PRODUCTIVITY BENCHMARKING OF APPAREL INDUSTRY USING HIERARCHICAL EVIDENTIAL REASONING

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BY
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A thesis submitted to the Department of Industrial & Production Engineering, Bangladesh University of Engineering & technology, in partial fulfillment of the requirements for the degree of Master of Science in Industrial & Production Engineering

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CERTIFICATE OF APPROVAL

The thesis titled **"Productivity Benchmarking of Apparel Industry Using Hierarchical Evidential Reasoning"** submitted by Nafisa Mahbub, Student no: 1014082002 P has been accepted as satisfactory in partial fulfillment of the requirements for the degree of Master of Science in Industrial & Production Engineering on August 8, 2017.

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It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Nafisa Mahbub

To the Almighty

To my family

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ABSTRACT

In the last two decades, productivity assessment of apparel organizations has attracted significant attention. The apparel industry of Bangladesh has been making crucial contribution to rebuilding the country and its economy. Apparel sector is now the single biggest export earner for Bangladesh. Productivity is a key determinant for the success of any organization. Traditional productivity measures are based on measuring the quantities of outputs produced as well as the inputs used in the production process. However, these quantitative methods cannot usually be applied to measure the organization's productivity, if it's any output or input has a qualitative type of nature. Therefore, there is a need for a new measurement method that this type of organizations could use in managing their productivity. Subjective productivity measurement is a measurement approach that collects information about qualitative inputs or outputs of productivity through a questionnaire or an interview targeted to an interest group. The productivity assessment process of apparel organizations is aligned with several sources that can be uncertain, including incomplete information, limited domain knowledge from decision-makers, and failures to provide accurate judgments from experts. In this study, the Hierarchical Evidential Reasoning (HER) approach is developed to manage this expanding complexities and uncertainties in assessment problems. The HER approach is employed here to develop a multiple criteria framework to assess the apparel productivity. A case study of our apparel organizations is provided to illustrate the implementation process. Results shows that using the HER approach the apparel productivity performance index are determined and according to this performance index the organizations are ranked. After analyzing the productivity of these apparel organizations, a sensitivity analysis is conducted to find out the most influential attribute of each industry. Thus, it has been found that it is possible to use HER for benchmarking of our apparel enterprises. This model can also be used for the performance assessment purpose and benchmarking of different fields.

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LIST OF ABBREVIATIONS

AHP	Analytical Hierarchy Process
bpa	Basic Probability Assignment
CDF	Cumulative Distribution Function
DEA	Data Envelopment Analysis
DST	Dempster-Shafer Theory
FANP	Fuzzy Analytical Network Process
GDP	Gross Domestic Product
HER	Hierarchical Evidential Reasoning
MADA	Multiple-attribute Decision Analysis
MCDM	Multi-criteria decision-making
MFP	Multi-factor Productivity
OECD	Organization for Economic Co-operation and Development
PDF	Probability Density Function
R&D	Research and Development
RMG	Readymade Garment
TFP	Total Factor Productivity
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

CHAPTER 1
INTRODUCTION

In developing countries, despite increased global integration, it is generally seen that large gaps exist in productivity levels between different sectors, as well as between firms within a sector. Such gaps indicate inefficiencies in resource allocation and wastage. The movement of resources and workforce to activities with higher productivity levels assist in improving overall productivity in the economy [1]. However, institutional framework and weakness at the domestic-level results in a competitive disadvantage and lowers productivity levels of firms in developing countries [2]. Productivity gain in the manufacturing sector draws immense significance for all developing countries, particularly due to its contribution in enhancing competitiveness and promoting economic growth in the long run.

Textiles and apparel industry in Bangladesh is employment-intensive and considered to have great export potential. The apparel industry acts as a catalyst for the development of Bangladesh. The "Made in Bangladesh" tag has also brought glory for the country, making it a prestigious brand across the globe. Bangladesh with its limited resources has been maintaining 6% annual average GDP growth rate and has brought about remarkable social and human development. The industry that has been making crucial contribution to rebuilding the country and its economy is none other than the readymade garment (RMG) industry which is now the single biggest export earner for Bangladesh. The sector accounts for 81% of total export earnings of the country [3]. Bangladesh is the 2nd largest readymade garment exporter in the world. But in terms of productivity, its performance is below the mark. However, certain constraints that may hinder growth are very high interest rates, poor and costly power supply, exchange rate fluctuations and costly raw materials. Bangladesh needs to position itself for greater participation in domestic and global market by improving productivity in textile manufacturing.

To improve the performance of an organization, one need to constantly evaluate operations or processes related to production of products, services, marketing and selling. Performance evaluation and Benchmarking is a widely used process for comparing performance metrics to sector bests or best practices from other sectors. Many studies were performed to increase the productivity of our apparel industry by applying proper line balancing, time study, lean manufacturing system etc. This research will attempt to analyze the potential increase in garment productivity by decomposing it into its different criteria and their comparison with standard measurements, or similar measurements of its peers, which is generally called benchmarking. The objectives of benchmarking are to determine what and where improvements are called for, to analyze how organizations achieve their high performance levels, and to use this information to improve performance of other organizations by focusing on their weak points.

1.1 RATIONALE OF THE STUDY

Multi-criteria decision-making (MCDM), which is concerned with designing computational and mathematical tools for supporting the subjective evaluation of performance criteria by decision-makers, has been gaining some serious attentions as a part of operations research in recent times [4]. It is recognized that organizational performance measurement is an MCDM problem and involves a hierarchical structuring of the decision variables [5]. Some well-known MCDM methods include Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Data Envelopment Analysis (DEA), Analytical Hierarchy Process (AHP), etc. The Hierarchical Evidential Reasoning (HER) approach is the latest development in the MCDM arena. In decision theory, the HER is a generic evidence-based approach for dealing with problems having both quantitative and qualitative criteria under various uncertainties including ignorance and randomness. It has been used to support various decision analysis, assessment and evaluation activities such as organizational self-assessment [6], supplier prioritization [7], condition assessment of construction units [8, 9], system capability assessment [10], efficiency of R&D project assessment [11], etc. based on a range of quality models.

The HER approach has been developed on the basis of decision theory in particular utility theory [12], artificial intelligence in particular the theory of evidence [13], statistical analysis and computer technology. It uses a belief structure to model an assessment with uncertainty, a belief decision matrix to represent an MCDM problem under uncertainty, evidential reasoning algorithms [14] to aggregate criteria for generating distributed assessments, and the concepts of the belief and plausibility functions to generate a utility interval for measuring the degree of ignorance.

Benchmarking of the organizations by assessing the productivity as a multi criteria decision making problem provides a rational way to assess and analyze the capabilities of each and every criterion to compare. The data required for productivity measurement of apparel organizations have both qualitative and quantitative nature as well as there are many incomplete information and vagueness in subjective judgments [15, 16], which clearly indicates aptness of the HER approach in this regard. But this approach has not been applied for apparel organizations yet. If the performances of a number of organizations are evaluated and compared, HER can further be applied to perform sensitivity analysis to identify the critical measures that contribute to enhance the performance [17]. Hence, HER can facilitate productivity benchmarking enabling organizations to compare themselves to the market place in a given sector of industry as well as investigate the processes behind excellent performance, and thus yields the scope of this proposed research.

1.2 OBJECTIVES OF THE STUDY

The detailed research objectives of this research are:

- Incorporating epistemic uncertainty in the form of data conflict and incompleteness in the apparel productivity assessment hence improving its accuracy and informativeness
- To develop a hierarchical structure for appropriately defining the productivity of apparel organization and evaluating them using HER approach.
- To implement HER approach as a comprehensive tool for productivity benchmarking.

So, in short the proposed research will develop HER approach as a tool to assess productivity of an organization as well as to facilitate benchmarking in the apparel industry.

1.3 OUTLINE OF THE METHODOLOGY

The research methodology is outlined as follows:

- The hierarchical structure with appropriate qualitative and quantitative attributes has been developed for defining the productivity of apparel industry.
- The data required for measuring the productivity of the apparel organizations is collected from the apparel organizations nearby Dhaka.

- A set of evaluation grades is then developed to assess each basic attribute (bottom level attributes), so that the assessment can be conducted with reference to individual or a subset of the evaluation grades with different degrees of belief.
- With regard to qualitative attributes, subjective assessment information of assigning belief degrees to each evaluation grade has been collected from decision makers and experts directly.
- For quantitative attributes, a set of referential values is defined to cover the value interval of evaluation grades.
- Then for the quantitative attributes, an information transformation technique is used to generate the corresponding belief distribution equivalent to the original ones in terms of their utilities or values.
- For the purpose of aggregating assessments, the recursive evidential reasoning algorithm is used.
- The utility of the evaluation grades has then been appraised to precisely rank the alternative organizations.
- Sensitivity analysis of different attributes is conducted to identify the critical measures that contribute to enhance the performance for the purpose of benchmarking of the apparel industry.

1.4 ORGANIZATION OF THE REPORT

This research work has been organized in seven chapters, along with a list of references and appendices. Chapter 1 is entitled as ―Introduction”, which describes the motivation, background and justification of the research on benchmarking our apparel industry. The research objectives and the outline of methodology followed in this thesis are also depicted there.

The theoretical background of different stages of production along with their corresponding process variables to modeling the productivity are discussed in the following Chapter 2, termed as ―Theoretical and Mathematical Foundation”. A basic concept on hierarchical evidential reasoning approach is also discussed in this chapter.

Evolution of researches on productivity assessment of apparel organization and different MCDM techniques used so far for benchmarking by international researchers is summarized in the following Chapter 3, termed as ―Literature Review”.

The latter portion of this paper deals with developing benchmarking framework using HER and its detailed formulation, which is illustrated in Chapter 4, named as ―Productivity Modeling of the Apparel Industry”. This chapter also includes the detailed data analysis along with the formulations.

In Chapter 5, which is called ―Case Study of Our Apparel Industry”, the survey in apparel organizations and key performance indicators for each company is analyzed based on the formulated model of chapter 4. Data simulation, performed with the help of Visual Basic Application and Microsoft Excel software, is briefed here.

In Chapter 6, termed as ―Results and Discussion”, discusses on the different results and findings which can be interpreted from the formulated models and benchmarking. Chapter 7 incorporates the research conclusion, with potential recommendations for the future researchers. The ―Reference” enlists all the relevant references, while the ―Appendices” at the end focus on the programming language used to simulate the data for productivity assessment and to benchmark the organizations.

CHAPTER 2

LITERATURE REVIEW

The technique of Hierarchical Evidential Reasoning (HER) has been applied in various instances to evaluate the relative performance of different area, such as, risk assessment, project performance assessment, system capability assessment, condition assessment, etc. This method has been used where the assessment parameters are both qualitative and quantitative as well as has vague or incomplete source of data. In this chapter the literature review part is discussed and presented briefly based on applications to the following broad sectors:

2.1. TECHNIQUES OF PRODUCTIVITY ASSESSMENT

The rapid growing challenges like global competition, dependency on raw material, increased product variety, demanding customer and, globalization have a major influence on apparel industries. Apparel manufacturers need to produce the high quality products reducing the difficulties in operations for acquiring demand for higher value at lower price. In order to survive, they need to combat the constraints associated with the operations. In order to improve the productivity, it is vital to identify, quantify and remove the constraints. The industry can gain higher productivity and profitability with improved quality product by identifying and overcoming the problems that reduce the productivity, cost and improve internal throughput time. The following parts of this section is discussed about the productivity assessment techniques used so far for analyzing the apparel organizations and apparel industry as well as other techniques that is used for productivity assessment in other sectors.

2.1.1 Apparel Productivity Assessment

Several researchers have worked in RMG sector and focused on measuring the productivity of it. Among them Gambhir and Sharma (2015) [18] analyzed productivity performance of Indian textile manufacturing industry using firm-level panel data of 160 companies for the period 2007-2008 to 2012-2013. The output-oriented Malmquist productivity index has been computed through data envelopment analysis. Further, the sources of productivity gain are identified for the entire textile industry as well as for the small and large-scale sector companies separately.

Joshi and Singh (2010) [19] analyzed the firm-level panel data collected from the Centre for Monitoring Indian Economy for the years 2002-2007. One output variable, namely, gross sale and four input variables, namely, net fixed assets, wages & salaries, raw material, and energy & fuel, have been selected. The DEA-based Malmquist Productivity Index (MPI) approach has been applied to measure the Total Factor Productivity (TFP).

Ramcharran (2001) [20] estimated the productivity and efficiency of US textile industry for the period 1975-93 utilizing a variable elasticity of substitution production function. Bhandari and Ray (2012) [21] used both a *grand frontier* applicable to all firms and a *group frontier* specific to firms from any individual state, ownership or organization type in order to evaluate the technical efficiency Indian textile industry. Mokhtarul Wadud (2004) [22] examines firm level technical efficiency of Australian textile and clothing firms using a Cobb Douglas stochastic production frontier in the time varying inefficiency effect model with technical inefficiency effects assumed as an independently distributed truncated normal variable. Bhandari and Maiti (2007) [23] used translog stochastic frontier production function to estimate the technical efficiency of Indian textile manufacturing firms. Erdumlu (2016) [24] evaluated the efficiency of Turkish textile, apparel and leather sector using measure-specific DEA.

2.1.2 Other Approaches to Measuring Performance

Several researchers used other different performance or productivity measurement techniques for assessment purpose. Rouyendegh and Erol (2010) [26] Proposed a hybrid model for supporting the department selection process within Iran Amirkabir University. This research is a two-stage model designed to fully rank the organizational departments where each department has multiple inputs and outputs. First, the department evaluation problem is formulated by Data Envelopment Analysis (DEA) and separately formulates each pair of units. In the second stage, the pairwise evaluation matrix generated in the first stage is utilized to fully rank-scale the units via the Fuzzy Analytical Network Process (FANP).

Zeydan and Çolpan (2009) [27] used integrated criteria in the performance measurement of modern organizations in the context of measuring the performance of the 2nd Air Supply and Maintenance Center Command manufacturing/maintenance jobshops of Turkey by using a new framework which combines fuzzy TOPSIS (technique for order preference by similarity to ideal solution) for measuring qualitative performance with DEA (data envelopment analysis) for measuring quantitative performance. Daneshvar (2011) [28] also used DEA and Intuitionistic Fuzzy TOPSIS approach for departments' performance assessment.

Ramanathan (2006) [29] is developed a performance assessment model where data envelopment analysis (DEA) is proposed to generate local weights of alternatives from pair-wise comparison judgment matrices used in the analytic hierarchy process (AHP).

2.2 RELATED LITERATURE ON HIERARCHICAL EVIDENTIAL REASONING APPROACH

The process of assessing schools involves many attributes as discussed by Borhan and Jemain (2012) [30]. They propose an innovative approach called Evidential Reasoning (ER) that could be used to assess school performance in a multilevel or hierarchical setting which involves indirect measurement of quality by using standardized examination results, rather than directly measuring the quality of the processes unfolding within the schools. The approach is different from most conventional decision making modeling methods in that it employs a belief structure to represent an assessment as a distribution. They conclude by revealing there is little similarity when comparing the school ranking with the normal practice currently adopted.

Wang et.al. (2013) [31] proposed an accident analysis model to develop cost-efficient safety measures for preventing accidents using the Bayesian Network and Evidential Reasoning (ER) approach. The ER approach provides a procedure for aggregating calculations, which can preserve the original features of multiple attributes with various types of information. ER provides a solution for processing subjective risk assessment possibly with academic bias resulting from various opinions of different individuals. They discuss an ER-based cost-benefit analysis method considering risk reduction.

Xu (2012) [32] discussed the Evidential Reasoning (ER) approach and how it is used to analyze multiple criteria decision problems under various types of uncertainty using a unified framework. He describes how the ER approach is surveyed from two aspects: 1) theoretical development and 2) applications. He then discusses how the ER approach is outlined with a focus on the links among its various developments.

Jian et.al. (2011) [10] discussed Weapon System Capability Assessment (WSCA), how it is the initial point of quantification of capabilities in the military capability planning, and how

Evidential Reasoning (ER) was used to develop various types of uncertainties such as ignorance and subjectiveness. The HER approach is used to aggregate the capability measurement information from sub-capability criteria to top-capability criterion. They present results using the ER approach.

Wang et.al. (2008) [8] and Bolar et.al. (2013) [9] used hierarchical evidential reasoning (HER) framework for infrastructure risk management practices to enable decision-makers to effectively monitor and assess structural condition for repairing/replacing elements before major damage or collapse state is reached. The approach involves condition assessment of bridges which used a HER framework for classifying bridge data into primary, secondary, tertiary and life safety-critical elements.

Liu et.al. (2008) [11] used HER for the assessment of strategic R&D projects for a car manufacturer as it is in essence a multiple-attribute decision analysis (MADA) problem. In such problems, qualitative information with subjective judgments of ambiguity is often provided by people together with quantitative data that may be imprecise or incomplete.

Zhang et.al. (2016) [33] used fuzzy rule base technique and an Evidential Reasoning (ER) algorithm to conduct the navigational risk assessment of an Inland Waterway Transportation System (IWTS). A hierarchical structure for modeling IWTS hazards (hazard identification model) are first constructed taking into account both qualitative and quantitative criteria. The quantitative criteria are converted to qualitative ones by applying a fuzzy rule-based quantitative data transformation technique, which enables the use of ER to synthesize the risk estimates from the bottom to the top along the hierarchy.

Nair et.al. (2015) [34] used evidential reasoning approach for assessing confidence in safety evidence. They proposed a novel approach to automatically construct these confidence arguments by enabling assessors to provide individual judgments concerning the trustworthiness and the appropriateness of the evidence. The approach is based on Evidential Reasoning and enables the derivation of a quantified aggregate of the overall confidence. The proposed approach is supported by a prototype tool (EviCA) and has been evaluated using the Technology Acceptance Model.

Solic et.al. (2015) [35] used the evidential reasoning approach for information systems' security level assessment. Ji et.al (2017) [36] proposed a hierarchal risk assessment model using the evidential reasoning rule for fire/explosion risk assessment of marine vessels. Gong et.al (2017) [37] proposed an approach for evaluating cleaner production performance in iron and steel enterprises involving competitive relationships. On the basis of the evidential reasoning (ER) approach and the data envelopment analysis (DEA) cross-efficiency concept, they first constructed a nonlinear programming model to portray the competitive relationship among iron and steel enterprises (ISEs), and obtain the optimal weight and the optimal utility value. Then, by applying the ER approach to the aggregate evaluation information, they obtained the ranking of the ISE cleaner production performance.

Sellak et.al. (2016) [38] researched on energy planning decision-making under uncertainty based on the evidential reasoning approach. Where the evidential reasoning (ER) approach has been developed for managing the expanding complexities and uncertainties in assessment problems. The ER approach is employed as a multiple criteria framework to assess the appropriateness regarding the use of different renewable energy technologies.

2.3 RELATED LITERATURE ON BENCHMARKING

Benchmarking is recognized as an essential tool for continuous improvement of quality. A large number of publications by various authors reflect the interest in this technique. Reviews of literature on benchmarking have been done in the past by a few authors. However, considering the contributions in the recent times, a more comprehensive review is attempted here. The term ‗benchmark' originally referred to a mark on a permanent object that indicated elevation and served as a reference point for topographical surveys and tidal observations (American Productivity & Quality Center, 1993) [39]. The term has subsequently been applied to business management, in which it refers to an achievement that is considered the best in a class, and which thus provides an appropriate standard for others to aspire to. The advantage of such ‗benchmarking' is that it offers a broader view of performance evaluation by encouraging a search for outstanding performance (Camp, 1995) [40]. Nations have even adopted benchmarking management to improve international competitiveness (Mittelstaedt, 1992) [41]. Cusack and Rowan (2009) [42] concluded that benchmarking is a valuable tool for improving performance and is a window enabling organizations to improve productivity performance relative to their peers.

