DESCRIPTIVE AND PREDICTIVE STATISTICAL MODELING OF A RING SPINNING PROCESS

by

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ABSTRACT

DESCRIPTIVE AND PREDICTIVE STATISTICAL MODELING OF A RING SPINNING PROCESS

In the textile industry, spinning process is one of the most important stages to determine the yarn structure, on which the desired fabric properties highly depend, throughout the manufacturing chain. In the production of wool yarn, “ring spinning” is the most frequently used technology since wool is principally ring-spun. In the current study, it is aimed to determine how probability of end breakage, which is one of the most important quality variables, changes with respect to process variables using statistical methods. Process data are collected under normal operating conditions of YUNSA Worsted and Woolen Company in Turkey between 2012-2014. Nominal process variables consist of color and composition of the fed fiber, ring spinning machine number, spinning, and twist direction, while continuous process variables are lot size, roving count, draft, twist level, ring traveler number, yarn count, spindle speed, and machine age. In the first part of the study, Principal Component Analysis (PCA) is used to examine how historical operating conditions described by continuous process variables and binary nominal variables change for different runs, while Correspondence Analysis (CA) is employed to elucidate which machines are preferred for certain operating conditions. In the second part, failure probability is modeled with respect to process variables using logistic regression. The predictive powers of the regression models constructed for the first, second and third types of machines, area under its ROC was found to be 0.66, 0.70 and 0.75 with optimal true positive and false positive rates as 0.64 and 0.40, 0.67 and 0.40, and 0.65 and 0.28, respectively.

ÖZET

RING İPLİK EĞİRME PROSESİNİN BETİMSEL VE KESTİRİMSEL OLARAK İSTATİSTİKSEL MODELLENMESİ

Tekstil endüstrisinde iplik yapısını belirleyen en önemli proses iplik eğirme prosesidir. Üretim zinciri boyunca kumaşın istenen özellikleri taşıması iplik yapısına bağlıdır. Yün elyafı yapı olarak ring iplikçiliğine uygun olduğundan, yün iplik üretiminde ring iplik eğirme sistemi yaygın olarak kullanılır. Yapılan bu çalışmanın amacı istatistiksel yöntemlerle iplik üretim verimini etkileyen kalite değişkenlerinden en önemlisi olan iplik kopuşunun proses değişkenlerine göre nasıl değiştiğinin incelenmesidir. Proses verileri 2012 ve 2014 yılları arasında YÜNSA Yünlü San. ve Tic. A.Ş.'nin normal çalışma koşullarında toplanmıştır. Nominal proses değişkenleri renk, kompozisyon, makina numarası, eğirme ve büküm yönünden oluşur. Sürekli proses değişkenleri ise parti büyüklüğü, fitil numarası, çekim, büküm seviyesi, kopça numarası, iplik numarası, iğ devri ve makina yaşıdır. Çalışmanın ilk kısmında, Temel Bileşenler Analizi (TBA) kullanılarak tarihsel operasyon koşullarının farklı iplik partilerinde sürekli değişkenler ve ikili nominal değişkenler tarafından nasıl tanımlandığı incelenmiştir. Belli işletme koşullarında hangi makinaların tercih edildiğini ortaya koymak için ise Uygunluk Çözümlemesi (UC) yöntemi kullanılmıştır. Çalışmanın ikinci kısmında ise Lojistik Regresyon Analizi (LRA) kullanılarak hata olasılığı proses değişkenlerine göre modellenmiştir. Üç farklı makina tipi için kurulan regresyon modellerinin tahminleme gücü, işlem karakteristiği eğrisinin (ROC) altında kalan alan sırasıyla 0.66, 0.70 ve 0.75 bulunurken, optimum doğru pozitiflik ve yanlış pozitiflik oranları sırasıyla 0.64 ve 0.40, 0.67 ve 0.40, ve 0.65 ve 0.28 bulunmuştur.

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LIST OF SYMBOLS/ABBREVIATIONS

ANN	Artificial Neural Networks
CA	Correspondence Analysis
Col	Color
Comp	Composition
CV	Coefficient of Variation
D	Draft
ES	Spinning
GEP	Gene Expression Programing
LRA	Logistic Regression Analysis
LS	Lot Size
MA	Machine Age
MLP	Multilayer Perceptron Algorithm
MLR	Multiple Linear Regression
MSub	Machine Number
PC	Principal Component
PCA	Principal Component Analysis
RC	Roving Count
ROC	Receiver Operating Characteristic Curve
RTN	Ring Traveler Number
SS	Spindle Speed
SZ	Twist Direction
TL	Twist Level
YC	Yarn Count
W	Wool
W/L	Wool/Lycra
W/N	Wool/Nylon
W/N/L	Wool/Nylon/Lycra
W/N/P	Wool/Nylon/Pagastic

W/P	Wool/Pagastic
W/PES	Wool/Polyester
W/PES/L	Wool/Polyester/Lycra

1. INTRODUCTION

Textile is a major manufacturing industry based on transformation fiber into yarn, yarn into fabric, and finally fabric into textiles. To reach the final product, there are various steps in textile industry such as spinning, weaving, dyeing and finishing (Lawrence, 2003). Because of wide range and complex processes, process control plays key role in textile industry. By using statistical tools, a large number of variables in the textile processes can be monitored, and disturbances can be detected and eliminated easily. Ring spinning has been the most significant yarn production process from past to present due to satisfactory yarn quality results, and no limitation in raw materials and linear density. Attenuation of parallel fibers in order to obtain desired linear density, imparting twist to enable the yarn strength, and winding on a bobbin are the basic principles of the ring spinning. End breakage rate is one of the most important quality variables, and mainly used to determine the yield of the ring spinning process.

In the current thesis, the ring spinning process converting fiber into yarn is examined in YUNSA Worsted and Woolen Company in Turkey. This process is elucidated because of its importance in the production chain in textile industry, and its bridging place inbetween the production chain, playing a significant role in the yield of the other processes. Process data consisting of on-line measurements of lot size, machine number, machine age, spindle speed, ring traveler number, draft, roving count, color, composition, yarn count, twist level, twist direction (S/Z) and spinning (E Siro/Elit) have been collected from year 2012 to 2014, and statistical models are obtained relating these process variables to yarn end breakage, which is taken to be the quality variable. Principal component analysis (PCA) and correspondence analysis (CA) are used as multivariate descriptive statistical tools to determine the normal process operating conditions of the process. CA, particulary, is used in analyzing the categorical variables such as machine numbers, colors and compositions. Then, logistic regression analysis (LRA) is used to determine predictive models between process variables and end breakage rate probabilities.

A detailed explanation of ring spinning process and the examination of other studies in this issue are discussed in Chapter 2. Chapter 3 consists of an overall explanation of the three statistical methods (LRA, PCA and CA) that have been employed in this study. Data collective conditions, and structure of the resulting data are discussed in Chapter 4. Descriptive statistics of process variables, the results of principal component analysis, the results of analysis of ring spinning machines, and the models of ring spinning machines are presented in Chapter 5. Finally, conclusions and recommendations are stated.

2. RING SPINNING PROCESS

The human body needs clothing to be protected from the external factors. These clothes should allow the body to move comfortably, thus they need to be flexible. The flexibility of the cloths and fabrics depends on the yarns, so yarns are produced by assembling and twisting fibers in order to make them flexible. Spinning is one of the processes employed in assembling and twisting fibers to form a yarn of desired thickness and strength. Spinning process has a vital role in textile industry because of its high influence on the quality of final product. The eventual goal of spinning is to manufacture yarn of the required linear density, exceptional evenness, tensile characteristics and a minimum number of faults (Lawrence, 2010).

Spinning is achieved via spinning machines, which was invented in 1832 by John Thorp. Spinning machines can be split into two basic groups, intermittent ones such as mule spinning machines, and continuous ones such as ring, flyer, cap, open-end, self-twist, twistless, and wrap-spinning machines (Simpson and Crawshaw, 2002). To date, the ring spinning machine has been exposed to many modifications, while the basic concept has remained the same.

The most common spinning methods are ring spinning, twist spinning, and wrap spinning. Among these methods, ring spinning is the most widely used process for yarn manufacturing, mainly due to its potential for modifications, such as automatic doffing, roving stop motions, yarn break indicators, electronic speed, lot building programs, automatic piecening, data collection, and ring cleaning (Klein and Stalder, 2008; Simpson and Crawshaw, 2002; Lawrence, 2010). Each of the remaining two spinning methods may further be divided into two subgroups: twist spinning is divided into open-end spinning (rotor spinning and friction spinning) and self-twist spinning, while wrap spinning is divided into surface fiber wrapping (friction spinning and air-jet spinning) and filament wrapping (selfil spinning and hollow-spindle spinning) (Lawrence, 2010). While, next to ring spinning, rotor and air-jet spinning processes have been the most common spinning processes developed throughout the 20th century, these processes have had difficulties in making breakthrough to the market. This is mainly due to the relative versatility of ring spinning methods, which yield a wide range of fiber types and counts, yarn with good features and have well-established and reachable know-how for handling.

2.1. Working Principles of Ring Spinning

Basic operations performed in the ring spinning machines are attenuation of the feed material such as roving, sliver (semi-worsted) or slubbing (woolen) to the required yarn count, imparting strength to the yarn by twist insertion and winding the produced yarn on to a suitable package (cop) for storage, transportation and further processing (Simpson and Crawshaw, 2002; Lawrence, 2010). A spinning frame is the machine that transforms the roving into yarn (Figure 2.1). Following is a description of the spinning machine, and the numbers in parentheses correspond to the same numbered items in Figure 2.1. The roving (2) from the roving bobbin (1), which is inserted in holders (3), is guided by guide bar (4) into the drafting system (5), which is placed on an angle of 45-60°. The drafting system plays an important role on yarn uniformity (Abd-Ellatif, 2013; Klein and Stalder, 2008). The thin fiber strand (6) leaving the drafting system is twisted by high speed spindle (8), in order to provide the required strength to the yarn. In this continuous process, each rotation of the traveler (9) on the spinning ring (10) creates a twist in the yarn. Furthermore, ring traveler number is related to traveler mass. For instance, the ring traveler number of 14 corresponds to 250 g which specifies the mass of 1000 travelers in gram according to ISO standard. The ring traveler also enables yarn to wind on cop which is placed on the rotating empty spindle. Moreover, the ring traveler is drifted by spindle because it does not have its own drive mechanism. Due to the high friction between ring traveler and spinning ring, atmospheric resistance of the traveler and balloon formation between the traveler and yarn guide (7), the rotation of the ring traveler delays when comparing to spindle. This speed difference between spindle and traveler allows the yarn to wind on cop (Klein and Stalder, 2008).

