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A New Methodology for Evaluation of Worker Performance in the Manufacturing Process

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Doctoral Dissertation

A New Methodology for Evaluation of Worker Performance in the Manufacturing Process

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Abstract

The production environment has a lot of revolutions in recent decades, with most companies taking part in mass customization production. The style of products, quality requirements from customers, materials, and even the machines involved in manufacturing are evolving quickly and orders are decreasing in size. In this situation, the employee is the important factor that determines the productivity and quality of product in a production process. This is why the selection of the right workers for operating tasks in an assembly line is always an important question, especially today because many tasks are becoming increasingly complex, as they must deal with the development of technologies, materials, and machines in the manufacturing process. If a task is more complex, the worker needs more skill and time to finish it. For all of the main purposes of the manufacturing enterprise, such as planning and scheduling, operators training or line balancing, the main requirement is almost always on predicting operator performance.

In a manufacturing process, the performance of the worker can be identified as their ability to accomplish a task based on the expectations of a standard. To determine how well a worker performs their job, various performance evaluation techniques can be used, such as the Synthetic Rating, Pace Rating method or the Westinghouse system. These methods have been applied recently to calculate operator performance ratings. The three traditional performance methods just apply effectively in the manufacturing process that the workstation is designed well. In these contexts, the manufacturing scheduling is completely based on machine capacity and the task characteristics remain consistent between customer's requirements. This makes it simple to set up standards to compare orders. Additionally, the impact of employee performance on production capacity is accounted for by very large orders. That is, workers have adequate time to meet the target performance, so production managers are not concerned with calculating operator skill level and task complexity to predict whether a worker's performance capacity is best suited to a specific task. Further, in this conventional context, operator skills are learned and improved through comprehensive, industry standard training, and skill are enhanced gradually through precise, continuous repetitions of work processes. However, in the new manufacturing environment, the worker's performance results from the interaction between the skill levels of workers and the fluctuation of the characteristics of tasks. The new and changing environment of the manufacturing industry, however, means that the usual ways of allocating workers tasks are less effective at forecasting workers' performance requirements. Moreover, such outdated approaches also lack success in driving workers to gain and master the new skills required to enhance quality and productivity. In addition, managers base their decisions only on their previous experience without the support of a systematic knowledge base. They merely observe the operation of workers and evaluate their performance based on subjective judgments. The accuracy of these judgments will mainly be dependent on the amount of experience the manager possesses.

My research proposal aims to propose a new methodology for the prediction of worker performance in manufacturing that is capable of effectively handling multiple factors of both a quantitative and qualitative nature that involve uncertainty and imprecision. Firstly, a methodology for evaluating worker skill levels is devised with the combination of the Delphi method, the principal component analysis and the ordinal logistic regression. Secondly, this research presents a method that combines the Analytic hierarchy process and Proportional 2-tuple linguistic representation model to evaluate the level of complexity of tasks in the manufacturing process. With regard to how the worker skill level and the complexity level of a task is evaluated, this research will pay closer attention to analysis of the relationship between task complexity and worker skill level, to clearly understand the interaction between them in order to predict the performance of workers. The newly developed methodology will be illustrated with a case study in the clothing industry to demonstrate its practical applicability in industrial contexts.

Keywords: worker's performance, skill level of worker, task complexity, decision support technique, rule-based support system.

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Chapter 1

Introduction

Section 1.1 introduces the background to my research. Section 1.2 outlines my research motivations and goals. The ways this research contributes to the wider field are detailed in Section 1.3. Lastly, Section 1.4 provides the structure of this thesis.

1.1 Background

The manufacturing environment has changed drastically in recent decades, with most companies taking part in mass customization production [1]. Product designs, customer quality requirements, materials, and even equipment now change at a rapid pace. Customer's orders are constantly decreasing in size. Further, today's customers have more demands than previously in terms of product quality, cost, and delivery time: these must be higher, lower, and non-negotiable with a significant penalty given for any delay, respectively. Due to these changes, workers in an assembly line are required to learn a lot of new tasks far more frequently. As product cycle times and production runs compress, workers require constantly updated skills, technologies, and processes to align with the altered pace.

The most important factor in the manufacturing process for predicting the effectiveness of an assembly line is the worker's performance. When setting up an assembly line, worker's performance is often chose with care to complete tasks using a range of measures, including standard productivity, quality requirements, task natures, and skill level requirements [2]. Of these, skill level of worker and task characteristics are the factors that receive the most consideration when assigning or re-assigning workers to a task.

A mixture of employee skill level and nature of task determines operator performance. To figure out how well workers might complete a task, performance evaluation methods are often adopted. In recent times, several such techniques have been used to systematically set out worker performance ratings. These include the Speed rating method, the Synthetic Rating, and the Westinghouse system. The only factor considered by the Speed rating method is the employee's speed operation. To determine this, the manager detects the speed with which the worker operates and measures this against the level expected. In doing so, they are able to consider the link between the two to determine the rating speed factor, which can be used for various factors. However, the expected level of speed is purely based on the manager's subjective judgment: there is no overarching benchmark. Conversely, in the Synthetic Rating method, there are values already decided by a Predetermined Motion time system, against which the employee's performance is rated accordingly. A time study is performed as normal and then the times recorded for each element of the task are measured against the predetermined standards. Then, a ratio is calculated between these two values and the average ratio is determined [3].

The Westinghouse system is the most commonly employed operator performance rating system. It allows production managers to approximate operator performance, thus enabling them to predict production capacity. Four factors are used to inform the rating: skill, effort, worker consistency, and work conditions. To ascertain a worker's skill factor, their proficiency rate when completing the job is measured. This reflects a combination of the worker's mental and physical aptitude in performing the operation. The effort factor refers to the employee's mindset and willingness to perform effectively. The worker's effort should be measured according to the efficacy of the task towards which this effort is focused. Sometimes, workers complete tasks rapidly but in a careless manner, leading to a heightened defect rate. Consistency reveals the method and rhythm with which the worker performs the job, ideally at a steady speed. The Westinghouse system's final factor, work conditions, identifies and measures the environmental aspects that might impact a worker's job, such as ventilation, temperature, lighting, and noise. Within the Westinghouse system, there are six classes for each factor. For example, work conditions comprises of ideal, excellent, good, average, fair, and poor. Each class is separated by one degree. In determining the work conditions, managers take into consideration temperature, lighting, ventilation, and noise, and then allocate it into the appropriate class. Once the Westinghouse system has been used to designate the class, the rating is converted into its corresponding percentage value, ranging between +6% to 7%. A similar methodology is used to calculate the ratings for skill, effort, and consistency. The ratings, including each of the four factors, are the combined to form the final worker performance rating. In this way, managers are able to ensure operator performance properly aligns with production unit productivity and quality targets.

These methods have been applied recently to calculate operator performance ratings. The three traditional performance methods just apply effectively in the manufacturing process in a well-designed workplace. In these contexts, production scheduling is completely based on machine capacity and the task characteristics remain consistent between customer's requirements. Additionally, the impact of operator performance on production capacity is accounted for by very large orders. That is, workers have adequate time to meet the target performance, so production managers are not concerned with calculating operator skill level and task complexity to predict whether a worker's performance capacity is best suited to a specific task. Further, in this conventional context, operator skills are learned and improved through comprehensive, industry standard training, and skill are enhanced gradually through precise, continuous repetitions of work processes.

Yet the manufacturing environment has shifted significantly due to mass customization production. Product designs, customer quality requirements, materials, and even the equipment involved in manufacturing are evolving quickly and orders are decreasing in size. Further, today's customers have more demands than previously in terms of product quality, cost, and delivery time: these must be higher, lower, and non-negotiable with a significant penalty given for any delay, respectively. Due to these changes, the old methods for assigning workers to tasks have become outdated. They can no longer precisely forecast workers' performance needs and so are less useful in planning the work. Such methods have also failed to drive workers to improve their and adopt new ones, both of which are key for enhancing quality and productivity. In this new manufacturing environment, the worker must learn and adapt quickly to the growing customer requirements and the speed with which the company implements these new processes [4]. Worker performance should be estimated and predicted based on the interaction of task characteristics, worker skill level, and environment functions.

1.2 Research Motivation

My research proposal aims to develop a new methodology for evaluation of worker performance in manufacturing that is capable of effectively handling multiple factors of both a quantitative and qualitative nature that involve uncertainty and imprecision. Firstly, I propose a new method for grading operator skill levels. Secondly, this research presents a method to evaluate the level of complexity of tasks in the manufacturing process. With regard to how the worker skill level and the complexity level of a task is evaluated, this research will pay closer attention to analysis of the relationship between task complexity and worker skill level, to clearly understand the interaction between them in order to predict the performance of workers. The newly developed methodology will be illustrated with a case study in the clothing industry to demonstrate its practical applicability in industrial contexts. The research process is shown in Figure 1.1. In the first step, I develop a method for grading operator skill in the manufacturing process. The key results of applying the ordinal logistic regression method showed that three formulas could grade and predict worker skill level through three independent variables. Additionally, I have proposed an approach to evaluating the task complexity using the AHP and Proportional 2-tuple linguistic methods. Finally, I pay closer attention to analysis of the relationship between task complexity and worker skill level, to clearly understand the interaction between them for predicting the performance of worker based on the rule-based systems.

1.3 Research Contributions

This thesis contributes by:

- Proposing a new way of grading employee skill level in the production industry that equips managers to devise a skill level scale for their manufacturing process, inform skill evaluators, and to assess and oversee operator's skill level and skill development.
- Determining the complexity of task in an assembly line through evaluating how

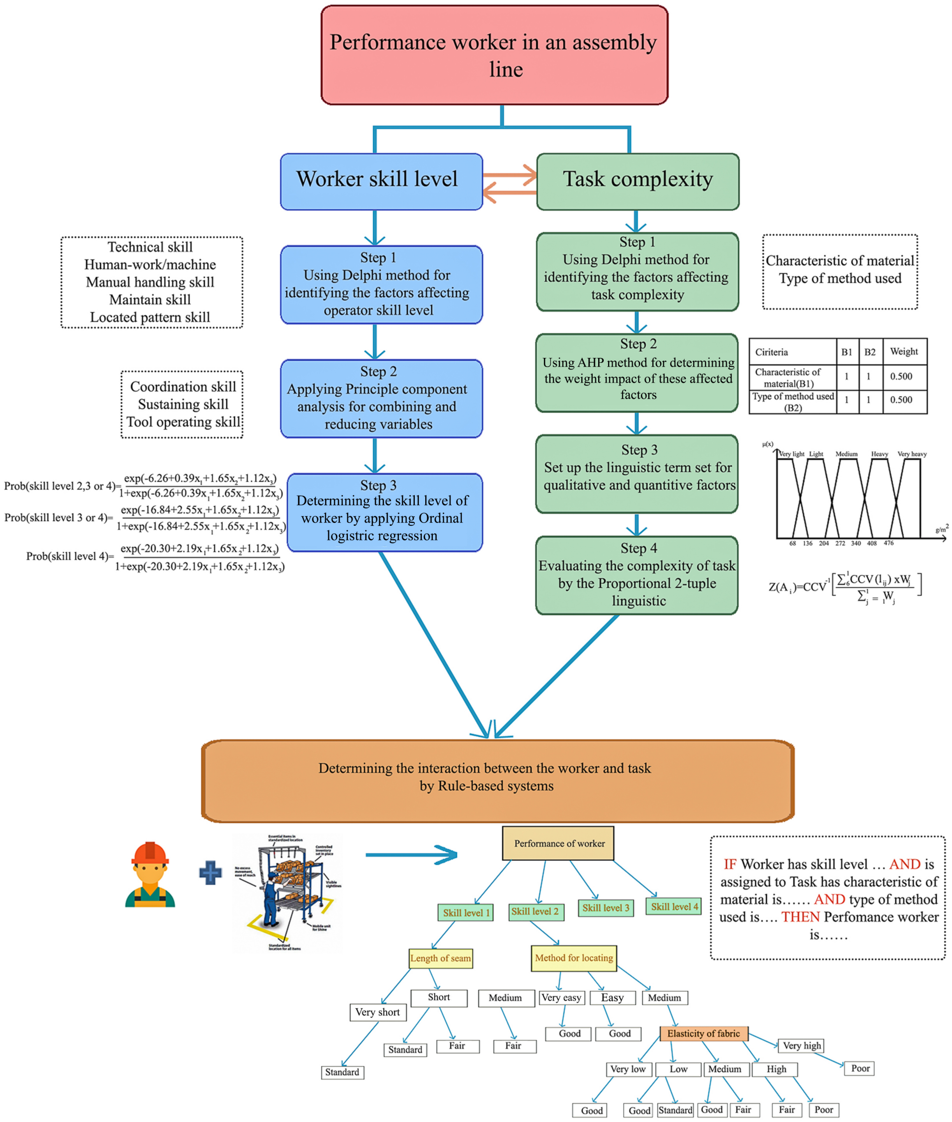

Figure 1.1: The research process.

these sub-factors impact on the complexity level. This result can be applied to assigning or reassigning workers in the assembly line. The proposal approach takes into consideration a great deal of decision-makers' ambiguities, uncertainties, and vagueness in evaluating task complexity level.

- Providing relevant data about the performance of workers for determining manufacturing scheduling, estimating time standards, and setting labor costs during the manufacturing process.

1.4 Thesis Outline

The rest of this thesis is organized as follows:

- Chapter 2: Literature review—this chapter summarizes the previous result of research in related fields. In addition, it compares the previous research to the value provided by the unique and innovative approaches used in my research.

- Chapter 3: Grading operator skill using Principal component analysis and Ordinal logistic regression—this chapter presents a new method for grading operator skill levels based on the Delphi method, the principal component analysis, and the ordinal logistic regression method.

- Chapter 4: Evaluation model for the complexity level of tasks in an assembly line based on AHP and Proportional 2-tuple linguistic—this chapter presents a method that combines the Analytic hierarchy process and the Proportional 2-tuple linguistic representation model to evaluate the level of complexity of tasks in the manufacturing process.

- Chapter 5: Predicting operator performance by interaction between operator skill level and task complexity—this chapter pays closer attention to analysis of the interaction between the complexity of task and operator skill level, to clearly understand the interaction between them and determine operator performance.

- Chapter 6: Conclusion—this final chapter summarizes the new results of my research and discuss the development of research in the future.

Chapter 2

Literature Review

The previous results in the related field is summarized in this chapter. In addition, the unique innovative points that constitute the value of my research are compared with the previous research.

2.1 Worker's performance measurement methods

In the manufacturing environment, the worker's performance measurement is an important issue that is often considered. Neely defined a system for measuring the performance include a set of metrics applied to determine both the efficiency and effectiveness of activities [5]. A worker's performance could be measured in various dimensions that are defined in term of quality, time, cost, reliability, and flexibility [6]. In my research, I consider the worker's performance measurement in term of the completion time of the task. The completion time of the task is described as a key of competitive advantage as well as a fundamental measure of manufacturing performance [7]. Under the just-in-time production environment, if a product's production or delivery time is too late or too early, that is labeled as waste.

2.1.1 Westinghouse System Method

One of the oldest and most widely used systems for determining worker performance is the one developed at the Westinghouse Electric Corporation; it was originally published in 1927 [8]. The Westinghouse method examines four factors, including skills, effort, conditions and stability to assess worker performance, as shown in Table 2.1 .

Table 2.1: The Westinghouse system.

Skill			**Effort**		
+0.15	A1	Superskill	+0.13	A1	Superskill
+0.13	A2		+0.12	A2	
+0.11	B1	Excellent	+0.10	B1	Excellent
+0.08	B2		+0.08	B2	
+0.06	C1	Good	+0.05	C1	Good
+0.03	C2		+0.02	C2	
0.00	D	Average	0.00	D	Average
-0.05	E1	Fair	-0.04	E1	Fair
-0.10	E2		-0.08	E2	
-0.16	F1	Poor	-0.12	F1	Poor
-0.22	F2		-0.17	F2	
Consistency			**Work condition**		
+0.04	A	Perfect	+0.06	A	Ideal
+0.03	B	Excellent	+0.04	B	Excellent
+0.01	C	Good	+0.02	C	Good
0.00	D	Average	0.00	D	Average
-0.02	E	Fair	-0.03	E	Fair
-0.04	F	Poor	-0.07	F	Poor

- Skill: the proficiency or mastering capacity when performing a given method, whereby the skill is related to the professional competence of the worker. It demonstrates the ability to combine mind and limbs. The operator's experience and innate ability, including their inherent coordination and flow, determines their level of skill. Skill is usually enhanced by practice, however this can not completely counteract a lack of natural ability.

- Effort: an expression of the manner of the employee in their readiness to work well. When judging a worker's effort, managers should consider the effectiveness of the task towards which this effort is concentrated. Sometimes, workers complete tasks hastily without adhering to the rules, resulting in a heightened defect rate.

- Consistency: the sequence and frequency with which worker operations in the task are repeated at a steady speed.

- Work condition: the environmental factors impacting the worker's performance, including temperature, lighting, ventilation, and noise.

The Westinghouse system comprises six classes for each factor. The work conditions classes are: ideal, excellent, good, average, fair, and poor, with one degree between each. Managers consider temperature, lighting, ventilation, and noise, which are then categorized into the six classes. The Westinghouse system approximates the corresponding percentage value of each class of work conditions, so the rating is converted accordingly, ranging from +6% to -7%. The ratings for skill, effort, and consistency are similarly calculated. The final worker performance rating is estimated by a combination of the ratings with respect to each of the four factors. For example, when a worker operates a task, if the production manager observes and rates *the worker's skill* as $C1$, *effort* as $B2$, *consistency* as good, and *work condition* as fair, then the rating factor is:

$$1.00 + (0.06 + 0.08 + 0.01 - 0.03) = 1.12$$

The overall worker's performance rating is about 12% faster than for the average operator. This method enables production managers to adjust employee performance with productivity and quality objectives in their production units. However, in the Westinghouse system, the characteristics of the average operator are not previously established. The production managers determine skill, effort, consistency, and work condition based on their experience; they may not necessarily be able to explain why they assigned the worker's performance this value.

2.1.2 Synthetic Rating Method

A non-subjective system is the Synthetic rating method, which analyzes an operator's speed based on predetermined time systems, creates a performance rating of workers. The system, developed by Morrow and based on time data developed by Barnes et al C in 1937, provides consistent results [9]. One of the significant Predetermined time systems is the MTM (Methods - Times Measurement) system, which is actually a "family" of systems operating at different levels and applicable to different types of work. The MTM time calculation method is a system method of predetermined time values. The activities of work are analyzed as basic motions. Each basic motion has a predetermined standard time value. Based on this, the setting of the standard time required for operations is carried out. Because the activity-to-basic motion analysis is very small, the MTM method does not use the conventional time measurement unit but the Time Measurement Unit (TMU) for high accuracy.

The MTM method analyzes human activities into 20 basic motions, including 9 hands, 9 legs and trunk motions, and 2 eye motions. They are the basis for establishing methods of performing any human activity. For example, MTM separates these motions for finger such as reach, grasp, move, position, and release, as shown in Figure 2.1.

