the number of non-defective or usable pieces resulted. Table 4 shows an average number of usable wood pieces gained from 250 simulation runs (remark t=3 mm, e=50 mm).

From the table, a cutting plan satisfying the first objective function (minimum wood loss) is the plank no. 391 cut by the 312 cutting method, i.e., the plank with a_c of 1058 mm^2 and l_c of 55 mm. But if cost is more of a concern than the loss of material, the plank no. 412 with the 213 cutting method (a_c of 1265 mm^2 and l_c of 46 mm) must be chosen. This cutting method allows the plank no. 412 to be cut into more number of wood pieces (18). Once this number is deducted by the number of defective pieces, the number of usable pieces (16) resulted. Its price is less expensive than the plank no. 391, with more number of pieces obtained. This plank is even more fitted to the second objective function. It can be seen that a cutting plan satisfying the first objective function (minimum wood loss) does not necessarily satisfy the second function (minimum cost). The second function is sensitive to market prices of the planks where the first one is less dynamic. The plans from both functions can be coincident, but if not, one of them must be chosen depending on business policies of the factory.

4.2 Performance of the models

Performance of the proposed model was evaluated against its contender, i.e., the parametric model. The

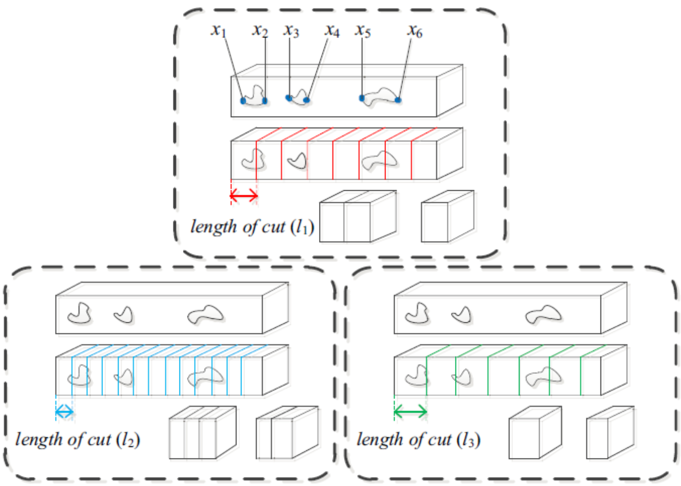

Fig. 12 Applying different cutting methods ending in different number of defect-free pieces

Table 3 A list of wood planks that are applicable for producing "horse"

Plank no.	C_w	W (mm)	H (mm)	L (mm)	C_m
1	3.47	15.88	15.88	1000.00	NA
2	9.73	15.88	44.45	1000.00	NA
3	11.12	15.88	50.80	1000.00	NA
…	…	…	…	…	…
391	28.68	25.00	48.00	1000.00	312
392	31.14	25.00	50.00	1000.00	312
393	28.68	25.00	51.00	1000.00	312
394	33	25.00	55.00	1000.00	312
395	37.78	25.00	60.00	1000.00	213, 312
…	…	…	…	…	…
412	16.77	25.40	57.15	1000.00	213, 312
…	…	…	…	…	…
698	69.15	55.00	70.00	1000.00	123, 213, 312, 321
…	…	…	…	…	…
733	136.80	101.60	101.60	1000.00	132, 123, 213, 231, 312, 321

defect-induced loss (obtained from Eq. (2)) and unit material cost (obtained from Eq. (3)) from both models are compared with actual data. The comparison is made on only loss from defects because the past models did

Table 4 Results of the defect simulation model

Plank no.	C_m	l_c (mm)	n (piece)	q (piece)	$LOSS_{sp}$ (mm^3)	$LOSS_d$ (mm^3)	LOSS (mm^3)	C_u
…	…	…	…	…	…	…	…	…
391[a, b, c]	312	55	15	13	290,641.00	342,000.00	632,641.00	2.21
392	312	55	15	13	326,391.00	356,250.00	682,641.00	2.40
393	312	55	15	13	344,266.00	363,375.00	707,641.00	2.21
394	312	55	15	13	415,766.00	391,875.00	807,641.00	2.54
395	213	46	18	16	405,712.00	396,000.00	801,712.00	2.36
	312	55	15	13	505,141.00	427,500.00	932,641.00	2.91
…	…	…	…	…	…	…	…	…
412[d]	213	46	18	16	370,096.96	383,225.04	753,322.00	1.04
	312	55	15	13	470,542.15	413,708.85	884,251.00	1.28
…	…	…	…	…	…	…	…	…
698	123	23	34	31	1,392,117.00	1,104,950.00	2,497,067.00	2.23
	213	46	18	16	2,135,312.00	1,016,400.00	3,151,712.00	4.32
	312	55	15	13	2,185,391.00	1,097,250.00	3,282,641.00	5.32
	321	55	15	13	2,185,391.00	1,097,250.00	3,282,641.00	5.32
…	…	…	…	…	…	…	…	…
733	132	23	34	31	6,007,052.28	2,962,574.72	8,969,627.00	4.41
	123	23	34	31	6,007,052.28	2,962,574.72	8,969,627.00	4.41
	213	46	18	16	6,899,116.16	2,725,155.84	9,624,272.00	8.55
	231	46	18	16	6,899,116.16	2,725,155.84	9,624,272.00	8.55
	312	55	15	13	6,813,271.40	2,941,929.60	9,755,201.00	10.52
	321	55	15	13	6,813,271.40	2,941,929.60	9,755,201.00	10.52