Benchmarking management has been studied in a variety of business contexts, for example, assessing the performance of international tourist hotels [43], [44], [45]. In the construction industry, El-Mashaleh et al. (2007) [46] used DEA to analyze (and critique) the traditional performance measures used in the industry. Furthermore, Ross and Droge (2002) [47] employed DEA in relation to supply chains to propose an integrated benchmarking framework for a large supply chain with 102 distribution centers. Furthermore, in the financial sector, Cook et.al. (2004) [48] used DEA to assess the influence of e-business activities on banking performance, and found that benchmarking could help banks examine their business options and identify weaknesses in branch operations. Kuosmanen (2007) [49] used DEA and stochastic dominance criteria to identify a dominant benchmark portfolio for each evaluated mutual fund. Lee and Kim (2012) [50] proposed a data envelopment analysis (DEA) approach to computation of a measure of overall service quality and benchmarking when measuring service quality with SERVQUAL. Lee and Kim (2014) [51] proposed a data envelopment analysis (DEA) approach to measurement and benchmarking of service quality. Dealing with measurement of overall service quality of multiple units with SERVPERF as multiple-criteria decision-making (MCDM), the proposed approach utilized DEA. Chitnis and Vaidya (2016) [52] proposed efficiency ranking method using DEA and TOPSIS for benchmarking and performance evaluation of Indian bank. Karbassi Yazdi et.al (2017) [53] Designed a robust model for banks benchmarking based on Rembrandt method and DEA.

This brief review of the literature clearly shows that Stochastic Frontier Analysis, DEA, TOPSIS or MCDM have been applied in a variety of industries for benchmarking analysis. However, as noted above, these techniques have shortcomings in terms of their relatively weak explanatory power. The present study contends that the MCDM tool known as ‗HER' can be used to resolve these shortcomings in a benchmarking analysis. Moreover, the literature lacks the application of ‗HER 'in apparel industry.

CHAPTER 3

THEORETICAL AND MATHEMATICAL FOUNDATION

The theoretical background in this work scopes over the topics of productivity assessment and uncertainty analysis formulations. This chapter explains basic concepts in productivity characterization and its assessment along with the detail of the method used in this research for evaluation and the concept of benchmarking.

3.1 CONCEPTS OF PRODUCTIVITY ASSESSMENT

In evaluating the performance of any production system productivity measures an index number, which is a ratio between the output(s) produced and the input(s) consumed. Economists refer to productivity at the broadest level; they are referring to an economy‘s ability to convert inputs into outputs. Productivity is a relative concept with comparisons either being made across time or between different production units. For example, if it is possible to produce more output in period 2, when using the same amount of inputs that were used in period 1, then productivity is said to have improved. In other words, productivity is higher in the second period compared to the first.

There are different measures of productivity and the choice between them depends either on the purpose of the productivity measurement and/or data availability. One of the most widely used measures of productivity is Gross Domestic Product (GDP) per hour worked. This measure captures the use of labor inputs better than just output per employee. Generally, the default source for total hours worked is the Organization for Economic Co-operation and Development (OECD) Annual National Accounts database, though for a number of countries other sources have to be used.

Capital productivity is measured by dividing total output by a measure reflecting the total amount of physical capital used in the production process. Productivity measures, such as labor productivity and capital productivity, which only relate to one class of inputs, are known as partial productivity measures. Caution needs to be applied when using partial productivity measures as changes in input proportions can influence these measures.

After computing the contributions of labor and capital to output, the so-called multi-factor productivity (MFP) can be derived. It measures the residual growth that cannot be explained by the rate of change in the services of labor, capital and intermediate outputs, and is often interpreted as the contribution to economic growth made by factors such as technical and organizational innovation.

The level of total factor productivity (TFP) can be measured by dividing total output by total inputs. Total inputs are often an aggregation of only physical capital and labor, and may overlook inputs such as land. When all inputs in the production process are accounted for, TFP growth can be thought of as the amount of growth in real output that is not explained by the growth in inputs. This is why Abramovitz (1956) [54] described the TFP residual as a _measure of our ignorance‘. As TFP levels are sensitive to the units of measurement of inputs and outputs, they are rarely of primary interest. Rather, the measurement of TFP growth is of primary interest.

The apparel industry is truly global in nature. Apparel manufacturing being labor intensive has been migrating from the high wage developed world to developing countries. However, the developing countries will need to have efficient manufacturing operations if they are to retain their competitiveness in the apparel industry. As productivity measures how efficiently productions inputs, such as labor and capital, are being used in a production organization to produce a given level of output, this is considered a key source of defining growth and competitiveness. Productivity is basic statistical information for many national and international comparisons as well as organizational performance assessments. For example, productivity data are used to investigate the impact of product and labor market regulations on organizational performance. Productivity growth constitutes an important element for modeling the productive capacity of production organizations. It also allows analysts to determine capacity utilization, which in turn allows one to gauge the position of organization in the business cycle and to forecast economic growth.

3.2 MATHEMATICAL FRAMEWORK OF HIERARCHICAL EVIDENTIAL REASONING

The mathematical framework of the HER approach in illustrated below:

3.2.1 Uncertainty Modeling

Uncertainty arises from current and future unknowns and includes unknowns in current physical measurements or the occurrence of future events. In philosophical terms, uncertainty has been subject of extensive research and is hence non-uniformly regarded among different disciplines. This is reflected in the variety of proposed epistemological categorizations [55]. This thesis adopts the definition by Ayyub and Klir (2006) [55] for the fields of engineering and sciences: uncertainty is one type of ignorance (all unknown) and is a conscious ignorance, ―a recognized self-ignorance through reflection"; it arises when knowledge is incomplete due to inherent deficiencies with acquired knowledge.

Uncertainty in the productivity may also be represented from the viewpoint of the procedures that bases it. In the process of modeling the productivity, uncertainty inevitably arises due to humans' inability to capture the true complexity of the production systems. This inherent inability requires applying simplifications in the creation of abstract models of the productivity features and mechanisms. This deliberate departure from comprehensive modeling is one source of uncertainty in productivity data and models. The resulting uncertainty undermines the accuracy and reliability of the outputs obtained from productivity models.

By analyzing the uncertainty associated with productivity modeling, it is possible to reduce the consequences from uncertain data and models. This can be done through managing uncertainty, e.g., by reducing uncertainty, or by communicated uncertainty, e.g., by providing uncertainty-driven results enabling more informed decision making. Uncertainty analysis in productivity has recently become more important as productivity modeling has ―matured", moving beyond the traditional deterministic approaches [56].

As our understanding about the nature and types of uncertainty has improved, methods to handle uncertainty have expanded. Uncertainty has been categorized into two major types: aleatory and epistemic uncertainty [57], [58], [59]. Aleatory uncertainty is also termed variability, stochastic uncertainty or simply stochasticity. This uncertainty is irreducible as it arises from the natural variations within a system. For example, monthly precipitation is treated stochastically since precise knowledge that would otherwise determine its causing mechanism is unavailable. Variability is regularly parameterized and represented by either probability density functions (PDF) or cumulative distribution functions (CDF).

Epistemic uncertainty (also termed subjective uncertainty) arises from limited knowledge about the system. It can be reduced by improving the means by which systems are observed and modeled. Some types of epistemic uncertainty include incompleteness, vagueness, ambiguity and conflict. Ayyub and Klir (2006) [55] provided a taxonomy of various epistemic uncertainty and methods to handle them. Among epistemic uncertainties, incompleteness and conflict frequently occur in productivity analysis. Incompleteness arises from missing data and can be handled by Dempster-Shafer Theory (DST) [60], [61]. Conflict arises from disagreement between multiple data available for a given phenomenon, such as measurements from different persons, methods or models. Conflict can similarly be handled by DST and is discussed in detail in the following sections.

Traditionally, in handling uncertainty, probabilistic methods have predominantly been used. Such applications usually focus on aleatory uncertainty. As such, some researchers still emphasize the capability of probabilistic methods for handling different uncertainties [26]. On the other hand, probabilistic methods have been challenged by others for handling data that are subject to epistemic uncertainties that result from lack of knowledge about the system [62]. These include additional types of epistemic uncertainty such as vagueness and ambiguity [63], [64]. For instance, information may be expressed in linguistic terms (e.g., ‗low‘, ‗medium‘ and ‗high‘) which are inherently vague, and not probabilistic. Expert opinion is one case of such information and is efficiently modeled by methods such as fuzzy logic [65]. Ambiguity arises when information is missing that would otherwise specify the choice between alternatives [66].

Ayyub and Klir (2006) [55] provide a taxonomy of different types of uncertainty and methods to handle them. From this taxonomy those uncertainties appearing in productivity data and handling methods have been addressed in this work.

3.2.2 Dempster–Shafer Theory (DST)

Dempster-Shafer Theory (DST) is a mathematical theory of evidence. The seminal work on the subject is [Shafer, 1976] [61], which is an expansion of [Dempster, 1967] [60]. In a finite discrete space, Dempster-Shafer theory can be interpreted as a generalization of probability theory where probabilities are assigned to sets as opposed to mutually exclusive singletons. In traditional probability theory, evidence is associated with only one possible event. In DST, evidence can be associated with multiple possible events, e.g., sets of events. As a result, evidence in DST can be meaningful at a higher level of abstraction without having to resort to assumptions about the events within the evidential set. Where the evidence is sufficient enough to permit the assignment of probabilities to single events, the Dempster-Shafer model collapses to the traditional probabilistic formulation. One of the most important features of Dempster-Shafer theory is that the model is designed to cope with varying levels of precision regarding the information and no further assumptions are needed to represent the information.

It also allows for the direct representation of uncertainty of system responses where an imprecise input can be characterized by a set or an interval and the resulting output is a set or an interval.

For example, if hypotheses include sets of: {low}, {medium} and {high}, DST would enable probability to be assigned to an additional {low, medium} set. Similarly, if a cumulative distribution function is thought to contain a set of scalar hypotheses for a variable, DST can additionally assign probability to interval hypotheses. As such, by formally allowing a more precise allocation of evidence to both disjoint and non-disjoint sets, DST enables a finer representation of uncertainty information compared to Bayesian theory. If data consist of disjoint hypotheses, DST's frame of discernment reduces to that of a Bayesian characterization.

One of the advantages of DST is its capacity to handle conflict and incompleteness simultaneously in a formal unified framework. This capacity renders this framework well for modeling uncertainties specific to productivity data. DST can also model additional types of epistemic uncertainties such as vagueness by using its extensions. Vagueness can be handled by incorporating fuzzy membership functions within the framework of fuzzy Dempster-Shafer (FDS) [67].

The frame of discernment (Θ) is the fundamental set in DST and consists of an exhaustive set of mutually exclusive hypotheses or propositions. For example, for ‗worker education level' the set of propositions can be defined to include ‗low' (L), ‗medium' (M) or ‗high' (H). No other sets exist in the frame of discernment (the property of being exhaustive), and the intersection between pairs of sets is a null set (e.g., $L \cap M = \emptyset$), i.e., they are mutually exclusive. The power set, 2^{Θ} is defined as the set of all possible subsets of Θ (including the empty set Ø). For example, if the frame of discernment is comprised of three sets, Θ = {L, M, H}, its power set will consist of 8 subsets as following:

$2^{\Theta} = \{\emptyset, \{L\}, \{M\}, \{H\}, \{L, M\}, \{M, H\}, \{L, H\}, \{L, M, H\}\}$.

Among the subsets, the last subset ({L, M, H} = Θ) denotes complete ignorance as it fails to provide any specific information. Each subset in the power set of Θ is called a focal element. Subsets can also be intervals, such as {[2.5 4]} or {[4 17] ∪ [22 35]}.

Based on the evidence provided, each focal element may be assigned a degree of belief ∈ [0, 1], where 0 represents no belief and 1 represents complete belief. The degree of belief for each proposition is termed a basic probability assignment (*bpa*), or mass function (m), e.g., m ({L, M}) = 0.5.

DST uses a generalized notion of probability termed a basic probability assignment *bpa*, or mass function, m. *bpa* is the proportion of all relevant and available evidence (such as empirical evidence or expert knowledge), that support a particular focal element. The *bpa* ranges between 0 and 1.

It should be noted that *bpa* is not analogous to the classical definition of probability, rather, it is a mapping of the power set to the interval between 0 and 1, where the *bpa* of the null set is m(∅) = 0, and the summation of the *bpa*s of all subsets (i.e., all possibilities) of the power set is 1 [33]. The proposition m (A) has the following properties:

$$\sum_{A \subseteq \Theta} m(A) = 1 \tag{3.1}$$

$$\forall\, A \subseteq \Theta \; 0 \leq m(A) \leq 1 \tag{3.2}$$

i.e., according to (3.2), the probability of an event lies between 0 and 1. Suppose that the evidence is m (M) = 0.7 on a frame of discernment Θ = {L, M, H}. As required by (3.1), the total *bpa* should sum to 1, therefore 0.3 is assigned to ignorance, i.e., m (Θ) = m (L, M, H) = 0.3. All the remaining subsets have zero probability mass. In comparison to Bayesian theory, DST requires all missing evidence to be assigned to ignorance while Bayesian theory equally distributes missing evidence to the remainder disjoint subsets (Laplace Principle of Insufficient Reason).

Equation (3.1) corresponds to a closed world (exhaustive) assumption, meaning that no other state than the universal set elements can possibly be achieved. If no evidence relevant to any focal element is available, the remainder *bpa* is assigned to ignorance (Θ). Equation (3.2) requires the summation of *bpa*'s of focal elements to equal to 1.

The lower bound for probability in DST (as well as in other frameworks) is belief. For a proposition of interest A_i, the belief function is defined as the sum of all the *bpa*'s of the proper subsets A_k of the proposition of interest A_i, i.e., $A_k \subseteq A_i$ for proposition A_i. The general relation between *bpa* and belief is expressed as:

$$bel\,(\mathrm{A_i}) = \sum_{\mathrm{A_k} \subseteq \mathrm{A_i}} m(\mathrm{A_k}) \quad (3.3)$$

The belief function has two other properties:

$$\begin{cases} bel\,(\emptyset) = 0 \\ bel\,(\Theta) = 1 \end{cases} \quad (3.4)$$

Consider the frame of discernment given in Table 3-1; for intervals in the first row *bpa* are given in second row.

Table 3.1: An Example Frame of Discernment

A_i	Ø	[2.5 6]	[6 9]	[9 11.2]	[2.5 9]	[6 11.2]	[2.5 6] ∪ [9 11.2]	[2.5 11.2]
$m(A_i)$	0	0.5	0.3	0	0	0	0	0.2

The calculation of belief functions for two focal elements are shown below. See Table 3-2 for belief functions of the entire interval.

bel ([2.5 6] ∪ [9 11.2]) = m ([2.5 6]) + m ([9 11.2]) = 0.5

bel ([2.5 11.2] = m ([2.5 6]) + m ([6 9]) + m ([9 11.2]) + m ([2.5 9]) + m ([6 11.2]) + m ([2.5 6] ∪ [9 11.2]) + m ([2.5 11.2]) = 1

The upper bound for probability is plausibility, which is the summation of *bpa*'s of all sets, A_k that intersect with the set of interest, A_i, i.e., $A_k \cap A_i \neq \emptyset$. Plausibility is defined as:

$$pl(\mathrm{A_i}) = \sum_{\mathrm{A_k} \cap A_i \neq \emptyset} m(\mathrm{A_k}) \quad (3.5)$$

Belief and plausibility functions are linked to each other through the doubt function, defined as the complement of belief:

$$pl(\mathrm{A_i}) = 1 - bel(\neg \mathrm{A_i}) \quad (3.6)$$

Where $\neg A_i$ is the complement of A_i. It is also possible to derive the following relationships for belief and plausibility:

$pl\,(A_i) \geq bel\,(A_i)$; $pl\,(\emptyset) = 0$; $pl\,(\Theta) = 1$; $pl\,(\neg A_i) = 1 - bel\,(A_i)$

For the data provided in Table 3-1, the plausibility function for [2.5 6] can be derived as:

Pl ([2.5 6]) = m ([2.5 6]) + m ([2.5 9]) + m ([2.5 6] ∪ [9 11.2]) + m ([2.5 11.2]) = 0.7

In similar fashion the calculated plausibility functions for all intervals is given in Table 3-2.

Table 3.2: Belief and Plausibility Functions for the Example Interval

A_i	∅	[2.5 6]	[6 9]	[9 11.2]	[2.5 9]	[6 11.2]	[2.5 6] ∪ [9 11.2]	[2.5 11.2]
$m(A_i)$	0	0.5	0.3	0	0	0	0	0.2
$bel(A_i)$	0	0.5	0.3	0	0.8	0.3	0.5	1
$pl(A_i)$	0	0.7	0.5	0.2	1	0.5	0.7	1

3.2.3 Dempster–Shafer (DS) Rule of Combination

The DS rule of combination, also sometimes referred to as the orthogonal sum of evidence, can be used to aggregate multiple sources information. Assume two bodies of evidence exist in Θ, i.e. two basic probability assignments m_1 *(A)* and m_2 *(A)* to a subset $A \subseteq \Theta$. The combined probability assignment, m_{12} *(A),* based on the DS rule of combination is,

$$m_{12}(A) = m_1(A) \oplus m_2(A)$$
$$= \begin{cases} 0 & \text{When, } A=\emptyset \\ \dfrac{\sum_{X \cap Y = A, \forall X, Y \subseteq \Theta} m_1(X)\, m_2(Y)}{1-K} & \text{When, } A \neq \emptyset \end{cases} \tag{3.7}$$

Where, $K = \sum_{X \cap Y = \emptyset, \forall X, Y \subseteq \Theta} m_1(X)\, m_2(Y)$. The combined mass probability assignment, m_{12} (A), for a subset A is computed from m_1 and m_2 by adding all products of the form ‗$m_1(X).m_2(Y)$', where X and Y are the subsets and their intersection is always A. The conflict between subsets X and Y is represented by factor K, where the intersection of X and Y (i.e. $X \cap Y = \emptyset$) is an empty or void set.

The commutative property of the DS rule of combination ensures that the rule yields the same value regardless of the order in which the two bodies of evidence are combined [34]. Therefore, the DS rule of combination can be generalized to more than two bodies of evidence as,

$$m_{1,2,\ldots,M} = m_1 \oplus m_2 \oplus m_M \tag{3.8}$$

Figure 3.1 shows a generic framework for Productivity HER framework. Where, e^i_k is i^{th} parameter in the aggregation, $S(e^i_k)$ is evaluation for a parameter e^i_k, $m(e^i_k)$ is basic probability assignment set for parameter e^i_k, λ^i_k is normalized relative weight of parameter e^i_k contribute to attribute E_k.