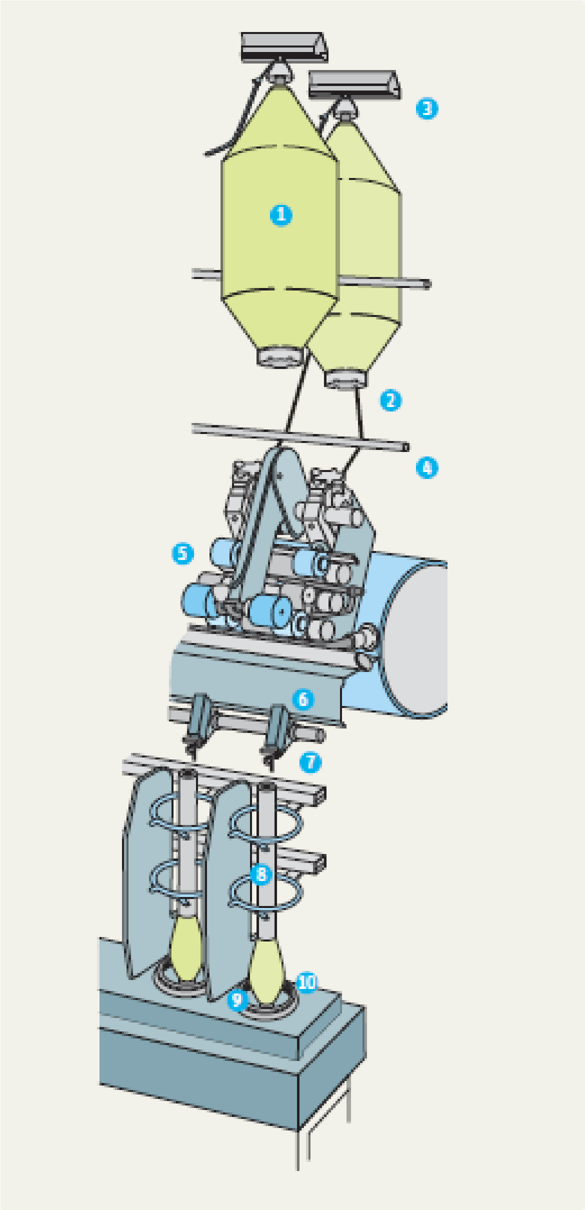

Figure 2.1. Ring spinning machine (Source: Klein and Stalder, 2008).

Approximately 85% of the total power consumption of a ring frame is expended in driving the spindles adjusting yarn count, lot size, spindle speed, and so on, and while the remaining 15% is consumed by the drafting and lifter mechanisms (Oxtoby, 1987). Spinning conditions are affected by the following factors: ring diameter, balloon height, spindle speed and traveler mass. Ring diameter influences lot size, yarn tension, traveler and spindle speed, power consumption, capital costs, floor space and doffing costs; whereas balloon height influences power consumption, capital costs, floor space, doffing costs and balloon collapse.

While quality of the ring spinning process is evaluated by the number of end breakages, yarn imperfection, yarn hairiness and yarn irregularity (Purushothama, 2011), end breakage is deemed to be the most crucial quality variable since it directly affects the overall yield of the spinning mill. End breakage in spinning occurs when the balloon tension exceeds the strength of the weakest point of the yarn in the spinning zone (Raja and Suryaprakasa Rao, 2007). In order to increase the yield of the ring spinning, end breakage rate must be kept at a minimum level. In worsted ring spinning, the acceptable number of end breakage of yarn is 50 per 1000 spindle hours, explained in Section 4 (Lawrence, 2010). In order to decrease the number of end breakages, the raw material quality, the spindle speed, which determines the production rate, and the mechanical conditions of ring spinning machine are adjusted accordingly (El-Sayed, 2009).

2.2. Examination of Variables Affecting Spinning System Performance

Spinning system performance has been studied using various approaches in the textile literature. Some studies compare the performance of different types of machines using various quality measures, while other studies use multiple linear regression (MLR), or artificial neural network (ANN) in examining ring spinning performance, and some studies compare the performances of these two techniques. Controlled experiments are used in the majority of the studies, while studies which analyze historical industrial data are also available in the literature.

Nikolic *et al.* (2003) compared two brands (Suessen and Zinser) of compact and conventional spinning machines. Experiments are performed with fibers of three different compositions on compact and conventional types of machines operated at traveler speeds of 34.5 and 36.3 m/s, at twists of 778 and 780 turns/m, at a constant spindle speed of 16500 rpm, with two different ring diameters, and the identical traveler type. Quality of manufactured yarns are measured with real fineness, coefficient of variation (CV) of fineness, twist, CV of twist, breaking force, CV of breaking force, tenacity, elongation at break, CV of elongation at break, work to break, irregularity, thin places, thick places and neps. It is concluded that compact yarns have significant advantages over conventional yarns in diminishing hairiness, having smooth surface, high gloss, similar Uster properties, and better resistance to rubbing, softer touch and lower pilling effect in woven and knitted fabrics.

Strength and tension are two variables which characterize the structural properties of a manufactured yarn. Studies published by Huang and Oxenham (1994) and Huang *et al.* (1994) are the leading studies on this issue. In the former study, strength and tension of yarns produced in a single spindle on a ring frame at different yarn counts (16-28 tex), spindle speeds (5000-9000 rpm), roving quality (combed and recombed worsted rovings), and cop positions were determined by experimental methods. In the latter study, a new mathematical model was constructed relating the end breakages with the strength and tension of the manufactured yarns, and with respect to yarn count, showing that end breakages decline as yarn counts increase from 16 to 28 tex.

Prendzova (2000) investigated the effect of cotton yarn properties on end breakage by using linear regression analysis. He used linear density of 20, 25 and 36 tex, three levels of twists for each linear density (820, 893 and 923 m^{-1}, 723, 740 and 820 m^{-1}, 629, 675 and 690 m^{-1}, respectively), tensile strength, elongation at break and irregularity as input variables. Hence, nine different cotton yarn samples were produced to estimate the end breakages. The results demonstrated that the yarn with lower linear density 20 tex and average number of twists 836 m^{-1} yielded maximum end breakage. Additionally, the lowest yarn end breakage was obtained for the yarns with higher tensile strength and lower irregularity. Effects of spindle speed on production per spindle and end breakage rate in different yarn counts were examined by Khan and Chowdhury (2006). 30/1 karded, 40/1 combed and 80/1 combed cotton yarns were produced at spindle speeds between 15000-19000 rpm. It was found that production per spindle increased with increasing spindle speed, which, in turn, increased the end breakage rate of three different yarn samples.

Breaking elongation is another important quality variable, which contributes to spun yarn quality, and has been the focus of various studies. In a study by Majumdar and Majumdar (2004), breaking elongation of ring spun cotton yarns was estimated using various fiber properties, and yarn count, which spans a range between 15.8 to 30.8 Ne. Multiple linear regression with first order regressors, and artificial neural network (ANN) with 6 to 14 neurons in a single hidden layer were employed to predict the breaking elongation. ANN model was found to estimate the breaking elongation with the least prediction error. In a follow-up study, Majumdar and Sarkar (2005) employed linear regression, ANN and neuro-fuzzy algorithms to predict the breaking elongation of rotor-spun yarns of cotton. Eventually, they found that the breaking elongation of rotor-spun cotton yarns could be predicted with these methods over than 95% average accuracy. The ANN and neuro-fuzzy models provided better prediction performance compared to linear regression model. In addition, micronaire of cotton fiber and yarn count were found to be the most dominant parameters.

Ureyen and Kadoglu (2006) examined the influences of fiber properties on tenacity, elongation, unevenness and hairiness of yarn. They involved the roving properties in their experimental input data, in addition to the variables considered in the studies stated above. Besides roving and fiber properties, they used four different yarn counts (20s, 25s, 30s and 35s) and three different twist coefficients (3.8, 4.2 and 4.6) as input variables. Linear regression model was performed to predict the yarn tensile properties which were yarn tenacity and yarn elongation, unevenness and hairiness.

Proceeding studies by Ureyen and Gurkan (2008a) used ANN and linear regression models in predicting the tenacity and elongation of ring spun cotton yarns. In multiple linear regression and ANN models, fiber properties, roving properties, yarn count and yarn twist were used as input parameters in order to estimate the yarn tenacity and yarn elongation. The yarn counts and twist multipliers of ring spun cotton yarns were 20-35 Ne and 3.8-4.6, respectively were produced using 15 different blends. Because of nonlinear relationship between input and output data, prediction performance of ANN was found to be more powerful than regression model. In their follow-up study (Ureyen and Gurkan, 2008b), they predicted the yarn hairiness and unevenness using the same methods and input parameters, they used in their previous study. This study showed that roving properties had significant effect on yarn properties. While linear regression model showed good prediction performance due to the linear relationship between fiber and yarn properties, ANN models were able to model the nonlinear effects of fiber properties on the yarn properties, and had higher prediction accuracy than the regression model.

Relationship between spinning performance and yarn irregularity, and prediction of end breakage rate were investigated by Lappage (2005) using statistical models on experimental data. Experiments were performed with linear density, which is related to yarn count, in the range of 30.9-39.2 tex, and twist in the range of 545-681 tpm, and observed end breakages varied from 2.12 to 50.77 breaks/10^6m. It was determined that when spindle speed decreased from 9000 to 7500 rpm, end breakages decreased from 50.63 to 4.61 breaks/10^6m. Using yarn evenness parameters with proposed model, the tension in the spinning balloon, the tenacity in the thin places in the spinning triangle, and end breakages could be predicted, and the end breakage rate per unit length of yarn was found to be highly dependent on the evenness of yarn.

Dayik (2009) conducted a study to estimate the breaking strength of ring spun cotton yarns and compared three algorithms: multiple linear regression, ANN and gene expression programing (GEP) for prediction the tensile properties such as foreign matter, micronaire, uniformity, elongation, fiber strength, fiber length, neps and short fiber index using experimental data. All 100% cotton yarn samples were manufactured at six different yarn counts of 16, 20, 24, 28, 30 and 40 Ne and three different twist multipliers of 3.6, 4.0 and 4.4. The performance of GEP was found better than ANN and multiple linear regression. Owing to the nonlinear relationship between fiber properties and breaking strength of yarn, multiple linear regression yielded poor performance, while GEP model could estimate nonlinear relationships very well.