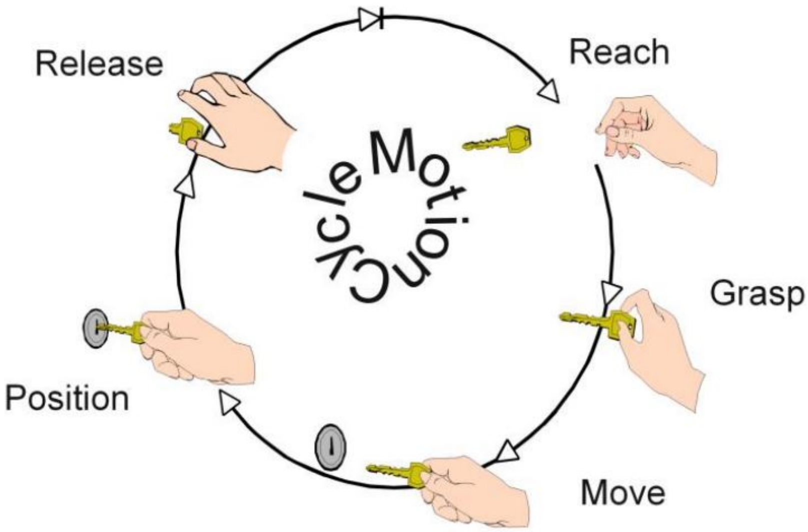

Figure 2.1: Five basic motions of the finger.

To use this system, conduct a time study in the normal manner, and then measure the actual time for as many motions as possible against the time values that were predetermined as standard for the same motions. Then, calculate a ratio between the actual time value for that task and the predetermined time value for the task. To calculate the performance rating factor, use the following formula:

$$R = \frac{A}{P} \tag{2.1}$$

where R : performance rating value

A : the average value of actual time (selected time) for the same activity, minutes

P : predetermined time for the activity, minutes

In this method, only the amount of worker's motion is considered. In the manufacturing process, however, there are many specific parameters that influence a worker's speed motion. For example, in the *Grasp* motion, the size of the product will be deeply impact the speed of workers. If the characteristics of the task and the work conditions are not properly considered, the worker's performance will not be measured accurately.

2.1.3 Pace Rating

'Pace Rating' is a term used by some companies, such as U.S. Steel Corporation, to label the system of performance in operation. The technique not only includes many of the notions around effort rating, but also two other devices to support the person performing the rating and to broaden its application. By acknowledging that all tasks are not conducted at the same pace, this system ensures the concept of a normal speed is relevant to the specific type of work under consideration. When a time study analyst is considering tasks limited to one type or a few, the standards or normals would be correspondingly limited. A set of benchmarks has been developed for various types of work in order to ensure uniformity for all analysts. Specific rate of production are the quantification of these benchmarks. For example, one standard is: walking on a flat surface, without load, at X miles per hour. These standards can be replicated or viewed on film and can thus offer an objective analysis of the pace described. A performance percentage is calculated that is expressed as above, below, or at normal. The ratio or factor is then used on the relevant time for the element. Qualified and well-trained operators are carefully studied in order to lessen the impacts of other variables.

2.2 Disadvantage of previous methods

Previous methods for measuring worker performance have some disadvantages, such as:

- They only consider the worker's qualifications, but do not analyze the interaction between the worker's qualification and the fluctuation of the characteristics of the task.

- They determine the performance of the worker through a comparison with an average worker, but do not devise a standard for the average worker; instead, the production managers determine the worker's performance through their subjective experience.

- In the manufacturing process, predicting the operator's performance is very important, but of the three most prominent methods, only the Synthetic rating method can be used to make such predictions. Even still, the accuracy of such predictions is not high because they do not consider how specific parameters impact on worker's speed motion.

- These systems were designed for application in the environment of a centralized economy, mass production, technology-oriented production, and a well-designed workplace. In such an environment, production planning can be solely and adequately based on machine capacity; there is no need to predict operator performance. The influence of operator's performance on production capacity is fully compensated with very large orders for which operators have enough time to reach target performance.

Today, in the new manufacturing environment with the rapid change in design and quality of products, equipment, and materials, and decreasing numbers of products in orders, it is very difficult to develop a general standard for all industrial sections. Therefore, the performance of the worker should be determined through the interaction between the skill level of the worker and the nature of the task. My research proposal aims to develop a new methodology for predicting worker's performance in manufacturing that is capable of effectively handling multiple factors of both a quantitative and qualitative nature that contain uncertainty and imprecision. I aim to achieve this through devising a rule-based system that describes the interaction between the skill level of the worker and the characteristics of the task. In the following chapters, I will discuss the progress of my research in detail.

Chapter 3

Grading Operator Skill Using Principal Component Analysis and Ordinal Logistic Regression

In this chapter, we presents a new method for grading operator skill levels based on the Delphi method, the principal component analysis and the ordinal logistic regression method

3.1 Introduction

Nowadays, in manufacturing, the worker is the most crucial determinant of the standard and output of an assembly line. Each worker has a certain ability to operate task in an assembly line. Commonly, workers are selected to perform tasks based on various performance benchmarks, such as target productivity, cross-training programs, task characteristics, and skill level [10]. These factors influence the worker's ability to receive, learn knowledge to improve proficiency and eliminate redundant motions that create the better quality products. Therefore, when production managers allocate worker to task, they should get attention about the suitability of workers for the assigned work. The factor that gains the most prominence when assigning or reassigning workers to a task is skill level. The degree to which a worker has "mastered" a skill determines their perceived operator skill in completing a task. The better the worker has mastered the relevant skill, the less time is needed to perform it and the greater the standard of the output. Operator skill level represents the previous experience that contains all the knowledge or skills which operators acquired through the learning, training and working process before the starting of a job. In production, the transfer of knowledge and skills from the old tasks to new ones often happens. The skill or knowledge primarily consists in choosing the correct method for each situation and the transfer of knowledge or skills from one task to other happened when the operating method of the old task is suitable for the new task. However, much of this transfer depends on the standards chosen rather than on the similarity in method between jobs.

The methods previously used to grade the performance of operators are no longer relevant. They are not as effective in measuring operator skill level, meaning they are not as useful in getting operators to learn new skills or enhance skill mastery, limiting improvements to quality and productivity. Over-reliance on a manager's individual judgment makes such assessments overly subjective. Further, variation in skill levels are not clearly expressed by such systems. For example, if two levels are quite close, it becomes very difficult to ascertain the level at which the worker should be categorized and the production managers also could not explain clearly why they assigned this worker to this skill level.

To solve this issue, this chapter offers a new methodology for assessing worker skill levels based on the Delphi method, the principal component analysis and the ordinal logistic regression method. The sewing assembly line is the context for this proposal. This innovative approach to grading worker skill level will assist managers in the manufacturing industry to create a skill level scale for their production unit, educate skill evaluators, and manage the skill level and development of all operators.

3.2 Preliminary Methods

3.2.1 Delphi method

The Delphi method was developed by the Rand Corporation in the early 1960s. This method consist of a group of implementation processes to ensure a high consensus in determining and predicting the future events from the consultation with experts. This method collects the knowledge of experts in the different expertise fields to build a forecast

[11–13]. This method was developed based on two propositions:

- Experts participate in the Delphi panel that can reach consensus answer on a question in their field of expertise, answers are collected by the expert group's knowledge, and the result will be better than that reached by a single expert;
- The personality dominance that could interfere the independent judgment of individual experts in face-to-face interaction have to eliminated; anonymity is required in the sense that no one knew who else was participating.

Delphi method implementation requires three conditions [14]:

- The Delphi questions that are the subject of elaboration may be of any sort that involves judgment;
- The experts participate in the Delphi panel that reach the high level of practical experience or intimate knowledge to answer questions;
- In the Delphi process, the personality-independence of expert ideas should be ensured.

The Delphi method is also the subject of many critics; it depends on the experience level and responsibility of individual experts, so this method is limited when applied. To ensure effective prediction, it is necessary to combine with a quantitative method, such as the predictive mathematical model and then use the experience of the administrator to adjust accordingly. However, it is the best method to support a group to make a decision based on group consensus [15]. Today, the Delphi method has been commonly used in public health, educational and manufacturing researches. In addition, the application of the Delphi method is to facilitate group consensus and support in generating the creative ideas [16].

3.2.2 Principal Component Analysis

Principal component analysis is one of the simplest methods of analyzing data [17] that the new variables are a linear combination of the old variables that are not interrelated [18], if there are 100 initial variables that are linearly correlated with each other, we can use the old spatial acoustics principal component as the new spatial dimension, where only five variables have no linear correlation. The maximum amount of information from the initial variables is still obtained. Some of the features of the principal component analysis are [19]:

- It helps to reduce the amount of data when there is too much information. As the original data has a large number of variables, the principal component analysis supports the rotation of the coordinate axis to create a new coordinate axis. This ensures the variability of data and retains most of the information without affecting the accuracy of forecasting models;

- Principal component analysis helps to create a new coordinate system so that, in the mathematical meaning, the principal component helps to create new variables that are linear combinations of initial variables. In the new space, we can discover new, valuable information when the old information axis is lost.

In 1982, Johnson and Wichern developed the principal component model: given the random vector $X = [X_1, X_2, ...X_k]$, it has the covariance matrix V with eigenvalues $\lambda_{1\geq}\lambda_2 \geq ...\lambda_{k\geq}0$ and normalized eigenvectors $l_1, l_2, ..., l_k$. Considering the linear combination, the first principal component represents:

$$PC_1 = l_1 X_1 + l_2 X_2 + ... + l_k X_k \tag{3.1}$$

The first principal component contains most of the information from the k original variables that formed as a linear combination of the original variables. It continues to refer to the second major component that is linearly represented from the k original variables. However, the second principal component must not be orthogonal to the first primary component. In theory, we can build many principal components from a set of original variables, but we should find the spatial axis so that the fewest components can represent most of the information from the original variables [20].

3.2.3 Ordinal Logistic Regression

Logistic regression is a statistical method applied to predict the value of a categorical dependent variable based on one or some independent variables [21–23]. The use of logistic regression modeling has been explored during the past decade. This method is now commonly applied in many fields, including business and finance, health policy, ecology, linguistics, manufacturing processes, and education [24]. Steyerber and Harrell state that the logistic regression has three types of model, as shown in Table 3.1 [25].

Table 3.1: Three kinds of logistic regression model.

Varible type	Number of categories	Characteristic	Example
Binary	2	Two levels	Male of female
Ordinal	3 or more	Natural ordering of the levels	Bad, Good, Excellent
Norminal	3 or more	No natural ordering of the levels	Yellow, Green, Red

In the clothing manufacturing process, the worker skill levels have more than 3 levels, and these skill levels order naturally so that the ordinal logistic regression is the most suitable model to apply for grading operator skill levels. The ordinal logistic regression model estimates a set of regression coefficients that predict the cumulative probability of the level and all levels that are ordered before it [26].

Proportional Odds Model

Walker and Duncan [27] described the most commonly used ordinal logistic model, later called the Proportional odds model by McCullagh. The Proportional odds model is best stated as follows, for a dependent variable having levels $0, 1, 2, \ldots, m$:

$$Logit\left(P\left(Y \leq j\right)\right) = ln\left(\frac{P\left(Y \leq j\right)}{1 - P\left(Y \leq j\right)}\right) = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k \qquad (3.2)$$

where

$P\left(Y \leq j\right)$: cumulative probability will fall into the j^{th} category or lower (where $j = 0, 1, 2, .., m$)

$x_1, x_2, x_3, ..., x_k$: the independent variables

α_j: intercepts are different for each j^{th} categories

$\beta_1, \beta_2, ..., \beta_k$: coefficients are same for all j^{th} categories

The cumulative probability of the level j^{th} and all levels that are ordered before it is calculated as:

$$P\left(Y \leq j\right) = \frac{1}{1 + e^{-(\alpha_j + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k)}} \qquad (3.3)$$

From the estimated cumulative probabilities, we can easily calculate the estimated probability of each category, using the formula:

$$P(Y = i) = P(Y \leq i) - P(Y < i) \tag{3.4}$$

The Proportional odds model is the most popular model in ordinal logistic regression because it is straightforward, intuitive, and easy to interpret. However, in this model, a request about parallel lines assumption must be achieved. In a way, this assumption states that the dependent variable's categories are parallel to each other, which mean correlation between independent variable and response variable does not change for dependent variable categories, so the coefficients are the same for all j^{th} categories. When the assumption does not hold, it means that there is no parallelity between categories. In practice, some researchers ignore this assumption when applying the proportional odds model, meaning their results are not precise [28].

Partial Proportional Odds Model

Peterson and Harrell [29] suggested the Partial proportional odds model can be applied whether the request about parallel lines assumption holds or not. The Partial proportional odds model has the same characteristics as the Proportional odds model. The Partial proportional odds model has the key advantage of having different intercepts and some of the coefficients being same for all categories, while others can differ. The Partial proportional odds model can be written as:

$$P(Y > j) = \frac{exp(\alpha_j + \beta_{1j}x_1 + \beta_2 x_2 + ... + \beta_k x_k)}{1 + exp(\alpha_j + \beta_{1j}x_1 + \beta_2 x_2 + ... + \beta_k x_k)} \tag{3.5}$$

where

$P(Y > j)$: cumulative probability will fall into the larger j^{th} category (where $j = 0, 1, 2, .., m$)

$x_1, x_2, x_3, ..., x_k$: the independent variables

α_j: intercepts are different for each j^{th} categories

β_{1j}: the coefficients differ for each j^{th} categories

$\beta_2, ..., \beta_k$: coefficients are same for all j^{th} categories

In this grading method, two kinds of models, including the Proportional odds model and the Partial proportional odds model, are applied to grading sewing operator skill level. Based on a Goodness of fit indicator, such as AIC, the best model will be chosen for evaluating the worker skill level. Akaike Information Criterion (AIC) is the most widely used to estimate the relative quality of statistical models for a given set of data [30], AIC is calculated to estimate the quality of each model, relative to each of the other models. The model with the smallest AIC value is considered the best. The AIC is calculated as:

$$AIC = -2LogLikelihood + 2\left((J-1)+K\right) \tag{3.6}$$

where

J: number of levels of the response variable in the model

K: number of independent variables in the model

The predicted probability of each response category could be applied to assign cases to categories. For instance, in the worker skill levels, a worker is assigned to the skill level for which it has the largest predicted probability.

3.3 A Methodology for grading operator skill level

Currently, the ranking of worker skill level within the manufacturing sector relies on the subjective assessment of managers. They oversee the worker's activity, approximate their global employee skill, and then allocate the employee to a particular level. The variation between skill levels is not clearly expressed by this approach; most managers are not able to justify their assessments or provide concrete examples for improvement. Moreover, when the skill levels of worker is determined that just based on the global skill, it is very difficult for the production manager when developing the training program for improving the skill levels of worker because they can not answer the question “What skill the worker should improve to reach the higher skill level”. Separating the global operator skills according to the factors that influence on the skill levels is one way to address this issue. In doing so, these factors could be applied to assess worker skill level.

The current research occurred at a clothing manufacturing firm, Nha Be Garment Corporation in Ho Chi Minh city- VietNam. This company was established in 1975 with two clothing factories, including Ledgine and Jean Symi in Saigon Export Processing Zone. Nha Be garment Corporation is one of the garment companies concentrated on training and developing the worker's skill level for meeting the high quality requirements as well as focus on developing core values, creating new values, increasing the position of company in Vietnam and world garment market. The manufacturing process at this firm comprises many different sewing tasks that involve both worker and paced machinery. The most crucial determinant for productivity and the quality of products in this process is the workers. In this research, I present a new method to grading sewing worker skill according to this context.

3.3.1 Step 1- Identifying the Factors Affecting Worker Skill Levels Using the Delphi Method

Preparation

In 2016, NBC Human Resources Training Center was established with the main purpose that developing these training courses for directors, vice directors, factory managers, heads of lines, etc. This project aims at developing the high quality human resources in company. The first step was to identify all of the technical-management personnel within the company. Their responsibilities and experiences regarding training, coaching and managing operators in the company were recorded. Nine experts in this project were found, five of which were chosen for inclusion in the Delphi process: two experts from the manufacturing department, with experience in overseeing the sewing assembly line; two experts from the training department, with expertise in training and coaching workers; and one expert from the planning department, responsible for approximating and forecasting worker performance. These experts not only have the best experience as operators; they are also the most experienced leaders. Further, they demonstrate good observational skills and comfort conveying their opinions. We acknowledge that there are also some benefits for the experts in taking part in a Delphi study, including the chance to: (1) study and enhance their experience and learning through the consensus conference; and (2) improve their own standing in their organization and the industry.

Such advantages create a high incentive for the experts, which is needed to attract them. The next step was devise of a list of elements that have impact on sewing worker skill level. This was established according to prior research through the synthesis of all supporting evidence. Next, a sample of sewing operators was identified in a preliminary stage. These were workers that the experts considered to reflect each of the various sewing skill levels.

Applying the Delphi method

Firstly, the five experts confirmed the operator skill elements and their structure. They used all available supporting evidence on the representative operators to do so. Sewing operation skill elements are the factors revealed through the operation behaviors of the operator or their interactions with their workstation.
A Delphi conference is facilitated to find consensus regarding the factors that impact on the sewing skill level and on the relative difference in operator skill levels. The experts confirm a list of operation sewing skill elements compiled by the facilitator through a prior literature search. The group also deliberates and decides upon the sources of information/evidence that assist with assessment of the skill elements. Table 3.2 shows the six elements that were found to an impact on skill levels. The group of experts also lists a selection of eleven operators whom they agree are representative of the range of sewing skill levels. Further debate amongst the researchers led to seven operators being excluded, leaving four workers to represent the four possible skill levels that occur in the production unit:

- Level 1: Workers belong level 1 that have weak skill, the workers operate task in the slow and unequivocal speed, they need more training.
- Level 2: Workers belong level 2 that have fair skill, but they accomplish task with the slow speed and not consistent.
- Level 3: Workers belong level 3 that gain good skill, they accomplish task with the quick and consistent speed, and they can accomplish almost sewing tasks in assembly line .
- Level 4: Workers belong level 4 that reach excellent skill, the coordination of sub-operations in their motions is suitable, does not have the redundant operations, and they gain the quick and consistent speed in their motions.

Table 3.2: Six elements for grading sewing skill levels of workers.

No.	Element	Description
1	Technical skill	represents the required knowledge and abilities related to sewing technology
2	Human-Work/Machine	interactions between operator physical characteristics and workstation that affect operator performance
3	Manual handing skill	ability to handle material, parts, tools correctly in workstation
4	Maintenance skill	ability to maintain work pace and attentiveness overtime
5	Located pattern skill	ability to control and adjust semi-finish product for sewing operation
6	Consistency skill	ability remains the sub-manipulation having same standard time

3.3.2 Step 2 - Reducing These Qualitative Variables by Using Principal Component Analysis

After finishing to determine these factors that influence sewing worker skill level through the consensus from five experts in the Delphi panel, we recognize that six variables are qualitative. In the experts' opinion, in a practical environment, production managers will meet a lot of difficulties when using directly the six qualitative variables to determine the sewing worker skill levels through observing. The production managers can not capture all of six values for six variables through directly observing the worker operations. Many biases may be involved when estimating a large number of qualitative variables at the same time. When they try to estimate the value of technical skill, they could miss a particular point in time determining other skills when worker operated. One way of solving this problem is to reduce and combine groups of similar variables by applying principal component analysis. In some cases, we can create an interpretation of these new variables. The variance structure of a matrix of data achieved through combining these original variables consequently reduces the data to smaller principal components that generally describe 80-90% of the variance in the data.