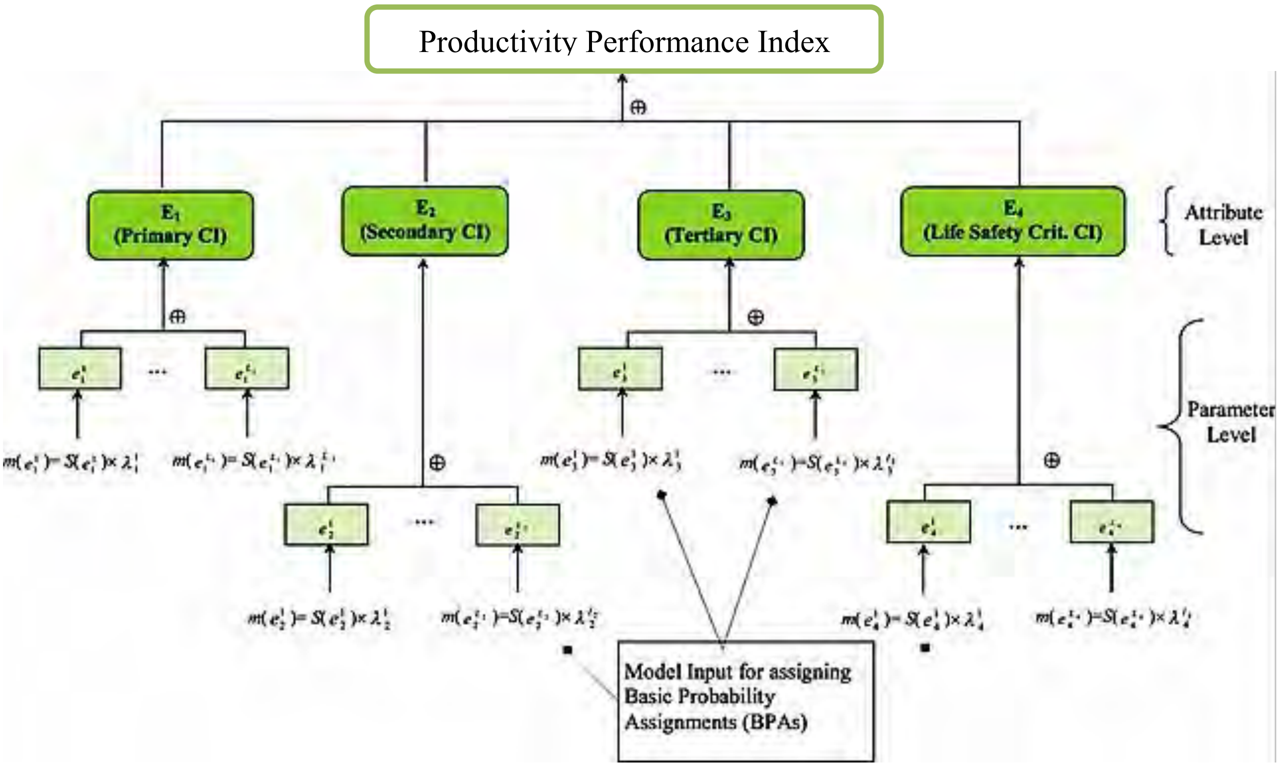

Figure-3.1: Generic Productivity Hierarchical Evidential Reasoning (HER) framework.

The direct use of the combination rule in Equation (3.8) will result in an exponential increase in the computational complexity. Generally, the DS rule of combination is used recursively to avoid this complexity. In this research, the recursive DS algorithm is applied to the hierarchical framework and the calculations are done according to Yang and Xu (2002) [14].

Let, $m_{n,i}$ be a basic probability mass representing the degree to which the i^{th} basic attribute e_i supports the hypothesis that the attribute e_i is assessed to the n^{th} grade H_n. i.e. $H = \{H_1\ H_2 \ldots H_n \ldots H_N\}$. A given assessment for e_i (i = 1, 2… L) of an alternative may be mathematically represented as the following distribution:

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1,2, \ldots, N\} \tag{3.9}$$

Where, $\beta_{n,i} \geq 0, \sum_{n=1}^{N} \beta_{n,i} \leq 1$ and $\beta_{n,i}$ denotes a degree of belief. The above distributed assessment reads that the attribute e_i is assessed to the grade H_n with the degree of belief of $\beta_{n,i}$, n= 1, 2… N. An assessment $S(e_i)$ is complete if $\sum_{n=1}^{N} \beta_{n,i} = 1$ and incomplete if $\sum_{n=1}^{N} \beta_{n,i} < 1$.

Let $m_{H,i}$ be a remaining probability mass unassigned to any individual grade after all the N grades have been considered for assessing the general attribute as far as e_i is concerned. $m_{n,i}$ is calculated as follows:

$$m_{n,i}=\omega_i \beta_{n,i}, \text{ n=1,2, … ,N} \tag{3.10}$$

Where, ω_i is weight for assessing an attribute e_i or E_i which should be normalized. $m_{H,i}$ is given by,

$$m_{H,i} = 1 - \sum_{n=1}^{N} m_{n,i} \tag{3.11}$$

Define $E_{I(i)}$ as the subset of the first i basic attributes as follows:

$$E_{I(i)} = \{e_1\ e_2 \ldots e_i\} \tag{3.12}$$

Let $m_{n,I(i)}$ be a probability mass defined as the degree to which all the i attributes in $E_{I(i)}$ support the hypothesis that y is assessed to the grade H_n. $m_{H,I(i)}$ is the remaining probability mass unassigned to individual grades after all the basic attributes in $E_{I(i)}$ have been assessed. The remaining probability mass initially unassigned to any individual evaluation grades will be treated separately in terms of the relative weights of attributes and the incompleteness in an assessment. In this way, the upper and lower bounds of the belief degrees can be generated using the concepts of the belief measure and the plausibility measure in the D–S theory of evidence. This is one of the distinctive features of the HER approach from other MCDA approaches.

A quantitative attribute can be assessed using numerical values according to the proposed rule based approach by Yang (2001) [68]. In this case equivalence rules need to be extracted from the decision maker to transform the value to an equivalent expectation so that quantitative attribute can be aggregated in conjunction with other qualitative attributes. To carry out such a transformation, it is fundamental for a decision maker to provide rules retaining each evaluation grade to a particular value. In general, suppose a value $h_{n,i}$ for an attribute e_i is judged to be equivalent to a grade H_n. The value h_j can be represented by the following equivalent expectation.

$$S(h_j) = \{(H_n, \beta_{n,j}), n = 1,2, \dots, N\} \tag{3.13}$$

Where,

$$\beta_{n,j} = \frac{h_{n+1,i} - h_j}{h_{n+1,i} - h_{n,i}}, \beta_{n+1,j} = 1 - \beta_{n,j} \quad \text{if } h_{n,i} \le h_j \le h_{n+1,i} \tag{3.14}$$

$$\beta_{k,j} = 0 \quad \text{for, k=1,2,...N, k} \neq n, n+1 \tag{3.15}$$

Note that, the remaining probability mass initially unassigned to any individual grades is decomposed into two parts: 1) $\bar{m}_{H,i}$ and 2) $\tilde{m}_{H,i}$, Where,

$$\bar{m}_{H,i} = 1 - \omega_i \tag{3.16}$$

$$\tilde{m}_{H,i} = \omega_i(1 - \sum_{n=1}^{N} \beta_{n,i}) \tag{3.17}$$

$$m_{H,i} = \bar{m}_{H,i} + \tilde{m}_{H,i} \tag{3.18}$$

$\bar{m}_{H,i}$ is the first part of the remaining probability mass that is not yet assigned to individual grades due to the fact that attribute i (denoted by e_i) only plays one part in the assessment relative to its weight. $\bar{m}_{H,i}$ is a linear decreasing function of ω_i. $\bar{m}_{H,i}$ will be one if the weight of e_i is zero or $\omega_i = 0$; $\bar{m}_{H,i}$ will be zero if e_i dominates the assessment or $\omega_i = 1$. In other words, $\bar{m}_{H,i}$ represents the degree to which other attributes can play a role in the assessment. $\bar{m}_{H,i}$ should eventually be assigned to individual grades in a way that is dependent upon how all attributes are weighted and assessed.

$\tilde{m}_{H,i}$ is the second part of the remaining probability mass unassigned to individual grades, which is caused due to the incompleteness in the assessment $S(e_i)$. $\tilde{m}_{H,i}$ will be zero if $S(e_i)$ is complete, or $\sum_{n=1}^{N} \beta_{n,i} = 1$; otherwise, $\tilde{m}_{H,i}$ will be positive. $\tilde{m}_{H,i}$ is proportional to ω_i and will cause the subsequent assessments to be incomplete.

The combined probability masses are generated by aggregating (denoted by $\oplus$) the assessments $S(e_i)$ and $S(e_j)$ as follows. Let $m_{n,I(i)}$ (n= 1,2, …, N), $\tilde{m}_{H,i}$ and $\bar{m}_{H,i}$ denote the combined probability masses generated by aggregating the first i assessments. The following HER algorithm is then combine the first i assessments with the $(i+1)^{th}$ assessment using the recursive manner.

$$\{H_n\}: m_{n,I(i+1)} = K_{I(i+1)} [m_{n,I(i)} m_{n,i+1} + m_{H,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1}] \tag{3.19}$$

$$m_{H,I(i)} = \bar{m}_{H,I(i)} + \tilde{m}_{H,I(i)} \qquad n = 1,2, \dots ,N \tag{3.20}$$

$$\{H\}: \tilde{m}_{H,I(i+1)} = K_{I(i+1)} [\tilde{m}_{H,I(i)} \tilde{m}_{H,i+1} + \bar{m}_{H,I(i)} \tilde{m}_{H,i+1} + \tilde{m}_{H,I(i)} \bar{m}_{H,i+1}] \tag{3.21}$$

$$\{H_n\}: \bar{m}_{H,I(i+1)} = K_{I(i+1)} [\bar{m}_{H,I(i)} \bar{m}_{H,i+1}] \tag{3.22}$$

$$K_{I(i+1)} = \Big[1 - \sum_{t=1}^{N} \sum_{\substack{j=1 \\ j\neq t}}^{N} m_{t,I(i)}\, m_{j,i+1}\Big]^{-1} \qquad i = 1, 2, \dots, L-1 \tag{3.23}$$

The terms $\bar{m}_{H,I(i)} \tilde{m}_{H,i+1}$ and $\tilde{m}_{H,I(i)} \bar{m}_{H,i+1}$ are assigned to $\tilde{m}_{H,I(i+1)}$, rather than to $\bar{m}_{H,I(i+1)}$ so that the incompleteness synthesis axiom can be satisfied. After all L assessments have been aggregated, the combined degrees of belief are generated by assigning $\bar{m}_{H,I(L)}$ back to all individual grades proportionally using the following normalization process:

$$\{H_n\}: \beta_n = \frac{m_{n,I(L)}}{1-\bar{m}_{H,I(L)}} \qquad n = 1, 2, \dots, N \tag{3.24}$$

$$\{H\}: \beta_H = \frac{\tilde{m}_{H,I(L)}}{1-\bar{m}_{H,I(L)}} \tag{3.25}$$

β_n generated above is a likelihood to which H_n is assessed. β_H is the unassigned degree of belief representing the extent of incompleteness in the overall assessment.

In summary, the HER algorithm is composed of Eq. (3.9) for information acquisition and representation, (3.10,), (3.11), (3.16) and (3.17) for basic probability assignments, (3.19)–(3.23) for attribute aggregation, and (3.24) and (3.25) for generating combined degrees of belief.

Similar to (3.9), the generated assessment for y can be represented by the following distribution:

$$S(y) = \{(H_n, \beta_{n,i}), n = 1,2, \dots, N\} \tag{3.26}$$

Which reads that y is assessed to the grade H_n with the degree of belief of β_n (n= 1, 2… N).

3.2.4 Expected Utility and Utility Interval of the HER Approach

There may be occasions where distributed descriptions are not sufficient to show the difference between two assessments. In such cases, it is desirable to generate numerical values equivalent to the distributed assessments in a sense. The concept of expected utility is used to define such values. Suppose $u(H_n)$ is the utility of the grade H_n with

$$u(H_{n+1}) > u(H_n) \qquad \text{if } H_{n+1} \text{ is preferred to } H_n. \tag{3.27}$$

$u(H_n)$ may be estimated using the probability assignment method or by constructing regression models using partial rankings or pairwise comparisons [14]. If all assessments are complete and precise, there will be $\beta_H = 0$ and the expected utility of the attribute y can be used for ranking alternatives, which is calculated by

$$u(y) = \sum_{n=1}^{N} \beta_n u(H_n) \tag{3.28}$$

An alternative a is preferred to another alternative b on y if and only if $u(y(a)) > u(y(b))$.

If any assessment for the basic attribute is incomplete, β_H become positive. Within the HER assessment framework, β_n given in (3.24) represents the belief measure in the D–S theory and thus provides the lower bound of the likelihood to which y is assessed to H_n [14]. The upper bound of the likelihood is given by a plausibility measure [72]. It can be shown that the plausibility measure for H_n within the HER evaluation framework is given by $(\beta_n + \beta_H)$. Thus the belief interval $[\beta_n, (\beta_n + \beta_H)]$ provides the range of the likelihood to which y may be assessed to H_n. It is obvious that the interval will reduce to a point β_n if all assessments are complete.

The above discussion shows that if any basic assessment is incomplete, the likelihood to which y may be assessed to H_n is not unique and can be anything in the interval $[\beta_n, (\beta_n + \beta_H)]$. In such circumstances, we define three measures to characterize the assessment for y, namely the minimum, maximum and average expected utilities.

Without loss of generality, suppose H_1 is the least preferred grade having the lowest utility and H_n the most preferred grade having the highest utility. Then the maximum, minimum and average expected utilities on y are given by

$$u_{max}(y) = \sum_{n=1}^{N-1} \beta_n u(H_n) + (\beta_N + \beta_H)u(H_N) \quad (3.29)$$

$$u_{min}(y) = (\beta_1 + \beta_H)u(H_1) + \sum_{n=2}^{N} \beta_n u(H_n) \quad (3.30)$$

$$u_{avg}(y) = \frac{u_{max}(y) + u_{min}(y)}{2} \quad (3.31)$$

If all original assessments $S(e_i)$ are complete, then $\beta_H = 0$ and $u(y) = u_{max}(y) = u_{min}(y) = u_{avg}(y)$. Note that the above utilities are only used for characterizing an assessment but not for attribute aggregation.

The ranking of two alternatives a_l and a_k is based on their utility intervals. a_l is said to be preferred to a_k on y if and only if $u_{min}(y(a_l)) > u_{max}(y(a_k))$; a_l is said to be indifferent to a_k if and only if $u_{min}(y(a_l)) = u_{min}(y(a_k))$ and $u_{max}(y(a_l)) = u_{max}(y(a_k))$. Otherwise, average expected utility may be used to generate a ranking, though such a ranking is inconclusive. For instance, if $u_{avg}(y(a_l)) > u_{avg}(y(a_k))$ but $u_{max}(y(a_k)) > u_{min}(y(a_l))$, one could say that a_l is preferred to a_k on an average basis. However, this ranking is not reliable, as there is a chance that a_k may have higher utility than a_l. In such cases, to generate a reliable ranking the quality of the original assessments must be improved by reducing incompleteness present in the original assessments associated with a_l and a_k. Note that to clarify the relationship between a_l and a_k there is no need to improve the quality of information related to other alternatives.

3.3 CONCEPTS OF BENCHMARKING

Relative performance evaluations or using modern terminology—benchmarking is the systematic comparison of the performance of one firm against other firms. More generally, it is comparison of production entities. The idea is that the comparison of entities that transform the same type of resources to the same type of products and services. The production entities can be firms, organizations, divisions, industries, projects, decision making units, or individuals. For convenience, the discussion is simply about the comparison of firms.

Benchmarking can be used in many different settings. It can be used to make intra-organizational comparisons, as when a headquarters wants to promote costs efficiency in its different subunits. Motivating a combination of profit and service objectives in a chain of fast food outlets is an obvious example; the owners can evaluate the individual managers by comparing the sales and cost measures of such outlets. The owners can formalize the evaluations and introduce performance based payment schemes to motivate appropriate behavior. Benchmarking can also be and most often is used to make inter-organizational comparisons. A primary example that we shall often refer to involves a regulator seeking to induce cost–efficiency or to avoid the misuse of monopoly power among a set of firms enjoying natural monopoly rights in different regions.

It is worthwhile emphasizing that the use of benchmarking is not restricted to for profit organizations. Modern benchmarking methods can handle multiple objectives that are not explicitly aggregated. This opens the door for usage in non-profit / organizations, including most public organizations where there is no single objective or success criterion like profit maximization. Indeed, the ability to handle multiple objectives is one explanation of the popularity and numerous applications of modern benchmarking techniques. In more general terms, the objectives of benchmarking can be related to one or more of the basic issues in any economic system, namely learning, coordination and motivation. Or using accounting terminology, benchmarking can be used to facilitate decision making (learning and coordination) and control (motivation). Although the preliminaries of performance assessment exercises normally contain arguments from all three categories, the design and execution of the model often reveals the importance associated to each task. The stated objective of most benchmarking studies is to learn or get insight. This is certainly the case in scientific studies where researchers examine the relative efficiency of firms in an industry, the relative efficiency of one industry against another or the impact of some policy measure on industry performance. Often, this is also the stated objective in industry applications. When several firms compare their performance, the official objective is often to support the learning and efficiency improvement of individuals. Firms are interested to know how well they are doing compared to others and which ones they can learn from.

The nonparametric (Data Envelopment Analysis -DEA) approaches that provide particular strengths in such cases as the peers or the dominating firms provide valuable and concrete information for performance improvement targets. As the various decompositions of the overall productivity can point towards more specific means to improve productivity, the new member in the MCDM arena hierarchical evidential reasoning; have all those properties for proper benchmarking along with an informative model that has the property for dealing with qualitative, quantitative and uncertain types of values. Still, the actual operational changes will necessitate in-depth process benchmarking that may, or may not, be promoted by the participating firms. Competition may for obvious reasons limit the sharing of information about best practices. Recent advances in interactive benchmarking is an attempt to push the learning perspective by allowing individual firms in a benchmarking exercise to define the comparison basis (potential peers), the objective (e.g. cost reduction or sales expansion), the aspiration level (e.g. to be in the top-ten) etc. of the evaluations. It has typically been used in industries where firms sees themselves as colleagues more than competitors, e.g. among waterworks, energy–networks, and farmers.

CHAPTER 4

PRODUCTIVITY MODELING OF THE APPAREL INDUSTRY AND METHODOLOGY OF THE RESEARCH

4.1 PROBLEM DEFINITION AND SOLVING METHODOLOGY

In the textile sector, the term garments industry usually covers the apparel industry where fabrics are outsourced, cut and sewn to the desired shapes and sizes and converted to garments as per requirement of the buyer. Due to the cheap labor forces of Bangladesh, the cutting and making process has gained popularity. The garment industry of Bangladesh began in an unorganized way in the sense that scattered small players entered the business to avail the benefit of the small-scale industry policies. This character was further enhanced by the reservation of garments for exclusive production in the small sector. As a result, the industry is highly disintegrated and consists of mostly small-scale firms. As a consequence, estimation of number of garment firms operated in the industry becomes quite difficult. There has so far not been any credible survey of the industry that makes an estimate of the size of the industry. Earlier studies on the industry have also suffered due to unavailability of relevant data [16]. So, the data required for productivity measurement of apparel organizations has both qualitative and quantitative nature as well as there are many incomplete information and vagueness in subjective judgments, which clearly indicates aptness of the HER approach in this regard. The HER approach is a powerful tool in dealing with MCDM under uncertainties. This methodology advocates a multi-level hierarchy in the evaluation process, Dempster-Shafer evidence theory, evaluation analysis model and decision theory. This is the only method so far capable of handling MCDM problems with uncertainties, incommensurable units, mixture of qualitative and quantitative attributes, as well as mixture of deterministic and probabilistic attributes. The main advantages of the HER approach in dealing multiple quantitative and qualitative information under uncertainty as follows:

- To handle incomplete, uncertain and vague as well as complete and precise data.
- To provide its users with a greater flexibility by allowing them to express their judgments both subjectively and quantitatively.
- To accommodate or represent the uncertainty and risk that is inherent in assessment program.

- As a hierarchical evaluation process, to offer a rational and reproducible methodology to aggregate the data assessed.