Beltran *et al.* (2004) developed an ANN model in order to predict worsted spinning performance. They used 250 data sets which are randomly produced from Sirolan Yarnspec™ included fiber properties, yarn count (13-61 tex), twist (227-912 tpm) and machine operation conditions such as draft, spinning speed, ring size, and traveler weight; whereas the number of fibers in cross section, unevenness, thin places, thick places, neps, yarn tenacity, breaking elongation, breaking force, ends-down per 1000 spindle hours, irregularity index and hairiness served as outputs of target spinning performance. They carried out mill specific performance predictions comparing the ANN model and Yarnspec predicted results with measured values, and they found that there was a good agreement between the predicted and measured values. In conclusion, they stated that the ANN was a useful tool in order to predict worsted yarn quality for a specific mill. In their follow-up study, Beltran *et al.* (2006) presented an application of multilayer perceptron algorithm (MLP) neural network in order to predict the worsted spinning performance, using much larger number of mill specific data sets and compared the obtained results with the empirical technique Sirolan Yarnspec^{TM}. Using tops properties, yarn properties (yarn count in the range of 26.5-63 tex, twist in the range of 431-669 tpm, etc.) and spinning properties such as draft of 29.3-21.8, spindle speed of 8000-9000 rpm, ring size of 45-60 mm, traveler weight of 24-31 Europe as input variables, output variable was taken to be ends-down per 1000 spindle hours (8-328.9) in order to monitor spinning performance. ANN method was shown to provide more accurate results for estimation of mill specific spinning performance over the established empirical technique. Furferi and Gelli (2010) constructed an ANN with 98 data sets and validated with 50 new tests which were obtained from New Mill S.p.A. Textile Company from Italy, and then compared with the error of multiple regression models. While the input data used to train the model consisted of yarn count (35.52-76.23 tex), twist (281-416 g/m), length and fineness of roving that included wool blends, the output was yarn strength.

2.3. The Ring Spinning Process in YUNSA

YUNSA was established in 1973 in Cerkezkoy-Tekirdag and it has become Turkey's and Europe's largest worsted and woolen producer exporting to more than 50 countries. The factory has an annual production capacity of 14500 km of fabric and 4500 tons of worsted yarn. The majority of production is composed of 100% wool, as well as their blends with polyester (PES), cotton, nylon, viscose, lycra, silk, and cashmere. The factory has four main departments: yarn-spinning mill, warping and weaving mill, dying mill, and finishing mill. The yarn spinning mill has 4500 tons per year production capacity, while warping and weaving capacities are 50000 m and 48000 m per day, respectively. The dying mill consists of three different sub-divisions: tops dying mill with a capacity of 5500 kg per day, bobbin dying mill with capacity of 3500 kg per day and top dying mill with capacity of 22000 m per day. The finishing mill has capacity of 45000 m per day.

The spinning mill in YUNSA consists of carding, gilling, combing, drawing, spinning, winding, clearing and lubrication, and yarn setting departments for manufacturing mainly worsted yarns (Figure 2.2). Carding is the initial process, which is aimed to disentangle and lay the fibers as parallel as possible. The next process is gilling, in which the purpose is to remove hooks and shorter staples, align, straighten, and blend the fibers, and improve uniformity of sliver. In the combing process, fibers are lined up and removed from shorter fibers than 20-30 mm, vegetable matters and neps. The drawing process, being one of the most important processes, is a preparation step for spinning by converting the top into a roving in order to make it appropriate for spinning. During drawing process, the sliver linear density and evenness are reduced. This operation provides a roving required count for the profitable spinning. The fundamental principles and working methodology of spinning process, which is the area of interest in the current study, have already been described in detail above. The next process is the winding process; this process is essential for transferring the yarn from the cops to bobbin, weighing 1.8-2.0 kg, and formed by cops weighing 60 g. This means that a bobbin consists of approximately 30 cops. Moreover, the winding process clears the yarn by eliminating the yarn faults such as thin, thick places, neps and so on and lubricate the yarn for weaving process. Yarn is set by heat to reduce the liveliness of twist and strengthen for weaving process.

In YUNSA, properties of yarn are determined and put into work by spinning mill according to customer demands regarding fabrics. After rovings are produced as required count, they are sent to the ring spinning machine. In the ring spinning frame, draft, spindle speed, ring traveler number are set in order to draw the roving to the desired degree of fineness. Then, the twist process, which is a spiral rotation imparted to yarn for holding the fibers together and gain strength, is operated after choosing the twist level in order to give the maximum strength.

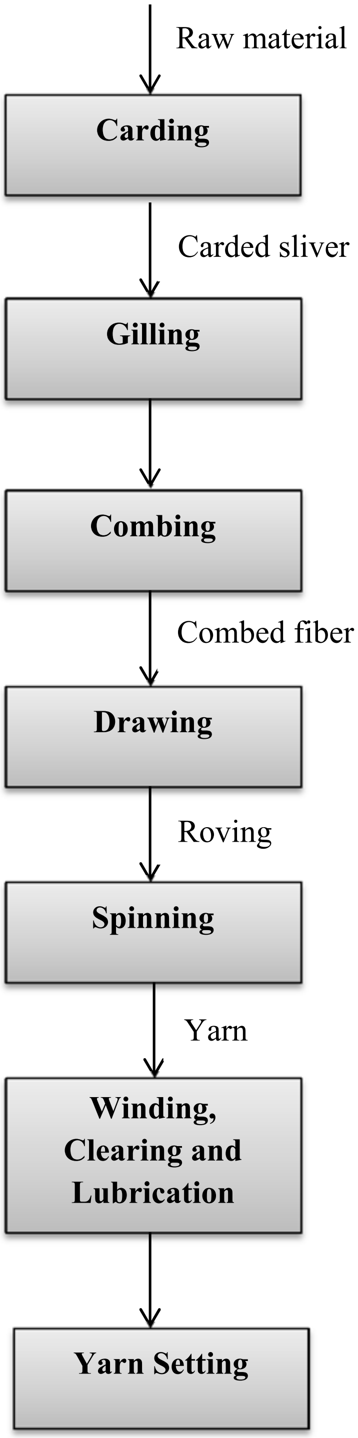

Figure 2.2. Worsted spinning mill processes.

3. STATISTICAL MODELING TOOLS

3.1. Principal Component Analysis (PCA)

Multivariate statistical analysis techniques are commonly used for detection and diagnosis of disturbances in industrial applications. PCA is one of the most frequently used techniques in handling large numbers of highly correlated variables (Zhao and Gao, 2014). PCA is a data-based analysis method used to determine a linear transformation of high-dimensional data to a convenient lower dimensional subspace, called latent space, with minimal loss of information (Sliskovic *et al.*, 2012; Gallagher *et al.*, 1996; Rao *et al.*, 2013). PCA yields orthogonal latent variables are the resulting transformed variables are called principal components (PCs). In PCA, the $n \times m$ (n: number of samples, m: number of variables) data matrix $\mathbf{X}$ is the starting point, and $\mathbf{X}$ is decomposed into the sum of the product of n pairs of vectors:

$$\mathbf{X} = \mathbf{T}\mathbf{P}^{\mathbf{T}} + \mathbf{E} \tag{3.1}$$

where $\mathbf{T}_{n \times l}$ and $\mathbf{P}_{m \times l}$ are the principal component scores and loadings, respectively, $\mathbf{E}_{n \times m}$ is residual, l is the number of principal components, m is the number of multivariate observations and n is the number of process variables (Sliskovic *et al.*, 2012; Gallagher *et al.*, 1996).

In PCA, only the first l of total m eigenvectors are retained, and the projection of a new sample $\mathbf{x}_i$ to the principal component plane can be determined by the following transformation:

$$\mathbf{\hat{x}_i} = \mathbf{t_i P^T} = \mathbf{x_i P P^T} \tag{3.2}$$

where $\hat{\mathbf{x}}_i$ is the prediction of $\mathbf{x}_i$ using the the principal component subspace, $\mathbf{t}_i$ is the projection score of the sample $\mathbf{x}_i$ (Sliskovic *et al.*, 2012).

3.2. Correspondence Analysis (CA)

CA is a method targeted especially to determine collective trends in categorical data, such as machine numbers, colors and compositions. CA has capability to extract the most significant dimensions in order to allow data simplicity for interpretation. It is used in many areas such as marketing, ecology, sociology, archeology, geology, medicine and psychology. Contrary to many statistical techniques, CA is an explanatory technique that analyzes two-way or multi-way contingency tables with each row and column existing a point in a low dimensional space called biplot, such that the positions of the row and column points are appropriate to their associations in the table. The aim is to have a comprehensive point of view of the complex data in order to obtain accurate interpretation (Lee, 1996). CA uses the chi-square statistic which is defined as a weighted Euclidean distance to measure the distance between points on the biplot. More specifically, the chi-square distance measures the associations between variables (Doey and Kurta, 2011). The chi-square statistic is calculated as follows:

$$(\chi^{\mathbf{2}}) = \sum_{\mathbf{i=1}}^{\mathbf{r}} \sum_{\mathbf{j=1}}^{\mathbf{c}} \frac{(\mathbf{fo_{ij}} - \mathbf{fe_{ij}})^{\mathbf{2}}}{\mathbf{fe_{ij}}} \tag{3.3}$$

In this equation, r and c represents rows and columns in the contingency table, and the observed and expected frequencies of the cell in row i and column j are designated by $\mathbf{fo}_{ij}$ and $\mathbf{fe}_{ij}$, respectively. This calculated statistic is checked with the critical value which obtained from statistical tables with $(r-1) \times (c-1)$ degrees of freedom (Bendixen, 2003). The difference of general use of chi-square test from its use in CA is that chi-square test in CA does not specify if the association between variables is statistically significant. This means CA does not promote significance testing; instead it uses post-hoc as an explanatory method. CA uses singular value decomposition on the standardized contingency matrix with deviances from the independence, and aims to explain the highest inertia (variance) using the least number of factors (Doey and Kurta, 2011). The ratio of the eigenvalue of any axis to the trace indicates the proportion of the total inertia/chi-square value explained by that axis (Bendixen, 2003).

CA is similar to PCA; the principle in CA is to diminish dimensions of complex data matrix and visualize it in a low-dimensional subspace. Nevertheless, CA is focused on examining the associations between variables; whereas PCA extracts which variables explain the largest amount of variance in the data set (Nenadic and Greenacre, 2007). Furthermore, PCA may only be used on cardinal variables, while CA may also be used on nominal variables.

3.3. Logistic Regression Analysis (LRA)

The rigorous statistical assumptions for handling dichotomous outcomes made LRA an alternative to ordinary least squares regression and linear discriminant function analysis (Peng and So, 2002). The natural logarithm of an odds ratio, i.e. ratio of success probability (p) to failure probability (1-p), is called logit, and it is the response variable in logistic regression. In general, logistic regression is convenient for identifying and testing hypotheses about relationships between one or more (categorical, or continuous) predictor variables, and one categorial outcome variable. In summary, the logistic model predicts the logit of y from x.

The simple logistic model has the form of following:

$$\mathbf{logit}\,(\mathbf{y}) = \ln\left(\mathbf{odds}\right) = \ln\left(\frac{\mathbf{p}\,(\mathbf{x})}{\mathbf{1} - \mathbf{p}\,(\mathbf{x})}\right) = \beta_{\mathbf{0}} + \beta_{\mathbf{x}} \tag{3.4}$$

Solving this equation for p gives the probability of the occurrence of the outcome of interest as follows:

$$\mathbf{p}\,(\mathbf{x}) = \frac{e^{\beta_0+\beta_x}}{1+e^{\beta_0+\beta_x}} \tag{3.5}$$

where p(x) is the probability of the outcome of interest, that is the probability of occurrence of end breakage in the current study, β_0 is the y intercept and β is the regression coefficient. While x can be categorical or continuous, y is always categorical. Furthermore, the relationship between logit (y) and x is linear in Eq. 3.4, the relationship between the probability of y and x is nonlinear in Eq. 3.5. The natural log transformation of the odds in Eq. 3.4 is essential in order to make the relationship linear between a categorical outcome variable and predictors. The value of the coefficient β specifies the direction of the relationship between x and logit of y. When β is less than zero, larger (or smaller) x values are related to smaller (or larger) logits of y. Otherwise, if β is greater than zero, larger (or smaller) x values are related to larger (or smaller) logits of y.