In this procedure, five experts determined the importance level of each of the six sub-skill on the worker skill level through using a Likert scale from 1 to 5, with 5 describing that a particular attribute is extremely important and 1 describing that the criterion is not important in relation to the sewing skill level of a worker. Table 3.3 conveys the scores

Table 3.3: Experts'evaluation scores

	Expert 1	**Expert 2**	**Expert 3**	**Expert 4**	**Expert 5**
Technical skill (E_1)	3	5	2	2	3
Human-Work/Machine (E_2)	3	4	2	2	2
Manual handling skill (E_3)	2	3	4	3	2
Maintenance skill (E_4)	4	2	1	5	4
Located pattern skill (E_5)	2	4	3	4	2
Consistency skill (E_6)	4	2	2	5	3

from the five experts.

The result of principal component analysis for reducing the qualitative variables is described in Table 3.4. The first principal component has variance of 4.8642 and explains 57.9% of the total variance. The coefficients listed under PC_1 show how the principal component is calculated:

$PC_1 = 0.281E_1 + 0.196E_2 + 0.215E_3 - 0.714E_4 + 0.105E_5 - 0.562E_6$

Table 3.4: Eigenanalysis of the covariance matrix

Eigenvalue	4.8642	2.0937	1.2577	0.1844	0.0000	0.0000
Proportion	0.579	0.249	0.150	0.022	0.000	0.000
Cumulative	0.579	0.828	0.978	1.000	1.000	1.000
Variable	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6
Technical skill (E_1)	0.281	**-0.726**	0.024	-0.239	-0.575	0.075
Human-work/machine (E_2)	0.196	**-0.497**	0.127	0.637	0.493	0.220
Manual handling skill (E_3)	0.215	0.363	**0.397**	0.085	-0.272	0.763
Maintenance skill (E_4)	**-0.714**	-0.302	0.061	-0.372	0.247	0.442
Located pattern skill (E_5)	0.105	-0.045	**0.859**	-0.288	0.218	-0.345
Consistency skill (E_6)	**-0.562**	-0.023	0.291	0.554	-0.493	-0.220

The second principal component explains an additional 24.9 % of variance. It is calculated from the original data using the coefficients listed under PC_2:

$PC_2 = -0.726E_1 - 0.497E_2 + 0.363E_3 - 0.302E_4 - 0.045E_5 - 0.023E_6$

The last principal component used to explain the variance of original data PC_3 was calculated as follows:

$PC_3 = 0.024E_1 + 0.127E_2 + 0.397E_3 + 0.061E_4 + 0.8595E_5 + 0.291E_6$

where $E_1, E_2, E_3, E_4, E_5, E_6$: the six original variables from Delphi consensus.

PC_1 consists of a weighted average of six the variables, and maintenance skill and consistency skill have the greatest emphasis, which primarily represents the ability of operators to repeat operations consistently as required over time. We can describe and measure PC_1 with a new named variable, sustaining skill variable. Similarly, PC_2 emphasizes the influence of technical skill and the human-work/machine element. Two elements describing skill demonstrate the operator's ability to coordinate their mind and hands in the operation, and their ability to coordinate between manipulations in operation. The PC_2 can be estimated using the coordination skill concept. Finally, PC_3 concentrates on estimating located pattern skill and manual handling skill. These two skills' emphasis on the skill element demonstrates the worker's ability in using tools and equipment in assembling parts, called the tool operating skill. It is better to combine the expert's opinions with the quantitative methods, and then use the experience of the administrator to adjust accordingly. The principal component analysis method is applied to reduce the six qualitative variables from the Delphi conference to three principal components that explain 97.8% of the variance from the original data, include sustaining skill, coordination skill, and tool operating skill.

3.3.3 Step 3 - Ranking and Predicting the Sewing Worker Skill Level by Applying Ordinal Logistic Regression

With the purpose of determining the effect rating value of three independent variables on the grading sewing worker skill levels, a questionnaire is designed to collect data from an assembly line.

The questionnaire includes information in the form of twenty videos that describe the working process of operators. These videos describe the various tasks which employees must operate in the sewing line. One of the most important issues when making the video is that video must represents clearly all of worker 's operations, describes completely accuracy of worker basic motions. The standard time for operating sewing task that is described during the worker normal working process to support estimation of the skill elements. These experts watch the operation of sewing worker in twenty videos and then evaluate three variable, including coordination skill, sustaining skill, and tool operating skill of workers based on a Likert scale from 1 to 5. The respondents must determine three variables concurrently in the work cycle of each worker. After estimating the values of three sub-skill, the experts determine which worker belongs to skill level 1, 2, 3, or 4. The represented questionnaire is shown in Figure 3.1.

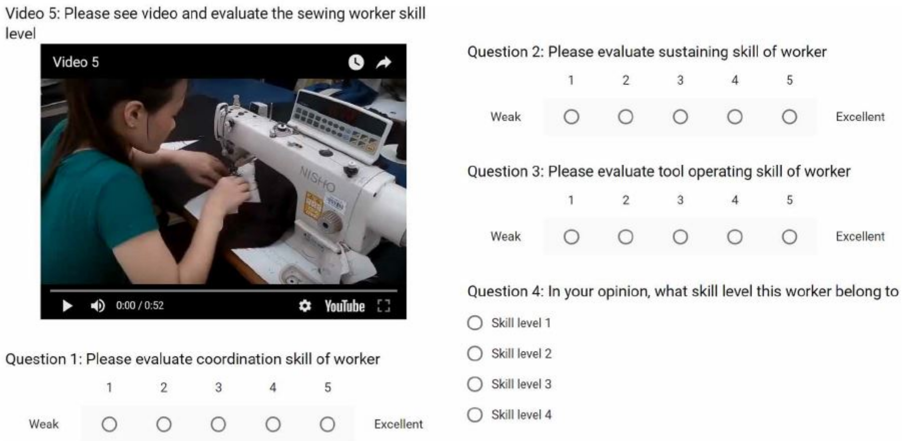

Figure 3.1: The example of the questionnaire

For example, in the video of Figure 3.1, the worker is sewing the front pattern of vest. The experts must observe the operator's ability to coordinate between manipulations when putting the small pattern on the large pattern, aligning the edge of fabric and making the sewing line for estimating the coordination skill. In addition, these respondents must compare the difference between two cycles time and determine the consistency of sub-operations for evaluating the sustaining skill. The tool operating skill is determined through the worker's ability in using the lock-stitch sewing machine. Finally, the experts will compare with the benchmark of four skill levels and determine this worker will belong in which skill level.

Input data was collected that will be applied to two kinds of ordinal logistic regression model, including Proportional odds model and Partial proportional odds model, to estimate the effect of three independent variables and build mathematical rules for ranking the sewing worker skill levels. The accumulative probability of each level will be computed based on the input value of three independent variables. A worker should belong in the skill level that has the highest predicted probability. In this research, we applied the STATA 12 software package that can calculate two kinds of ordinal logistic regression model. The dependent variable is coded as '1' skill level 1, '2' skill level 2, '3' skill level 3, and '4' skill level 4.

3.4 Results and Verification

3.4.1 Results of the Proportional Odds Model

In the results, the Log-Likelihood from the maximum likelihood iterations is described along with the statistic G. This statistic tests the null hypothesis that all the coefficients associated with independent variables equal zero versus these coefficients not all being equal to zero. In this case, $G = 117.403$, with p-value of $0.000 < 0.05$, indicating that there is sufficient evidence that at least one of the coefficients is different from zero, given that accepted $\alpha = 0.05$.

In addition, the Proportional odds table (Table 3.5) shows the estimated coefficients (parameter estimates), standard error of the coefficients, $z - values$, and $p - values$. From the output, three independent variables, include coordination skill, sustaining skill, and tool operating skill have $p - values$ less than 0.05, indicating that there is sufficient evidence that the three variables have an effect on the sewing worker skill levels, and the parameters are not zero using the significant level of $\alpha = 0.05$. In addition, in the proportional odds model, the coefficients for coordination skill, sustaining skill, and tool operating skill are negative, which indicates that, generally, the workers who have the larger values of the three independent variables, the higher the probability of assigning the higher skill level.

3.4.2 Results of the Partial Proportional Odds Model

This section analyzes the Partial proportional odds model as an alternative to the Proportional odds model, the parallel lines hypothesis is relaxed, and coefficients of some independent variables are allowed to vary. In this case, we can see the coefficients of sustaining skill and tool operating skill are the same for all j^{th} levels, and the coefficient of coordination skill varies for each j^{th} category.

Table 3.5: Results of the proportional odds model

Predictor	**Coef.**	**SE Coef.**	**Z**	**P**
Const(1)	8.88645	1.45867	6.09	0.000
Const(2)	12.7880	1.81274	7.05	0.000
Const(3)	16.9262	2.25915	7.49	0.000
Coordination skill	-1.62388	0.365373	-4.44	0.000
Sustaining skill	-1.48972	0.374035	-3.98	0.000
Tool operating skill	-1.02710	0.277562	-3.70	0.000
Log-Likelihood = -69.563066 Test that all slopes are zero: G= 117.403, P-value = 0.000 AIC = 151.126				

This means that two variables sustaining skill and tool operating skill do not violate the parallel lines hypothesis; coordination skill is the only parameter that does not hold the parallel lines hypothesis. The result is displayed in Table 3.6.

From the output, three independent variables, include coordination skill, sustaining skill, and tool operating skill have p-values less than 0.05 in at least one comparison, indicating that there is sufficient evidence that the three variables have an effect on the sewing worker skill levels, and the parameters are not zero using the significant level of $\alpha = 0.05$.

3.4.3 Final Results

Based on the *AIC* result, which allows us to compare two types of model, the Partial proportional odds model has smaller *AIC* and is therefore the best model. The predicted equations for estimating probabilities of sewing worker skill level show that:

$$Prob\,(> \text{skill level 1}) = \frac{exp(-6.26 + 0.39x_1 + 1.65x_2 + 1.12x_3)}{1 + exp(-6.26 + 0.39x_1 + 1.65x_2 + 1.12x_3)} \tag{3.7}$$

$$Prob\,(> \text{skill level 2}) = \frac{exp(-16.84 + 2.55x_1 + 1.65x_2 + 1.12x_3)}{1 + exp(-16.84 + 2.55x_1 + 1.65x_2 + 1.12x_3)} \tag{3.8}$$

$$Prob\,(> \text{skill level 3}) = \frac{exp(-20.30 + 2.19x_1 + 1.65x_2 + 1.12x_3)}{1 + exp(-20.30 + 2.19x_1 + 1.65x_2 + 1.12x_3)} \tag{3.9}$$

where: x_1: value of coordination skill (from 1 to 5)

x_2: value of sustaining skill (from 1 to 5)

Table 3.6: Results of the partial proportional odds model

Skill level	**Coef.**	**SE Coef.**	**Z**	**P**
1				
Coordination skill	0.392121	0.511684	0.77	0.443
Sustaining skill	1.652372	0.410296	4.03	0.000
Tool operating skill	1.117337	0.301224	3.71	0.000
Intercept	-6.260836	1.645029	-3.81	0.000
2				
Coordination skill	2.546332	0.665638	3.83	0.000
Sustaining skill	1.652372	0.410296	4.03	0.000
Tool operating skill	1.117337	0.301224	3.71	0.000
Intercept	-16.8374	3.094424	-5.44	0.000
3				
Coordination skill	2.19227	0.764779	2.87	0.004
Sustaining skill	1.652372	0.410296	4.03	0.000
Tool operating skill	1.117337	0.301224	3.71	0.000
Intercept	-20.30396	3.788390	-5.36	0.000
Log-Likelihood = -65.419044 Test that all slopes are zero : G= 125.740, P-value = 0.000 AIC = 142.838088				

x_3: value of tool operating skill (from 1 to 5)

The probability of each of the four skill levels can be calculated from Eq 3.7, 3.8, and 3.9, when we have the estimated values of the three independent variables. A worker is assigned to the skill level for which there is the largest predicted probability.

In the Likert scale from 1 to 5, for instance, a operator has coordination skill = 3, sustaining skill = 4, and tool operating skill = 2. Some experts can assign s/he to skill level 2 on the basis of a subjective assessment, while other experts may determine this worker belongs in skill level 3 . These expert's evaluations are subjective, depend on their knowledge, and make it difficult to reach a consensus. Moreover, they can not explain the accuracy reason why this worker is assigned in which skill level. However, we can obtain an answer by applying these predicted formulas to calculate skill level. In this case, the predicted probability of each skill level was analyzed as follows:

$Prob\,(>\text{ skill level }1) = \frac{exp(-6.26+0.39.3+1.65.4+1.12.2)}{1+exp(-6.26+0.39.3+1.65.4+1.12.2)} = 0.977$

$Prob\,(>\text{ skill level }2) = \frac{exp(-16.84-2.55.3+1.65.4+1.12.2)}{1+exp(-16.84+2.55.3+1.65.4+1.12.4)} = 0.413$

$Prob\,(>\text{ skill level }3) = \frac{exp(-20.30-2.19.3+1.65.4+1.12.2)}{1+exp(-20.30+2.19.3+1.65.4+1.12.2)} = 0.0074$

$Prob\,(\text{skill level }1) = 1 - Prob\,(>\text{ skill level }1) = 0.023$

$Prob\,(\text{skill level }2) = Prob\,(>\text{ skill level }1) - Prob\,(>\text{ skill level }2) = 0.562$

$Prob\,(\text{skill level }3) = Prob\,(>\text{ skill level }2) - Prob\,(>\text{ skill level }3) = 0.4056$

From this calculation result, we can see the probability of skill level 2 and skill level 3 is close, but probability of skill level 2 has the largest value, so this worker is assigned to skill level 2.

3.4.4 Verification

A data sample is collected for verifying this model, we must test the difference between the real assigned operator's skill level in the sewing manufacturing process at NhaBe company and the predicted operator skill levels computed from this model.

The data sample includes ten sewing workers, one expert will give the opinion for value of the independent variables, based on a Likert scale. The values of three independent variables are then used to compute the predicted skill level of the ten workers. The data is represented in Table 3.7.

The skill levels of the workers is a kind of ordinal data, so we apply the Mann-Whitney

Table 3.7: Model verification data

Worker	Coordination skill	Sustaining skill	Tool operating skill	Predicted skill level	Real skill level
1	4	4	1	3	2
2	3	2	1	1	2
3	3	4	1	2	2
4	4	3	1	2	3
5	2	2	1	1	1
6	3	3	1	2	2
7	4	4	4	3	3
8	4	5	4	4	3
9	3	3	2	2	2
10	4	3	4	3	4

test. This technique evaluates whether the medians on a test variable differ significantly between two treatments. The variable divides cases into two groups or categories, in this case, the predicted skill level and real assigned skill level of a worker in an assembly line. The hypothesis is given below, and the test is run at the 5% level of significance:

H_0: the two populations are equal versus

H_1: the two populations are not equal

The result is calculated using Minitab software and is shown in Table 3.8.

The test statistic $W = 102$ has a $p - value$ of 0.8501 or 0.8403 when adjusted for ties. If the $p - value < 0.05$, we will reject H_0. However, in this case, the $p - value > 0.05$ shows that we do not have sufficient evidence to reject H_0, that mean there is not a difference between the predicted skill level and real skill level of the workers. Hence, it can be concluded that the grading operator skill level model could be applied effectively in the production process.

The main result in this chapter showed that three mathematical formulas could be applied to forecast operator skill level in the clothing industry. In this model, to ensure the accuracy of prediction, I combined the expert's opinion with the quantitative methods, and then use the experience of the administrator to adjust accordingly. From the probability of each skill levels, an operator is assigned to the skill level that gain the highest

Table 3.8: The results of the Mann-Whitney Test

	N	Median
Predicted skill level	10	2.00
Real skill level	10	2.00
Point estimate for ETA1-ETA2 is -0.000 95.5 Percent CI for ETA1–ETA2 is (-0.999,1.000) W=102.0 Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.8501 The test is significant at 0.8403 (adjusted for ties)		

predicted probability. The findings are positive and highly encouraging, particularly in respect of consensus-based skill levels that can be checked statistically for performance ratings. The new ranking system has the advantage of using the correct knowledge and experience of experts while restricting and modifying personal prejudices and misjudgments in consensus-based conversation.

Chapter 4

An evaluation methodology for the complexity level of tasks

In the production process, operator performance is determined based on the interaction of task characteristics, worker skill level, and environment functions. Task complexity is one of the significant factors that influences and be used for forecasting employee performance. This chapter presents a new method for evaluating the complexity level of tasks using a combination of the Analytic hierarchy process and a proportional 2-tuple linguistic representation model. The proposal approach takes into consideration a great deal of decision-makers' ambiguities, uncertainties, and vagueness in evaluating task complexity level.

4.1 Introduction

In the production process, operator performance is estimated based on the interaction of task characteristics, worker skill level, and environment functions. Task complexity is one of the key factors that affects and be used for predicting employee performance. Tasks have been found to be an important component in research on worker performance [31]. Tasks are defined as the collection of activities that workers need to accomplish within a defined period of time. Many tasks are becoming more and more complex, as they must deal with the development of technology, materials, and machines in manufacturing process. If a task is more complex, the worker needs more skill and time to finish it.

In previous research, Robinson studied the effect of cognitive complexity on task complexity, difficulty, and production interactions for learner perceptions in language production [32]. The results show that cognitive complexity significantly influences learner perceptions. De Koning et al. researched the influence of task complexity and task performance on the validity of computational models of attention [33]. The experiment included 22 male students and 20 female students. This research suggested that the performance of the combined model was higher than the performance of the other models for both simple and complex tasks, poor and good performers. Bedny et al. proposed a methodology for evaluating the task complexity of computer-based tasks using the systemic-structural activity theory-SSAT [34]. They determined the complexity of computer-based tasks, including cognitive and motor actions, which are evaluated according to two different scales. In most of previous researches, the researchers concentrated their efforts on analyzing the influence of task complexity on these other factors.

To understand how task complexity produces an effect on worker performance, it should be clearly identified. It is important to note that task complexity is a different concept to task difficulty. The complexity of task is an objective characteristic of a task: for instance, material characteristics, equipment, required information, and the environment in which the task is performed [35]. In the literature, there are many definitions of task complexity. Three perspectives shape the definitions: structuralist, resource requirement, and interaction [36]. From the structuralist viewpoint, the complexity of a task is determined according to its structure. In this sense, a single task may involve numerous task components, for example, three fundamental elements, such as acts, information prompts, and products that are all linked together. The most popular task complexity model belonging to this viewpoint is Wood's [37]. Wood divided task complexity into three dimensions: 1) component complexity, including the number of distinct actions and information cues necessary for accomplishing the task, 2) coordinative complexity, such as the connection between task inputs and the required output of the task, and 3) dynamic complexity, which describes the steady condition of the relationships between task inputs and products. From the resource requirement viewpoint, resource requirements or other parallel concepts in human information processing are applied to evaluate the task complexity. From this perspective, the concept of resource explains the resource according to human information processing aspects, including auditory, cognitive, knowledge, skill, and even time. For more complex tasks, the worker needs to invest and learn using more resources during task performance. The interaction viewpoint of task complexity is the process of the interaction between task and task performer characteristics. In this concept, the complexity of a task will be determined and measured based on the task performer's standpoint.