If the performances of a number of organizations are evaluated and compared, HER can further be applied to perform sensitivity analysis to identify the critical measures that contribute to enhance the performance. Hence, HER can facilitate productivity benchmarking enabling organizations to compare themselves to the market place in a given sector of industry as well as investigate the processes behind excellent performance. This research aims at evaluating the productivity of the apparel organizations using HER approach and comparing the companies to identify the lacking in the performance in different attributes to become a more productive company by benchmarking them. The outline of the research methodology is as follows –

- The hierarchical structure with appropriate qualitative and quantitative attributes has been developed for defining the productivity of apparel industry.
- The data required for measuring the productivity of the apparel organizations is collected from the apparel organizations nearby Dhaka.
- A set of evaluation grades is then developed to assess each basic attribute (bottom level attributes), so that the assessment can be conducted with reference to individual or a subset of the evaluation grades with different degrees of belief.
- With regard to qualitative attributes, subjective assessment information of assigning belief degrees to each evaluation grade has been collected from decision makers and experts directly.
- For quantitative attributes, a set of referential values is defined to cover the value interval of evaluation grades.
- Then for the quantitative attributes, an information transformation technique is used to generate the corresponding belief distribution equivalent to the original ones in terms of their utilities or values.
- For the purpose of aggregating assessments, the recursive evidential reasoning algorithm is used.
- The utility of the evaluation grades has then been appraised to precisely rank the alternative organizations.

- Sensitivity analysis of different attributes is conducted to identify the critical measures that contribute to enhance the performance for the purpose of benchmarking of the apparel industry.

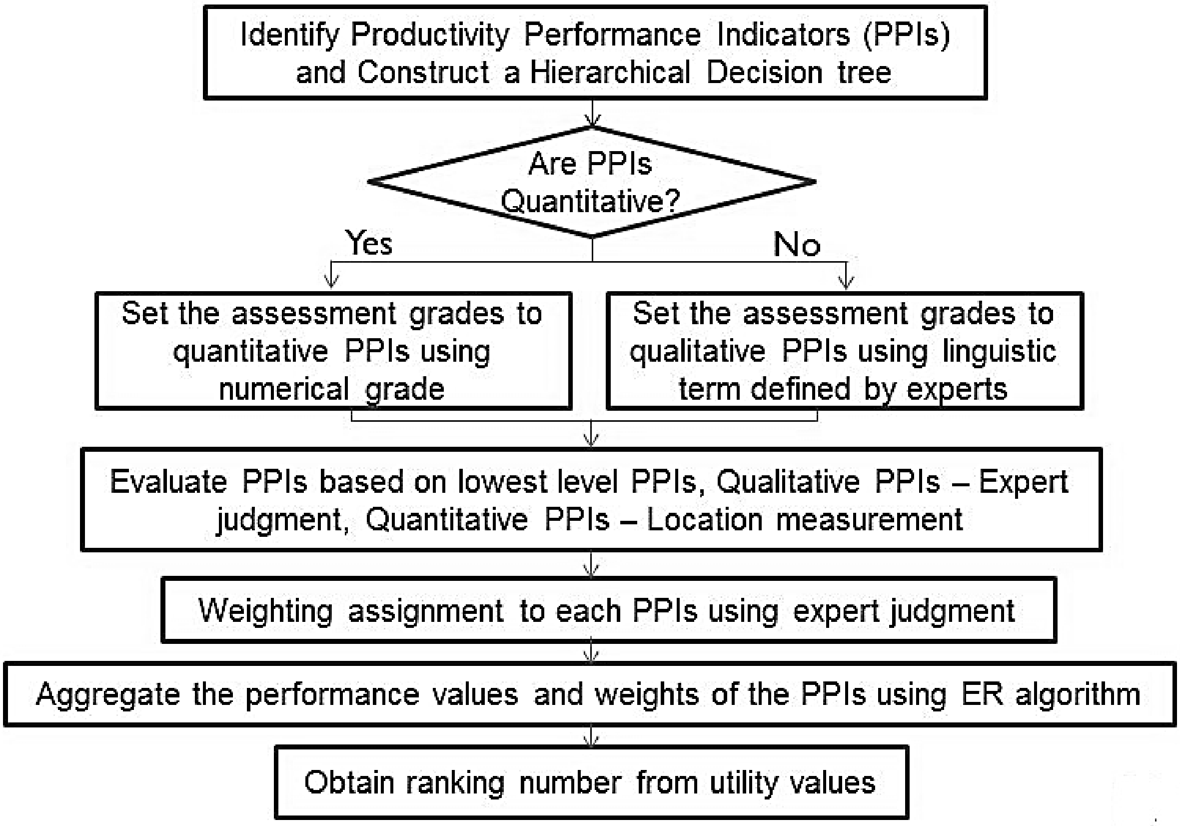

Figure-4.1: Methodology of the Hierarchical Evidential Reasoning Framework

The specific objectives of this research are:

- To develop a hierarchical structure for appropriately defining the productivity of apparel organization and evaluating them using HER approach.
- To implement HER approach as a comprehensive tool for productivity benchmarking.

4.2 PRODUCTIVITY ASSESSMENT MODEL FORMULATION

Performance measurement deals with problems of multiple attribute decision making. However, measurement inaccuracy has been the problem due to deficiencies of the traditional scoring approaches. First, evaluators are forced to make complete assessments even though they are not fully confident about the situation. Second, the approaches require evaluators to give a single average score on a measurement item, which weaken assessment accuracy and is unfavorable to the identification of strengths and areas for improvement. In order to ensure better measurement accuracy, this study adopts hierarchical evidential reasoning (HER) scoring method to support the multiple attribute decision making of both a quantitative and qualitative nature under uncertainties. The assessment problem is modeled by a belief decision matrix and the attributes are aggregated by the HER algorithm. The HER scoring method employs a belief structure to represent an assessment [73], [74]. In this study, the evaluation grades used are represented in H_n and the assessment of sub-criterion e_i, $S(e_i)$ is represent as the following structure:

$$S(e_1) = \{(H_1, \beta_{1,1}), (H_2, \beta_{2,1}), (H_3, \beta_{3,1}), (H_4, \beta_{4,1}), (H_5, \beta_{5,1})\} \tag{4.1}$$

Where H_n is an evaluation grade, $b_{n,1}$ denotes the degree of belief that e_1 is assessed to an evaluation grade H_n, which satisfies $1 \geq \beta_{n,1} \geq 0$ and $\sum_{n=1}^{5} \beta_{n,1} \leq 1$. An assessment is completed when $\sum_{n=1}^{5} \beta_{n,1} = 1$, and incomplete when $\sum_{n=1}^{5} \beta_{n,1} < 1$. Incomplete assessment is common as assessments are subjective and the evidence for assessments could be incomplete, vague and uncertain. Unlike the conventional scoring approaches, using the belief structure, assessors are not forced to make a complete judgment when they are not 100 percent sure about the subjective judgments or when evidence is not complete. Moreover, the belief structure enables the representation of an assessment as a distribution instead of a single average score. In this way, assessors can make judgments more accurately. It also facilitates the identification of strengths and improvement areas which is the main purpose of the productivity measurement.

4.2.1 Identification of Productivity Assessment Attributes

A set of criteria or generally referred as attributes need to be first investigated and carefully identified. These attributes enable a comparison of the alternatives from different perspectives. Several examples from studies in the literature have already tried to capitalize all existing attributes used to compare different apparel organization in terms of their productivity [75], [76]. However, only a few works proposed to deal with both quantitative and qualitative criteria under uncertainty [38]. Fourteen basic attributes (lowest level attribute) and eight general level attributes (attributes generated by combining basic attributes) are proposed here to form the hierarchical structure that will measure the apparel productivity performance index for productivity assessment. The basic attributes are level of technology, worker education level, application of industrial engineering, raw material quality, style changeover time, labor efficiency, line efficiency, machine utilization, raw material utilization, on time deliver rate, defective percentage level, working environment, level of job satisfaction, and availability of utility. The general attributes are primary performance index, secondary performance index, effectiveness, efficiency, process parameters, product parameters, technical efficiency, and right first time quality. The selected attributes are summarized in Table 4.1. The type of the variables, unit of assessment, optimization required to the different attributes are shown here.

Table-4.1: Overview of the Selected Attributes

Attribute	Type	Unit	Optimize*
Primary Performance Index	Qualitative (General)	Qualitative (1-5)	Maximize
Effectiveness	Qualitative (General)	Qualitative (1-5)	Maximize
Efficiency	Qualitative (General)	Qualitative (1-5)	Maximize
Process Parameter	Qualitative (General)	Qualitative (1-5)	Maximize
Product Parameter	Qualitative (General)	Qualitative (1-5)	Maximize
Level of Technology	Qualitative (Basic)	Qualitative (1-5)	Maximize
Worker Education Level	Qualitative (Basic)	Qualitative (1-5)	Maximize
Application of Industrial Engineering	Qualitative (Basic)	Qualitative (1-5)	Maximize
Raw Material Quality	Qualitative (Basic)	Qualitative (1-5)	Maximize
Style Changeover Time	Quantitative (Basic)	Minute	Minimize
On Time Delivery Rate	Quantitative (Basic)	Percentage (%)	Maximize
Technical Efficiency	Qualitative (General)	Qualitative (1-5)	Maximize
Labor Efficiency	Quantitative (Basic)	Percentage (%)	Maximize
Line Efficiency	Quantitative (Basic)	Percentage (%)	Maximize
Machine Utilization	Quantitative (Basic)	Percentage (%)	Maximize
Raw Material (fabric) Utilization	Quantitative (Basic)	Percentage (%)	Maximize
Right First Time Quality	Qualitative (General)	Qualitative (1-5)	Maximize
Defective Percentage Level	Quantitative (Basic)	Percentage (%)	Minimize
Secondary Performance Index	Qualitative (General)	Qualitative (1-5)	Maximize
Working Environment	Qualitative (Basic)	Qualitative (1-5)	Maximize
Level of Job Satisfaction	Qualitative (Basic)	Qualitative (1-5)	Maximize
Availability of Utility	Quantitative (Basic)	Percentage (%)	Maximize

*Optimize refers to whether a high or a low value for a given attribute is preferred.

4.2.2 Structuring the Hierarchy for Productivity Measurement of Apparel Organization

With the aid of literatures reviewed in this study and using expert‘s opinion, the hierarchical structure of apparel organization‘s productivity measurement model is proposed where performance-based indices have been used as indicator of apparel productivity. The hierarchical structure is depicted in Figure 4.1. The level 1 of hierarchy indicates the goal, known as apparel productivity performance index. Level 2 of hierarchy shows two assessment criteria, known as primary performance index and secondary performance index. Primary performance index is that, which is directly related to the production process. This can be assessed by decomposing primary performance index into two basic elements that are actually generates primary performance index: effectiveness and efficiency.

Efficiency refers to doing things in a right manner. Scientifically, it is defined as the output to input ratio and focuses on getting the maximum output with minimum resources. Effectiveness, on the other hand, refers to doing the right things. It constantly measures if the actual output meets the desired output. Since efficiency is all about focusing on the process, importance is given to the ‗means‘ of doing things whereas effectiveness focuses on achieving the ‗end‘ goal. Efficiency is concerned with the present state or the ‗status quo‘. Thinking about the future and adding or eliminating any resources might disturb the current state of efficiency. Effectiveness, on the other hand, believes in meeting the end goal and therefore takes into consideration any variables that may change in the future. In the earlier days of mass production, efficiency was the most important performance indicator for any organization. However, with consumers facing an increasing number of choices, effectiveness of an organization is always questioned. In order to be a successful organization, there needs to be a balance between effectiveness and efficiency.

Effectiveness of an apparel organization consists of improvement of two types of parameters: process parameters and product parameters. Process parameters include level of technology used, level of worker‘s educational qualification and application of industrial engineering. On the other hand, efficiency of an apparel organization consists of on time delivery rate, e.g. how efficiently the organization can meet the order lead time. Other efficiency indicators are technical efficiency and right first time quality. Technical efficiency also consists of another four types of efficiency named: labor efficiency, line efficiency, machine utilization, raw material utilization. Raw material utilization is generally known as marker efficiency, e.g.

how efficiently the marker of any design of dresses can be used with minimum wastage of fabrics. Right first time quality is defined by percentage level of defective products. The less the defective percentage level, the more the value of right first time quality.

Secondary performance index is that, which is not directly related to the production process, but improvement of its constituents can affect the improvement of the overall productivity performance index. Secondary performance index consists of working environment, level of job satisfaction and availability of utility.

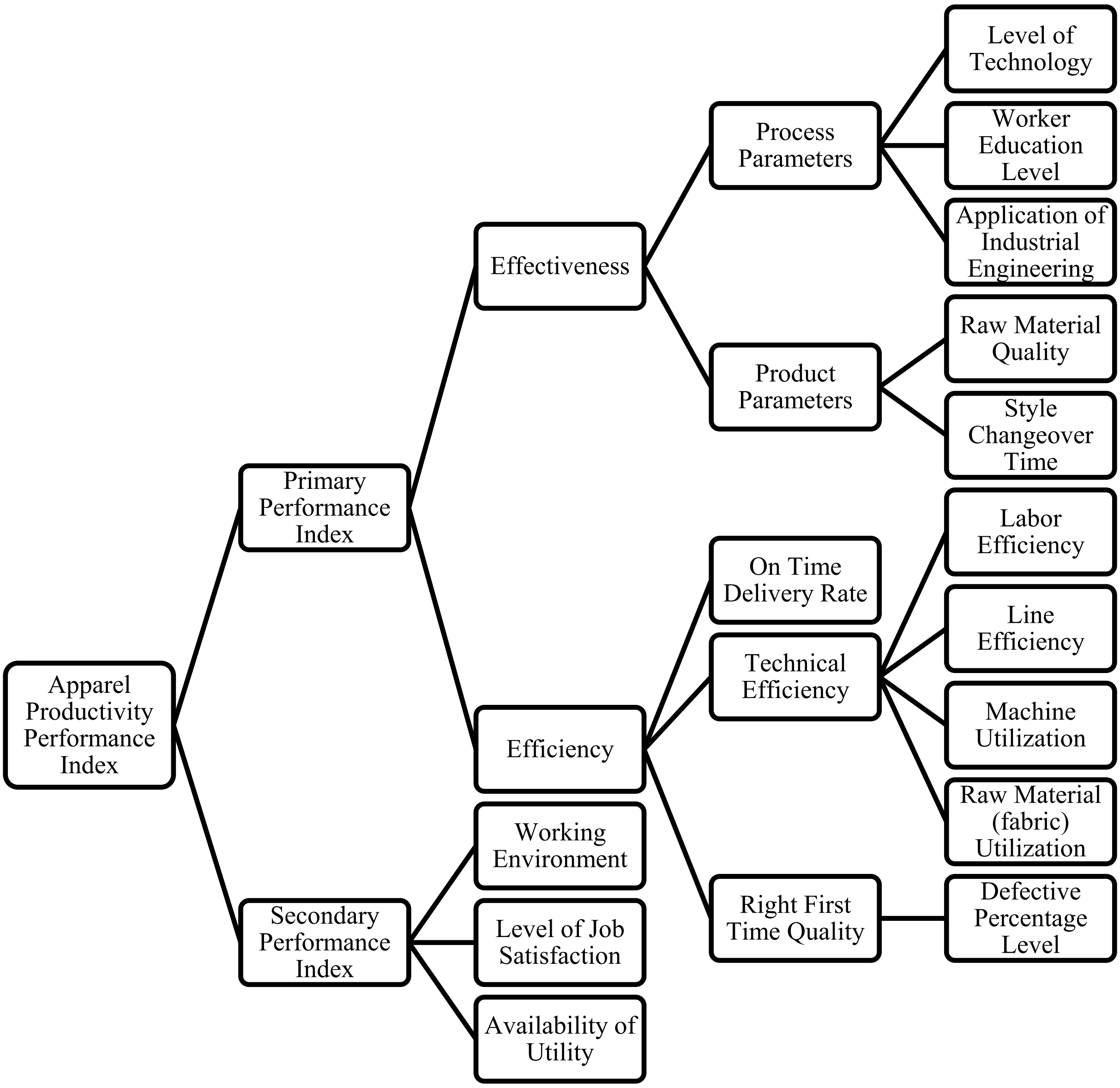

Figure-4.2: Hierarchical Representation of Apparel Organization‘s Productivity

4.2.3 Determination of Weights, Assessment Grades and Utility Quantification

The identified attributes usually have different importance and play different roles in the assessment process of productivity. Some of them are crucial, some of them are very important, some of them are important but not very important or crucial compared with the others. In this study, using expert opinion the weights of all attributes has therefore been assigned. The weights of all attributes are shown in the Table 4.2.

Table-4.2: Weights of the Attributes

Attributes				Weight
Primary Performance Index				0.6
	Effectiveness			0.5
		Process Parameter		0.6
			Level of Technology	0.3
			Worker Education Level	0.3
			Application of Industrial Engineering	0.4
		Product Parameter		0.4
			Raw Material Quality	0.7
			Style Changeover Time	0.3
	Efficiency			0.5
		On Time Delivery Rate		0.3
		Technical Efficiency		0.5
			Labor Efficiency	0.2
			Line Efficiency	0.1
			Machine Utilization	0.3
			Raw Material Utilization	0.4
		Right First Time Quality		0.2
			Defective Percentage Level	1.0
Secondary Performance Index				0.4
	Working Environment			0.4
	Level of Job Satisfaction			0.4
	Availability of Utility			0.2

On the other side, assessment standards or generally known as evaluation grades need to be defined. There were several evaluation grades examples proposed and defined depending on the domain problem. Some studies have used 0 or 1 (i.e., yes or no) as a rating concept, some used good and worst to describe the performances, whilst others used three assessment grades: good, fair, and poor. What kind of standards should be used depends on the requirement from the problem at hand. The most used and preferred evaluation grades in the literature are: Poor (P), Fairly Poor (F), Average (A), Good (G), and Excellent (E) [77]. For simplicity reasons, the same set of evaluation grades has been used in this study. The values that are used for quantitative attributes for converting them into the evaluation grades Poor (P), Fairly Poor (F), Average (A), Good (G), and Excellent (E) are shown in the Table 4.3.

Table-4.3: Measurement Standards for Quantitative Attributes

	EVALUATION GRADES				
Quantitative Variables	Poor	Fairly Poor	Average	Good	Excellent
Style Changeover Time (Min)	70	65	60	55	50
On Time Delivery Rate (%)	80	85	90	95	100
Labor Efficiency (%)	55	60	65	70	75
Line Efficiency (%)	55	60	65	70	75
Machine Utilization (%)	80	85	90	95	100
Raw Material/ Marker Utilization (%)	75	80	85	90	95
Defective Percentage Level (%)	25	20	15	10	5
Availability of Utility (%)	75	80	85	90	95

The evaluation grades of productivity assessment attributes can be quantified using utility in a unified manner as follows:

$u(H_1) = u(Poor) = 0$

$u(H_2) = u(Fairly\ Poor) = 0.25$

$u(H_3) = u(Average) = 0.5$

$u(H_4) = u(Good) = 0.75$

$u(H_5) = u(Excellent) = 1$

The apparel organization's productivity measurement is in a form of hierarchy constituting assessment categories and assessment factors. The overall assessment results can be obtained by combining the assessments of the low-hierarchies. Based on the evaluation analysis model and the evidence combination rule of the Dempster–Shafer theory, the HER scoring method is able to synthesize both complete and incomplete assessments by aggregating the degree of belief of lower level criteria based on their weightings.

CHAPTER 5

CASE STUDY OF OUR APPAREL INDUSTRY

5.1 DATA COLLECTION

This study includes garment manufacturers producing homogenous products (i.e. manufacturing garments). As the selected firms are in the same business and produce the same products, the HER is considered to be the most suitable productivity assessment and benchmarking technique. The data is extracted from twelve apparel (garment) organizations nearby Dhaka. However, most of these companies were very reluctant to share their productivity data. The organization that supports the research by providing their valuable data is listed below:

1. ABM Fashions Ltd. (Ananta Group)
2. Al- Muslim Group
3. Jinnat Complex (DBL)
4. DK Knit Wear Ltd.
5. Fakir Apparels Ltd.
6. Gramtech Knit Dyeing Finishing & Garments Industries Ltd.
7. Liz Fashion Industry Ltd.
8. Masco Industries Ltd.
9. Pioneer Group
10. The Rose Dresses Ltd.
11. Silken Sewing Ltd.
12. Suprov Composite Knit Ltd.