When the logic of the simple logistic regression is extended to multiple predictors:

$$\mathbf{logit}\,(\mathbf{y}) = \ln\left(\frac{\mathbf{p}\,(\mathbf{x})}{\mathbf{1} - \mathbf{p}\,(\mathbf{x})}\right) = \beta_{\mathbf{0}} + \beta_{\mathbf{1}}\mathbf{x_1} + \beta_{\mathbf{2}}\mathbf{x_2} + \cdots \tag{3.6}$$

Hence,

$$\mathbf{p}\left(\mathbf{x}\right) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots}} \tag{3.7}$$

where p(x) is the probability of the event, β_0 is the y intercept and β_s are regression coefficients and x_s are a set of predictors. The null hypothesis states that all β_s are zero. Rejecting the null hypothesis indicates that at least one β does not equal to zero in the population. Thereby, the probability of the outcome can be predicted by using the logistic regression equation (Peng *et al.*, 2002).

4. DATA COLLECTION

There are a total of 55 different ring spinning machines, of different ages and three different models (types). Process data are collected under normal operating conditions between 2012 and 2014, on daily 24 h basis, totaling a sum of 11074 samples. Nominal and continuous process variables are summarized in Table 4.1. Moreover, abbreaviations of each process variables which will be used in Section 5.5 are stated in Table 4.1. Spinning and twist directions consist of two levels: E-Siro/Elit and S/Z, respectively. Color corresponds to different colors used in dying the fed fiber in a previous process, and there are more than 15 different ordered colors, such as black, dark blue, brown, marengo, grey, etc. even including some colors which corresponds to less than 1% of total production. Composition, likewise, covers a wide range of ordered compositions, such as 100% wool, 96/4 Wool/Lycra, 43/53/4 Wool/Polyester/Lycra, etc. These two factors (color and composition) have a quite high number of levels, making it difficult for statistical modeling purposes, so they will be handled via combining different levels as explained in the following section(s). The types and numbers of ring spinning machines will also be considered in the following models. There are three brands of ring spinning machines used in YUNSA, Zinser, Suessen and Gaudino; and logistic regression models are constructed for each machine type separately.

The quality variable in the current study is taken to be the spinning end breakage. It occurs when the actual spinning tension is higher than the actual yarn strength during the spinning process. The number of end breakages during the operation of each spindle was counted for a one-hour period, and this number was divided by the number of spindles utilized, and then multiplied by 1000 to obtain a normalized measure of end breakages, which is the number of breaks per 1000 spindle hours. In the current study, 50 end breaks per 1000 spindle hours is taken as the threshold, which is the conventional limit (Lawrence, 2010) for acceptable yarn production. Thus, a value of 1 is assigned to runs with end breaks exceeding this limit, representing “success” in terms of Bernoulli distribution as the response variable, and a value of 0 is assigned to the rest of the runs, representing a failure. It should be noted that success in the current model corresponds to actual "failure" in terms of the quality of production, and vice versa. In the binary regression model, it is aimed to model how the probability of success (probability of faulty production) changes with respect to the yarn properties and process conditions.

Table 4.1. Nominal and quantitative process variables in ring spinning process.

Nominal Process Variables	**Quantitative Process Variables**
Color (Col_1, Col_2, Col_3)	Draft (unitless) (D)
Composition ($Comp_1$, $Comp_2$, $Comp_3$)	Lot size (kg) (LS)
Machine number ($MSub_1$, $MSub_2$)	Machine age (years) (MA)
Spinning (Elit/E-Siro) (ES)	Ring traveler number (unitless) (RTN)
Twist direction (S/Z) (SZ)	Roving count (Nm) (RC)
	Spindle speed (rpm) (SS)
	Twist level (T/m) (TL)
	Yarn count (Nm) (YC)

5. RESULTS AND DISCUSSION

In this section, descriptive statistics of ring spinning process variables under normal operating conditions (Sections 5.1 to 5.4) and faulty product probability of three different ring spinning machines are modelled with respect to machine types (Section 5.5). Nominal and quantitative variables of ring spinning process are analyzed separately. While PCA is applied on quantitative process variables, CA is applied to find out the relationship between lot size and machine number.

5.1. Descriptive Statistics of Process Variables under Normal Process Conditions

Descriptive statistics of the nominal and quantitative process variables shown in Table 4.1 are presented in this section. Analysis is divided into two subgroups as nominal (Section 5.1.1) and continuous (Section 5.1.2).

5.1.1. Descriptive Statistics of Nominal Process Variables

Nominal process variables are color, composition, machine number, spinning and twist direction. Each nominal variable is examined with respect to number of occurences in all 11074 runs. The color distribution in yarn production can be seen from Figure 5.1, which shows that production is mostly composed of ecru, black and dark blue colored yarns.

As it can be seen from Figure 5.2, most of the yarn production is conducted in Zinser type of ring spinning machines. Spinning of yarn means that being single or double of yarn. While E-Siro is doubled yarn, Elit is singled yarn. Figure 5.3 demonstrates that E-Siro yarn production is mainly higher than Elit yarn production. The yarn production rate of S-direction and Z-direction yarns is almost the same (Figure 5.4). The yarn production in ring spinning machines is dominantly comprised of 100% wool and 43/53/4 Wool/Polyester/Lycra compositions (Figure 5.5).

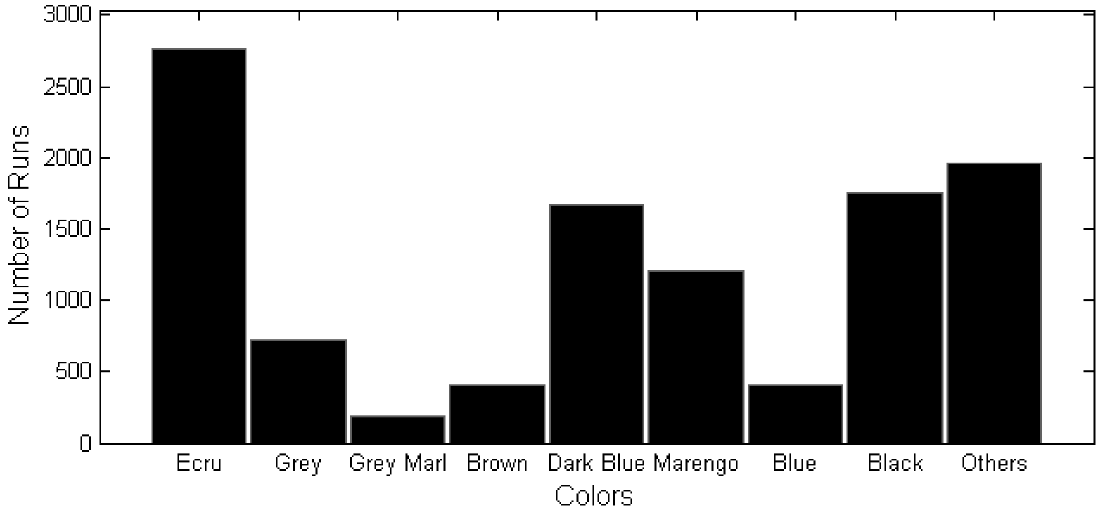

Figure 5.1. Histogram of color.

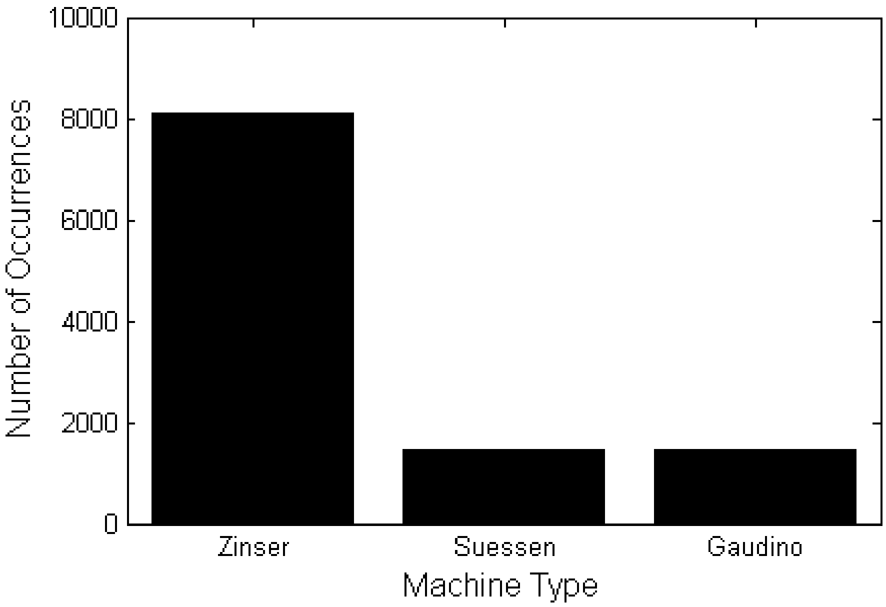

Figure 5.2. Histogram of machine type.

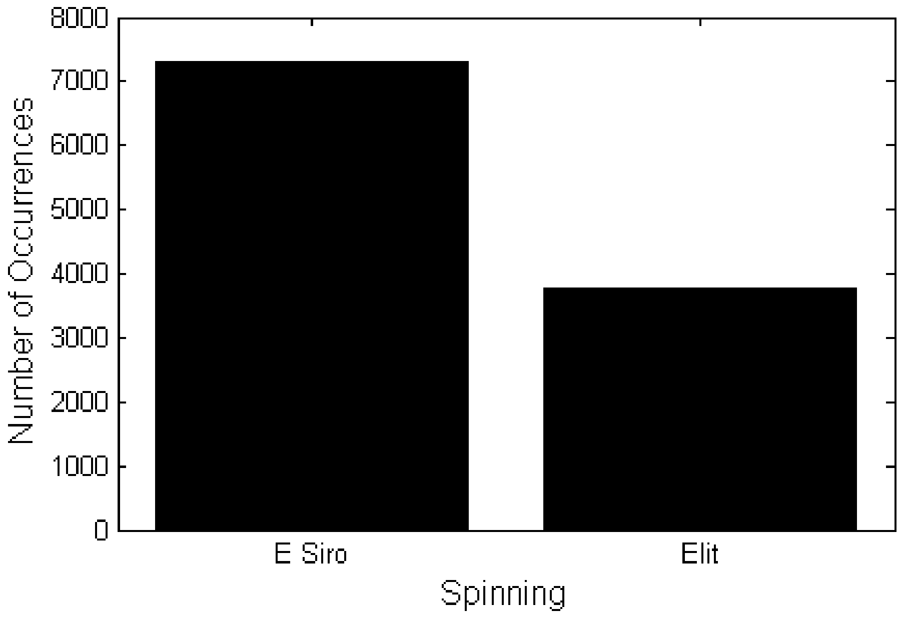

Figure 5.3. Histogram of spinning.