In this research, we will analyze the complexity level of tasks based on the structuralist concept. Using the structure of task, we will define the factors that significantly affect the task complexity in an assembly line, and evaluate the complexity level of the task by measuring the constituent elements. The factors that have an effect on task complexity often combine both types of qualitative and quantitative criteria. It is very difficult for managers to measure the function of task complexity exactly using numerical values. The best feasible method is to use linguistic variables to represent expert's subjective judgments. This research presents a method that combines the Analytic hierarchy process and Proportional 2-tuple linguistic representation model to evaluate the level of complexity of tasks in the manufacturing process. The proposal approach takes into consideration a great deal of decision-makers' ambiguities, uncertainties, and vagueness in evaluating task complexity level.

4.2 Preliminaries

In our research, we will focus on evaluating the complexity of sewing tasks in an assembly line. In this section, we will present two methods that can be applied to evaluate the complexity level of tasks: the Analytic hierarchy process and the Proportional 2-tuple linguistic model.

4.2.1 Analytic hierarchy process

Devised by Saaty, the Analytic hierarchy process is a type of decision-making approach used to rank options when several criteria are involved [38]. The Analytic hierarchy process (AHP) is a multi-criteria decision-making approach designed for situations in which expert opinions are quantified based on subjective judgment to provide a numeric scale or prioritizing decision alternatives [39].

AHP methodology supports complex decision problem solving through structuring the problem goal, attributes, and alternatives as a hierarchy tree [39]. This provides an overall structure of the complex relationships relevant to the decision-making problem and helps the decision-maker to assess and compare elements accurately [40]. The hierarchy construction will separate complex problem into the attributes that provide decision-makers with a better focus on primary criteria and sub-criteria when allocating the weights. Separating the complex problem into a hierarchical structure is very important, because a different hierarchical tree may obtain a different overall ranking. When developing a AHP hierarchical tree with a large number of criteria, the decision maker should make an effort to cluster these attributes in groups so they do not have the difference in extreme ways [41].

One of the strongest points of the AHP method is its ability to support experts in performing paired comparisons, through which experts more easily express their judgments of the elements of the decision with respect to each of their parent criteria. A matrix is used to describe the paired comparison judgments between these criteria. Priorities are derived from this matrix, as its principal eigenvector is later synthesized in a valid way to determine the final evaluation. The Analytic Hierarchy Process includes four steps:

1. Define the requirements and develop the objective of the problem.

2. Establish the hierarchy, beginning with the purpose of the decision at the top, followed by the aims from a wide perspective, then the intermediary set of criteria and sub-criteria, and ending with the lowest level of the set of options.

3. Construct a set of pairwise comparison matrices between these criteria. Each attribute is used to make comparisons with respect to the attributes in the same level with it. The pairwise comparison between the attributes will be based on a scale from 1 to 9, where 1 means two attributes have equal influence and 9 means extremely strong influence.

4. Weigh the priorities in the next level below using the priorities derived from the comparisons. Add together the weighted values of each aspect in the level below to determine its overall priority. Obtain the ultimate priorities of the alternatives in the lowest level by repeating this weighting and adding process. Although there have been many critics of the AHP method, it still is the most popular one that supports ranking decision-making

where subjective information is either the only available or the only source at all. Applications of AHP in similar decision situations have been reported in the international literature.

4.2.2 Proportional 2-tuple linguistic representation model

Linguistic variable and Fuzzy term set

In the manufacturing process, most multiple attribute decision-making problems combine both types of qualitative and quantitative attributes. Often, some of the attributes are uncertain and unable to be estimated by numerical values. A practical way to solve this problem is the use of the linguistic approach. A linguistic variable is not a number; rather, it is described by words or sentences in a natural or artificial language [42]. A linguistic value is less accurate than a numerical value, but it is closer to the human thinking processes of experts that are used to successfully solve problems dealing with uncertainty. The linguistic term set is the basis concept of linguistic decision-making, and the decision-makers can make these judgments about the attributes of alternatives through these linguistic terms. The most widely used is the additive linguistic term set, which is finite and totally ordered, and can be defined as follows [43]:

$$S = \{s_\alpha \mid \alpha = 0, 1, ..., \tau\} \tag{4.1}$$

where s_α shows a possible values for a linguistic variables, and s_0 with s_τ describe the lower and upper limit of linguistic term set that the decision maker can apply to evaluate the characteristic of attributes. For example, when $\tau = 5$, linguistic term set S can be included:

$S = \{s_0 = \text{very poor}, s_1 = \text{poor}, s_2 = \text{average}, s_3 = \text{rich}, s_4 = \text{very rich}\}$

Fuzzy sets are used to represent the restrictions associated with the values of a linguistic variable [44]. In the fuzzy theory, fuzzy set A of universe X is defined by function $\mu_A(X)$ called the membership function of set A

$$X \to [0,1], \mu_A(X) = \begin{cases} \mu_A(X) = 1 & \text{if x is totally in A} \\ \mu_A(X) = 0 & \text{if x is not in A} \\ 0 < \mu_A(X) < 1 & \text{if x is partly in A} \end{cases} \tag{4.2}$$

In the multiple attribute decision-making problems, the trapezoidal fuzzy numbers are often applied to describe the values of linguistic variable. A trapezoidal fuzzy number $\tilde{n}$ can be defined by a set (n_1, n_2, n_3, n_4), with a lower limit n_1, an upper limit n_4, a lower support limit n_2, and an upper support limit n_3, where $n_1 < n_2 < n_3 < n_4$. The membership function $\mu_{\tilde{n}}(x)$ is defined as

$$\mu_{\tilde{n}}(x) = \begin{cases} 0, x < n_1 \mathrm{or} x > n_4 \\ \frac{x-n_1}{n_2-n_1}, n_1 \leqslant x \leqslant n_2 \\ 1, n_2 \leqslant x \leqslant n_3 \\ \frac{n_4-x}{n_4-n_3}, n_3 \leqslant x \leqslant n_4 \end{cases} \tag{4.3}$$

For example, each of linguistic terms is described by one of five trapezoidal fuzzy numbers whose membership function are shown in Table 4.1, the decision maker can use the linguistic term to evaluate attributes and alternatives.

Table 4.1: Linguistic variable

Linguistic variable	**Trapezoidal fuzzy number**
Very low (s_0)	(0, 0, 0.1, 0.2)
Low (s_1)	(0.1, 0.25, 0.25, 0.4)
Average (s_2)	(0.3, 0.5, 0.5, 0.7)
High (s_{3S})	(0.6, 0.75, 0.75, 0.9)
Very high (s_4)	(0.8, 0.9, 1, 1)

Proportional 2-tuple Linguistic Model

In practical applications, due to lack of experience and time pressure, some decision-makers tend to confuse several possible linguistic terms when they give their opinions. It is more difficult when experts estimate the attributes just using one linguistic term due to the uncertainty and complication of the practical problem. In order to overcome this disadvantage, there are some similar techniques that consider distinguishing the positions of possible linguistic term. Wang and Hao created the Proportional 2-tuple linguistic model [45]. This model can assist the expert to give their opinion using a more accurate expression, when linguistic information is represented by proportional 2-tuples,such as

$(0.4s_3, 0.6s_4)$ for an attribute when decision-makers decide that the characteristic of the attribute is distributed as 40% high and 60% very high.

The concept of Canonical characteristic values of linguistic labels (CCV) is applied to describe weighted aggregation operators for aggregating linguistic information that are represented by linguistic proportional 2-tuples [46]. If these semantics of s_i is defined by $T\left[b_i - \sigma_i, b_i, c_i, c_i + \sigma_i\right]$ in the proportional 2-tuples, the canonical characteristic value $CCV\left(s_i\right) = \frac{b_i + c_i}{2}$

Definition 1 Give $S = \{s_0, s_1, s_2 ... s_n\}$ to be an ordinal term set, and $IS = IxS = \{(\alpha, s_i)\}, \alpha \in [0,1], i = 0, 1, 2..., n$. Given a pair (s_i, s_{i+1}) belong to ordinal terms of S, any two elements $(\alpha, s_i), (\beta, s_{i+1})$ of IS will be called a symbolic proportion pair and α, β will be called a pair of symbolic proportions of pair (s_i, s_{i+1}) if $\alpha + \beta = 1$. Let $\bar{S} = \{\alpha s_i, (1-\alpha) s_{i+1}\}, \alpha \in [0,1], i = 0, 1, ..., n$ then $\bar{S}$ is called the ordinal proportional 2-tuple set.

Definition 2 Let $S = \{s_0, s_1, s_2 ... s_n\}$ be an ordinal term set, $\alpha \in [0,1]$, $c_i \in [0,1]$ and $c_0 < c_1 < c_2 < .... < c_n$, for $CCV\left(s_i\right) = c_i, (\alpha s_i, (1-\alpha) s_{i+1}) \in \bar{S}$, define the function CCV on S by:

$$CCV\left(\alpha s_i, (1-\alpha) s_{i+1}\right) = \alpha CCV\left(s_i\right) + (1-\alpha) CCV\left(s_{i+1}\right) = \alpha c_i + (1-\alpha) c_{i+1} \quad (4.4)$$

Definition 3 Let $S, \bar{S}$ and CCV on S be as before, $\alpha \in [0,1]$ for $CCV\left(s_i\right) = c_i, (\alpha s_i, (1-\alpha) s_{i+1}) \in \bar{S}$, the function CCV^{-1} is defined as:

$$CCV^{-1}(\beta) = CCV^{-1}\left(\alpha c_i + (1-\alpha) c_{i+1}\right) = \left(\alpha s_i, (1-\alpha) s_{i+1}\right) \quad (4.5)$$

The greatest advantage of proportional 2-tuple is that the decision-maker's opinion can be expressed using not just one linguistic variable, as is normally the case, but can be spread by combining two linguistic variables.

4.3 The proposed approach

In the sewing manufacturing process, the task complexity is contributed to by many factors, from the characteristics of the material to the method applied for the task. The defined process for estimating the task complexity based on the Analytic hierarchy process combined with Proportional 2-tuples is given as follows the diagram in Fig 4.1

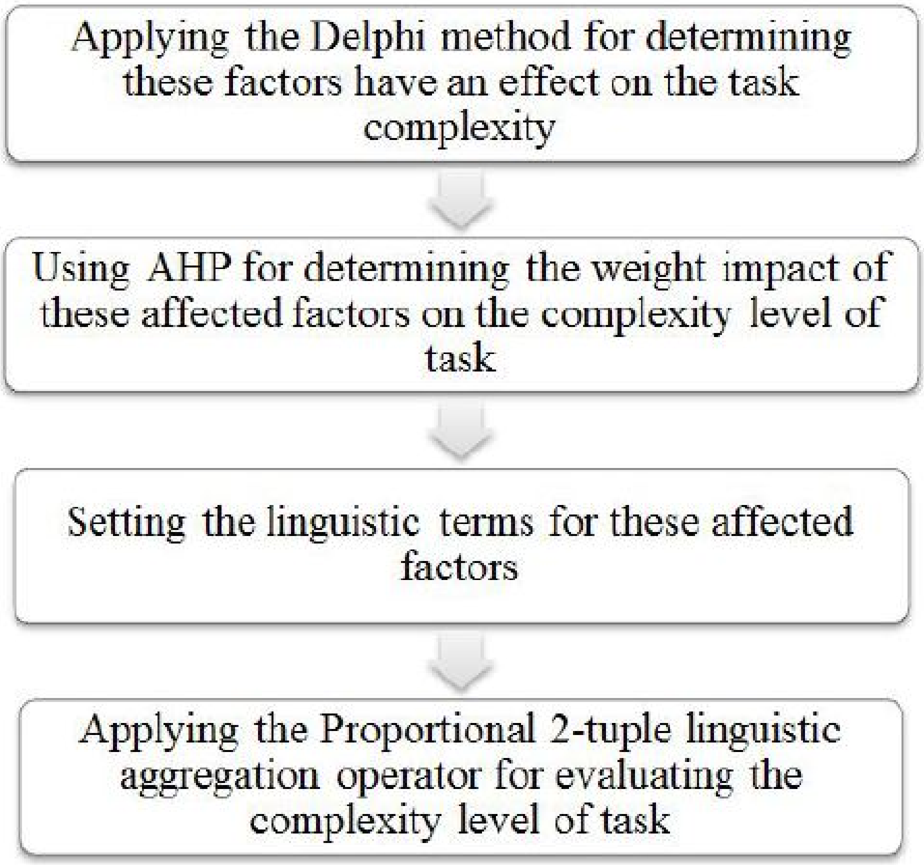

Figure 4.1: The procedure for evaluating the complexity levels of task.

- Step 1: Identify a committee of experts and applying the Delphi method to determine these factors have an effect on the complexity level of the task. The Delphi method is the most popular method to support experts to reach a consensus when solving a complex problem [47].

- Step 2: Develop the hierarchical structure of task complexity based on the attributes, and determine the weight impact of attributes on task complexity through the AHP method. Because these attributes have interactive and simultaneous effects on task complexity, the pairwise comparisons are made between all factors to be considered with the grades ranging from 1-9. The procedure for the AHP involves determining the priority weights of criteria from a square matrix of pairwise comparison $A = [a_{ij}]$, in which a_{ij} is the pair comparison value between i^{th} attribute and j^{th} attribute [48]. The final normalized weight of $i^{th} factor$, W_i, is given by two steps: 1) Normalize the column entries by dividing each entry by the sum of the column. 2) Take the overall row averages. The next step is to find a consistency ratio (CR) to determine how consistent the consensus has been compared with large samples of completely random judgments. The recommended eigen value method evaluates W as the main right eige value of the matrix A or W satisfies the following system of n linear equations $[Ax = \lambda_{max} X]$, where λ_{max} is the maximum eigen value of A. The accepted determinant of inconsistency or deviation from consistency, known as the consistency index (CI), is expressed as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{4.6}$$

$$CR = \frac{CI}{RI} \tag{4.7}$$

where RI is function of matrix size and n is the number of attributes. The value of RI is shown in Table 4.2.

If the CR is higher than 0.1, the expert judgments are untrustworthy because the data suggests they have just given their opinions randomly and the estimation process is valueless or must be repeated [49].

Table 4.2: Random index (RI)

Matrix order	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

- Step 3: The linguistic setting for these attributes has an influence on the complexity level of the task. In the decision-making process, the expert opinions are often expressed using numerical values. However, in task complexity, these impacted factors cannot be assessed precisely in a quantitative format, therefore, experts often use linguistic assessments instead of numerical values. In this situation, for each attribute in the hierarchical structure, experts who join the evaluation process to express their judgments apply a suitable linguistic label set. The trapezoidal fuzzy number is implemented to transform an exact variant into a fuzzy variant; this creates a hybrid of exact and fuzzy variants.

- Step 4: Applying the Proportional 2-tuple linguistic aggregation operator with linguistic evaluation matrixes $X^1, X^2, ..., X^n$ and decision-maker weighting vector $w_1, w_2, ..., w_n$ are aggregated into an overall proportional 2-tuple linguistic comprehensive evaluation matrix L_{ij}

$$L_{ij} = CCV^{-1}\left[\frac{\sum_{k=1}^{q} CCV\left(x_{ij}^{k}\right) \times CCV'\left(w_k\right)}{\sum_{k=1}^{q} CCV'\left(w_k\right)}\right], i = 1, 2..., m, j = 1, 2, .., n \quad (4.8)$$

  Apply the aggregation operator with linguistic weights to calculate the collective overall preference values L_i of the level complexity of task A_i

$$L_i = CCV^{-1}\left[\frac{\sum_{j=1}^{n} CCV\left(l_{ij}\right) \times W_j}{\sum_{j=1}^{n} W_j}\right], i = 1, 2.., n \quad (4.9)$$

4.4 The results

The industrial garment manufacturing process is a complex one, combining various amounts of machines and equipment, hundreds of workers, and a series of semi-finished products with many different designs and sizes. The tasks used in the sewing assembly line are increasingly more complex than ever before. The managers have to evaluate the complexity level of tasks to assign the most suitable worker to finish tasks, and estimate the cost of products. The proposed method to determine and rank the complexity level of sewing tasks is composed of the following steps:

4.4.1 Identify the criteria that affect the complexity level of sewing tasks

Firstly, five experts are selected based on their responsibilities and technical management experience in the company to become members of a Delphi panel. Two experts come from the production department, two from the planning department, and one is the leader of the quality assurance department. With wide-ranging experience and excellent observational aptitude, these experts are all able to communicate their views effectively.
Based on the structuralist viewpoint of task complexity, a Delphi conference is organized to reach consensus on the factors that influence sewing task complexity. The group of experts separates tasks into constituent elements that are characteristic of the task. In

addition, the group considers and finds consensus regarding the sources of data at the basis of determining task complexity. As indicated, the group identifies two elements and six sub-factors that impact sewing task complexity.

Characteristic of material

In the sewing assembly line, the characteristics of raw materials, especially fabric, are constantly changing from one order to another, so the properties of fabric in the sewing process will greatly influence the complexity level of sewing task [50]. Characteristic of material includes two sub-factors:

- Elasticity of fabric: the elasticity of the fabric can make the sewing process difficult for sewing workers, and could greatly affect the quality of the final product. The higher the elasticity of the fabric involved, the more complex the sewing task because the workers have to perform many cultivation operations to adjust details during sewing.
- Weight of fabric: similar to the elasticity of the fabric, the weight of the fabric is also one of the factors that will affect the task complexity in the sewing production process. If the fabric is thinner, the worker will operate at a slower speed because the fabric layers will be very easily defected, leading to a wrinkled seam and greatly affecting the product quality.

Type of method used

The sewing method is based on the product type and the shape of semi-finished products, including the length of the seam, the shape of the seam, the size of the semi-finished product, and the method for locating products. These parameters play an important role in affecting the complexity level of the sewing task.

- Shape of the seam: a garment often has three types of seam shapes, such as the straight seam, curve seam, and circle seam. Workers sew the straight seam faster than they sew the curve and circle seam, so tasks involving curve and circle seams are more complex than those with straight seams.

- Length of the seam: we can easily see that the length of a seam directly affects the standard time for completing the task, and contributes to the complexity of the sewing task. In fact, an order can have many different sizes due to the fluctuation of product size parameters, so the complexity of the sewing task in the assembly line also fluctuates and depends on the length of the seam.
- Size of the semi-finished product: when the semi-finished product is of a large size, workers will meet more difficultly when controlling and operating the task. Tasks involving a larger size as a semi-finished product are therefore more complex for operating.
- Method for locating the product: many tasks in the sewing assembly line are combined between two or three layers o semi-product, therefore, the workers must determine how to locate the product during the sewing process. The time taken by workers to stop sewing and relocate a semi-product will contribute to the complexity level of the task.

4.4.2 Develop the hierarchical structure of task complexity

Based on these factors having an effect on the sewing task complexity, we form the hierarchical structure of task complexity, as is shown in Figure 4.2. The AHP structure includes three levels. The evaluation of task complexity is located at the top level. Two criteria, including the characteristic of material and the type of method used are put at the second level, and the third level includes six sub-criteria related to them. In this step, five experts will discuss and make a pairwise comparison between these criteria to determine the weights of two criteria and sub-criteria. Based on the expert's opinions, these criteria and sub-criteria have interactions between them, so the AHP method should be applied to determine the weight impact.