The data sheet is developed to collect the data for both qualitative and quantitative variables. Qualitative data is collected based on the subjective judgments of the respondents in the evaluation grades assigned in the model. These assessments can be summarized as in Table 5.1, where typical elements in a subjective judgment are listed, including the definitions of attributes, evaluation grades, and degrees of belief.

Table-5.1: Subjective Judgments for Evaluating Process Parameter of Liz Fashion

Basic Attribute	Degree of belief (β)	Evaluation Grades				
		Poor	Fairly Poor	Average	Good	Excellent
	Level of Technology (%)	0	0	0.35	0.65	0
	Worker Education Level (%)	0.1	0.5	0.35	0	0
	Application of Industrial Engineering (%)	0	0	0	0.3	0.7

Using the grades defined in previous chapter, the above three assessments can be represented using the following three distributions as defined in Equation (4.1).

S (Level of Technology) = {(average, 0.35), (good, 0.65)} 5.1

S (Worker Education Level) = {(poor, 0.1), (fairly poor, 0.5), (average, o.35)} 5.2

S (Application of Industrial Engineering) = {(good, 0.3), (excellent, 0.7)} 5.3

Only grades with nonzero degrees of belief are listed in the distributions. The quantitative attributes are collected as a single data and then rule based quantitative data transformation technique is applied to convert them in evaluation grades according to the following equation (2.14) and (2.15):

$$\beta_{n,j} = \frac{h_{n+1,i} - h_j}{h_{n+1,i} - h_{n,i}}, \beta_{n+1,j} = 1 - \beta_{n,j} \quad \text{if } h_{n,i} \leq h_j \leq h_{n+1,i}$$

$$\beta_{k,j} = 0 \quad \text{for, k=1,2,…N, k} \neq n, n+1$$

The other assessment information collected in terms of the basic attributes is mapped according to HER framework shown in Table 5.2. The assessment problem is summarized as in Table III, where P,F ,A ,G , and E are the abbreviations of the evaluation grades poor, fairly poor, average, good, and excellent, respectively, and a number in a bracket denotes a degree of belief to which an attribute is assessed to a grade. For instance, E (0.8) means ~~‒e~~xcellent to a degree of 0.8 (80%).”

Table-5.2: Generalized Decision Matrix for the Apparel Productivity

General Attribute				Basic Attribute	ABM	Al-Muslim	DBL	DK	Fakir	GramTech	Liz	Masco	Pioneer	Rose	Silken	Suprov
Apparel Productivity Performance Index	Primary Performance Index (0.6)	Effectiveness (0.5)	Process Parameters (0.6)	Level of Technology (0.4)	F(0.15), A(0.85)	G(0.75), E(0.25)	F(0.10), A(0.25), G(0.55)	F(0.25), A(0.20), G(0.55)	F(0.20), A(0.25), G(0.50)	F(0.25), A(0.65)	A(0.35), G(0.65)	A(0.25), G(0.65), E(0.10)	A(0.15), G(0.65)	A(0.20), G(0.50), E(0.20)	P(0.70), F(0.30)	F(0.20), A(0.60), G(0.20)
				Worker Education Level (0.3)	F(0.90), A(0.10)	F(0.10), A(0.25), G(0.60)	F(0.10), A(0.50), G(0.40)	P(0.35), F(0.25), A(0.40)	F(0.30), A(0.30), G(0.40)	P(0.30), F(0.20), A(0.50)	P(0.10), F(0.50), A(0.35)	F(0.20), A(0.80)	P(0.40), F(0.25), A(0.10)	F(0.20), A(0.60), G(0.15)	P(0.20), F(0.60), A(0.10)	F(0.30), A(0.70)
				Application of Industrial Engineering (0.4)	A(0.40), G(0.60)	A(0.50), G(0.45)	A(0.40), G(0.60)	P(0.60), F(0.25), A(0.15)	A(0.50), G(0.30)	F(0.10), A(0.50), G(0.40)	G(0.30), E(0.70)	F(0.05), A(0.35), G(0.45)	G(0.75)	G(0.45), E(0.50)	F(0.20), A(0.55), G(0.10)	F(0.10), A(0.60), G(0.30)
			Product Parameters (0.4)	Raw Material Quality (0.7)	A(1.00)	F(0.35), A(0.40), G(0.20)	G(0.10), E(0.90)	A(0.60), G(0.40)	F(0.20), A(0.40), G(0.15)	F(0.50), A(0.20), G(0.30)	A(0.70), G(0.20), E(0.10)	A(0.20), G(0.80)	A(0.20), G(0.65)	F(0.25), A(0.65), G(0.10)	F(0.50), A(0.50)	F(0.20), A(0.80)
				Style Changeover Time (0.3)	P(1.00)	P(1.00)	G(1.00)	P(1.00)	P(1.00)	A(1.00)	A(1.00)	P(1.00)	P(1.00)	P(1.00)	P(1.00)	P(1.00)
		Efficiency (0.5)	On Time Delivery Rate (0.3)		A(1.00)	F(1.00)	A(1.00)	E(1.00)	A(0.40), G(0.60)	G(1.00)	A(1.00)	F(0.20), A(0.80)	P(1.00)	G(0.20), E(0.80)	P(1.00)	P(0.40), F(0.60)
			Technical Efficiency (0.5)	Labor Efficiency (0.2)	G(1.00)	E(1.00)	A(1.00)	P(1.00)	A(1.00)	A(1.00)	E(1.00)	E(1.00)	E(1.00)	A(0.40), G(0.60)	P(1.00)	A(0.80), G(0.20)
				Line Efficiency (0.1)	P(1.00)	A(0.40), G(0.60)	P(1.00)	P(1.00)	P(1.00)	P(1.00)	F(0.80), A(0.20)	E(1.00)	A(1.00)	A(1.00)	P(1.00)	P(1.00)
				Machine Utilization (0.3)	F(1.00)	A(1.00)	G(0.40), E(0.60)	A(1.00)	A(0.60), G(0.40)	A(1.00)	F(1.00)	F(0.40), A(0.60)	A(1.00)	A(1.00)	F(1.00)	F(0.60), A(0.40)
				Raw Material Utilization (0.4)	F(0.20), A (0.80)	G(1.00)	A(1.00)	E(1.00)	A(0.80), G(0.20)	A(1.00)	F(1.00)	A(0.80), G(0.20)	G(1.00)	A(1.00)	F(0.20), A(0.80)	A(1.00)
			Right First Time Quality (0.2)	Defective Percentage Level (1.0)	A(1.00)	A(1.00)	E(1.00)	G(0.40), E(0.60)	G(0.98), E(0.02)	E(1.00)	F(0.60), A(0.40)	G(0.40), E(0.60)	E(1.00)	E(1.00)	E(1.00)	F(0.80), A(0.20)
	Secondary Performance Index (0.4)			Working Environment (0.4)	A(0.40), G(0.60)	F(0.15), A(0.45), G(0.30)	G(0.20), E(0.80)	F(0.35), A(0.15), G(0.50)	F(0.20), A(0.30), G(0.50)	F(0.40), G(0.60)	G(0.30), E(0.70)	F(0.30), A(0.40), G(0.25)	A(0.30), G(0.70)	A(0.40), G(0.45)	P(0.25), F(0.55)	P(0.10), F(0.20), A(0.70)
				Level of Job Satisfaction (0.4)	A(0.75), G(0.25)	F(0.50), A(0.15), G(0.25)	G(0.40), E(0.60)	F(0.10), A(0.55), G(0.35)	F(0.20), A(0.40), G(0.30)	A(0.65), G(0.25)	G(0.05), E(0.95)	F(0.30), A(0.45), G(0.20)	G(0.70)	F(0.10), A(0.35), G(0.55)	P(0.20), F(0.40), A(0.20)	F(0.35), A(0.55), G(0.10)
				Availability of Utility (0.2)	G(1.00)	E(1.00)	E(1.00)	P(0.40), F(0.60)	E(1.00)	E(1.00)	G(1.00)	G(0.20), E(0.80)	E(1.00)	G(1.00)	E(1.00)	G(1.00)

5.2 AGGREGATING ASSESSMENTS VIA EVIDENTIAL REASONING

A basic assessment problem is how the original judgments as given in Table 5.1 or equation 5.1-5.3 could be aggregated to arrive at an assessment about the value of the process parameters of Liz Fashion Industry Ltd. It is intuitively clear from Table 5.1 that the value of Liz Fashion's process parameters should be good to a large extent. To generate a precise assessment, however, the relative importance of the three attributes needs to be assigned. For the purpose of demonstrating the ER algorithm, weights of this analysis, are used from table 5.2.

To demonstrate the implementation procedure of the hierarchical evidential reasoning algorithm, calculation steps first generates the assessment for Liz Fashion's process parameters (y) by aggregating three basic attributes: level of technology, worker education level, and application of industrial engineering, as shown in equation 5.1-5.3 and denoted by e_1, e_2, e_3 respectively. The evaluation grades as defined in equation 2.12. Let, y = $e_1 \oplus e_2 \oplus e_3$. Where, $\oplus$ denotes the aggregation of two attributes. Then from equation 5.1-5.3 and equation 2.9 the degree of beliefs can be acquired. The degrees of belief are then multiplied with the corresponding weight of the attribute using equation 2.10, 2.11, 2.16-2.18 to get the probability masses.

Now use the recursive equations 2.19–2.23 can be used to calculate the combined probability masses. Let $m_{n,I(1)} = m_{n,1}$ for n= 1, 2… 5. Firstly, level of technology and worker education level have to be aggregated using these equations. Then, application of industrial engineering is to be combined with the above results for level of technology and worker education level. From equation 2.24 and 2.25, the combined degrees of belief are then calculated. The assessment for Liz Fashion's process parameter by aggregating level of technology, worker education level, and application of industrial engineering is therefore given by the following distribution [see equation (2.26)].

$$
\begin{aligned}
S(Process\ Parameters) \\
&= S(level\ of\ technology \oplus worker\ education\ level \\
&\oplus application\ of\ industrial\ engineering)
\end{aligned}
$$

= {(poor, 0.02), (fairly poor, 0.11), (average, 0.22), (good, 0.38), (excellent, 0.25)}

Note that changing the order of combining the three basic attributes does not change the final result at all.

A general assessment problem arises as to how the twelve organizations could be assessed and ranked on the basis of the attributes and the original assessments information related to the basic attributes as shown in Table 5.2. The same calculation procedure is followed at each level of the hierarchy to determine the assessment grades of the higher level. Thus, the ultimate assessment grades are found for the apparel productivity performance index. To get the index value in a single quantitative value the final assessment grades are then calculated using equation 2.29 and 2.30 and the utility value of the evaluation grades mentioned in chapter 4. These two equations give a range of final result, which is denoted by U_{max} and U_{min}. If uncertainty is present in the data set, the calculation gives a range of the final index, e.g. the final index should be with in this range. Usually an average value of these ranges is used for the simplicity of the assessment purpose. If there is no uncertainty the value of U_{max} and U_{min} become same. Thus, a productivity assessment index is obtained and using the same calculation procedure productivity index value of other organizations is obtained. The results are shown and discussed in the following chapter.

CHAPTER 6

RESULTS AND DISCUSSIONS

The results obtained from the HER application of our apparel industry and detailed discussion on this study have been presented here in the following categories –Overall assessment of the organizations using HER, Sensitivity analysis of the attributes and Benchmarking discussion.

6.1 OVERALL ASSESSMENT OF THE ORGANIZATIONS USING HER

After completing the overall assessment for all the twelve organizations it is clear that the Jinnat Complex of DBL group has highest value of the index, e.g. U_{avg}. This means that the overall performance of Jinnat Complex is the most preferred among the twelve organizations. On the other hand, Silken Sewing Ltd. has obtained the lowest performance index. Based on the same principle, the ranking of the twelve apparel organizations is shown in the following table.

Table-6.1: Ranking of the Organizations

Organization Name	U_{avg}	Ranking
Company A	0.769452	1
Company B	0.653925	2
Company C	0.652603	3
Company D	0.64321	4
Company E	0.586858	5
Company F	0.583512	6
Company G	0.581079	7
Company H	0.548128	8
Company I	0.540731	9
Company J	0.489075	10
Company K	0.437117	11
Company L	0.300092	12

The results obtained from the HER approach in terms of the assessment grades along with the uncertainty level encountered is depicted below in figure 6.1. Here, the assessment grades poor, fairly poor, average, good and excellent are shown in CS-1, CS-2, CS-3, CS-4 and CS-5 respectively. The degree of belief of the associated uncertainty is shown as β_H.

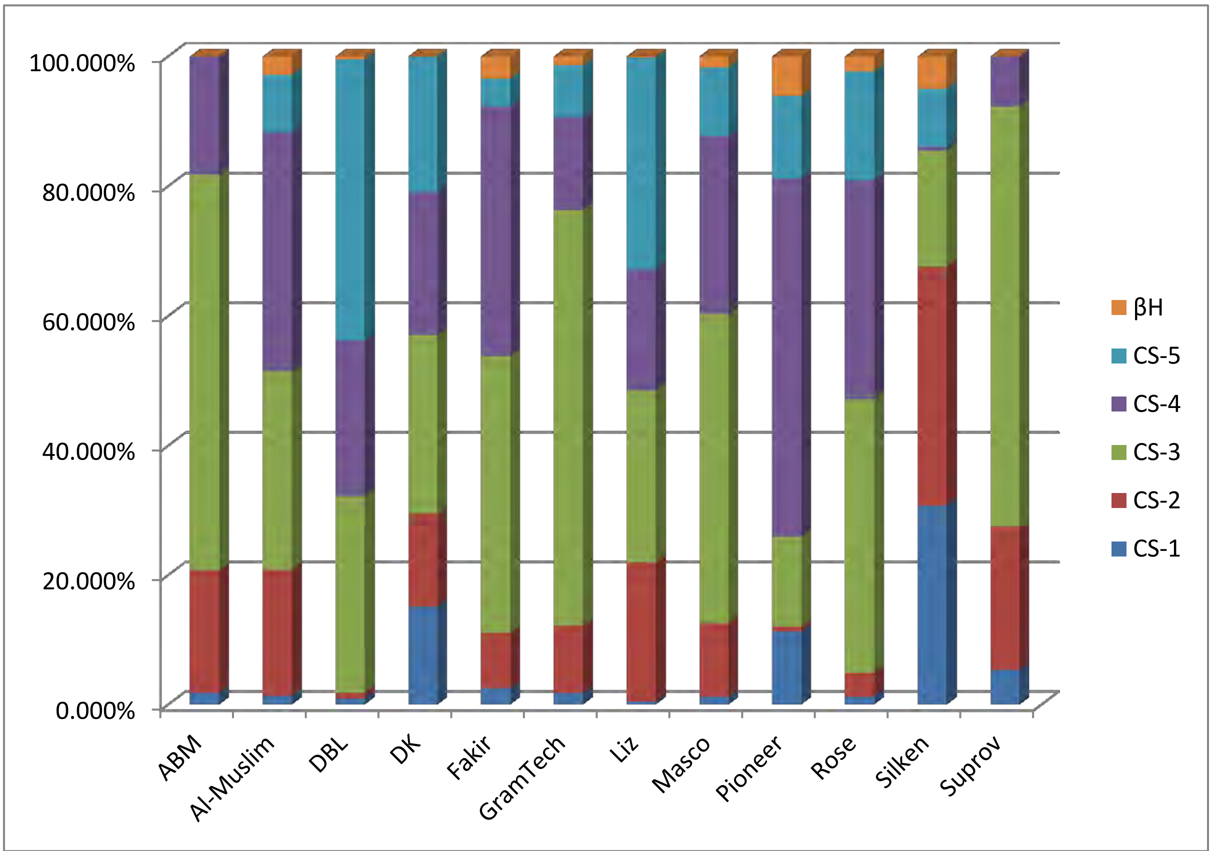

Figure- 6.1: Distribution of Assessment Grades in the Apparel Productivity Performance Index

6.2 SENSITIVITY ANALYSIS OF THE ATTRIBUTES

Sensitivity analysis of the attributes is done in this section to identify the influential attributes of the productivity performance, e.g. an organization can improve its productivity by focusing on those attributes specially. This sensitivity analysis is done by increasing the value of an attribute in a fixed interval to observe the effect of the attribute on the apparel productivity performance index. In doing so, as under a certain criteria the summation weights of all the attributes should be 1, while increasing the weightage value of a certain attribute 0 to 1, the weightage value of the other attributes kept equal. The sensitivity analysis for each of the basic level attributes is shown below.

6.2.1 Sensitivity Analysis of Level of Technology

Sensitivity Analysis of Level of Technology shows that the increase of the weightage value mostly influences Al-Muslim group and Silken Sewing Ltd. In this case, the two organizations had shown two different effects. The productivity of Al-Muslim has increased where the productivity of Silken sewing decreased. The other organizations very little impact on this attribute.

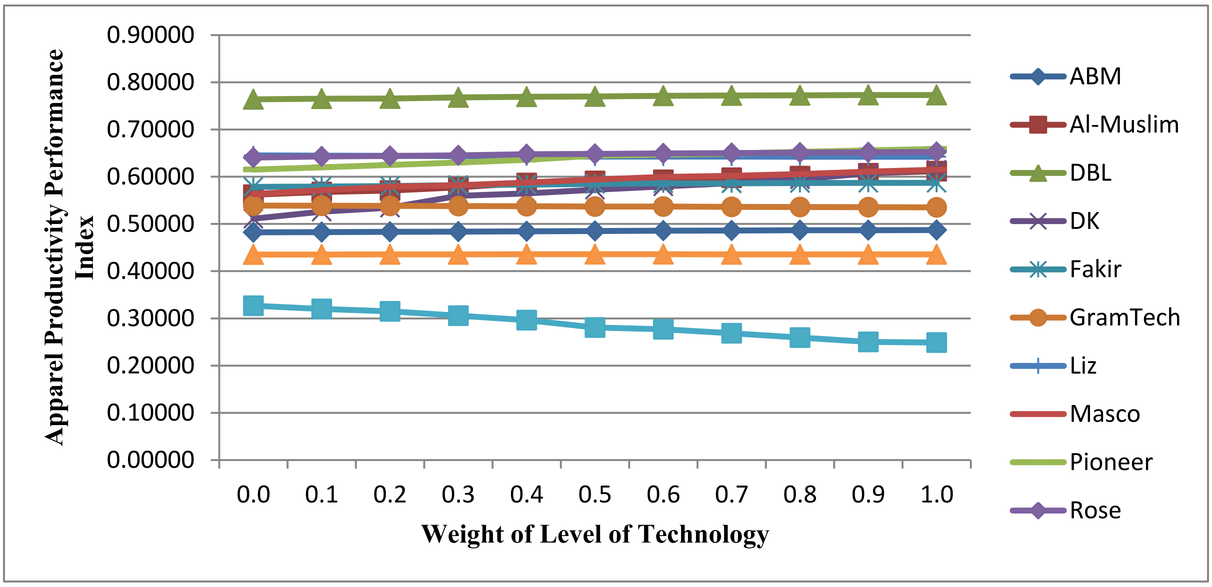

Figure- 6.2: Sensitivity Analysis of Level of Technology

6.2.2 Sensitivity Analysis of Worker Education Level

Sensitivity Analysis of Worker Education Level shows that the increase of the weightage value mostly influences Pioneer group and Rose dress. In this case, the productivity of the

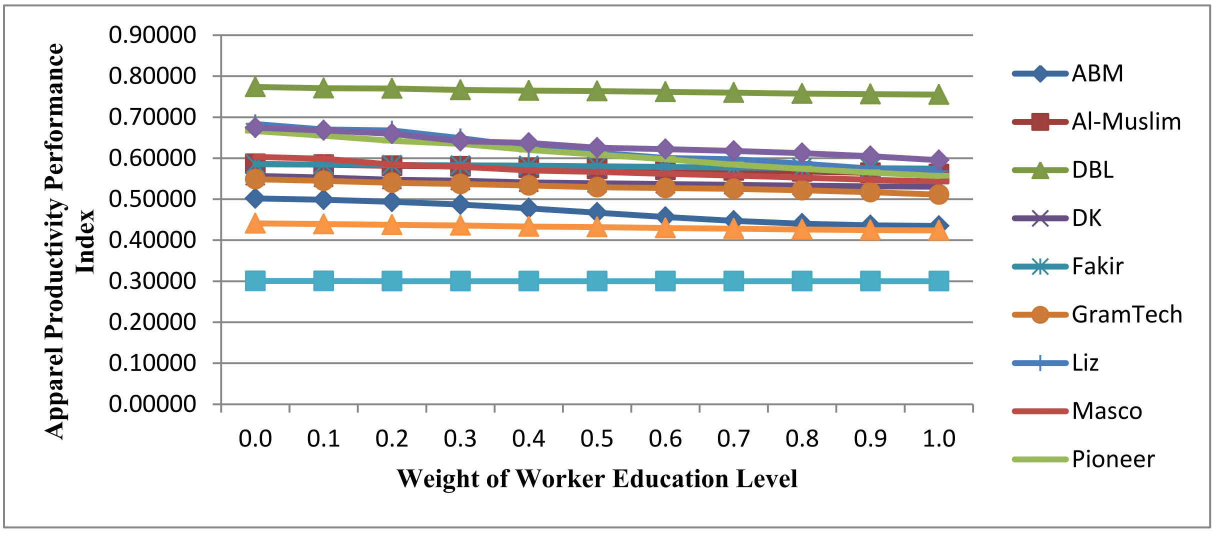

Figure- 6.3: Sensitivity Analysis of Worker Education Level two groups decreased with the increase of worker education level. The other organizations very little impact on this attribute.