[a] A plan with minimum wood loss from shaping process

[b] Minimum wood loss from defects

[c] Minimum total wood loss

[d] A plan with minimum unit cost

Table 5 Comparison between defect-induced losses and unit costs from two models and actual data

Plank no.	C_m	l_c	$LOSS_d$ (mm^3)			C_u			Percent difference in wood loss from Act. Data		Percent difference in unit cost from Act. data	
			Act.	Simu.	Para.	Act.	Simu.	Para.	Simu.	Para.	Simu.	Para.
…	…	…	…	…	…	…	…	…	…	…	…	…
391	312	55	342,000.00	342,000.00	210,000.00	2.21	2.21	1.91	0	−38.60	0	−13.57
392	312	55	356,250.00	356,250.00	218,750.00	2.40	2.40	2.08	0	−38.60	0	−13.33
393	312	55	363,375.00	363,375.00	223,125.00	2.21	2.21	1.91	0	−38.60	0	−13.57
394	312	55	391,875.00	391,875.00	240,625.00	2.54	2.54	2.20	0	−38.60	0	−13.39
395	213	46	396,000.00	396,000.00	327,000.00	2.36	2.36	2.22	0	−17.42	0	−5.93
	312	55	427,500.00	427,500.00	262,500.00	2.91	2.91	2.52	0	−38.60	0	−13.40
…	…	…	…	…	…	…	…	…	…	…	…	…
412	213	46	383,225.04	383,225.04	316,450.98	1.04	1.04	0.98	0	−17.42	0	−5.77
	312	55	413,708.85	413,708.85	254,031.75	1.28	1.28	1.11	0	−38.60	0	−13.28
…	…	…	…	…	…	…	…	…	…	…	…	…
698	123	23	1,016,400.00	1,104,950.00	927,850.00	2.16	2.23	2.1	+8.71	−8.71	+3.24	−2.78
	213	46	1,016,400.00	1,016,400.00	839,300.00	4.32	4.32	4.07	0	−17.42	0	−5.79
	312	55	1,097,250.00	1,097,250.00	673,750.00	5.32	5.32	4.61	0	−38.60	0	−13.35
	321	55	1,097,250.00	1,097,250.00	673,750.00	5.32	5.32	4.61	0	−38.60	0	−13.35
…	…	…	…	…	…	…	…	…	…	…	…	…
733	132	23	2,725,155.84	2,962,574.72	2,487,736.96	4.28	4.41	4.15	+8.71	−8.71	+3.04	−3.04
	123	23	2,725,155.84	2,962,574.72	2,487,736.96	4.28	4.41	4.15	+8.71	−8.71	+3.04	−3.04
	213	46	2,725,155.84	2,725,155.84	2,250,318.08	8.55	8.55	8.05	0	−17.42	0	−5.85
	231	46	2,725,155.84	2,725,155.84	2,250,318.08	8.55	8.55	8.05	0	−17.42	0	−5.85
	312	55	2,941,929.60	2,941,929.60	1,806,448.00	10.52	10.52	9.12	0	−38.60	0	−13.31
	321	55	2,941,929.60	2,941,929.60	1,806,448.00	10.52	10.52	9.12	0	−38.60	0	−13.31

Act.=actual data (wood loss and unit cost), Simu.=simulation model, and Para.=parametric model

not mention loss from shaping processes. Also, derivation of the latter seems straightforward, and it is likely that all models will share the same amount. Results of the comparison are tabulated in Table 5. It can be seen that resultant wood loss and costs estimated from the simulation and parametric model are fluctuated around the actual values. However, the results from the simulation model indicated much less variation. They swing within less than 8.71 and 3.04 % around the actual wood loss and costs. While compared with those from the parametric model, their maximum difference could be as high as 38.60 % in wood loss and 13.57 % in unit cost, respectively. The plus and minus signs indicate overestimation and underestimation of costs. Although overestimation may sound less catastrophic, it imperils business competitiveness. Prices will be unreasonably set high above the inaccurate cost. On the other hand, impacts of cost underestimation would lead the business toward financial losses. Accurate product cost estimation would certainly play a crucial role in maintaining enterprise competitiveness.

5 Conclusion

Establishment of a cutting plan, currently performed by human operations, may arrive at a non-optimal cutting plan due to subjectivity of human perception under existing material quality uncertainty. In wooden product manufacturing, defects in wood play a crucial role in determining material cost. When defects come in at random, planning for a material requirement as well as cost estimation becomes more complicated. The automated cutting planner proposed in this study is able to generate a set of feasible plans that lead to the identification of the optimal one. Results showed that quantification of loss using the defect model based on a probability theory employed herein is more accurate than the previously reported models. However, reevaluation of the defect distribution models is needed with changes in size, grade, and source of the planks.

Once the cutting plan is finalized, cost can be estimated and this information can be used in setting marketing and management policies. The automated approach proposed here could help accelerate and facilitate communication and production in a mass customization environment.

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