Pairwise comparisons are made with the grade ranking from *1 to 9*, with 1 meaning equally important and 9 meaning extremely important [51]. For example, the characteristic of material and the type of method used are compared using the question "How important are the characteristics of material when compared to the type of method used ?" If the answer is "strongly important", the value in the pairwise comparison is 5. The pairwise

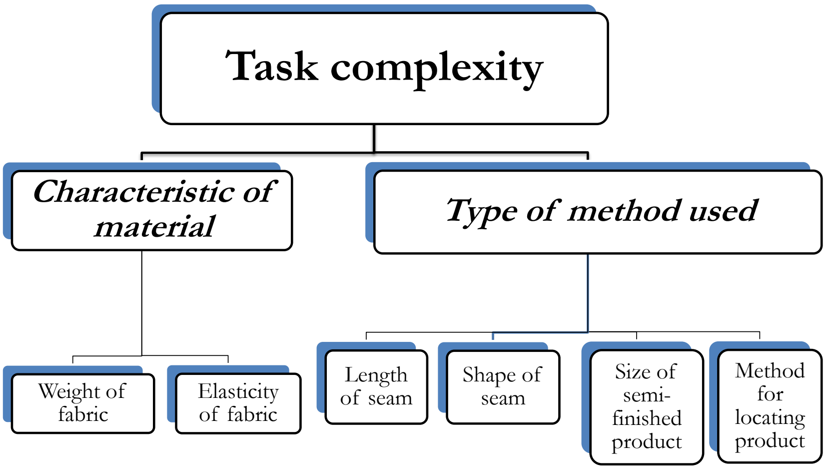

Figure 4.2: Hierarchical structure of task complexity

Table 4.3: Pairwise and weight of characteristic of material sub-criteria

Sub-criteria	C_{11}	C_{12}	*Weight*
Weight of fabric (C_{11})	*1*	*1/3*	**0.250**
Elasticity of fabric (C_{12})	*3*	*1*	**0.750**

comparison matrix for each sub-attribute is presented in Table 4.3 and Table 4.4, and the pairwise comparison matrix for attributes is shown in Table 4.5. Thus, the weight vector from Table 4.5 is determine to be $W = (0.50; 0.50)$, which means that, from the viewpoint of experts, the characteristics of the material and the type of method used have the same effect on the complexity level of the sewing task. Moreover, regarding the characteristics of the material, "elasticity of fabric" ($W = 0.75$) has more important than the "weight of fabric" ($W = 0.25$). In terms of the type of method used criterion, the most important degree has been allocated to "shape of seam" ($W = 0.544$) and the least important degree to "method for locating product" ($W = 0.049$). The Consistency Ratio (CR) is computed to find the degree of consistency between the judgments and large samples of completely random judgments. The judgments are determined to be reliable, as all of the CRs are less than 0.1 (including $0, 0.09, 0$).

Table 4.4: Pairwise and weight of type of method used sub-criteria

Sub-Criteria	C_{21}	C_{22}	C_{23}	C_{24}	*Weight*
Length of seam (C_{21})	*1*	*1/5*	1/3	5	**0.141**
Shape of seam (C_{22})	5	1	3	7	**0.544**
Size of semi-product (C_{23})	*3*	*1/3*	1	6	**0.266**
Method for locating product (C_{24})	1/5	1/7	1/6	1	**0.049**

Table 4.5: Pairwise and weight of criteria

Criteria	B_1	B_2	**Weight**
Characteristic of material (B_1)	*1*	*1*	**0.500**
Type of method used (B_2)	*1*	*1*	**0.500**

4.4.3 The linguistic setting for these attributes

Firstly, we must develop the trapezoidal fuzzy linguistic for six sub-criteria of sewing task complexity. In the sewing assembly line, the weight of the fabric is a quantitative variable with a measure unit of g/m^2, but when it contributes to the complexity level of a sewing task, the highly skilled experts often assess the weight of fabrics using their hands to evaluate certain physical actions on the fabric. They expressed what they felt about the weight of the fabric in terms of subjective sensations, such as very light, light, medium, heavy, and very heavy [52].

In addition, although such experts are highly skilled, with extensive experience, and sensitive and reliable judgments, they often confuse the boundary between these levels. One possible way to solve this problem is to develop a trapezoidal linguistic term set for connecting between the experts' subjective judgments and the quantitative measure of fabric weight, as shown in Figure 4.3. However, in the Proportional 2-tuple linguistic method, the linguistic values of trapezoidal fuzzy numbers should belong to the segment $[0; 1]$, therefore, we must normalize these values, as presented in Table 4.6. Moreover, the elasticity of the fabric and the length of the seam are also measured by technological methods in the clothing industry, but such methods are time consuming [53]. Managers often use linguistic terms to evaluate the properties of the sewing task. In such a situation, the appropriate linguistic label set is chosen by five experts and used to estimate the

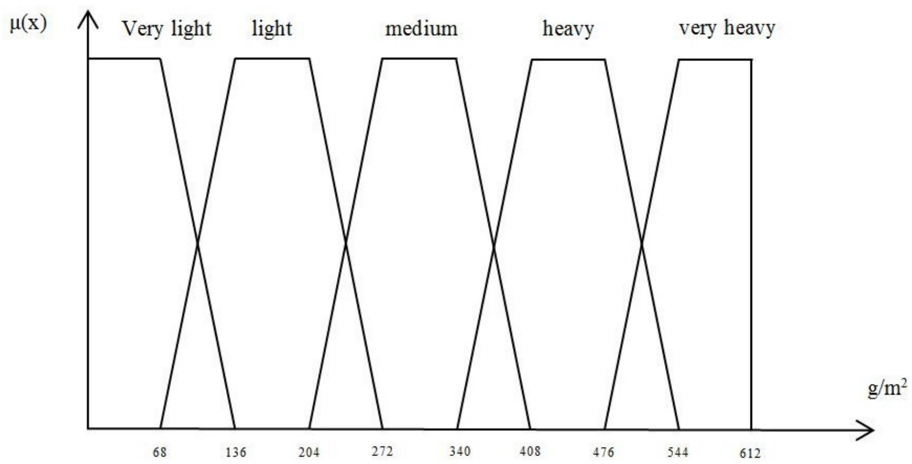

Figure 4.3: Five trapezoidal linguistic term set of the weight of the fabric

Table 4.6: Linguistic values of trapezoidal fuzzy numbers for the weight of the fabric.

Linguistic term	**Fuzzy number**	**CCV**
Very light (S_0^1)	(0, 0, 0.11, 0.22)	0.055
Light (S_1^1)	(0.11, 0.22, 0.33. 0.44)	0.275
Medium (S_2^1)	(0.33, 0.44, 0.55, 0.66)	0.495
Heavy (S_3^1)	(0.55, 0.66, 0.77, 0.88)	0.715
Very heavy (S_4^1)	(0.77, 0.88, 1, 1)	0.940

elasticity of the fabric and the length of the seam. We also normalize these values of five linguistic terms to belong to the segment $[0;1]$, as shown in Table 4.7 and Table 4.8. Three sub-attributes of the type of method used, including the shape of the seam, the size of the semi-finished product, and the method for locating the product, are the qualitative criteria. They also have a positive effect on the sewing task complexity. When three attributes increase in the linguistic term set, the complexity of the sewing task is also higher. These experts discussed and reached the consensus that these sub-attributes have five levels, which are measured, such as very easy, easy, medium, difficult and very difficult, and the associated fuzzy set semantics is shown in Table 4.9

Table 4.7: Linguistic values of trapezoidal fuzzy numbers for the elasticity of the fabric.

Linguistic term	**Fuzzy number**	**CCV**
Very low (S_0^2)	(0, 0, 0.2, 0.3)	0.100
Low (S_1^2)	(0.2, 0.3, 0.4, 0.5)	0.350
Medium (S_2^2)	(0.4, 0.5, 0.6, 0.7)	0.550
High (S_3^2)	(0.6, 0.7, 0.8, 0.9)	0.750
Very high (S_4^2)	(0.8, 0.9, 1, 1)	0.950

Table 4.8: Linguistic values of trapezoidal fuzzy numbers for the length of seam.

Linguistic term	**Fuzzy number**	**CCV**
Very short (S_0^3)	(0, 0, 0.11, 0.18)	0.055
Short (S_1^3)	(0.11, 0.18, 0.33, 0.40)	0.255
Medium (S_2^3)	(0.33, 0.40, 0.52, 0.59)	0.460
Long (S_3^3)	(0.52, 0.59, 0.74, 0.81)	0.665
Very long (S_4^4)	(0.74, 0.81, 1, 1)	0.905

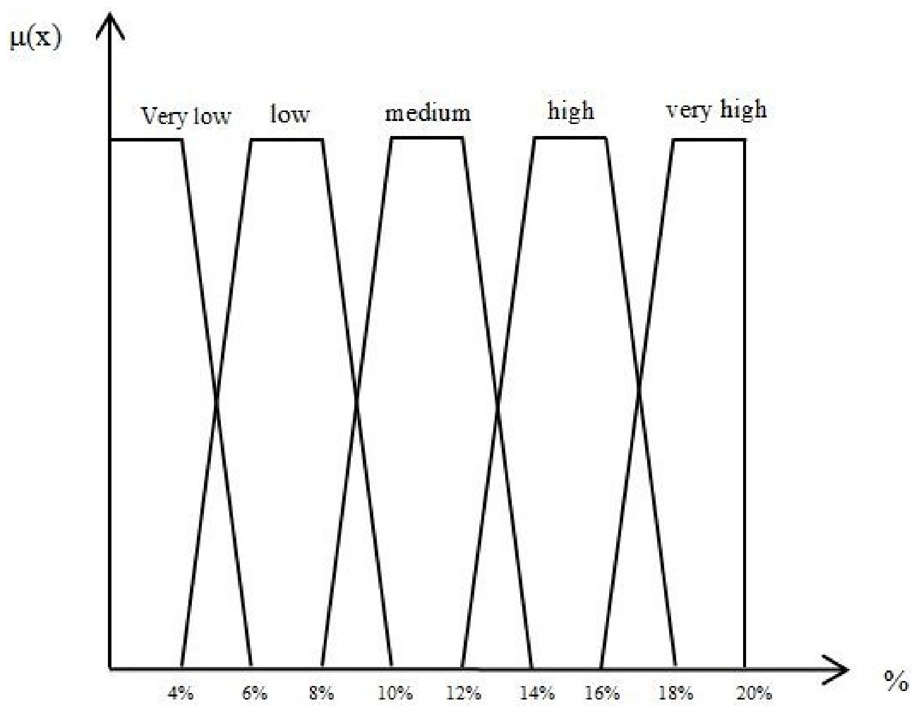

Figure 4.4: Five trapezoidal linguistic term set of the elasticity of the fabric

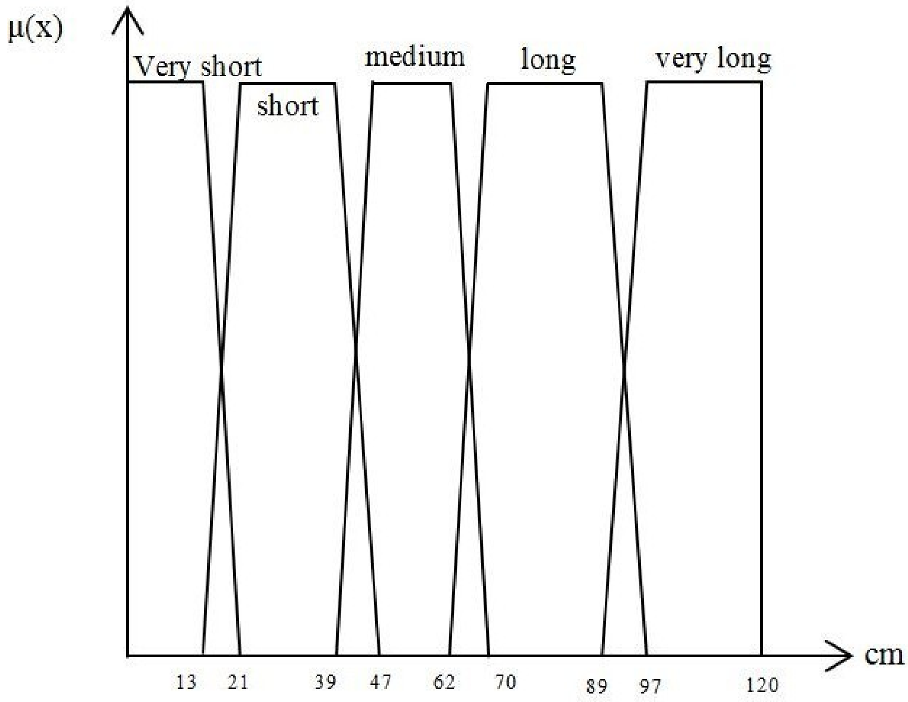

Figure 4.5: Five trapezoidal linguistic term set of length of seam

Table 4.9: Linguistic values of trapezoidal fuzzy numbers for three qualitative attributes.

Linguistic term	**Fuzzy number**	**CCV**
Very easy (S_0^4)	(0, 0, 0.10, 0.20)	0.050
Easy (S_1^4)	(0.10, 0.20, 0.30, 0.40)	0.250
Medium (S_2^4)	(0.30, 0.40, 0.50, 0.60)	0.450
Difficult (S_3^4)	(0.50, 0.60, 0.70, 0.80)	0.650
Very difficult (S_4^4)	(0.70, 0.80, 1, 1)	0.900

Table 4.10: The CCV and Trapezoidal fuzzy number of weight of decision marker

Linguistic variable	**Fuzzy number**	**CCV**
$(S_0^{'})$	(0, 0, 0, 0)	0
$(S_1^{'})$	(0, 0.20, 0.30, 0.50)	0.250
$(S_2^{'})$	(0.30, 0.45, 0.50, 0.65)	0.475
$(S_3^{'})$	(0.50, 0.70, 0.80, 1.00)	0.750
$(S_4^{'})$	(1.00, 1.00, 1.00, 1.00)	1.000

4.4.4 Applying the Proportional 2-tuple linguistic for estimating the complexity level of sewing task

In this step, three experts are chosen to attend the process of evaluating the complexity level of the sewing task through six sub-criteria. Nevertheless, three experts were highly skilled and their judgments sensitive and reliable, but their opinions will be different dependent upon their skills, training, and background. We should assign the weights of experts by means of linguistic assessments from the ordered linguistic term set of five levels, such as $S^{'} = \left[S_0^{'} = (None), S_1^{'} = (\text{Not important}), S_2^{'} = (\text{Medium}), S_3^{'} = (\text{Important}), S_4^{'} = (\text{Very important})\right]$
Table 4.10 shows both the CCV and trapezoidal fuzzy number in $[0;1]$ of each lable in $S^{'}$. The description regarding the weights of each expert is shown as follows: $w^T = \left\{(0.2S_3^{'}, 0.8S_4^{'}); (0.6S_2^{'}, 0.4S_3^{'}); (0.4S_0^{'}, 0.6S_1^{'})\right\}$.
We choose five various sewing tasks, including:
A_1: Sewing the collar attach to the band in the shirt.
A_2: Sewing the sleeve attach to the front and back section in the shirt.
A_3: Sewing the top-stitch neckline of a T-shirt.
A_4: Sewing the side of jean pants.
A_5: Sewing the top stitch on a packet in the length direction of a Polo-shirt.
To evaluate the complexity of the sewing task, let $A = \{A_1, A_2, A_3, A_4, A_5\}$ be a set of alternatives, let $C = \{C_{11}; C_{12}; C_{21}; C_{22}; C_{23}; C_{24}\}$ be a set of sub-criteria. Three experts estimated and gave their initial opinions about the linguistic values of six sub-criteria, as shown Table 4.11 $\sim$ Table 4.13.
We will find the complete proportional 2-tuple linguistic comprehensive evaluation ma-

Table 4.11: The evaluation matrix provided by expert E_1

E_1	C_{11}	C_{12}	C_{21}	C_{22}	C_{23}	C_{24}
A_1	$(0.3S_0^1, 0.7S_1^1)$	$(0.8S_0^2, 0.2S_1^2)$	$(0.6S_2^3, 0.4S_3^3)$	$(0.5S_1^4, 0.5S_2^4)$	$(0.3S_1^4, 0.7S_2^4)$	$(0.2S_3^4, 0.8S_4^4)$
A_2	$(0.6S_1^1, 0.4S_2^1)$	$(0.8S_1^2, 0.2S_2^2)$	$(0.8S_3^3, 0.2S_4^3)$	$(0.4S_3^4, 0.6S_4^4)$	$(0.2S_3^4, 0.8S_4^4)$	$(0.2S_2^4, 0.8S_3^4)$
A_3	$(0.4S_2^1, 0.6S_3^1)$	$(0.3S_3^2, 0.7S_4^2)$	$(0.5S_1^3, 0.5S_2^3)$	$(0.2S_3^4, 0.8S_4^4)$	$(0.3S_0^4, 0.7S_1^4)$	$(0.4S_2^4, 0.6S_3^4)$
A_4	$(0.1S_3^1, 0.9S_4^1)$	$(0.8S_0^2, 0.2S_1^2)$	$(0.2S_3^3, 0.8S_4^3)$	$(0.4S_0^4, 0.6S_1^4)$	$(0.3S_3^4, 0.7S_4^4)$	$(0.5S_1^4, 0.5S_2^4)$
A_5	$(0.4S_2^1, 0.6S_3^1)$	$(0.3S_2^2, 0.7S_3^2)$	$(0.7S_1^3, 0.3S_2^3)$	$(0.5S_0^4, 0.5S_1^4)$	$(0.7S_2^4, 0.3S_3^4)$	$(0.2S_3^4, 0.8S_4^4)$

Table 4.12: The evaluation matrix provided by expert E_2

E_2	C_{11}	C_{12}	C_{21}	C_{22}	C_{23}	C_{24}
A_1	$(0.5S_0^1, 0.5S_1^1)$	$(0.4S_0^2, 0.6S_1^2)$	$(0.8S_1^3, 0.2S_2^3)$	$(0.3S_1^4, 0.7S_2^4)$	$(0.3S_1^4, 0.7S_2^4)$	$(0.4S_3^4, 0.6S_4^4)$
A_2	$(0.2S_0^1, 0.8S_1^1)$	$(0.3S_0^2, 0.7S_1^2)$	$(0.1S_2^3, 0.9S_3^3)$	$(0.1S_2^4, 0.9S_3^4)$	$(0.5S_2^4, 0.5S_3^4)$	$(0.6S_3^4, 0.4S_4^4)$
A_3	$(0.5S_2^1, 0.5S_3^1)$	$(0.1S_2^2, 0.9S_3^2)$	$(0.3S_1^3, 0.7S_2^3)$	$(0.5S_3^4, 0.5S_4^4)$	$(0.8S_1^4, 0.2S_2^4)$	$(0.3S_3^4, 0.7S_4^4)$
A_4	$(0.3S_3^1, 0.7S_4^1)$	$(0.8S_1^2, 0.2S_2^2)$	$(0.4S_3^3, 0.6S_4^3)$	$(0.5S_0^4, 0.5S_1^4)$	$(0.7S_3^4, 0.3S_4^4)$	$(0.6S_1^4, 0.4S_2^4)$
A_5	$(0.4S_3^1, 0.6S_4^1)$	$(0.7S_3^2, 0.3S_4^2)$	$(0.4S_1^3, 0.6S_2^3)$	$(0.2S_1^4, 0.8S_2^4)$	$(0.6S_1^4, 0.4S_2^4)$	$(0.4S_3^4, 0.6S_4^4)$

trix L by using Equation 4.9 to total, for each sewing task, the linguistic rating values of three experts, as illustrated in Table 4.14. For example, the overall proportional 2-tuple linguistic estimation of attribute C_{11} of the sewing task A_1 is calculated as such:

$$CCV_{C_{11}}^{A_1} = \left[\frac{\sum_{k=1}^{3} CCV\left(x_{11}^k\right) \times CCV'(w_k)}{\sum_{k=1}^{3} CCV'(w_k)}\right] = 0.204$$

$$L_{C_{11}}^{A_1} = CCV^{-1}\left[\frac{\sum_{k=1}^{3} CCV\left(x_{11}^k\right) \times CCV'(w_k)}{\sum_{k=1}^{3} CCV'(w_k)}\right] = CCV^{-1}[0.204] = (0.32S_0^1, 0.68S_1^1)$$

where w_k is the decision-maker weighting vector and x_{11} is the proportional 2- tuple linguistic values of attribute C_{11}.