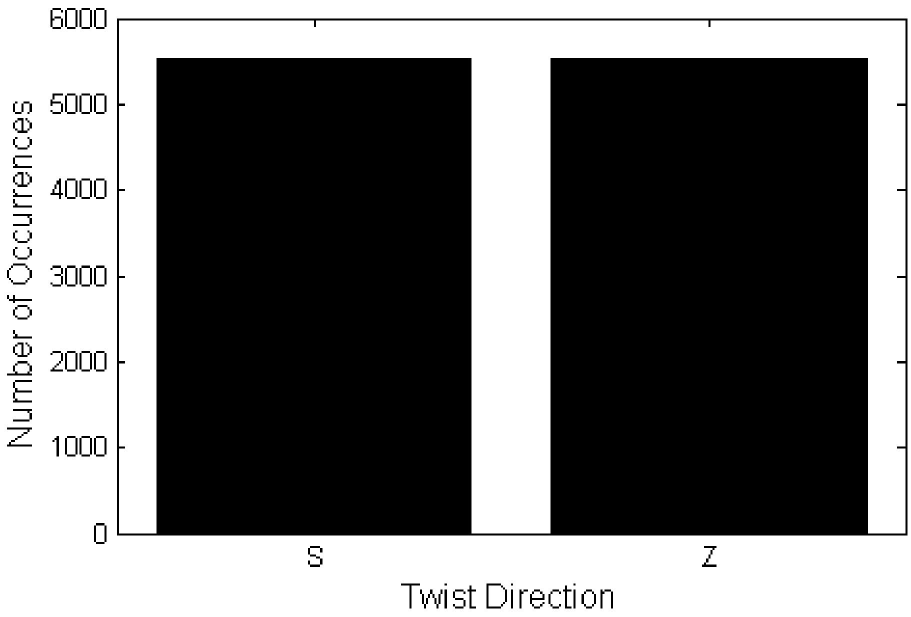

Figure 5.4. Histogram of twist direction.

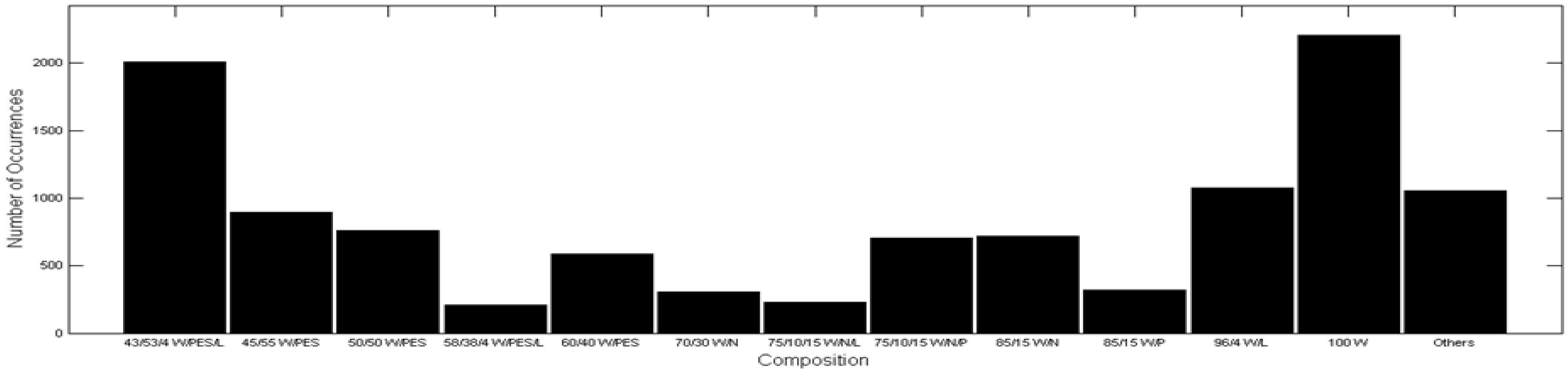

Figure 5.5. Histogram of composition.

Table 5.1. Numerical descriptive statistics of quantitative operating conditions in the ring spinning machine.

Variables/Statistics	Mean	Median	q_1*	q_3**	Standard deviation	IQR***	Max.	Min.
Draft	23.3	20	18.8	29	5.6	10.3	61.2	8.4
Lot size	567.6	230	84	703	788.1	619	5758	6
Machine age	18.8	19	19	19	2.1	0	27	14
Ring traveler number	24.4	24	24	25	1.4	1	30	19
Roving count	2.91	3	2	3.8	0.87	1.8	5.5	1.4
Spindle speed	9702.1	9946	9172	10411	1127.6	1239	12756	5100
Twist level	721.5	750	667	750	74.4	83	1000	450
Yarn count	41.6	38	30	48	12.8	18	100	18

* q_1: First quartile (25%) of variables.
** q_3: Third quartile (75%) of variables.
*** IQR: Interquartile range ($q_1 - q_3$).

5.1.2. Descriptive Statistics of Quantitative Process Variables

Basic statistics of quantitative process variables in the ring spinning machine are shown in Table 5.1. In the rest of this section, each quantitative process variables is examined with respect to the number of occurrences among the whole set of runs.

Draft value is calculated according to the desired yarn count. It is obtained from dividing yarn count by roving count. If the spinning is E-Siro, the finding value is multiplied with 2 because of doubled yarn. Draft values range from 8.4 to 61.2. While first quarter of yarn production has draft values smaller than 18.8, last quarter of production has higher than 29 of draft values. Distribution of draft values shown in Figure 5.6 is not far from symmetric.

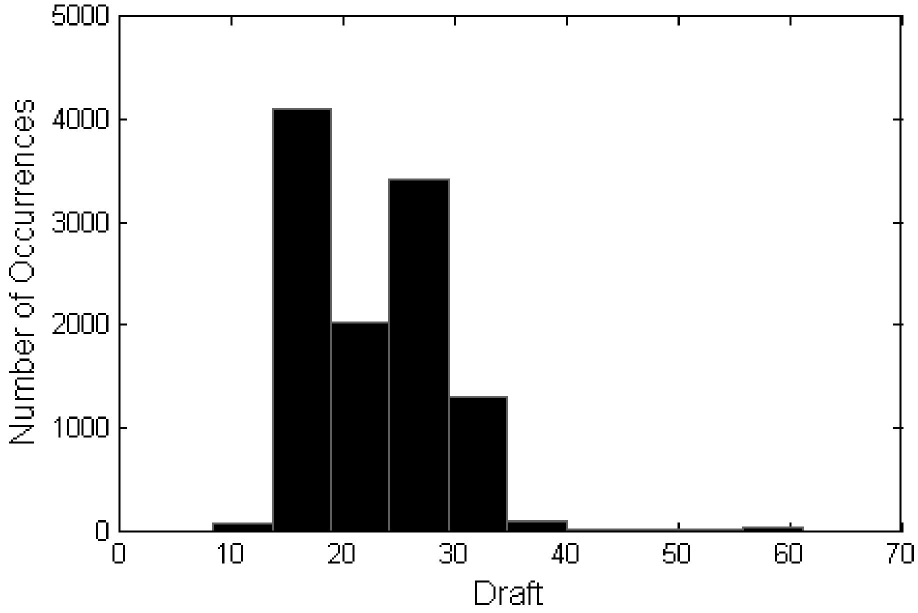

Figure 5.6. Histogram of draft.

Lot size ranges from 6 to 5758 kg. While the mean value of lot size is 567.6 kg, 25% of lot size is smaller than 84 kg and the other 25% of lot size is higher than 703 kg. It can be seen from Figure 5.7 that lot size is reminiscent of exponential distribution with a long tail. In order to prevent the effect of outliers in lot sizes on the resulting statistical models, log-transformation is employed on the lot sizes.

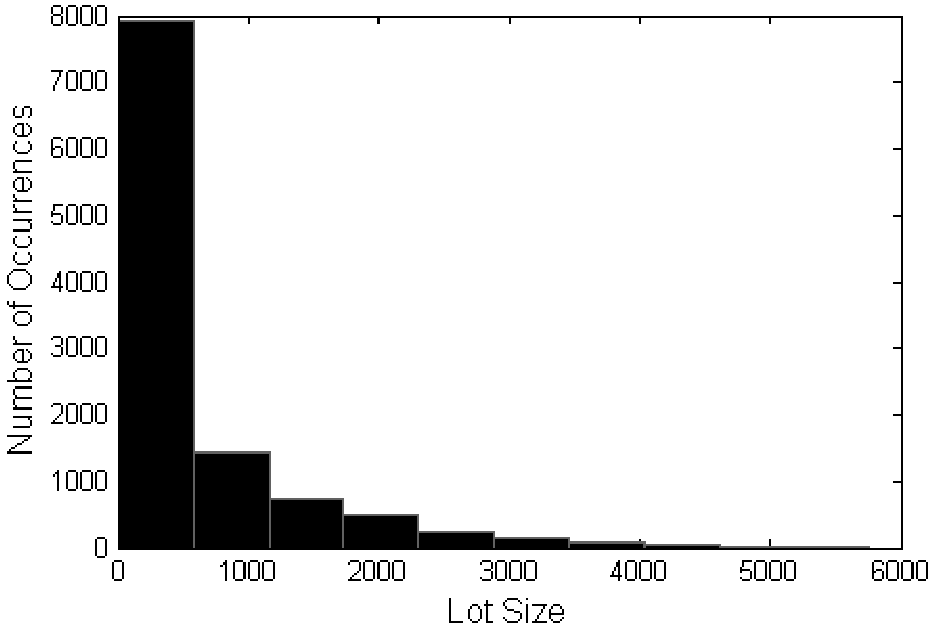

Figure 5.7. Histogram of lot size.

The ages of ring spinning machines range from 14 to 27 as shown in Figure 5.8. Majority number of machines is 19 years old. The statement made for the ring traveler number is valid for the machine age because machine age also gets discrete values.

Ring traveler imparts twist to the yarn and is responsible for winding the yarn onto the cop. Ring travelers are numbered according to their weights. The statistics in the Table 5.1 may be confusing at first sight, however, referring to Figure 5.9, it is clearer that ring traveler gets dicrete values. Ring traveler numbers change from 19 to 30. The ring traveler number of 24 is used in 51.23% of yarn production as shown in the Figure 5.9. Roving counts get values between 1.4 and 5.5 Nm. 50% of rovings to draw in the ring spinning machine is smaller than 3 Nm, rest of them is higher than 3 Nm. The distribution of roving counts shown in Figure 5.10 is close to uniform. In addition to ring traveler, spindle is required for winding. The spindle speed defined as rotational frequency of the spindle of the ring spinning machine, measured in revolutions per minute (rpm). Spindle speed gets values between 5100 to 12756 rpm. The mean value of spindle speed is 9702.1 rpm. Distribution of spindle speed shown in Figure 5.11 is skewed to the left but not very different from normal distribution.