6.2.3 Sensitivity Analysis of Application of Industrial Engineering

Sensitivity Analysis of Application of Industrial Engineering shows that the increase of the weightage value mostly influences Silken sewing. In this case, the productivity of this group increased with the increase of Application of Industrial Engineering. The other organizations have shown very little impact on this attribute.

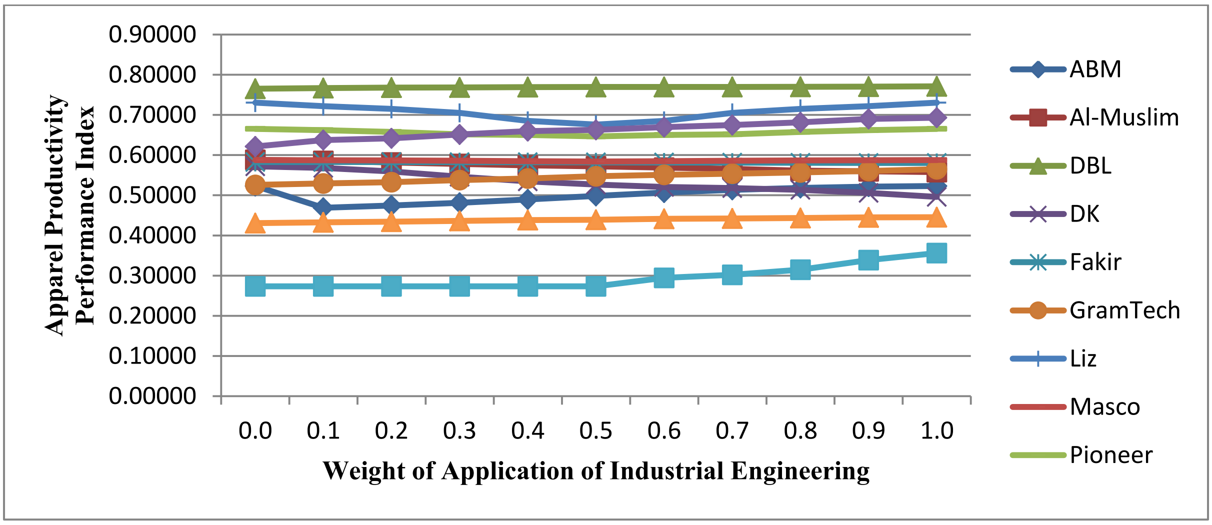

Figure- 6.4: Sensitivity Analysis of Application of Industrial Engineering

6.2.4 Sensitivity Analysis of Raw Material Quality

Sensitivity Analysis of Raw Material Quality shows that the organizations have shown very little impact on this attribute.

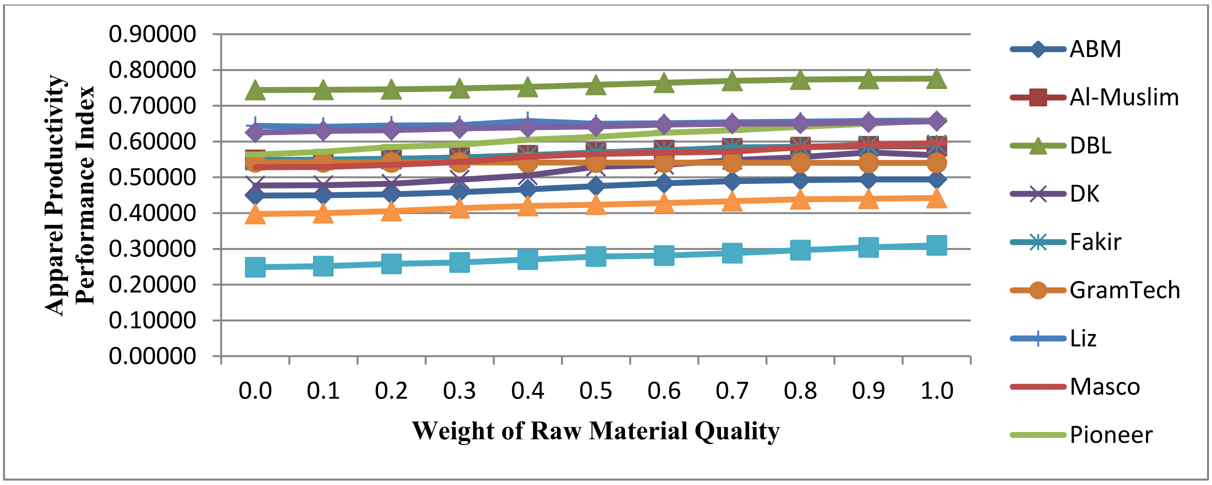

Figure- 6.5: Sensitivity Analysis of Raw Material Quality

6.2.5 Sensitivity Analysis of Style Changeover Time

Sensitivity Analysis of Application of Industrial Engineering shows that the increase of the weightage value mostly influences Silken sewing and DBL group. In this case, the productivity of these groups decreased with the increase of Style Changeover Time. The other organizations have shown very little impact on this attribute.

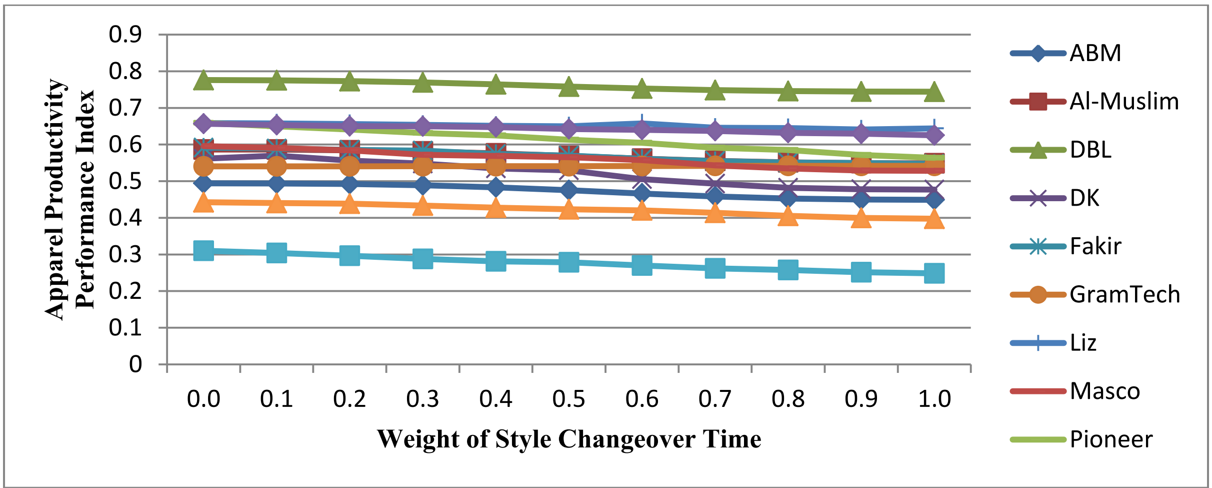

Figure- 6.6: Sensitivity Analysis of Style Changeover Time

6.2.6 Sensitivity Analysis of Labor Efficiency

Sensitivity Analysis of Labor Efficiency shows that the increase of the weightage value mostly influences Pioneer group and Rose dress. In this case, the productivity of the two groups decreased with the increase of Labor Efficiency. The other organizations very little impact on this attribute.

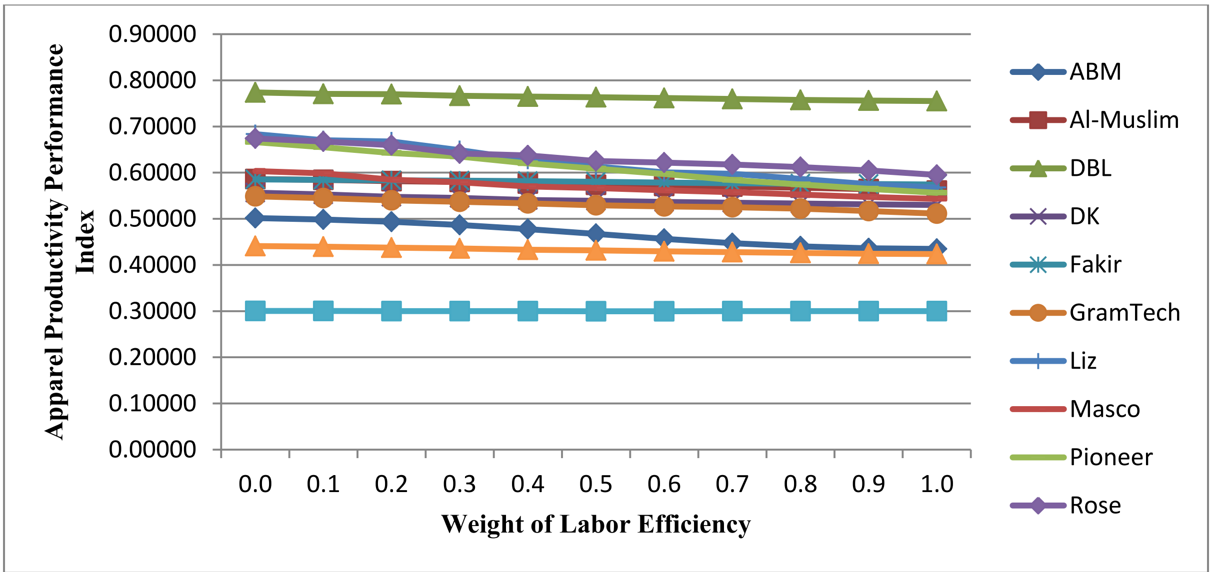

Figure- 6.7: Sensitivity Analysis of Labor Efficiency

6.2.7 Sensitivity Analysis of Line Efficiency

Sensitivity Analysis of Line Efficiency shows that the increase of the weightage value mostly influences Silken sewing and Masco group. In this case, the productivity of Silken is decreased with the increase of Line efficiency and the productivity of Masco is increased. The other organizations have shown very little impact on this attribute.

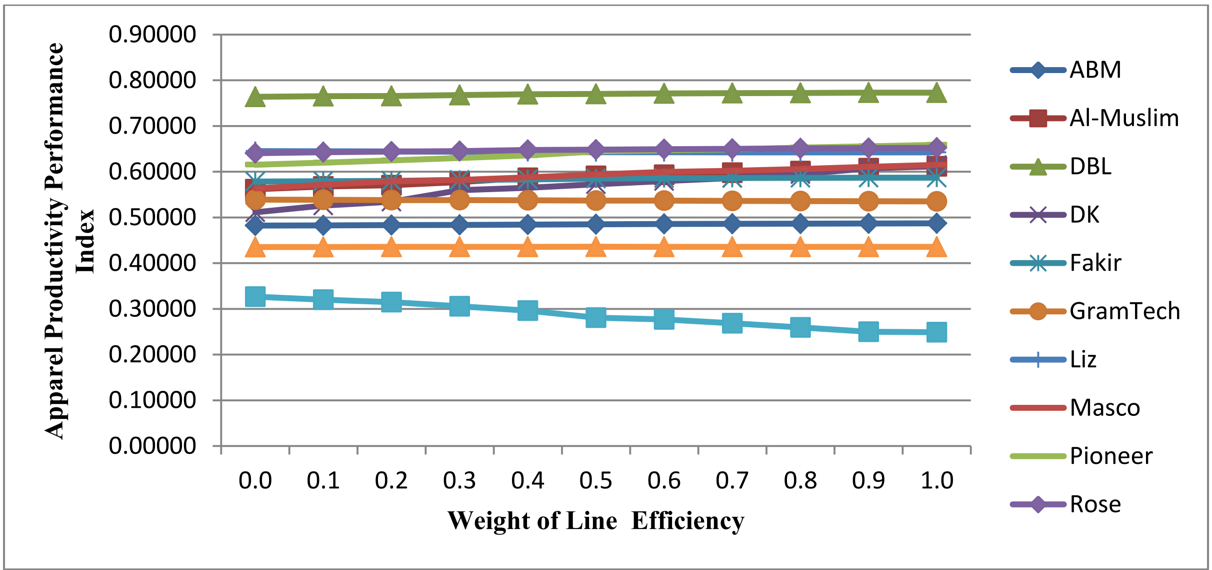

Figure- 6.8: Sensitivity Analysis of Line Efficiency

6.2.8 Sensitivity Analysis of Machine Utilization

Sensitivity Analysis of Machine Utilization shows that the increase of the weightage value mostly influences Silken sewing.

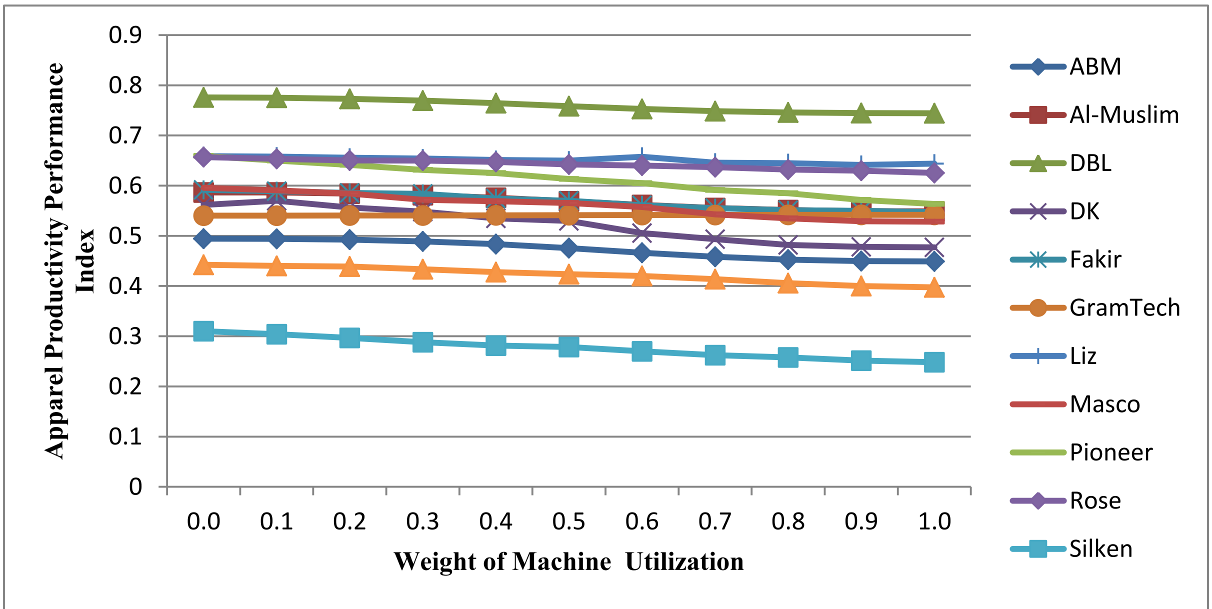

Figure- 6.9: Sensitivity Analysis of Machine Utilization

In this case, the productivity of Silken is decreased with the increase of Machine Utilization. The other organizations have shown very little impact on this attribute.

6.2.9 Sensitivity Analysis of Raw Material Utilization

Sensitivity Analysis of Raw Material Utilization shows that the increase of the weightage value mostly influences Silken sewing. In this case, the productivity of Silken is increased with the increase of Raw Material Utilization. The other organizations have shown very little impact on this attribute.

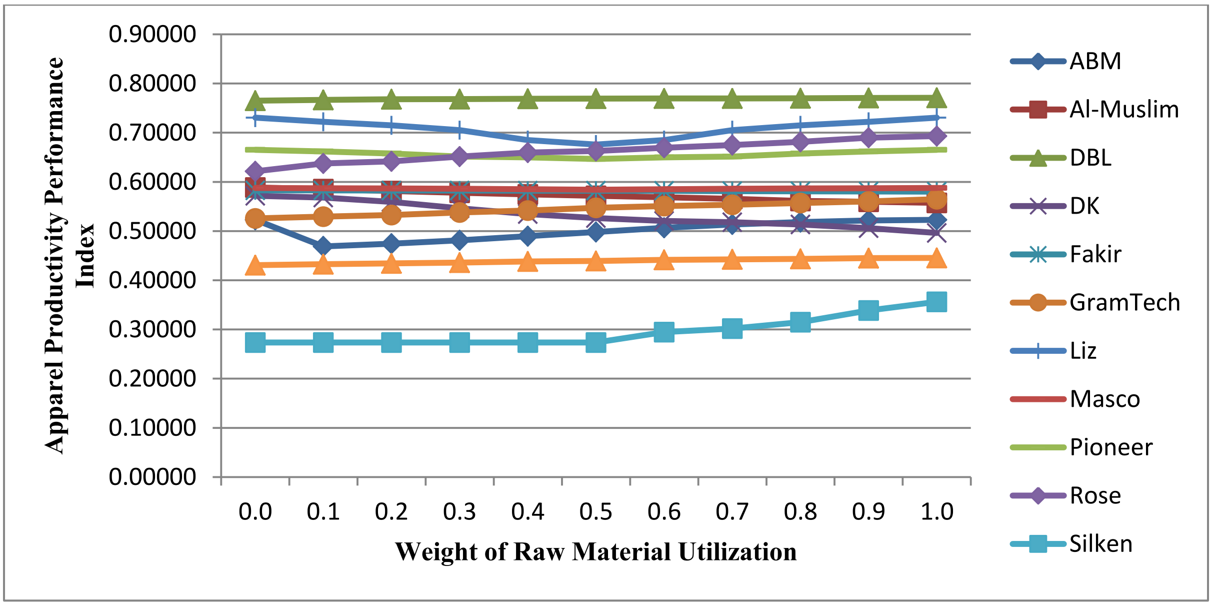

Figure- 6.10: Sensitivity Analysis of Raw Material Utilization

6.2.10 Sensitivity Analysis of Working Environment

Sensitivity Analysis of Working Environment shows that the increase of the weightage value mostly influences Silken sewing.