Finally, the complexity level of the sewing task is calculating based on the proportional 2-tuple linguistic aggregation operator. According to the final consensus evaluation matrix L, we applied the formula:

$$Z(A_i) = CCV^{-1}\left[\frac{\sum_1^6 CCV(l_{ij}) \times W_j}{\sum_{j=1}^{6} W_j}\right] \tag{4.10}$$

where W_j : the weight impact of sub-attributes.

However, while six sub-criteria have an effect on the complexity level of sewing task, the weight of the fabric has a negative effect on task complexity because when the level of fabric weight increases, the level of complexity of the sewing task will decrease. That means the coefficient of fabric weight will be minus. We can thus obtain the evaluation

Table 4.13: The evaluation matrix provided by expert E_3

E_3	C_{11}	C_{12}	C_{21}	C_{22}	C_{23}	C_{24}
A_1	$(0.8S_1^1, 0.2S_2^1)$	$(0.9S_0^2, 0.1S_1^2)$	$(0.8S_2^3, 0.2S_3^3)$	$(0.4S_1^4, 0.6S_2^4)$	$(0.7S_2^4, 0.3S_3^4)$	$(0.3S_3^4, 0.7S_4^4)$
A_2	$(0.7S_1^1, 0.3S_2^1)$	$(0.3S_1^2, 0.7S_2^2)$	$(0.9S_3^3, 0.1S_4^3)$	$(0.3S_3^4, 0.7S_4^4)$	$(0.6S_3^4, 0.4S_4^4)$	$(0.2S_2^4, 0.8S_3^4)$
A_3	$(0.3S_2^1, 0.7S_3^1)$	$(0.6S_3^2, 0.4S_4^2)$	$(0.5S_0^3, 0.5S_1^3)$	$(0.6S_3^4, 0.4S_4^4)$	$(0.6S_1^4, 0.4S_2^4)$	$(0.4S_2^4, 0.6S_3^4)$
A_4	$(0.1S_2^1, 0.9S_3^1)$	$(0.7S_0^2, 0.3S_1^2)$	$(0.7S_3^3, 0.3S_4^3)$	$(0.7S_0^4, 0.3S_1^4)$	$(0.3S_3^4, 0.7S_4^4)$	$(0.7S_2^4, 0.3S_3^4)$
A_5	$(0.5S_1^1, 0.5S_2^1)$	$(0.1S_2^2, 0.9S_3^2)$	$(0.5S_1^3, 0.5S_2^3)$	$(0.3S_1^4, 0.7S_2^4)$	$(0.3S_2^4, 0.7S_3^4)$	$(0.2S_3^4, 0.8S_4^4)$

Table 4.14: The overall proportional 2-tuple linguistic comprehensive evaluation matrix L

L	C_{11}	C_{12}	C_{21}	C_{22}	C_{23}	C_{24}
A_1	$(0.32S_0^1, 0.68S_1^1)$	$(0.67S_0^2, 0.33S_1^2)$	$(0.03S_1^3, 0.97S_2^3)$	$(0.42S_1^4, 0.58S_2^4)$	$(0.25S_1^4, 0.75S_2^4)$	$(0.28S_3^4, 0.72S_4^4)$
A_2	$(0.81S_1^1, 0.19S_2^1)$	$(0.96S_1^2, 0.04S_2^2)$	$(0.91S_3^3, 0.09S_4^3)$	$(0.63S_3^4, 0.37S_4^4)$	$(0.65S_3^4, 0.35S_4^4)$	$(0.96S_3^4, 0.04S_4^4)$
A_3	$(0.43S_2^1, 0.57S_3^1)$	$(0.61S_3^2, 0.39S_4^2)$	$(0.52S_1^3, 0.48S_2^3)$	$(0.34S_3^4, 0.66S_4^4)$	$(0.07S_0^4, 0.93S_1^4)$	$(0.96S_3^4, 0.04S_4^4)$
A_4	$(0.26S_3^1, 0.74S_4^1)$	$(0.46S_0^2, 0.54S_1^2)$	$(0.31S_3^3, 0.69S_4^3)$	$(0.46S_0^4, 0.54S_1^4)$	$(0.44S_3^4, 0.56S_4^4)$	$(0.47S_1^4, 0.53S_2^4)$
A_5	$(0.15S_2^1, 0.85S_3^1)$	$(0.08S_2^2, 0.92S_3^2)$	$(0.58S_1^3, 0.42S_2^3)$	$(0.94S_1^4, 0.06S_2^4)$	$(0.98S_2^4, 0.02S_3^4)$	$(0.27S_3^4, 0.73S_4^4)$

value of the five sewing tasks:

$$Z\left(A_1\right) = CCV^{-1}[\{\left(-CCV^{-1}(0.32S_0^1, 0.68S_1^1) \times 0.25\right) + \left(CCV^{-1}(0.67S_0^2, 0.33S_1^2) \times 0.75\right)\} \times 0.5 + \{\left(CCV^{-1}(0.03S_1^3, 0.97S_2^3) \times 0.141\right) + \left(CCV^{-1}(0.42S_1^4, 0.58S_2^4) \times 0.544\right) + (CCV^{-1}(0.25S_1^4, 0.75S_2^4) \times 0.266) + (CCV^{-1}(0.28S_3^4, 0.72S_4^4) \times 0.049)\} \times 0.5] = (0.01S_0^4, 0.99S_1^4)$$

$Z(A_2) = (0.96S_2^4, 0.04S_3^4)$
$Z(A_3) = (0.69S_2^4, 0.31S_3^4)$
$Z(A_4) = (0.33S_0^4, 0.67S_1^4)$
$Z(A_5) = (0.42S_1^4, 0.58S_2^4)$

From the result, we can see that the complexity level of the five sewing tasks can be expressed using the proportional 2-tuple linguistic variable. Of the five tasks, sewing task A_4 has the lowest complexity level; it ranged from 33% very easy to 67% easy. Moreover, sewing task A_3 has the highest complexity level; it ranged from 69% medium to 31% difficult. Based on the evaluating process, managers can determine the complexity level of sewing tasks and choose workers with suitable skills and experience for the task.

Besides, the cost of products often estimate based on the component of tasks to procedure product. From the results of task complexity, the managers can estimate and discuss the production cost of product with customers.

The proposed method described in this paper could be extended for application in many other cases where the worker is the essential element and task complexity is the most significant factor that affects worker performance. With regard to how the complexity level of a task is evaluated, in the future, research should pay closer attention to analysis of the relationship between task complexity and worker skill level, to clearly understand the interaction between them. Using this approach, the challenging and significant question which worker is most suitable for this task can be answered, as researchers will be able to more accurately forecast workers' potential performance ratings.

Chapter 5

Predicting Worker Performance Using A Decision Tree

In this chapter, we will analysis the relationship between the skill level of the worker and the complexity of the task in predicting the worker's performance on an assembly line.

5.1 Introduction

The selection of the right workers for operating tasks in an assembly line is always an important question, especially today because many tasks are becoming increasingly complex, as they must deal with the development of technologies, materials, and machines in the manufacturing process. If a task is more complex, the worker needs more skill and time to finish it. For all of the main purposes of the manufacturing enterprise, such as planning and scheduling, employee training or job-redesigning, the focus is almost on predicting worker performance [54].

In a manufacturing process, the performance of the worker can be identified as "the ability of a worker to accomplish his/her mission based on the expectations of a standard". Managers allocate jobs to workers according to their performance rating. This rating is determined based first on the worker's qualifications and second on their skills. A qualification is a reflection of a operator's ability to perform particular types of manual tasks and/or use certain kinds of machines. The higher the qualification, the better able the worker is to accomplish harder jobs. The operator's skills are classes in terms of how well they have mastered the skills needed to complete a task. A higher level of skill mastery means that the worker is able to perform the task more quickly and with greater efficiency. National or industry standards are often available to assist in qualification grading. On the other hand, skill grading is specific to a job. In addition, companies usually dictate and apply skill grading. The most commonly used performance rating system is the Westinghouse system. This system allows production managers to determine operator performance and, therefore, production capacity with precision, as well as to align operator performance with production unit productivity and attain their quality targets.

Yet the manufacturing environment has shifted significantly due to mass customization production. Product designs, customer quality requirements, materials, and even the equipment involved in manufacturing are evolving quickly and orders are decreasing in size. Further, today's customers have more demands than previously in terms of product quality, cost, and delivery time: these must be higher, lower, and non-negotiable with a significant penalty given for any delay, respectively. Due to these changes, the old methods for assigning workers to tasks have become outdated. They can no longer precisely forecast workers' performance needs and so are less useful in planning the work. Such methods have also failed to drive workers to improve their and adopt new ones, both of which are key for enhancing quality and productivity. The traditional methods failed because they do not consider the interaction between the skill levels of workers and the fluctuation of the characteristics of tasks. Managers often base their decisions on their previous experience but without the support of a systematic knowledge base. They just observe the operation of workers and evaluate their performance based on subjective judgments. The accuracy of these judgments will mainly be dependent on the amount of experience the manager possesses.

In previous research, Schmidt et al. found in their research that job experience results in skills, techniques, methods, and psychomotor habits, etc., being acquired, all of which lead to better performance capabilities [55]. Emin Kahya reported the influence of job characteristics, including physical efforts and job grade, and working conditions, such as environmental conditions and hazards on task performance [56]. The results showed that job grade and environmental conditions have an effect on employee performance. Poor workplace conditions lead to a decline in employee performance. Heikki Topi et al. verified the hypothesis regarding the effects of task complexity and time availability limitations on human performance in database query tasks [57]. The final results showed that, if the performance measures were adjusted by the time needed to perform the task, time availability did not affect task performance; meanwhile, task complexity did have a strong effect on task performance at all time availability levels. In addition, Amy H.I. Lee et al. evaluated the performance of an IT department in the manufacturing industry in Taiwan by using a combination of the fuzzy analytic hierarchy process and balanced scorecard [58]. The results guide IT departments in the manufacturing industry in Taiwan through developing strategies for improving department performance. However, the major results from these researches only focuses on studying which variables have an effect on employee performance; they do not analyze how the interaction between these factors influence worker performance to predict the final performance of workers.

In the final step of my research, I will analysis the interaction between the skill level of workers and these sub-factors of task complexity to predict the performance of workers by applying the decision tree. The combination of previous experience, historical data, and scientific knowledge can improve the productivity and quality of such predictions.

5.2 Background

5.2.1 Data mining in manufacturing process

Data mining is a process for collecting, extracting, storing, and analyzing data for specific insights or intelligent actions. The core issue of data mining is a statistical model that can be applied to linear or logistic regression. Combined with predictive analytics, it can uncover a range of previous trends, anomalies, and problems that companies can use to do better business.

Knowledge is always a valued asset of a manufacturing company and considered as a main factor in the development and success of a firm. Knowledge exists in most manufacturing functions, including design, marketing, production, planning and scheduling, and quality product control, but it is very difficult to identify, capture, and manage. If the product quality requirements on process routine, operation time, line/workstation design, and efficiency, production costs and time is mainly evaluated by departmentally distributed and isolated experts; therefore, the available knowledge has not been organized and institutionalized to support decision making when needed. This means the company will lose this knowledge when experts leave the company. That is the main reason why knowledge discovery, knowledge management, and knowledge engineering are currently the most important topics that manufacturing managers and researchers must make an effort to exploit.

Data mining could support a company in collecting, extracting, storing, and analyzing data for keeping and developing knowledge. In almost all manufacturing processes such as product and process design, material planning and quality control, line balancing, and scheduling, data are recorded. These data stores therefore offer an enormous potential as sources of new knowledge. The extracted knowledge can be applied to model, classify, predict, or make decisions in the manufacturing process [59].

The application of data mining in the manufacturing process first began in the 1990s and has gained increasing attention from production community [60]. Knowledge extracted by data mining techniques is now used in many different areas in the manufacturing process. Data can be collected and analyzed to determine the hidden patterns in the parameters for controlling manufacturing processes or improving the quality of products. The data needed for analysis can be gathered during routine operations of the manufacturing process being analyzed. This is a major benefit, as it means companies are usually not required to establish new or specific processes to collect data. Over the last 20 years, data mining has become a crucial part of the manufacturing industry. Therefore, it is an ideal time to consider and assess its development and use in the industry.

5.2.2 Classification

Classification is a method used to support the building of structures from examples of historical data; it can be used to make decisions from unseen cases [61]. The data classification process has two steps:

- In the first step, the data tuples from the training data, including a set of criteria, are analyzed for building a model. For each tuple in the training data, the value of the class label attribute is known. The classification algorithm is applied to the training data to build the model.

- The second step involves the use of test data to test the precision of the model. If the model is sufficiently accurate, then it can be used to categorize the unknown data tuples (i.e. class label are unknown). Standard classification techniques include: decision tree induction, Bayesian classification, Bayesian belief networks, and neural networks. Other methods can also be used for this purpose, such as genetic algorithms, rough sets, fuzzy logic, and case based reasoning.
In the classification technique, decision trees are one of the most common machine learning techniques because they can generate a clear rule that the final user can easily understand.

5.2.3 Decision trees

In machine learning, decision trees are a type of predictive model: a mapping from observations of an object or phenomenon to make conclusions about the objective value of an object or phenomenon. A training set, including data tuples consisting of a set of attributes and a class label, is used to devise a decision tree [62]. A decision tree mainly contains a root node, interior nodes, and leaf nodes, which are then connected by branches. Each interior node corresponds to an attribute; the line between it and its children represents a specific value for that attribute. Each leaf node represents the predicted value of the target attribute, given the values of the attribute represented by the path from the root node to that leaf node. The basic structure of a decision tree is shown in Figure 5.1 .The decision trees can handle missing values and qualitative data, plus the user can easily understand it through the friendly graphical format. Compared to other data mining methods, a decision tree has several advantages:

- The decision tree is easy to understand. An uninitiated student can understand the decision tree model after a brief explanation.
- Data preparation for a decision tree is basic while other techniques often require data normalization, with the need to create dummy variables and remove null values.
- Decision trees can handle both numerical data and categorical data. Other specialized techniques often used for analyzing data sets consist of only one type of variables. For example, relational laws are only applicable to categorical variables, and neural networks are only applicable to numerical variables.

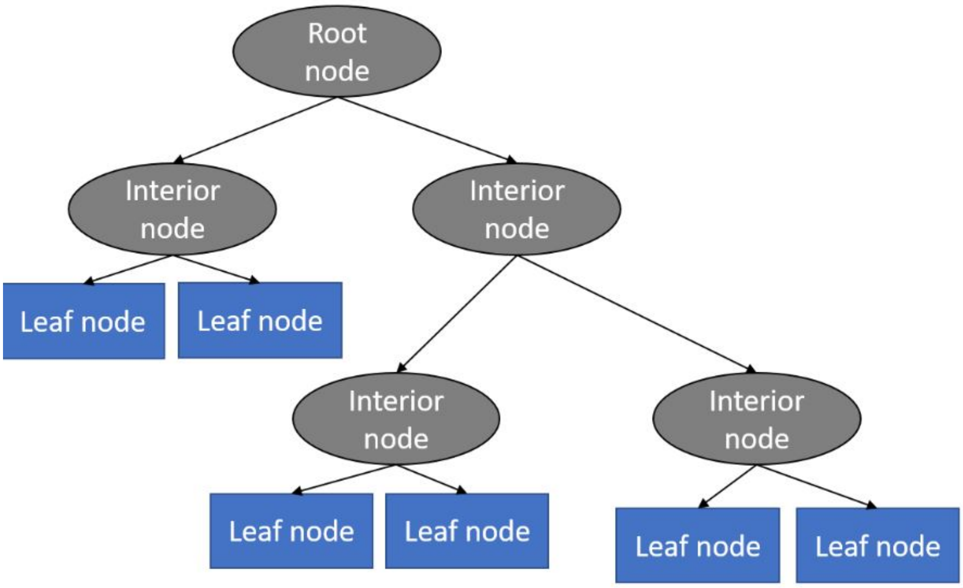

Figure 5.1: The basic structure of decision tree

- The decision tree is a white box model. If a given situation can be observed in a model, it can be easily explained by Boolean logic. The neural network is an example of a black box model, because the explanation for the results is too complex to understand.
- Statistical tests can be used to prove a model, meaning the model can be trusted.
- Decision trees can handle large amounts of data well in a short time. Personal computers can be used to analyze large amounts of data in a time short enough to allow strategists to make decisions based on the decision tree analysis.

Compared with decision trees, other techniques, such as neutral networks or support vector machines, present two major limitations for their implementation within industrial environments [63]:

- First, managers wanting to use these techniques need an artificial intelligence expert to perfect the limits of the model and determine their best set of values. Otherwise, a lengthy calculation time is needed to create a grid optimization of these limits [64].
- Second, the majority of these models are made as black boxes, with a particular set of input values. They give the predicted output values, but no straightforward

answer—meaning, no rules—that would allow the process engineer to understand the links between different inputs, their ideal ranges and groupings, plus the process outputs.

Both of these disadvantages are irrelevant when decision trees are used because they require almost zero parameter optimization and provide clear, visual rules on the relationships within variables. In decision trees, one of the most important functions is Entropy. The entropy function is relative to a Boolean classification, as the proportion $p_{\oplus}$ of positive objects varies between 0 and 1. Entropy $H(S)$ measures the amount of uncertainty in the data set S. If the data set has c distinct groups of objects, the entropy is calculated by:

$$H(S) = \sum_{i=1}^{c} -p_i log_2(p_i) \tag{5.1}$$

where S: the current data set for which entropy is calculated

c: the set of classes in S

p_i: the proportion of the number of elements in class i to the number of elements in set S.

The task of constructing a tree from the training set has been called tree induction or tree building, and follows these steps:

- Step 1: Compute the entropy for the data-set, based on Equation 5.1

- Step 2: for each attribute in the data set:

- calculate the entropy for all categorical values
- calculate the information gain for the current attribute. The information gain is defined by the effectiveness of an attribute in classification data. It is the expected reduction in entropy caused by partitioning the objects according to this attribute.

$$Gain(S, A) = H(S) - \sum_{v \in value(A)} \frac{|S_v|}{|S|} H(S_v) \tag{5.2}$$

where $value(A)$ is the set of all possible values for attribute A

S_v is the subset of S for which A has value v

- Step 3: Choose the highest information gain attribute, which becomes the top-most node in the tree

- Step 4: Repeat step 2 and 3 until we get the tree we wanted.

The decision tree is a promising technique and provides new opportunities for manufacturing to discover useful knowledge [65]. These information is extracted from the final decision tree can be easily applied by engineer responsible to improve the manufacturing process.