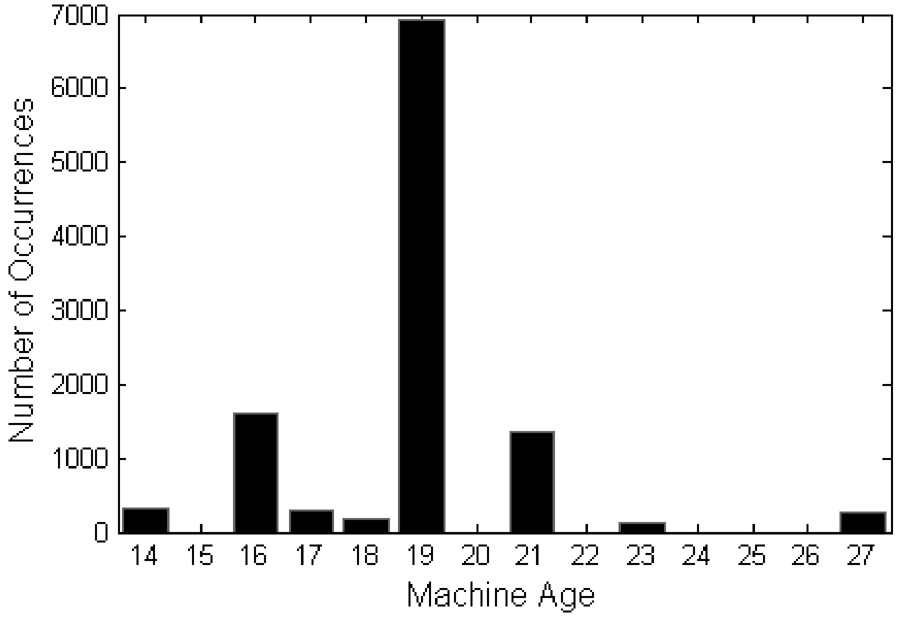

Figure 5.8. Distribution of machine age.

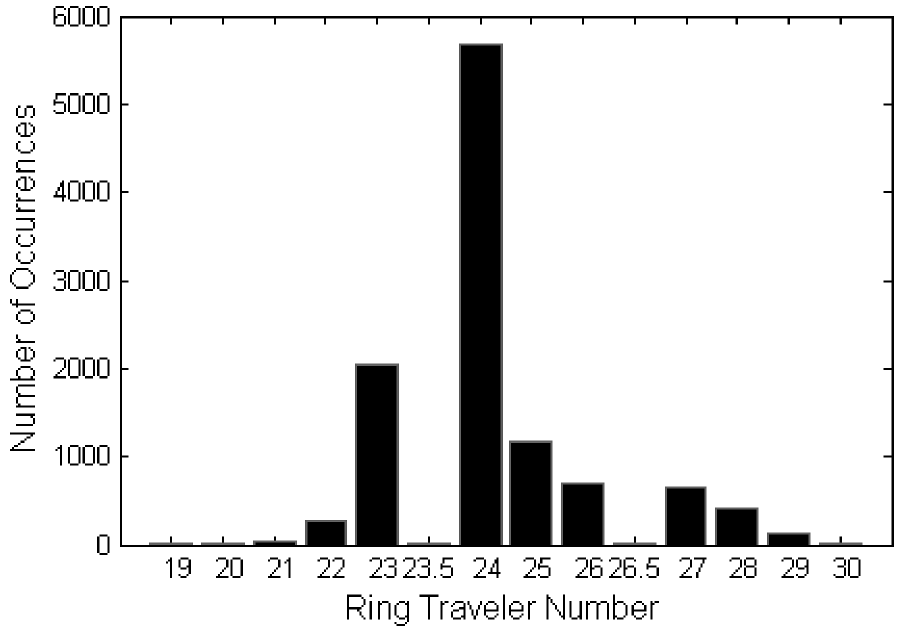

Figure 5.9. Distribution of ring traveler number.

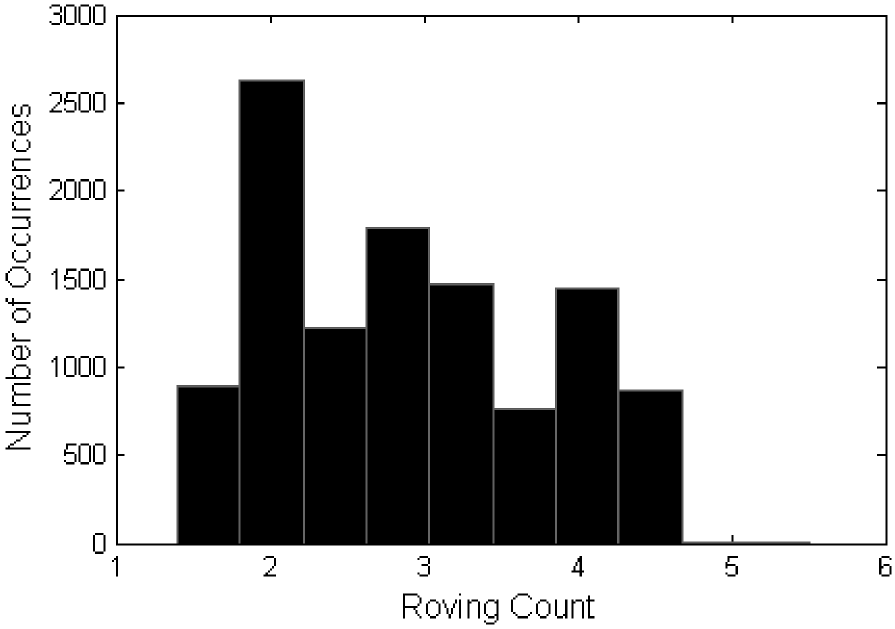

Figure 5.10. Histogram of roving count.

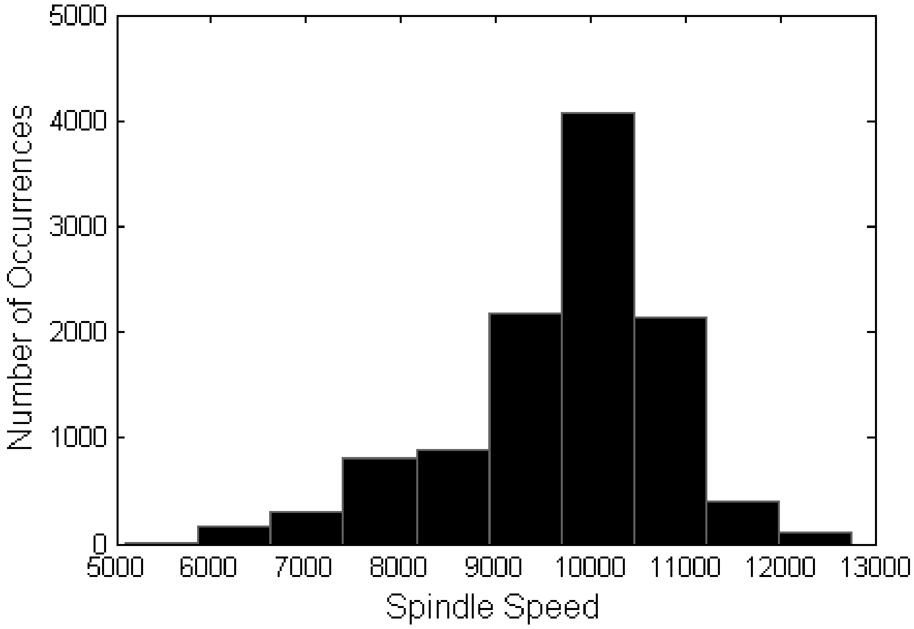

Figure 5.11. Histogram of spindle speed.

Twist is a spiral rotation imparted to yarn for holding the fibers together and gain strength. Twist levels get values between 450 to 1000 T/m. The mean value of applied twist level is 721.5 T/m. Distribution of twist level shown in Figure 5.12 is not far from normal distribution.

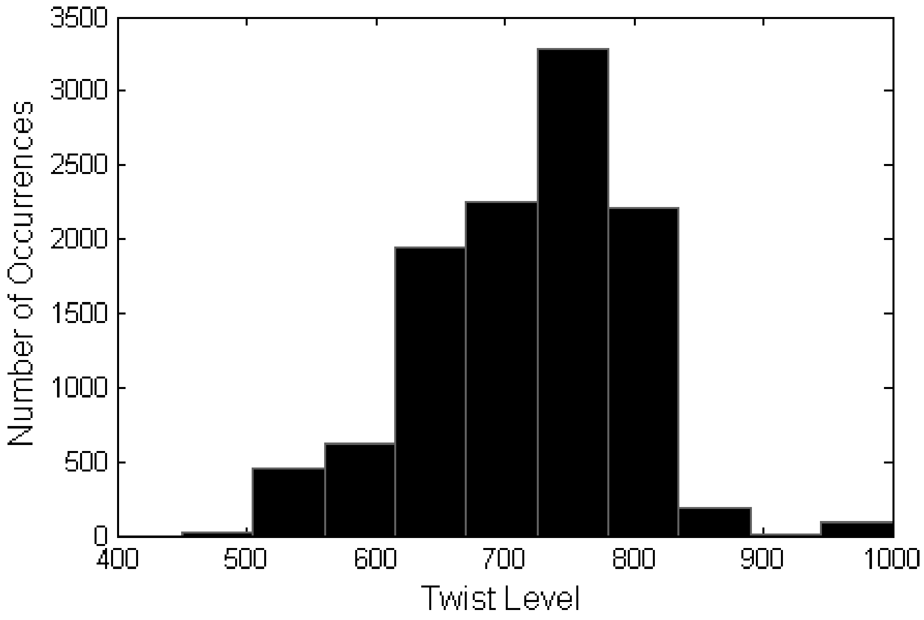

Figure 5.12. Histogram of twist level.

The unit of yarn count is the metric count. The metric count means length in meters per 1 gram of mass (Nm = length/weight). If the yarn count gets higher values, the fineness of yarn increases. As shown in Figure 5.13, yarn count ranges from 18 to 100 Nm. While first quarter of yarn production has yarn counts smaller than 30 Nm, last quarter of production has higher than 48 Nm of yarn counts. The mean value of yarn count is 42 Nm. Distribution of yarn count is slightly skewed to the right (higher values).