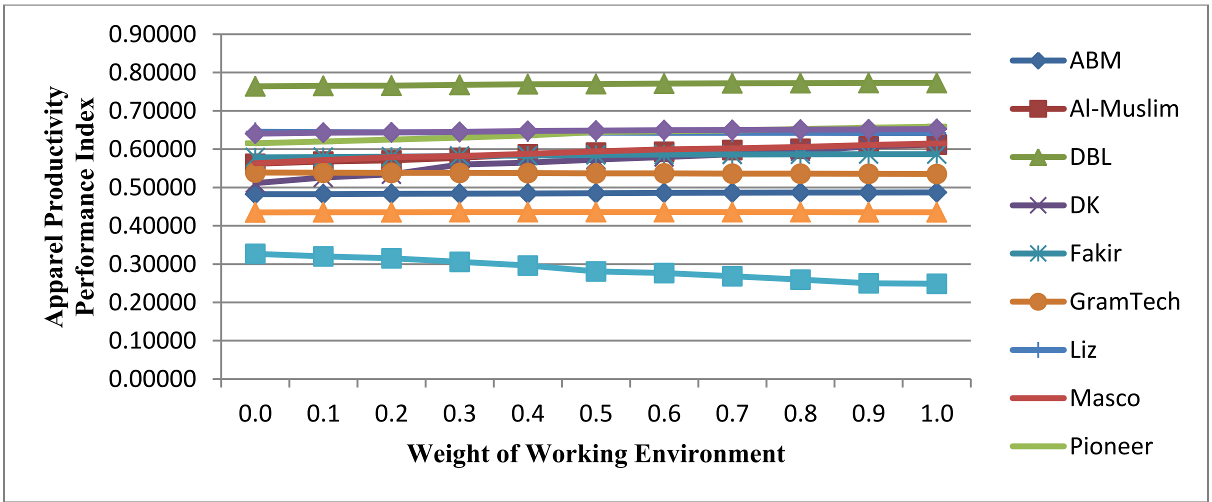

Figure- 6.11: Sensitivity Analysis of Working Environment

In this case, the productivity of Silken is decreased with the increase of Working Environment. The other organizations have shown very little impact on this attribute.

6.2.11 Sensitivity Analysis of Level of Job Satisfaction

Sensitivity Analysis of Level of Job Satisfaction shows that all the organizations have shown the increasing trend of productivity index to this attribute.

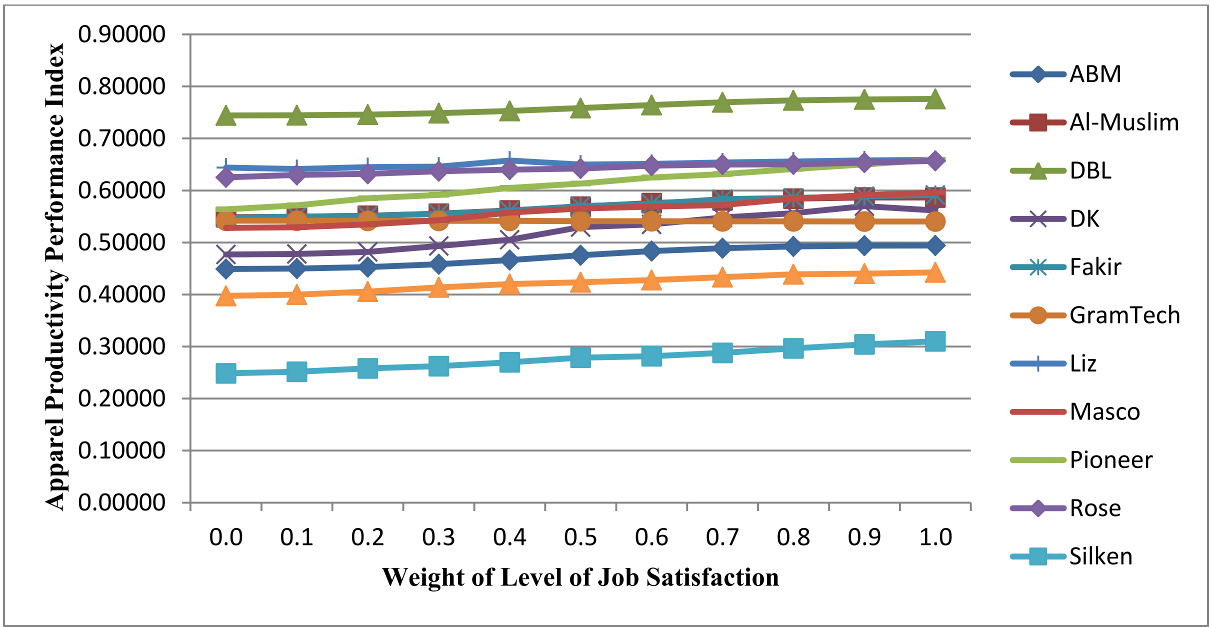

Figure- 6.12: Sensitivity Analysis of Level of Job Satisfaction

6.2.12 Sensitivity Analysis of Availability of Utility

Sensitivity Analysis of Availability of Utility shows that the increase of the weightage value mostly influences Silken sewing.

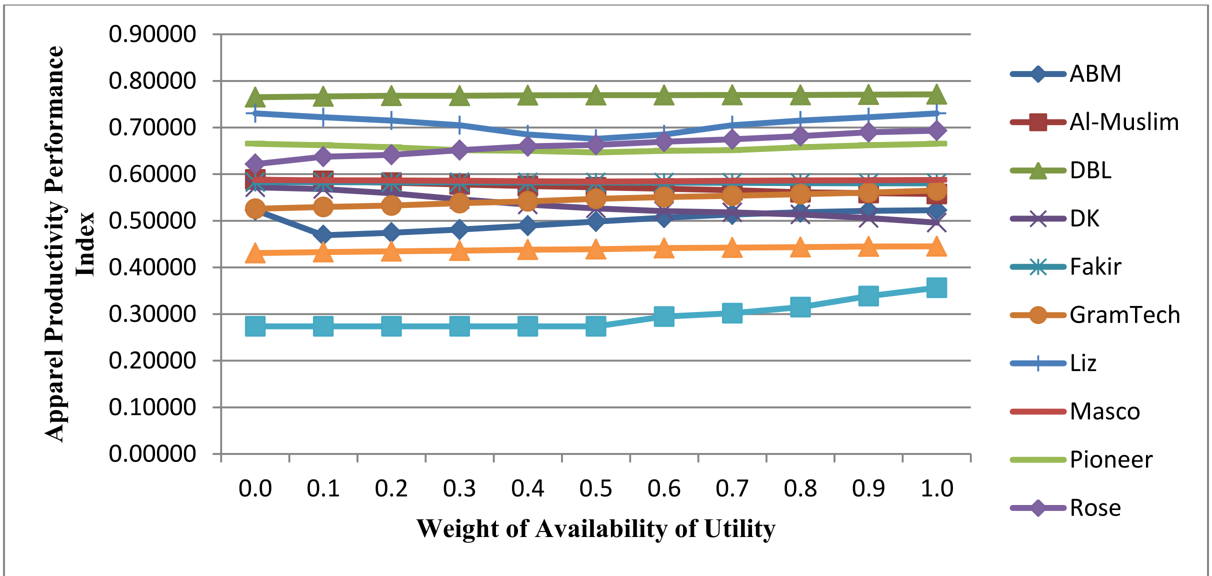

Figure- 6.13: Sensitivity Analysis of Availability of Utility

In this case, the productivity of Silken is increased with the increase of Availability of Utility. The other organizations have shown very little impact on this attribute.

6.3 BENCHMARKING DISCUSSION

Benchmarking is the systematic comparison of the performance of one firm against other firms. More generally, it is comparison of production entities. The idea is that the comparison of entities that transform the same type of resources to the same type of products and services. The production entities can be firms, organizations, divisions, industries, projects, decision making units, or individuals. After ranking the apparel organizations and performing the sensitivity analysis of the attributes, the position of the organizations in terms of their productivity index is clear and the significant attributes are also clear, e.g. to which sector they should focus to improve their performance. All the organizations need to focus on the productivity improve in comparison with their sector best organization DBL group and the Silken sewing Ltd. needs most attention on increasing their productivity.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

The rapid growing challenges like global competition, dependency on raw material, increased product variety, demanding customer and, globalization have a major influence on apparel industries. Apparel manufacturers need to produce the high quality products reducing the difficulties in operations for acquiring demand for higher value at lower price. In order to survive, they need to combat the constraints associated with the operations. In order to improve the productivity, it is vital to identify, quantify and remove the constraints. The industry can gain higher productivity and profitability with improved quality product by identifying and overcoming the problems that reduce the productivity, cost and improve internal throughput time.

The HER approach using belief structure and belief decision matrix can provide an appropriate and transparent MCDM approach for modeling productivity assessment index. Even if it will rarely be possible to obtain exact rankings of the apparel organization based on productivity due to the large uncertainties associated with the evaluation data, the HER approach in contrast to existing MCDM approaches is, therefore, applied to careful drawing conclusions and to explicitly address the associated uncertainties and sensitivities. In this research, a multiple criteria framework to assess the productivity of apparel organizations has been developed using HER approach. Both of the qualitative and quantitative attributes need to be considered in benchmarking productivity. This framework brings these issues together. The illustrative example indicated the importance of integrating managerial preferences and judgments into decision models and their impact on the final decisions. A case study of our apparel industry demonstrates the implementation process. Results show that using the HER approach when assessing the productivity of different apparel organizations under uncertainty allows providing robust decisions, which brings out a more accurate, effective, and better-informed benchmarking tool to conduct the evaluation process.

6.2 RECOMMENDATIONS

The following recommendations are being given:

1. Evaluating the performance of additional mathematical theories of uncertainty such as fuzzy sets theory and rough sets theory when applied to a similar problem.
2. The Simple Multi Attribute Rating Technique (SMART) method, Kim and Park method, Dubois and Prade's method for rule of combination and Yager's rule of combination can also be assessed to testify the validity of this Dempster-Shafer rule of combination based method for assessment in multiple criteria.
3. Further research on apparel organization's productivity modeling and their significance in enhancing overall improvement in this sector and competitiveness. The developed simulation model in this study constitutes a readily understood theory of tacit knowledge importance and effects on sustaining productivity performance. However, the model will not be adequate for practical use without combining both tacit and explicit knowledge sharing mechanism; such a model does not currently exist in the literature.
4. The thesis has provided some significant insights into the understanding of apparel productivity that influences on the organization's performance. Furthermore, it has provided a solid understanding of how individual organization's cultural values influence the productivity performance. Yet, there are many pieces of the puzzle regarding how these variables are measured and validity of instruments used that need to be addressed though future research to expand the knowledge of why some organizations with the same socioeconomic features, in the same regions, have the same size are performing better in general.

Finally, the researcher has learned a great deal about productivity calculation method and productivity performance measurements from this research. Investigating the effects of different attributes on productivity performance and reading vast amounts of the literature has been extremely useful and interesting, and thus researcher hopes to contribute to future knowledge in this context.

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Appendix

Code of Microsoft Visual Basic for Applications:

```
Option Explicit

Option Base 1


Sub SecondaryConditionIndexCombination()

Dim WorkingEnvironment(1, 8) As Double

Dim LevelOfJobSatisfaction(1, 8) As Double

Dim AvailailityOfUtility(1, 8) As Double

Dim SecondaryConditionIndex1(1, 8) As Double

Dim SecondaryConditionIndex2(1, 8) As Double

Dim RowCounter As Integer

Dim ColCounter As Integer


Dim Sum1 As Double

Dim Sum2 As Double


Dim K1 As Double

Dim K2 As Double


For RowCounter = 1 To 8

    WorkingEnvironment(1, RowCounter) = Cells(31, RowCounter + 9)

Next RowCounter
```

```
For ColCounter = 1 To 8
    LevelOfJobSatisfaction(1, ColCounter) = Cells(32, ColCounter + 9)
Next ColCounter
Sum1 = 0
For RowCounter = 1 To 5
    For ColCounter = 1 To 5
        Sum1 = WorkingEnvironment(1, RowCounter) * LevelOfJobSatisfaction(1, ColCounter) + Sum1
    Next ColCounter
Next RowCounter
Sum1 = Sum1 - (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) _
+ WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) _
+ WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5)
K1 = 1 / (1 - Sum1)
SecondaryConditionIndex1(1, 1) = K1 * (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 1) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 1))
SecondaryConditionIndex1(1, 2) = K1 * (WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) + WorkingEnvironment(1, 2) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 2))
SecondaryConditionIndex1(1, 3) = K1 * (WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 3) * _
```

```
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 3))

SecondaryConditionIndex1(1, 4) = K1 * (WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) + WorkingEnvironment(1, 4) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 4))

SecondaryConditionIndex1(1, 5) = K1 * (WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5) + WorkingEnvironment(1, 5) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 5))

SecondaryConditionIndex1(1, 7) = K1 * (WorkingEnvironment(1, 7) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 8) = K1 * (WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 7) * _

LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 6) = SecondaryConditionIndex1(1, 7) + SecondaryConditionIndex1(1, 8)

For RowCounter = 1 To 8

  AvailailityOfUtility(1, RowCounter) = Cells(33, RowCounter + 9)

Next RowCounter

Sum2 = 0

For RowCounter = 1 To 5

  For ColCounter = 1 To 5

    Sum2 = SecondaryConditionIndex1(1, RowCounter) * AvailailityOfUtility(1, ColCounter) + Sum2

  Next ColCounter

Next RowCounter
```

Sum2 = Sum2 - (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) _

+ SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) _

+ SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5))

K2 = 1 / (1 - Sum2)

SecondaryConditionIndex2(1, 1) = K2 * (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 1) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 1))

SecondaryConditionIndex2(1, 2) = K2 * (SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) + SecondaryConditionIndex1(1, 2) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 2))

SecondaryConditionIndex2(1, 3) = K2 * (SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 3) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 3))

SecondaryConditionIndex2(1, 4) = K2 * (SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) + SecondaryConditionIndex1(1, 4) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 4))

SecondaryConditionIndex2(1, 5) = K2 * (SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5) + SecondaryConditionIndex1(1, 5) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 5))

SecondaryConditionIndex2(1, 7) = K2 * (SecondaryConditionIndex1(1, 7) * AvailailityOfUtility(1, 7))

SecondaryConditionIndex2(1, 8) = K2 * (SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 7) * _

AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 7))

```
SecondaryConditionIndex2(1, 6) = SecondaryConditionIndex2(1, 7) + SecondaryConditionIndex2(1, 8)

For RowCounter = 1 To 8

   Cells(11, RowCounter + 9) = SecondaryConditionIndex2(1, RowCounter)

Next RowCounter

End Sub

Sub ProductParametersCombination()

Dim RawMaterialQuality(1, 8) As Double

Dim StyleChangeOverTime(1, 8) As Double

Dim ProductParameters(1, 8) As Double

Dim Sum As Double

Dim K As Double

Dim RowCounter As Integer

Dim ColCounter As Integer

For RowCounter = 1 To 8

   RawMaterialQuality(1, RowCounter) = Cells(19, RowCounter + 9)

Next RowCounter

For ColCounter = 1 To 8

   StyleChangeOverTime(1, ColCounter) = Cells(20, ColCounter + 9)

Next ColCounter

Sum = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5
```

```
Sum = RawMaterialQuality(1, RowCounter) * StyleChangeOverTime(1, ColCounter) + Sum

Next ColCounter

Next RowCounter

Sum = Sum - (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) + RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) _

+ RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) + RawMaterialQuality(1, 4) * StyleChangeOverTime(1, 4) _

+ RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5))

K = 1 / (1 - Sum)

'Range("P18") = K

ProductParameters(1, 1) = K * (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) + RawMaterialQuality(1, 1) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 1))

ProductParameters(1, 2) = K * (RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) + RawMaterialQuality(1, 2) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 2))

ProductParameters(1, 3) = K * (RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) + RawMaterialQuality(1, 3) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 3))

ProductParameters(1, 4) = K * (RawMaterialQuality(1, 4) * StyleChangeOverTime(1, 4) + RawMaterialQuality(1, 4) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 4))

ProductParameters(1, 5) = K * (RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5) + RawMaterialQuality(1, 5) * _
```

```
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 5))

ProductParameters(1, 7) = K * (RawMaterialQuality(1, 7) * StyleChangeOverTime(1, 7))

ProductParameters(1, 8) = K * (RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 8) +
RawMaterialQuality(1, 7) * _

StyleChangeOverTime(1, 8) + RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 7))

ProductParameters(1, 6) = ProductParameters(1, 7) + ProductParameters(1, 8)

For RowCounter = 1 To 8

   Cells(18, RowCounter + 9) = ProductParameters(1, RowCounter)

Next RowCounter

End Sub

Sub ProcessParametersCombination()

Dim WorkingEnvironment(1, 8) As Double

Dim LevelOfJobSatisfaction(1, 8) As Double

Dim AvailailityOfUtility(1, 8) As Double

Dim SecondaryConditionIndex1(1, 8) As Double

Dim SecondaryConditionIndex2(1, 8) As Double

Dim RowCounter As Integer

Dim ColCounter As Integer

Dim Sum1 As Double

Dim Sum2 As Double

Dim K1 As Double

Dim K2 As Double
```

```
For RowCounter = 1 To 8

    WorkingEnvironment(1, RowCounter) = Cells(15, RowCounter + 9)

Next RowCounter

For ColCounter = 1 To 8

    LevelOfJobSatisfaction(1, ColCounter) = Cells(16, ColCounter + 9)

Next ColCounter

Sum1 = 0

For RowCounter = 1 To 5

    For ColCounter = 1 To 5

        Sum1 = WorkingEnvironment(1, RowCounter) * LevelOfJobSatisfaction(1, ColCounter) + Sum1

    Next ColCounter

Next RowCounter

Sum1 = Sum1 - (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) _

+ WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) _

+ WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5))

K1 = 1 / (1 - Sum1)

SecondaryConditionIndex1(1, 1) = K1 * (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 1) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 1))

SecondaryConditionIndex1(1, 2) = K1 * (WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) + WorkingEnvironment(1, 2) * _
```

```
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 2))

SecondaryConditionIndex1(1, 3) = K1 * (WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 3) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 3))

SecondaryConditionIndex1(1, 4) = K1 * (WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) + WorkingEnvironment(1, 4) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 4))

SecondaryConditionIndex1(1, 5) = K1 * (WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5) + WorkingEnvironment(1, 5) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 5))

SecondaryConditionIndex1(1, 7) = K1 * (WorkingEnvironment(1, 7) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 8) = K1 * (WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 7) * _

LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 6) = SecondaryConditionIndex1(1, 7) + SecondaryConditionIndex1(1, 8)

For RowCounter = 1 To 8

   AvailailityOfUtility(1, RowCounter) = Cells(17, RowCounter + 9)

Next RowCounter

Sum2 = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5
```

```
    Sum2 = SecondaryConditionIndex1(1, RowCounter) * AvailailityOfUtility(1, ColCounter) + Sum2

  Next ColCounter

Next RowCounter

Sum2 = Sum2 - (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) _

+ SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) _

+ SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5))

K2 = 1 / (1 - Sum2)

SecondaryConditionIndex2(1, 1) = K2 * (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 1) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 1))

SecondaryConditionIndex2(1, 2) = K2 * (SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) + SecondaryConditionIndex1(1, 2) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 2))

SecondaryConditionIndex2(1, 3) = K2 * (SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 3) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 3))

SecondaryConditionIndex2(1, 4) = K2 * (SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) + SecondaryConditionIndex1(1, 4) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 4))

SecondaryConditionIndex2(1, 5) = K2 * (SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5) + SecondaryConditionIndex1(1, 5) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 5))
```

```
SecondaryConditionIndex2(1, 7) = K2 * (SecondaryConditionIndex1(1, 7) * AvailailityOfUtility(1, 7))

SecondaryConditionIndex2(1, 8) = K2 * (SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 7) * _

AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 7))

SecondaryConditionIndex2(1, 6) = SecondaryConditionIndex2(1, 7) + SecondaryConditionIndex2(1, 8)

For RowCounter = 1 To 8

   Cells(14, RowCounter + 9) = SecondaryConditionIndex2(1, RowCounter)

Next RowCounter

End Sub

Sub EffectivenessCombination()

Dim RawMaterialQuality(1, 8) As Double

Dim StyleChangeOverTime(1, 8) As Double

Dim ProductParameters(1, 8) As Double

Dim Sum As Double

Dim K As Double

Dim RowCounter As Integer

Dim ColCounter As Integer

For RowCounter = 1 To 8

   RawMaterialQuality(1, RowCounter) = Cells(14, RowCounter + 17)

Next RowCounter

For ColCounter = 1 To 8

   StyleChangeOverTime(1, ColCounter) = Cells(18, ColCounter + 17)
```

```
Next ColCounter

Sum = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5

      Sum = RawMaterialQuality(1, RowCounter) * StyleChangeOverTime(1, ColCounter) +
Sum

   Next ColCounter

Next RowCounter

Sum = Sum - (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) +
RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) _

+ RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) + RawMaterialQuality(1, 4) *
StyleChangeOverTime(1, 4) _

+ RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5))

K = 1 / (1 - Sum)

ProductParameters(1, 1) = K * (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) +
RawMaterialQuality(1, 1) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 1))

ProductParameters(1, 2) = K * (RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) +
RawMaterialQuality(1, 2) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 2))

ProductParameters(1, 3) = K * (RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) +
RawMaterialQuality(1, 3) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 3))

ProductParameters(1, 4) = K * (RawMaterialQuality(1, 4) * StyleChangeOverTime(1, 4) +
RawMaterialQuality(1, 4) * _
```

```
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 4))

ProductParameters(1, 5) = K * (RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5) + RawMaterialQuality(1, 5) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 5))

ProductParameters(1, 7) = K * (RawMaterialQuality(1, 7) * StyleChangeOverTime(1, 7))

ProductParameters(1, 8) = K * (RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 8) + RawMaterialQuality(1, 7) * _

StyleChangeOverTime(1, 8) + RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 7))

ProductParameters(1, 6) = ProductParameters(1, 7) + ProductParameters(1, 8)

For RowCounter = 1 To 8

   Cells(13, RowCounter + 9) = ProductParameters(1, RowCounter)

Next RowCounter

End Sub

Sub RightFirstTimeQualityCombination()

Dim RawMaterialQuality(1, 8) As Double

Dim RowCounter As Integer

For RowCounter = 1 To 8

   RawMaterialQuality(1, RowCounter) = Cells(29, RowCounter + 9)

Next RowCounter

For RowCounter = 1 To 8

   Cells(28, RowCounter + 9) = RawMaterialQuality(1, RowCounter)

Next RowCounter
```

```
End Sub

Sub TechnicalEfficiencyCombination()

Dim WorkingEnvironment(1, 8) As Double

Dim LevelOfJobSatisfaction(1, 8) As Double

Dim AvailailityOfUtility(1, 8) As Double

Dim RawMaterialUtilization(1, 8) As Double


Dim SecondaryConditionIndex1(1, 8) As Double

Dim SecondaryConditionIndex2(1, 8) As Double

Dim SecondaryConditionIndex3(1, 8) As Double

Dim RowCounter As Integer

Dim ColCounter As Integer

Dim Sum1 As Double

Dim Sum2 As Double

Dim Sum3 As Double

Dim K1 As Double

Dim K2 As Double

Dim K3 As Double

For RowCounter = 1 To 8

   WorkingEnvironment(1, RowCounter) = Cells(24, RowCounter + 9)

Next RowCounter


For ColCounter = 1 To 8
```

```
    LevelOfJobSatisfaction(1, ColCounter) = Cells(25, ColCounter + 9)
Next ColCounter
Sum1 = 0
For RowCounter = 1 To 5
    For ColCounter = 1 To 5
        Sum1 = WorkingEnvironment(1, RowCounter) * LevelOfJobSatisfaction(1, ColCounter) + Sum1
    Next ColCounter
Next RowCounter
Sum1 = Sum1 - (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) _
+ WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) _
+ WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5))
K1 = 1 / (1 - Sum1)
SecondaryConditionIndex1(1, 1) = K1 * (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 1) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 1))
SecondaryConditionIndex1(1, 2) = K1 * (WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) + WorkingEnvironment(1, 2) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 2))
SecondaryConditionIndex1(1, 3) = K1 * (WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 3) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 3))
```

```
SecondaryConditionIndex1(1, 4) = K1 * (WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) + WorkingEnvironment(1, 4) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 4))

SecondaryConditionIndex1(1, 5) = K1 * (WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5) + WorkingEnvironment(1, 5) * _

LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 5))

SecondaryConditionIndex1(1, 7) = K1 * (WorkingEnvironment(1, 7) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 8) = K1 * (WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 7) * _

LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 6) = SecondaryConditionIndex1(1, 7) + SecondaryConditionIndex1(1, 8)

For RowCounter = 1 To 8

   AvailailityOfUtility(1, RowCounter) = Cells(26, RowCounter + 9)

Next RowCounter

Sum2 = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5

      Sum2 = SecondaryConditionIndex1(1, RowCounter) * AvailailityOfUtility(1, ColCounter) + Sum2

   Next ColCounter

Next RowCounter
```

```
Sum2 = Sum2 - (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) _

+ SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) _

+ SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5))

K2 = 1 / (1 - Sum2)

SecondaryConditionIndex2(1, 1) = K2 * (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 1) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 1))

SecondaryConditionIndex2(1, 2) = K2 * (SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) + SecondaryConditionIndex1(1, 2) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 2))

SecondaryConditionIndex2(1, 3) = K2 * (SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 3) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 3))

SecondaryConditionIndex2(1, 4) = K2 * (SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) + SecondaryConditionIndex1(1, 4) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 4))

SecondaryConditionIndex2(1, 5) = K2 * (SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5) + SecondaryConditionIndex1(1, 5) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 5))

SecondaryConditionIndex2(1, 7) = K2 * (SecondaryConditionIndex1(1, 7) * AvailailityOfUtility(1, 7))

SecondaryConditionIndex2(1, 8) = K2 * (SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 7) * _

AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 7))
```

```
SecondaryConditionIndex2(1, 6) = SecondaryConditionIndex2(1, 7) + SecondaryConditionIndex2(1, 8)

For RowCounter = 1 To 8

   RawMaterialUtilization(1, RowCounter) = Cells(27, RowCounter + 9)

Next RowCounter

Sum3 = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5

      Sum3 = SecondaryConditionIndex2(1, RowCounter) * RawMaterialUtilization(1, ColCounter) + Sum3

   Next ColCounter

Next RowCounter

Sum3 = Sum3 - (SecondaryConditionIndex2(1, 1) * RawMaterialUtilization(1, 1) + SecondaryConditionIndex2(1, 2) * RawMaterialUtilization(1, 2) _

+ SecondaryConditionIndex2(1, 3) * RawMaterialUtilization(1, 3) + SecondaryConditionIndex2(1, 4) * RawMaterialUtilization(1, 4) _

+ SecondaryConditionIndex2(1, 5) * RawMaterialUtilization(1, 5))

K3 = 1 / (1 - Sum3)

SecondaryConditionIndex3(1, 1) = K3 * (SecondaryConditionIndex2(1, 1) * RawMaterialUtilization(1, 1) + SecondaryConditionIndex2(1, 1) * _

RawMaterialUtilization(1, 6) + SecondaryConditionIndex2(1, 6) * RawMaterialUtilization(1, 1))

SecondaryConditionIndex3(1, 2) = K3 * (SecondaryConditionIndex2(1, 2) * RawMaterialUtilization(1, 2) + SecondaryConditionIndex2(1, 2) * _
```

```
RawMaterialUtilization(1, 6) + SecondaryConditionIndex2(1, 6) * RawMaterialUtilization(1, 2))

SecondaryConditionIndex3(1, 3) = K3 * (SecondaryConditionIndex2(1, 3) * RawMaterialUtilization(1, 3) + SecondaryConditionIndex2(1, 3) * _

RawMaterialUtilization(1, 6) + SecondaryConditionIndex2(1, 6) * RawMaterialUtilization(1, 3))

SecondaryConditionIndex3(1, 4) = K3 * (SecondaryConditionIndex2(1, 4) * RawMaterialUtilization(1, 4) + SecondaryConditionIndex2(1, 4) * _

RawMaterialUtilization(1, 6) + SecondaryConditionIndex2(1, 6) * RawMaterialUtilization(1, 4))

SecondaryConditionIndex3(1, 5) = K3 * (SecondaryConditionIndex2(1, 5) * RawMaterialUtilization(1, 5) + SecondaryConditionIndex2(1, 5) * _

RawMaterialUtilization(1, 6) + SecondaryConditionIndex2(1, 6) * RawMaterialUtilization(1, 5))

SecondaryConditionIndex3(1, 7) = K3 * (SecondaryConditionIndex2(1, 7) * RawMaterialUtilization(1, 7))

SecondaryConditionIndex3(1, 8) = K3 * (SecondaryConditionIndex2(1, 8) * RawMaterialUtilization(1, 8) + SecondaryConditionIndex2(1, 7) * _

RawMaterialUtilization(1, 8) + SecondaryConditionIndex2(1, 8) * RawMaterialUtilization(1, 7))

SecondaryConditionIndex3(1, 6) = SecondaryConditionIndex3(1, 7) + SecondaryConditionIndex3(1, 8)

For RowCounter = 1 To 8

   Cells(23, RowCounter + 9) = SecondaryConditionIndex3(1, RowCounter)

Next RowCounter
```

```
End Sub

Sub EfficiencyCombination()

Dim WorkingEnvironment(1, 8) As Double

Dim LevelOfJobSatisfaction(1, 8) As Double

Dim AvailailityOfUtility(1, 8) As Double

Dim SecondaryConditionIndex1(1, 8) As Double

Dim SecondaryConditionIndex2(1, 8) As Double

Dim RowCounter As Integer

Dim ColCounter As Integer

Dim Sum1 As Double

Dim Sum2 As Double

Dim K1 As Double

Dim K2 As Double

For RowCounter = 1 To 8

   WorkingEnvironment(1, RowCounter) = Cells(22, RowCounter + 9)

Next RowCounter

For ColCounter = 1 To 8

   LevelOfJobSatisfaction(1, ColCounter) = Cells(23, ColCounter + 17)

Next ColCounter

Sum1 = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5
```

```
Sum1 = WorkingEnvironment(1, RowCounter) * LevelOfJobSatisfaction(1, ColCounter) + Sum1
  Next ColCounter
Next RowCounter
Sum1 = Sum1 - (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) _
+ WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) _
+ WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5))
K1 = 1 / (1 - Sum1)
SecondaryConditionIndex1(1, 1) = K1 * (WorkingEnvironment(1, 1) * LevelOfJobSatisfaction(1, 1) + WorkingEnvironment(1, 1) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 1))
SecondaryConditionIndex1(1, 2) = K1 * (WorkingEnvironment(1, 2) * LevelOfJobSatisfaction(1, 2) + WorkingEnvironment(1, 2) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 2))
SecondaryConditionIndex1(1, 3) = K1 * (WorkingEnvironment(1, 3) * LevelOfJobSatisfaction(1, 3) + WorkingEnvironment(1, 3) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 3))
SecondaryConditionIndex1(1, 4) = K1 * (WorkingEnvironment(1, 4) * LevelOfJobSatisfaction(1, 4) + WorkingEnvironment(1, 4) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 4))
SecondaryConditionIndex1(1, 5) = K1 * (WorkingEnvironment(1, 5) * LevelOfJobSatisfaction(1, 5) + WorkingEnvironment(1, 5) * _
LevelOfJobSatisfaction(1, 6) + WorkingEnvironment(1, 6) * LevelOfJobSatisfaction(1, 5))
```

```
SecondaryConditionIndex1(1, 7) = K1 * (WorkingEnvironment(1, 7) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 8) = K1 * (WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 7) * _

LevelOfJobSatisfaction(1, 8) + WorkingEnvironment(1, 8) * LevelOfJobSatisfaction(1, 7))

SecondaryConditionIndex1(1, 6) = SecondaryConditionIndex1(1, 7) + SecondaryConditionIndex1(1, 8)

For RowCounter = 1 To 8

   AvailailityOfUtility(1, RowCounter) = Cells(28, RowCounter + 17)

Next RowCounter

Sum2 = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5

      Sum2 = SecondaryConditionIndex1(1, RowCounter) * AvailailityOfUtility(1, ColCounter) + Sum2

   Next ColCounter

Next RowCounter

Sum2 = Sum2 - (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) _

+ SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) _

+ SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5))

K2 = 1 / (1 - Sum2)
```

SecondaryConditionIndex2(1, 1) = K2 * (SecondaryConditionIndex1(1, 1) * AvailailityOfUtility(1, 1) + SecondaryConditionIndex1(1, 1) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 1))

SecondaryConditionIndex2(1, 2) = K2 * (SecondaryConditionIndex1(1, 2) * AvailailityOfUtility(1, 2) + SecondaryConditionIndex1(1, 2) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 2))

SecondaryConditionIndex2(1, 3) = K2 * (SecondaryConditionIndex1(1, 3) * AvailailityOfUtility(1, 3) + SecondaryConditionIndex1(1, 3) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 3))

SecondaryConditionIndex2(1, 4) = K2 * (SecondaryConditionIndex1(1, 4) * AvailailityOfUtility(1, 4) + SecondaryConditionIndex1(1, 4) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 4))

SecondaryConditionIndex2(1, 5) = K2 * (SecondaryConditionIndex1(1, 5) * AvailailityOfUtility(1, 5) + SecondaryConditionIndex1(1, 5) * _

AvailailityOfUtility(1, 6) + SecondaryConditionIndex1(1, 6) * AvailailityOfUtility(1, 5))

SecondaryConditionIndex2(1, 7) = K2 * (SecondaryConditionIndex1(1, 7) * AvailailityOfUtility(1, 7))

SecondaryConditionIndex2(1, 8) = K2 * (SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 7) * _

AvailailityOfUtility(1, 8) + SecondaryConditionIndex1(1, 8) * AvailailityOfUtility(1, 7))

SecondaryConditionIndex2(1, 6) = SecondaryConditionIndex2(1, 7) + SecondaryConditionIndex2(1, 8)

```
For RowCounter = 1 To 8
   Cells(21, RowCounter + 9) = SecondaryConditionIndex2(1, RowCounter)
Next RowCounter
End Sub
Sub PrimaryPerformanceIndexCombination()
Dim RawMaterialQuality(1, 8) As Double
Dim StyleChangeOverTime(1, 8) As Double
Dim ProductParameters(1, 8) As Double
Dim Sum As Double
Dim K As Double
Dim RowCounter As Integer
Dim ColCounter As Integer
For RowCounter = 1 To 8
   RawMaterialQuality(1, RowCounter) = Cells(13, RowCounter + 17)
Next RowCounter
For ColCounter = 1 To 8
   StyleChangeOverTime(1, ColCounter) = Cells(21, ColCounter + 17)
Next ColCounter
Sum = 0
For RowCounter = 1 To 5
   For ColCounter = 1 To 5
```

```
    Sum = RawMaterialQuality(1, RowCounter) * StyleChangeOverTime(1, ColCounter) + Sum
  Next ColCounter
Next RowCounter
Sum = Sum - (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) + RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) _
+ RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) + RawMaterialQuality(1, 4) * StyleChangeOverTime(1, 4) _
+ RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5))
K = 1 / (1 - Sum)
ProductParameters(1, 1) = K * (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) + RawMaterialQuality(1, 1) * _
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 1))
ProductParameters(1, 2) = K * (RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) + RawMaterialQuality(1, 2) * _
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 2))
ProductParameters(1, 3) = K * (RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) + RawMaterialQuality(1, 3) * _
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 3))
ProductParameters(1, 4) = K * (RawMaterialQuality(1, 4) * StyleChangeOverTime(1, 4) + RawMaterialQuality(1, 4) * _
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 4))
ProductParameters(1, 5) = K * (RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5) + RawMaterialQuality(1, 5) * _
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 5))
```

```
ProductParameters(1, 7) = K * (RawMaterialQuality(1, 7) * StyleChangeOverTime(1, 7))

ProductParameters(1, 8) = K * (RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 8) +
RawMaterialQuality(1, 7) * _

StyleChangeOverTime(1, 8) + RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 7))

ProductParameters(1, 6) = ProductParameters(1, 7) + ProductParameters(1, 8)

For RowCounter = 1 To 8

   Cells(10, RowCounter + 9) = ProductParameters(1, RowCounter)

Next RowCounter

End Sub

Sub ApparelProductivityPerformanceIndexCombination()

Dim RawMaterialQuality(1, 8) As Double

Dim StyleChangeOverTime(1, 8) As Double

Dim ProductParameters(1, 8) As Double

Dim Sum As Double

Dim K As Double

Dim RowCounter As Integer

Dim ColCounter As Integer

For RowCounter = 1 To 8

   RawMaterialQuality(1, RowCounter) = Cells(10, RowCounter + 17)

Next RowCounter

For ColCounter = 1 To 8

   StyleChangeOverTime(1, ColCounter) = Cells(11, ColCounter + 17)
```

```
Next ColCounter

Sum = 0

For RowCounter = 1 To 5

   For ColCounter = 1 To 5

      Sum = RawMaterialQuality(1, RowCounter) * StyleChangeOverTime(1, ColCounter) +
Sum

   Next ColCounter

Next RowCounter

Sum = Sum - (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) +
RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) _

+ RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) + RawMaterialQuality(1, 4) *
StyleChangeOverTime(1, 4) _

+ RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5))

K = 1 / (1 - Sum)

ProductParameters(1, 1) = K * (RawMaterialQuality(1, 1) * StyleChangeOverTime(1, 1) +
RawMaterialQuality(1, 1) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 1))

ProductParameters(1, 2) = K * (RawMaterialQuality(1, 2) * StyleChangeOverTime(1, 2) +
RawMaterialQuality(1, 2) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 2))

ProductParameters(1, 3) = K * (RawMaterialQuality(1, 3) * StyleChangeOverTime(1, 3) +
RawMaterialQuality(1, 3) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 3))

ProductParameters(1, 4) = K * (RawMaterialQuality(1, 4) * StyleChangeOverTime(1, 4) +
RawMaterialQuality(1, 4) * _
```

```
StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 4))

ProductParameters(1, 5) = K * (RawMaterialQuality(1, 5) * StyleChangeOverTime(1, 5) + RawMaterialQuality(1, 5) * _

StyleChangeOverTime(1, 6) + RawMaterialQuality(1, 6) * StyleChangeOverTime(1, 5))

ProductParameters(1, 7) = K * (RawMaterialQuality(1, 7) * StyleChangeOverTime(1, 7))

ProductParameters(1, 8) = K * (RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 8) + RawMaterialQuality(1, 7) * _

StyleChangeOverTime(1, 8) + RawMaterialQuality(1, 8) * StyleChangeOverTime(1, 7))

ProductParameters(1, 6) = ProductParameters(1, 7) + ProductParameters(1, 8)

For RowCounter = 1 To 8

   Cells(8, RowCounter + 9) = ProductParameters(1, RowCounter)

Next RowCounter

End Sub
```