5.3 Predicting worker performance

5.3.1 Problem definition

The performance of workers is determined by the interaction between the skill level of the worker and task complexity. A representation of the problem is given in Figure 5.2. It describes the required information sources that combine to support the classification process. Each variable shown in Figure 5.2 is detailed as follows:

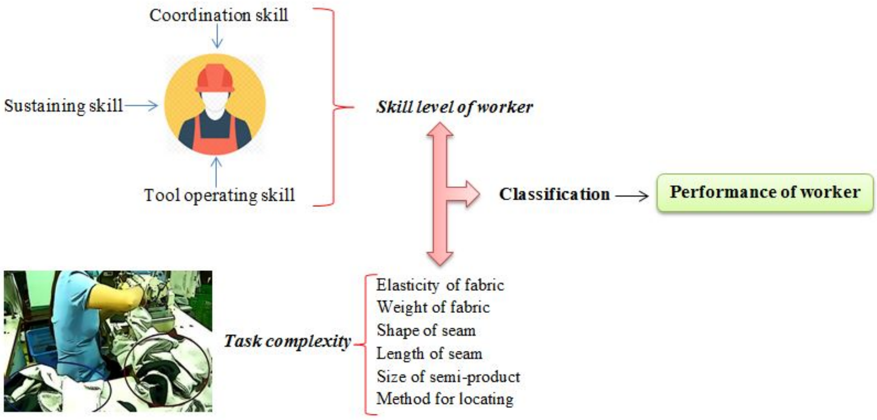

Figure 5.2: Problem definition

Skill level of worker

In an assembly line, the skill level of operators is always one of the most important factors when allocating operators to a task. The level of "mastery" of a skill is used to grade operator skills in performing these jobs. Worker has a higher skill level that operates a task in a shorter time or higher efficiency and performance. We already graded the skill levels of the operators into four possible skill levels in chapter 3, including:

- Level 1: Workers belong level 1 that have weak skill, the workers operate task in the slow and unequivocal speed, they need more training.

- Level 2: Workers belong level 2 that have fair skill, but they accomplish task with the slow speed and not consistent.

- Level 3: Workers belong level 3 that gain good skill, they accomplish task with the quick and consistent speed, and they can accomplish almost sewing tasks in assembly line .

- Level 4: Workers belong level 4 that reach excellent skill, the coordination of sub-operations in their motions is suitable, does not have the redundant operations, and they gain the quick and consistent speed in their motions.

When determining the skill level of operators for inputting data in the worker performance classification system, a decision marker will estimate the coordination skill, sustaining skill, and tool operating skill of the workers. After that, Equation 3.7 to Equation 3.9 are applied to estimate the final skill level of the operators.

Task complexity

For task complexity, we already analyzed six sub-factors that affect the value of task complexity, including three quantitative factors and three qualitative factors:

- Elasticity of fabric: the elasticity of the fabric can make the sewing process difficult for sewing workers, and could greatly affect the quality of the final product.

- Weight of fabric: similar to the elasticity of the fabric, the weight of the fabric is also one of the factors that will affect the task complexity in the sewing production process. If the fabric is thinner, the worker will operate at a slower speed because the fabric layers will be very easily defected, leading to a wrinkled seam and greatly affecting the product quality.

- Length of the seam: we can easily see that the length of a seam directly affects the standard time for completing the task, and contributes to the complexity of the sewing task.

- Shape of the seam: a garment often has three types of seam shapes, such as the straight seam, curve seam, and circle seam. Workers sew the straight seam faster than they sew the curve and circle seam, so tasks involving curve and circle seams are more complex than those with straight seams.

- Size of the semi-finished product: when the semi-finished product is of a large size, workers will meet more difficultly when controlling and operating the task. Tasks involving a larger size as a semi-finished product are therefore more complex to operate.

- Method for locating the product: many tasks in the sewing assembly line are combined between two or three layers of semi-product; therefore, the workers must determine how to locate the product during the sewing process. The time taken by workers to stop sewing and relocate a semi-product will contribute to the complexity level of the task.

In the process for determining the level of task complexity, we applied the proportional 2-tuple linguistic through the fuzzy linguistic values. This approach can support production managers to compare the differing complexity level of two tasks and increase precision in evaluating the task complexity in order to estimate the total cost of the product by determining the cost of the required tasks to complete product. However, when predicting the performance of a worker, when a worker has one skill level that is assigned to a task, just one difference in these sub-factors of the task will lead to a difference in the performance of that worker. That is the main reason that we will use directly six sub-factors of task as the input variables for predicting the performance of workers. In chapter 4, these experts already developed the trapezoidal fuzzy linguistic for three quantitative sub-criteria of task complexity, as shown in Figure 5.3.
From the Figure 5.3 it is evident that elasticity of fabric, weight of fabric and length of seam have five classes as described by the fuzzy number. To classify and predict the performance of workers based on fuzzy theory, we can apply the fuzzy decision tree. However, this technique has some disadvantages, such as it is very difficult to calculate the values of gain information for using classifying and at present we do not have any software and computer technical support for production managers to build the fuzzy decision tree

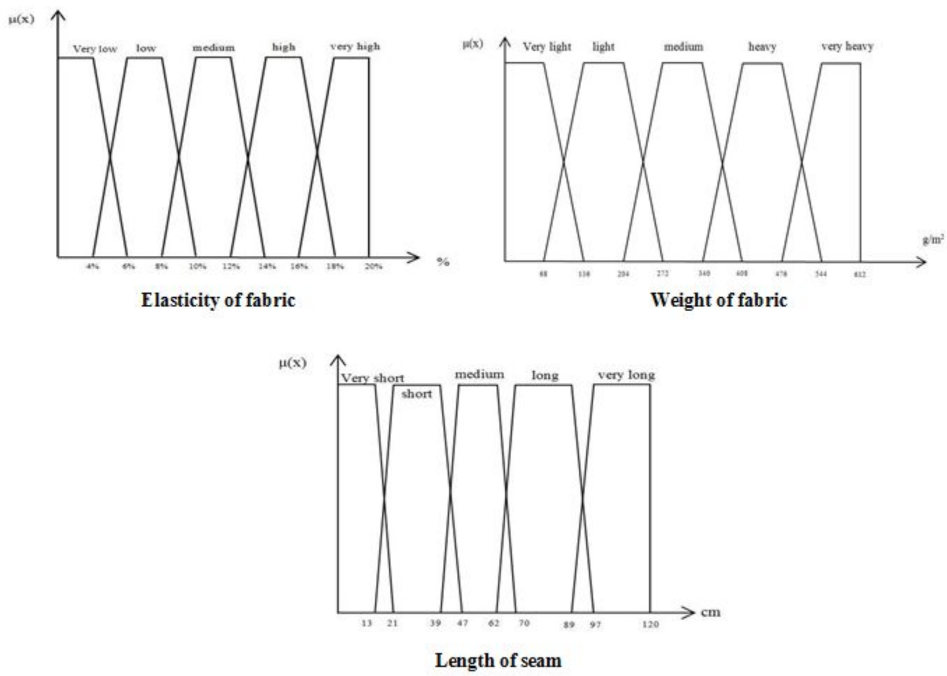

Figure 5.3: Fuzzy linguistic for three quantitative sub-criteria of task complexity.

in a short time. In this case, the decision tree is the best technique to apply. In a decision tree, the values of input variable should be the categorical data. We use the membership function for assigning the classes of three quantitative sub-factors of task complexity. The membership function $\mu_{\tilde{n}}(x)$ is defined as

$$\mu_{\tilde{n}}(x) = \begin{cases} 0, x < n_1 \text{or} x > n_4 \\ \frac{x-n_1}{n_2-n_1}, n_1 \leqslant x \leqslant n_2 \\ 1, n_2 \leqslant x \leqslant n_3 \\ \frac{n_4-x}{n_4-n_3}, n_3 \leqslant x \leqslant n_4 \end{cases} \tag{5.3}$$

From the numerical values of elasticity of fabric, weight of fabric and length of seam, the value of membership function will be calculated; the class that has the highest value of membership function will be chosen.

Beside the three quantitative sub-factors, three sub-attributes of the type of method used, including the shape of the seam, the size of the semi-finished product, and the method for locating the product, comprise the qualitative criteria. They also have a positive impact on the sewing task complexity. When three attributes increase in the linguistic term set, the complexity of the sewing task is also higher. After discussion, the experts reached

a consensus on five levels for these sub-attributes that are measured, such as very easy, easy, medium, difficult, and very difficult.
Six categorical variables of task complexity combined with the skill level of the worker will be the input data for classifying the performance of workers.

Performance of worker

In this research, the performance of the operator is determined through the level of job completion, which is compared with a predetermined time standard. A predetermined time standard is a measurement system that analyzes any manual operation of the worker into the basic human motions necessary to complete the operation and assigns each basic motion an amount of time. The standard time needed to complete this operation has been determined in advance based on the summary of the time of these required motions [66]. One of the greatest advantages of using a predetermined time standard is that the user can estimate the standard time (and therefore cost) for the operations in a given manufacturing process before production has begun.
Today, in the clothing industry, the General Sewing Data System (GSD) is a predetermined time standard system designed specifically for the clothing industry, based on the MTM system. In the GSD system, according to the method of "data code" analysis, sewing activities are divided into seven layers of 34 codes. There is also an 8^{th} grade for extra activities during sewing [67]. Many customers also use the standard time, which is set up from the GSD system, to estimate the delivery time order for the manufacturing supplier. The managers of the production process must answer the question, "For what percentage of orders can my workers satisfy the standard time for the customer?" so as to plan and schedule the production. In this research, the performance of a worker is computed as

$$Performance\ of\ worker = \frac{Actual\ time\ of\ worker}{Standard\ time\ from\ GSD\ system} \tag{5.4}$$

Based on the classifying level of worker skill in Westinghouse system, we classify the performance of the worker into five levels, as shown in Table 5.1.
The performance of workers will be classified into five levels with seven input variables through the decision tree.

Table 5.1: The levels of performance rating of worker.

Level	*Performance rating of worker*
Poor	$PR \leq 78\%$
Fair	$78\% < \text{PR} \leq 90\%$
Standard	$90\% < \text{PR} \leq 100\%$
Good	$100\% < \text{PR} \leq 111\%$
Excellent	$PR > 111\%$

5.3.2 Data collection

To represent the classification problem, each tuple requires seven decision variables. The value of each variable is defined, including:

- Skill level of worker {*Skill level 1, Skill level 2, Skill level 3, Skill level 4*}
- Elasticity of fabric {*Very-low, Low, Medium, High, Very-high*}
- Weight of fabric {*Very-light, Light, Medium, Heavy, Very-heavy*}
- Length of seam {*Very-short, Short, Medium, Long, Very-long*}
- Shape of seam {*Very-easy, Easy, Medium, Difficult, Very-difficult*}
- Size of semi-finished product {*Very-easy, Easy, Medium, Difficult, Very-difficult*}
- Method for locating product {*Very-easy, Easy, Medium, Difficult, Very-difficult*}

For each case, experts use the garment specification sheet to determine the values of these variables that belong to the characteristics of the material. Figure 5.4 is an example of a specification sheet for a menswear formal shirt. For example, elasticity and weight of fabric are determined from the information about the specification of fabric. In addition, the length and shape of seam are estimated through the measurement of size. Finally, experts determined the complexity level of the size of the semi-finished product and the method for locating the product through the description of the garment. The process for determining the skill level of workers when operating the task follows the process used for grading skill level in Chapter 3. One hundred and ten decision cases are collected from the historical cases in which a sewing production has been implemented. The historical decision case is shown in Table 5.2.

ANKITA MEHTA GARMENT SPECIFICATION SHEET

Garment Specification Sheet

Style No. # AM 001	Date : 20-09-2015
Category : Menswear	Size: Medium (40)
Season: Spring-Summer	Designers Name : Ankita Mehta
Description of Garment: Men Tailored Formal Evening Wear Shirt.	

S.No	Measurements (in Cms.)	
1	Neck Size	40cms
2	Chest	100cms
3	Scye Depth	24.4cms
4	Back Neck to Waist	44.2cms
5	Half Back	20cms
6	Shirt Length	77cms
7	Sleeve Length	82cms
8	Cuff Size	24cms

Front **Back**

Wash Care Instructions	Machine Wash, Line Dry, Iron Medium, Do not Bleach		
Fabrics / lining Light Cots-Wool Blend	Fabric 1 	Fabric 2	Fabric 3
Description of Fabric : (Fabric composition, Construction, Width)	Easily Ripping Fabric, Width 60"		
Trims and Accessories	0.5cm Satin Ribbon (on back yoke, shirt collar & concealed placket), Black Buttons Size 6 (plain) Microdot Fusing (placket) Buckram Fusing (collar & cuff)		
Remarks	All fabric patterns need to be overlocked before stitching; Satin Trim has to be attached to patterns before stitching begins.		

2

Figure 5.4: Menswear Formal Shirt Garment Specification Sheet.

Case ID	*Skill level of worker*	*Elasticity of fabric*	*Weight of fabric*	*Length of seam*	*Shape of seam*	*Size of semi-product*	*Method for locating product*	*Performance of worker*
1	Skill 1	Low	Medium	Short	Very easy	Difficult	Easy	**Fair**
2	Skill 3	High	Very heavy	Very short	Easy	Very easy	Medium	**Good**
3	Skill 4	High	Medium	Very long	Difficult	Very difficult	Difficult	**Fair**
4	Skill 2	High	Medium	Short	Difficult	Difficult	Easy	**Fair**
5	Skill 4	High	Light	Short	Medium	Very difficult	Easy	**Standard**
6	Skill 3	High	Medium	Medium	Difficult	Difficult	Medium	**Fair**
7	Skill 2	High	Light	Very short	Medium	Easy	Easy	**Poor**
8	Skill 1	Low	Medium	Medium	Difficult	Medium	Easy	**Fair**
9	Skill 2	Low	Very heavy	Short	Medium	Easy	Difficult	**Poor**
10	Skill 4	Low	Light	Medium	Difficult	Easy	Medium	**Good**
11	Skill 3	Low	Heavy	Long	Easy	Difficut	Medium	**Fair**
12	Skill 2	Medium	Heavy	Short	Very easy	Easy	Difficult	**Standard**
13	Skill 3	Medium	Light	Medium	Easy	Medium	Very easy	**Excellent**
14	Skill 4	Low	Medium	Long	Difficult	Medium	Difficult	**Good**
15	Skill 1	High	Very light	Very short	Difficult	Medium	Medium	**Poor**
16	Skill 2	Low	Heavy	Medium	Easy	Difficult	Difficult	**Fair**
17	Skill 3	Medium	Heavy	Long	Easy	Difficult	Very easy	**Excellent**
18	Skill 3	Low	Heavy	Very short	Easy	Difficult	Medium	**Fair**
19	Skill 4	High	Light	Medium	Difficult	Medium	Difficult	**Standard**
20	Skill 2	Low	Heavy	Short	Easy	Easy	Easy	**Fair**
21	Skill 2	Medium	Very heavy	Short	Difficult	Easy	Difficult	**Fair**
22	Skill 3	Low	Heavy	Very long	Medium	Medium	Difficult	**Fair**
23	Skill 1	Low	Light	Very short	Easy	Very easy	Easy	**Fair**
24	Skill 2	Medium	Heavy	Long	Easy	Difficult	Easy	**Fair**
25	Skill 2	High	Light	Short	Difficult	Medium	Difficult	**Fair**
26	Skill 3	Medium	Light	Very short	Easy	Difficult	Medium	**Fair**
27	Skill 2	Medium	Very heavy	Very short	Difficult	Easy	Very easy	**Standard**
28	Skill 2	High	Very light	Short	Easy	Easy	Easy	**Fair**
29	Skill 3	Medium	Heavy	Short	Medium	Difficult	Easy	**Good**
30	Skill 4	High	Light	Very short	Easy	Very difficult	Very difficult	**Fair**
31	Skill 3	Low	Heavy	Medium	Difficult	Medium	Difficult	**Fair**
32	Skill 3	High	Medium	Long	Easy	Difficult	Medium	**Fair**
33	Skill 2	Medium	Heavy	Very short	Easy	Medium	Easy	**Fair**
34	Skill 4	High	Very light	Medium	Medium	Difficult	Easy	**Standard**
35	Skill 4	Low	Medium	Very short	Easy	Easy	Very difficult	**Good**
36	Skill 2	Low	Light	Short	Medium	Easy	Medium	**Fair**
37	Skill 4	High	Heavy	Short	Medium	Medium	Difficult	**Standard**
38	Skill 3	Low	Very light	Short	Difficult	Easy	Difficult	**Fair**
39	Skill 4	Hight	Heavy	Medium	Easy	Difficult	Very difficult	**Good**
40	Skill 2	Medium	Heavy	Short	Difficult	Medium	Difficult	**Fair**
41	Skill 3	Very low	Very light	Medium	Very difficult	Easy	Difficult	**Fair**
42	Skill 2	High	Light	Long	Medium	Easy	Medium	**Poor**
43	Skill 2	High	Heavy	Very short	Medium	Easy	Very easy	**Poor**
44	Skill 2	Medium	Very heavy	Long	Difficult	Difficult	Medium	**Poor**
45	Skill 3	Low	Medium	Very short	Very difficult	Medium	Difficult	**Standard**
46	Skill 2	Low	Heavy	Medium	Easy	Easy	Difficult	**Fair**
47	Skill 4	Very high	Light	Medium	Very difficult	Medium	Very difficult	**Fair**
48	Skill 1	Very low	Light	Long	Difficult	Difficult	Easy	**Fair**
49	Skill 4	Low	Very heavy	Short	Difficult	Very difficult	Difficult	**Excellent**
50	Skill 3	Low	Heavy	Short	Very difficult	Very difficult	Difficult	**Fair**
51	Skill 2	Medium	Medium	Long	Very easy	Easy	Medium	**Standard**
52	Skill 4	Very high	Light	Medium	Medium	Very difficult	Very difficult	**Fair**
53	Skill 3	Very low	Medium	Short	Medium	Medium	Medium	**Standard**
54	Skill 2	Medium	Heavy	Very short	Easy	Medium	Medium	**Standard**
55	Skill 4	High	Medium	Short	Easy	Medium	Difficult	**Good**
56	Skill 3	Very low	Light	Medium	Difficult	Medium	Medium	**Standard**
57	Skill 1	Low	Medium	Short	Difficult	Medium	Difficult	**Poor**
58	Skill 4	High	Very light	Very short	Medium	Difficult	Easy	**Standard**
59	Skill 2	Medium	Medium	Very short	Medium	Very difficult	Easy	**Standard**
60	Skill 1	Very low	Medium	Short	Easy	Medium	Difficult	**Poor**