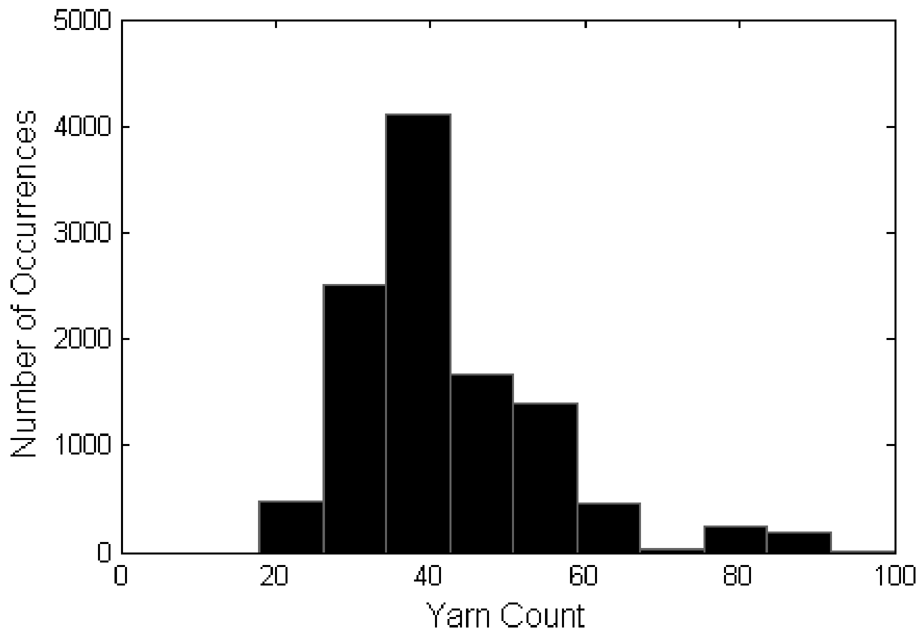

Figure 5.13. Histogram of yarn count.

5.2. Analysis of Ring Spinning Machines with respect to their Work Load in YUNSA

There are 3 brands and a total number of 55 ring spinning machines in the spinning mill. Grouping of machine types is based on brand names of the companies from which are purchased (Table 5.2). The first type of ring spinning machines is Zinser, which corresponds to machine numbers 1 to 15, 31 to 40 and 42 to 55. Second type of machines is Suessen, corresponding to machine numbers 16 to 20 and 41. The third type of machines is Gaudino, corresponding to machine numbers 21 to 30. This shows that 71% of ring spinning machines is of the first type, 11% of ring spinning machines is of the second type and 18% of ring spinning machines is of the third type (Figure 5.14). In Figure 5.15, it is seen that the first type of ring spinning machines are the most frequently used machines. Although the second type of ring spinning machines is less often used compared to the first one, the number of runs by the second type of ring spinning machine is still higher than those by the third type of ring spinning machines.

In Figure 5.16, while different colors represent different machine types, bars on the left and right for each machine type represent the % of machine numbers and the % of runs, respectively. In first and second type of ring spinning machines, % of runs (74% and 13%, respectively) are higher than % of machine numbers (71% and 11%, respectively). Furthermore, in third type of machine, despite % of number of machine is high, less number of runs is performed.

Table 5.2. Ring spinning machine numbers with respect to their brands.

Machine Type (Brand)	**Machine Number**
1 (Zinser)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55
2 (Suessen)	16, 17, 18, 19, 20, 41
3 (Gaudino)	21, 22, 23, 24, 25, 26, 27, 28, 29, 30

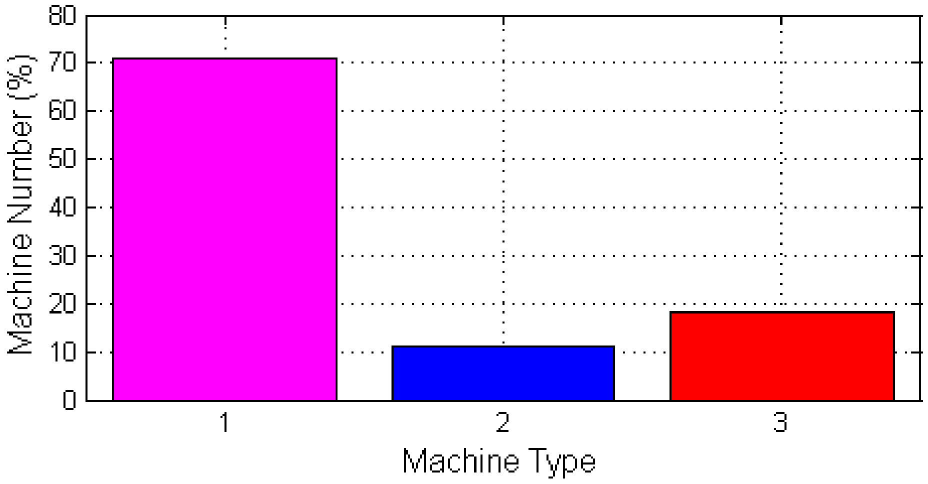

Figure 5.14. Machine type according to % of machine number.

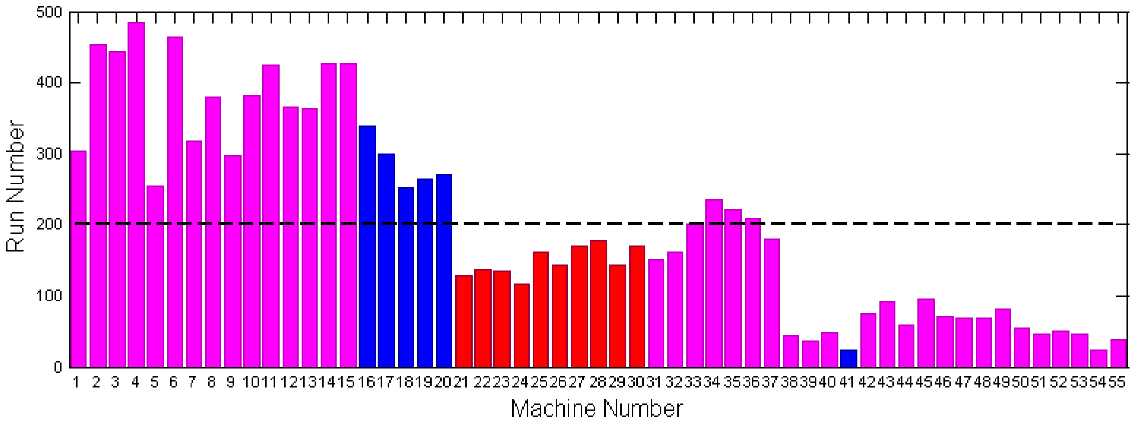

Figure 5.15. Number of runs according to the number of machines. Dashed line represents the mean value of runs per machine.

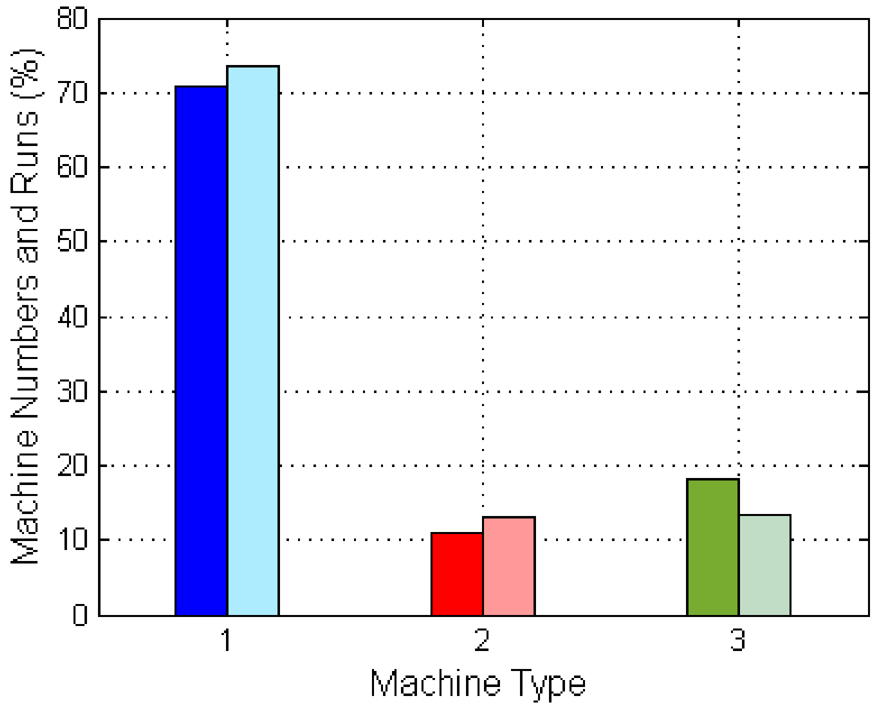

Figure 5.16. % of runs and machines with respect to types of machine.

5.3. Application of PCA on Process Variables

PCA of quantitative variables (the second column in Table 4.1) and two nominal variables, twist direction and spinning (the first column in Table 4.1), transformed into binary values of 0 and 1, is conducted in order to detect and diagnose the ring spinning process. The % of variance captured by each principal component (PC) is presented in Figure 5.17, in which dashed lines represent the expected variance explained by random PCs. Cross-validation shows the first 5 PCs to be significant. First five PCs capture the total 79% of variance and statistics are calculated based on this five PCs.

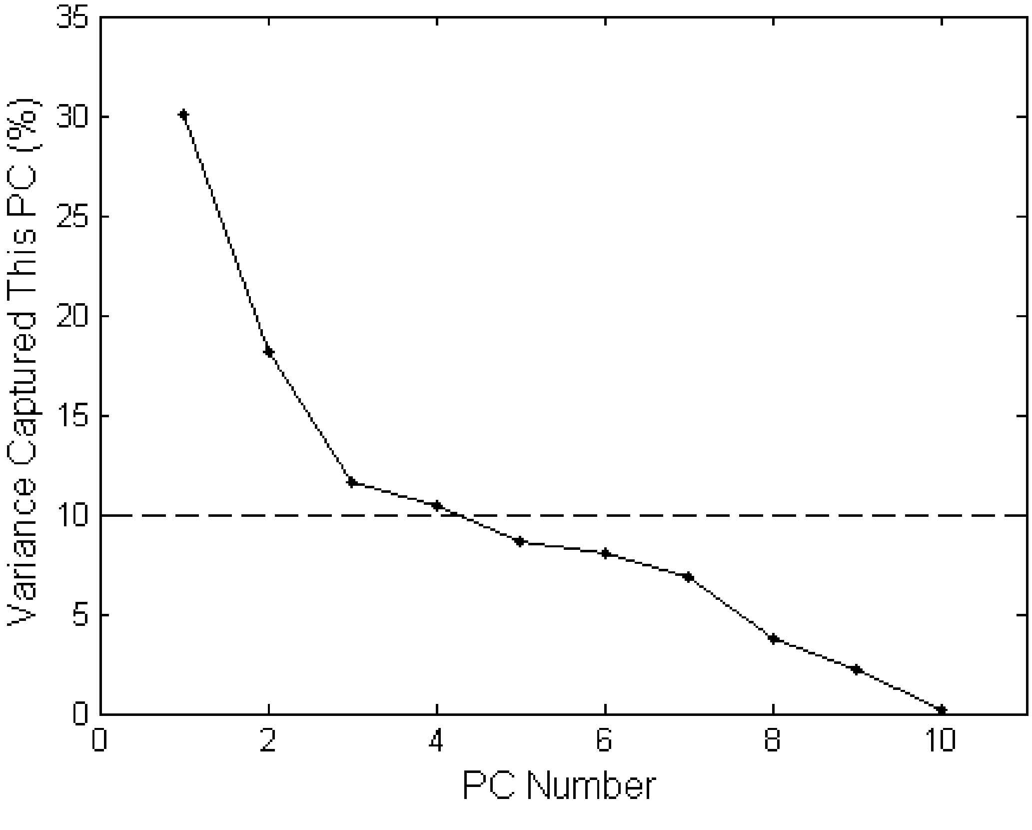

Figure 5.17. Variances captured by the PC's.