61	Skill 1	Medium	Light	Medium	Very easy	Difficult	Very difficult	**Poor**
62	Skill 2	Low	Heavy	Very short	Difficult	Medium	Medium	**Standard**
63	Skill 4	Very high	Medium	Medium	Easy	Medium	Difficult	**Good**
64	Skill 3	Very low	Light	Short	Difficult	Very easy	Medium	**Good**
65	Skill 4	High	Very light	Medium	Medium	Difficult	Very easy	**Good**
66	Skill 4	Low	Medium	Very short	Easy	Difficult	Very difficult	**Good**
67	Skill 2	Low	Light	Long	Medium	Easy	Medium	**Fair**
68	Skill 3	High	Heavy	Short	Medium	Medium	Difficult	**Fair**
69	Skill 2	High	Heavy	Very short	Medium	Easy	Medium	**Poor**
70	Skill 4	High	Heavy	Short	Difficult	Easy	Difficult	**Standard**
71	Skill 3	Low	Very light	Short	Difficult	Very difficult	Difficult	**Fair**
72	Skill 4	High	Heavy	Medium	Very difficult	Easy	Very difficult	**Fair**
73	Skill 2	Medium	Heavy	Short	Very difficult	Medium	Medium	**Poor**
74	Skill 3	Very low	Very light	Short	Very difficult	Easy	Medium	**Good**
75	Skill 2	High	Light	Long	Medium	Easy	Medium	**Poor**
76	Skill 2	High	Heavy	Very short	Medium	Very easy	Medium	**Good**
77	Skill 2	Medium	Very heavy	Long	Difficult	Difficult	Medium	**Poor**
78	Skill 3	Medium	Light	Very short	Very difficult	Medium	Difficult	**Fair**
79	Skill 2	Medium	Heavy	Medium	Easy	Easy	Easy	**Fair**
80	Skill 2	Medium	Medium	Long	Very easy	Easy	Difficult	**Standard**
81	Skill 1	Very low	Medium	Short	Medium	Difficult	Difficult	**Poor**
82	Skill 3	High	Very easy	Long	Easy	Medium	Medium	**Standard**
83	Skill 4	High	Medium	Very long	Difficult	Very difficult	Difficult	**Fair**
84	Skill 2	High	Medium	Short	Medium	Difficult	Easy	**Poor**
85	Skill 4	High	Light	Short	Medium	Very difficult	Easy	**Standard**
86	Skill 3	High	Medium	Long	Difficult	Difficult	Medium	**Fair**
87	Skill 2	High	Light	Very short	Medium	Easy	Easy	**Poor**
88	Skill 1	Low	Medium	Long	Medium	Difficult	Very easy	**Fair**
89	Skill 2	Very low	Very heavy	Very short	Difficult	Easy	Very easy	**Standard**
90	Skill 2	Very high	Heavy	Very short	Medium	Easy	Medium	**Poor**
91	Skill 2	Medium	Heavy	Long	Very difficult	Medium	Medium	**Poor**
92	Skill 4	Very low	Light	Medium	Difficult	Easy	Medium	**Excellent**
93	Skill 2	Medium	Heavy	Medium	Very difficult	Medium	Medium	**Poor**
94	Skill 2	Medium	Heavy	Very long	Very difficult	Medium	Medium	**Poor**
95	Skill 2	Medium	Heavy	Very long	Difficult	Medium	Difficult	**Poor**
96	Skill 4	Low	Very light	Very short	Easy	Difficult	Very difficult	**Good**
97	Skill 4	High	Very light	Very short	Very easy	Difficult	Easy	**Good**
98	Skill 4	Medium	Medium	Very long	Difficult	Very difficult	Difficult	**Good**
99	Skill 4	Medium	Light	Short	Difficult	Easy	Difficult	**Standard**
100	Skill 4	Medium	Heavy	Medium	Very difficult	Medium	Very difficult	**Good**
101	Skill 3	Medium	Light	Medium	Easy	Medium	Very Very easy	**Excellent**
102	Skill 3	Medium	Heavy	Short	Medium	Difficult	Easy	**Good**
103	Skill 4	Low	Light	Medium	Difficult	Easy	Medium	**Good**
104	Skill 4	Low	Very light	Very short	Easy	Difficult	Very difficult	**Good**
105	Skill 1	High	Very light	Very short	Difficult	Medium	Medium	**Poor**
106	Skill 3	Medium	Heavy	Short	Medium	Difficult	Easy	**Good**
107	Skill 4	Low	Light	Medium	Difficult	Easy	Medium	**Good**
108	Skill 2	Medium	Heavy	Short	Very easy	Easy	Difficult	**Standard**
109	Skill 2	Medium	Medium	Long	Very easy	Easy	Difficult	**Standard**
110	Skill 4	Low	Light	Medium	Difficult	Easy	Medium	**Good**

5.3.3 Results analysis

From the data set, the entropy is first computed using the class names identified. In total, 110 cases were collected: 22 Poor, 38 Fair, 22 Standard, 23 Good, and 5 Excellent. Thus:

$$H(\textit{22 Poor, 38 Fair, 22 Standard, 23 Good, 5 Excellent}) = -\frac{22}{110}log_2\frac{22}{110}$$
$$-\frac{38}{110}log_2\frac{38}{110} - \frac{22}{110}log_2\frac{22}{110} - \frac{23}{110}log_2\frac{23}{110} - \frac{5}{110}log_2\frac{5}{110} = 2.133$$

In the next step, the information gained of the seven attributes in the data is calculated to expand the tree. For example, here we demonstrate one attribute, the process for calculating the information gain of skill level of the worker:

$$H(\textit{Skill level, Skill 1}) = -\frac{6}{11}log_2\frac{6}{11} - \frac{5}{11}log_2\frac{5}{11} = 0.994$$

$$H(\textit{Skill level, Skill 2}) = -\frac{16}{40}log_2\frac{16}{40} - \frac{13}{40}log_2\frac{13}{40} - \frac{10}{40}log_2\frac{10}{40} - \frac{1}{40}log_2\frac{1}{40} = 1.689$$
$$H(\textit{Skill level, Skill 3}) = -\frac{14}{27}log_2\frac{14}{27} - \frac{4}{27}log_2\frac{4}{27} - \frac{6}{27}log_2\frac{6}{27} - \frac{3}{27}log_2\frac{3}{27} = 1.734$$
$$H(\textit{Skill level, Skill 4}) = -\frac{6}{32}log_2\frac{6}{32} - \frac{8}{32}log_2\frac{8}{32} - \frac{16}{32}log_2\frac{16}{32} - \frac{2}{32}log_2\frac{2}{32} = 1.703$$
$$G(S, \text{skill level}) = 2.133 - \left(\frac{11}{110} \times 0.994 + \frac{40}{110} \times 1.689 + \frac{27}{110} \times 1.734 + \frac{32}{110} \times 1.703\right) = 0.499$$

Similar to the process for getting the information gain on the value of skill level, the information gain scores of the remaining criteria are as follows:
$G(S, \text{elasticity of fabric}) = 0.156$
$G(S, \text{weight of fabric}) = 0.076$
$G(S, \text{length of seam}) = 0.130$
$G(S, \text{shape of seam}) = 0.201$
$G(S, \text{size of semi-product}) = 0.157$
$G(S, \text{method for locating}) = 0.210$
Therefore, the attribute *skill level of worker* has the highest score, so consequently we will use this attribute to expand the decision tree. After choosing the skill level of worker to become the root node, we continue calculating the information gain scores of the other attributes, so we can get the desired tree. In this study, we use Weka software to devise the final decision tree quickly. The resulting decision tree is shown in Figure 5.5.

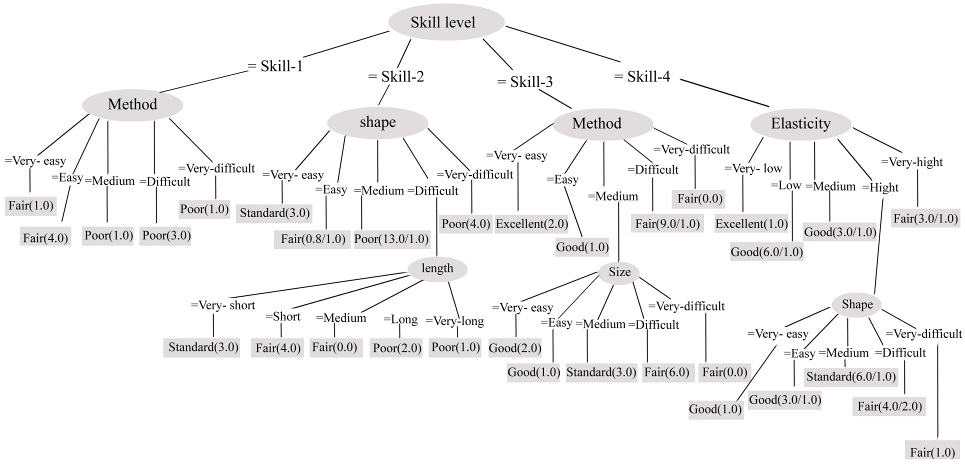

Figure 5.5: The final decision tree for classifying the performance.

The summary of the performance of the model is shown in Table 5.3. In the performance results of the model, accuracy is always the most crucial performance specification. Here, it is simply a ratio of the correctly predicted observations to the total observations. In our model, the correct classification instances comprise 76.36%. However, the accuracy is only a useful measure when you have symmetric data sets where the values of false positives and false negatives are almost same. In this case, we should also consider the measures of the model for each class. The true positives rate describes the correctly predicted positive values, which means that the value of the actual class is yes and the value of the predicted class is also yes. The higher the true positives rate, the better the model. In our model, the accuracy of classification for Poor, Fair, and Standard performance classes is better than the Good and Excellent classes. Precision measure is the ratio of correctly predicted positive observations to the total predicted positive observations. High precision relates to a low false positive rate. Our model demonstrates a good precision score for classifying these classes. Recall measure is the ratio of correctly predicted positive observations to all observations in the actual class-yes. Finally, F-measure score is calculated using the weighted average of the Precision and Recall scores. Therefore, this value takes both false positives and false negatives into account. F-measure is usually more useful than

Table 5.3: The performance of the model

Correctly classification instances	76.36%				
Incorrectly classification instances	23.64%				
Detailed Accuracy By Class					
Class	*True Positive rate*	*False Positive rate*	*Precision*	*Recall*	*F-Measure*
Poor	0.909	0.057	0.800	0.909	0.851
Fair	0.816	0.111	0.795	0.816	0.805
Standard	0.727	0.102	0.640	0.727	0.681
Good	0.609	0.046	0.778	0.609	0.683
Excellent	0.600	0.000	1.00	0.600	0.750
Average	*0.764*	*0.080*	*0.771*	*0.764*	*0.761*

accuracy, especially if the data set has an uneven class distribution. The results from the F-measure show that the model has good classification for Poor, Fair, and Excellent classes. The classification of the Standard and Good classes has lower results than the other three classes.

Finally, from the result of the decision tree, we can state these rules for classifying and predicting the performance rating of workers in an assembly line, as follows:

- IF the worker has the "skill level 1", AND he/she is assigned a task for which "method for locating" is "very easy" or "easy" THEN his/her performance is Fair.

- IF the worker has the "skill level 1", AND he/she is assigned a task for which "method for locating" is "medium", "difficult", or "very difficult" THEN his/her performance is Poor.

- IF the worker has the "skill level 2", AND he/she is assigned a task for which "shape of seam" is "very-easy" THEN his/her performance is Standard.

- IF the worker has the "skill level 2", AND he/she is assigned a task for which "shape of seam" is "easy" THEN his/her performance is Fair.

- IF the worker has the "skill level 2", AND he/she is assigned a task for which "shape of seam" is "medium" THEN his/her performance is Poor.

- IF the worker has the "skill level 2", AND he/she is assigned a task for which "shape of seam" is "Difficult" AND "length of seam" is "very short" THEN his/her performance is Standard.

- IF the worker has the “skill level 2”, AND he/she is assigned a task for which “shape of seam” is “Difficult” AND “length of seam” is “short” or “medium” THEN his/her performance is Fair.
- IF the worker has the “skill level 2”, AND he/she is assigned a task for which “shape of seam” is “Difficult” AND “length of seam” is “long” or “very long” THEN his/her performance is Poor.
- IF the worker has the “skill level 3”, AND he/she is assigned a task for which “method for locating” is “very easy” THEN his/her performance is Excellent.
- IF the worker has the “skill level 3”, AND he/she is assigned a task for which “method for locating” is “easy” THEN his/her performance is Good.
- IF the worker has the “skill level 3”, AND he/she is assigned a task for which “method for locating” is “Medium” AND “size of semi-product” is “very easy” or “easy” THEN his/her performance is Good.
- IF the worker has the “skill level 3”, AND he/she is assigned a task for which “method for locating” is “Medium” AND “size of semi-product” is “medium” THEN his/her performance is Standard.
- IF the worker has the “skill level 3”, AND he/she is assigned a task for which “method for locating” is “Medium” AND “size of semi-product” is “difficult” or “very difficult” THEN his/her performance is Fair.
- IF the worker has the “skill level 3”, AND he/she is assigned a task for which “method for locating” is “difficult” or “very difficult” THEN his/her performance is Fair.
- IF the worker has the “skill level 4”, AND he/she is assigned a task for which “elasticity of fabric” is “very low” THEN his/her performance is Excellent.
- IF the worker has the “skill level 4”, AND he/she is assigned a task for which “elasticity of fabric” is “low” or “medium” THEN his/her performance is Good.

- IF the worker has the “skill level 4”, AND he/she is assigned a task for which “elasticity of fabric” is “High” AND “shape of seam” is “very easy” or “easy” THEN his/her performance is Good.
- IF the worker has the “skill level 4”, AND he/she is assigned a task for which “elasticity of fabric” is “High” AND “shape of seam” is “medium” THEN his/her performance is Standard.
- IF the worker has the “skill level 4”, AND he/she is assigned a task for which “elasticity of fabric” is “High” AND “shape of seam” is “difficult” or “very difficult” THEN his/her performance is Fair.
- IF the worker has the “skill level 4”, AND he/she is assigned a task for which “elasticity of fabric” is “very high” THEN his/her performance is Fair.

Using these twenty rules for classifying the performance of workers, production managers can apply and predict the performance of workers before they are assigned a task in an assembly line through determining the skill level of the worker and the characteristics of the task. For example, in an assembly line, if a sewing task has these characteristic including: weight of fabric is “Medium”, elasticity of fabric is “Low”, length of seam is “Very short”, shape of seam is “Difficult”, Size of semi-finished product is “Easy” and method for locating product is “Medium”, the production managers can apply the results of decision tree for predicting the performance rating of worker, following:

- If the worker has skill level 1 that is assigned to this task, his/her performance will be Poor. In this case, the production manager just consider the method for locating product in this task.
- If the worker has skill level 2 that is assigned to this task, his/her performance will be Standard. In this case, the production manager should consider the shape and length of seam in this task.
- If the worker has skill level 3 that is assigned to this task, his/her performance will be Good. In this case, the production manager should consider the method for locating product and size of semi-finished in this task.

- If the worker has skill level 4 that is assigned to this task, his/her performance will be Good. In this case, the production manager just consider elasticity of fabric.

In this task, two workers have skill level 3 and skill level 4 having the same performance rating. In this case, production manager should choose the worker has skill level 3 for saving the labor cost. Results of decision tree in this chapter can support the production managers to predict worker's performance and choose the best suitable worker for assigning tasks in an assembly line.

Chapter 6

Conclusion

In this research, my main purpose was to develop a new methodology for forecasting the performance of workers in a production assembly line. From my standpoint, the performance of workers is the result of the interaction between the skill level of that worker and the complexity of the task they are undertaking. Then, according to this viewpoint, I developed a method for ranking the skill level of operators based on Principal component analysis and Ordinal logistic regression. The detail of the contents for grading the operator skill levels was presented in Chapter 3. In addition, I also determined the complexity level of tasks in an assembly line through estimating the values of six sub-factors that have an impact on task complexity. The complexity level of tasks was described as 2-tuple fuzzy linguistic representations. The methodology for computing the complexity level of tasks was presented in Chapter 4. Finally, a new methodology for forecasting the performance of workers through the interaction between the skill level of the worker and task complexity was developed by applying the decision tree method. The process was applied in the clothing industry to illustrate its practical application.

6.1 Main contributions

The main contributions of my study are summarized as follows:

- Firstly, this research developed a new methodology for determining the skill level of operators. In the first step, I determined six attributes that affect the skill level of workers. However, the production managers will face a lot of difficultly when determining the values of six attributes simultaneously. Overcoming this disadvantage, I apply Principle component analysis to combine the six attributes. This creates three variables. I then apply ordinal logistic regression to compute the probability of the skill levels of workers. According to this model, each worker is allocated to the skill level that has the highest predicted probability. The results are acceptable and very encouraging, particularly in terms of the consensus-based skill level standards that can be statistically authenticated to create performance ratings.

- Secondly, task complexity is one of the key criteria that affects and can be used to predict employee performance. Tasks have been found to be an important component in production management. The manager must estimate the complexity level of a task for production scheduling and costing. My research also analyzed the characteristics of tasks in an assembly line to estimate the complexity level by applying AHP and a proportional 2-tuple linguistic representation model. The proposal approach takes into consideration many of decision-makers' ambiguities, uncertainties, and vagueness in evaluating task complexity level.

- Thirdly, a rule-based system support for production managers predicting the performance of workers in an assembly line was also developed. In this step, the performance of a worker is predicted through the interaction between the skill level of the worker and the characteristics of the task. A decision tree was built for classifying the performance of the worker into five classes, including poor, fair, standard, good, and excellent. Based on the new worker performance system, production managers can predict the performance of a worker before they operate the task. This system will support productions manager when choosing to assign or reassign workers to tasks on an assembly line.

- Finally, the contribution of this research to Knowledge Science includes the development of three evaluation models for the skill level of workers, task complexity, and the performance rating of workers. This was achieved through collecting, analyzing, and modeling the knowledge in production systems. These three models could be regarded as new tools for representing and handling tacit knowledge in manufacturing systems. Moreover, they can create new knowledge for Knowledge Science.

6.2 Limitations

My research has some limitations, such as:

- In this research, when determining the skill level of workers through three sub-factors, including sustaining skill, coordination skill, and tool operating skill, I attempted to minimize the subjective biases in the skill levels measurement process by applying Principal component analysis. Despite this, the estimated value of the three variables is still biased and the accuracy relies almost completely on the production manager's experience. Therefore, this study is restricted by the difficulty of reducing personal biases in the assessment variables. Development of a comprehensive benchmark of three variables, based on the knowledge of experts and production managers, would enable less biased estimations on the values of coordination skill, sustaining skill, and tool operating skill.

- Moreover, in the prediction model of worker's performance, the accuracy of the model is not high as, in the dataset, I only had one hundred and ten tuples. The number of tuples in the dataset should increase to cover more classification scenarios of worker's performance.

- In addition, this research just concentrated on a kind of production process where operators have the main influence on the productivity and quality of products. In the automatic production process, such as car production or mobile production, this methodology could be not suitable when applying.

6.3 Future work

In the future, with regards to how a worker's skill level is classified, I will pay closer attention to developing these benchmarks for determining the value of coordination skill, sustaining skill, and tool operating skill. These benchmarks will support the production managers to more easily estimate the values of these skill variables and reduce personal opinion in the judgment variables. In addition, to increase the accuracy of the worker performance prediction model, more data should be collected in the future.

In my research, the case study was applied to the clothing industry. The proposed method described in this research could be extended for application in many other cases where the worker is the essential element and task complexity is the most significant factor that affects worker performance. I will continue to apply this approach in other industrial systems to validate the suitability and practice of the proposed method. For example, the wood furniture industry is also one of the kind of production industries that developing very quick in recent years. The wood furniture companies must analyze and develop strategy plans for improving the manufacturing processes and cost structures. In this industry, operators are also the most important factor that should be considered to create the good products. My research methodology can be applied in this case.

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