Figure 5.18 shows the contribution of process variables to each PC. Different colors represent the PCs such that dark blue bars relates to first PC, light blue bars relates to second PC, green bars relates to third PC, orange bars relates to fourth PC and dark red bars relates to fifth PC. The first three PCs are analyzed in detail in the following subsections.

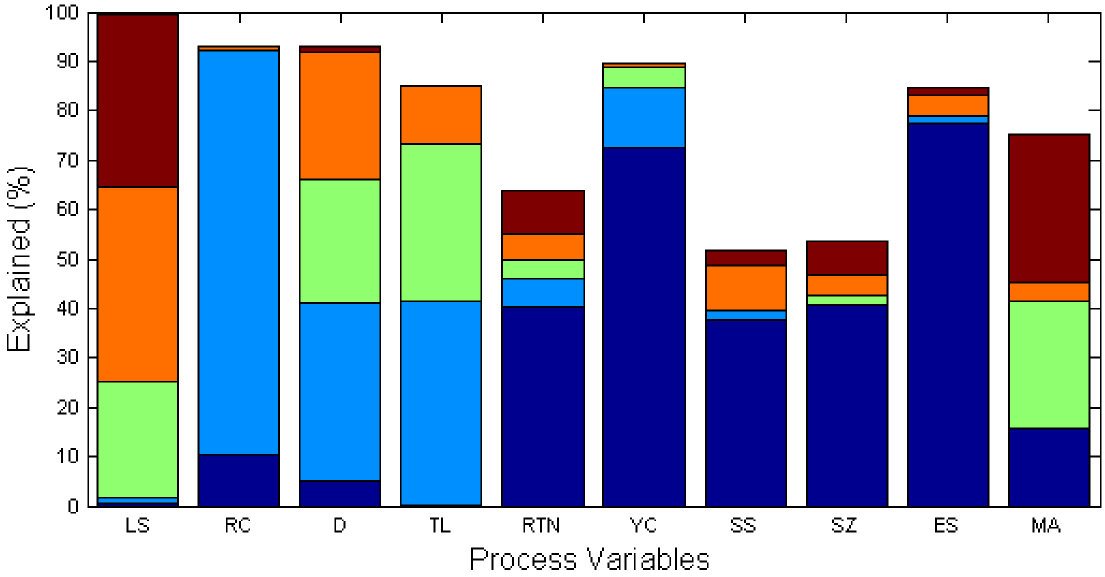

Figure 5.18. Contribution of process variables to each PC.

5.3.1. Interpretation of PC 1

The first principle component (PC 1) explains the 30% of the variance of the variables. Major contribution to PC 1 comes from two variables (dark blue bars in Figure 5.18): yarn count and spinning, while ring traveler number, spindle speed and twist direction make moderate contributions. Loadings of yarn count, spinning, ring traveler number and twist direction are positively correlated, while spindle speed is negatively correlated (Figure 5.19), showing that the overall trend in manufacturing is to use high yarn counts at elit spinning in addition that high ring traveler number at low spindle speed and Z direction of twist.

Distribution of Score 1 can be seen from Figure 5.20. It is consistent with the distributions of ring traveler number, yarn count, spindle speed, twist direction and spinning (Figures 5.3, 5.4, 5.9, 5.11 and 5.13).

As can be seen from Scores 1 in Figure 5.21, there is not change in the projection of process variables onto PC 1 with respect to time.

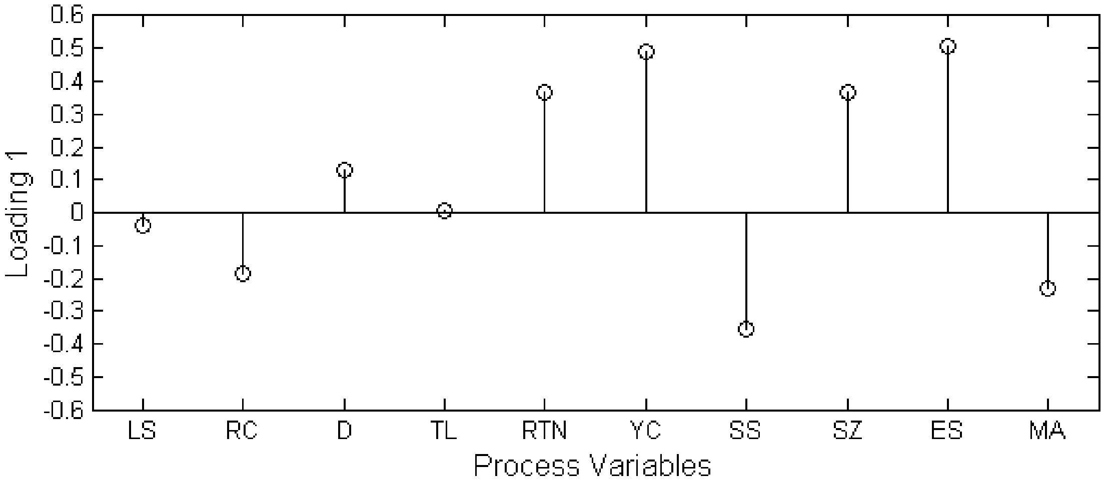

Figure 5.19. Loadings of PC 1.

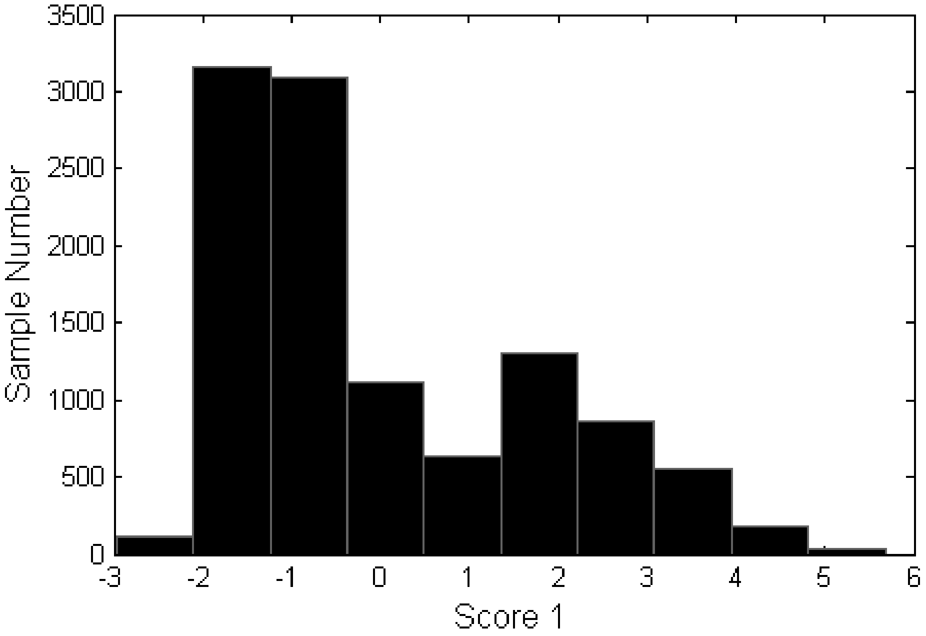

Figure 5.20. Distribution of Score 1.

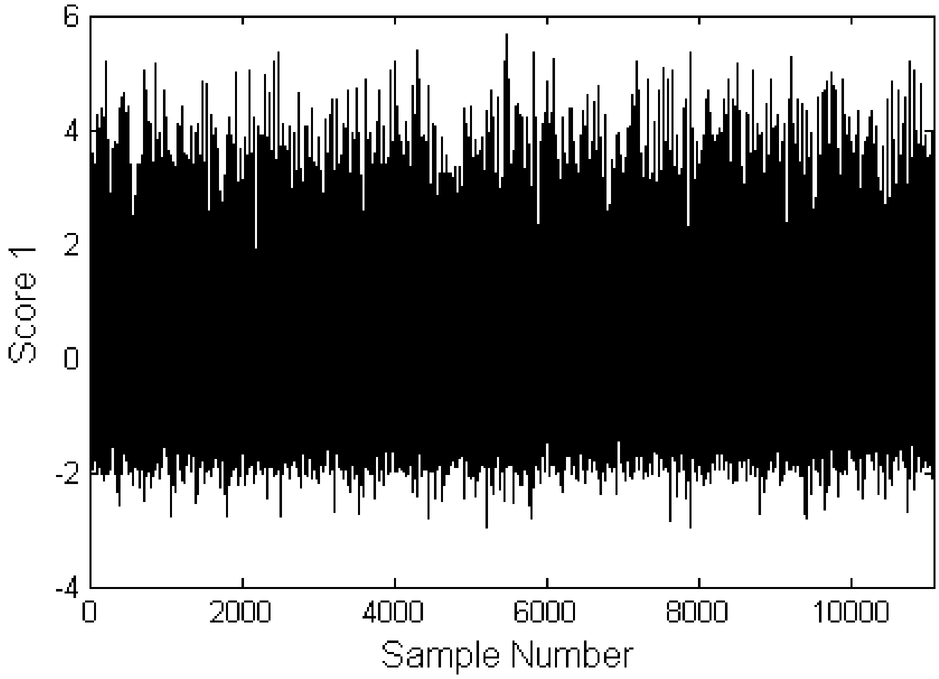

Figure 5.21. Change of process based on time according to Score 1.

5.3.2. Interpretation of PC 2

The second PC (PC 2) explains the 18% of the variance of the variables. Major contribution to PC 2 comes from three variables (light blue bars in Figure 5.18): roving count, draft and twist level. Loadings of roving count and twist level are positively correlated, while draft is correlated negatively (Figure 5.22), indicating that in the spinning process roving has high count, while twist level gets higher values, draft sets lower values.

It is seen that while distributions of draft and roving count are close to symmetric, distribution of twist level is negatively skewed (Figures 5.6, 5.10 and 5.12). When roving count and twist level get values of higher than their average values, draft has a tendency to get values lower than its average value. Distribution of Score 2 can be seen from Figure 5.23. It is consistent with the distributions of roving count, draft and twist level. As can be seen from Scores 2 in Figure 5.24, projection of process variables onto PC 2 seems to be constant with respect to time.

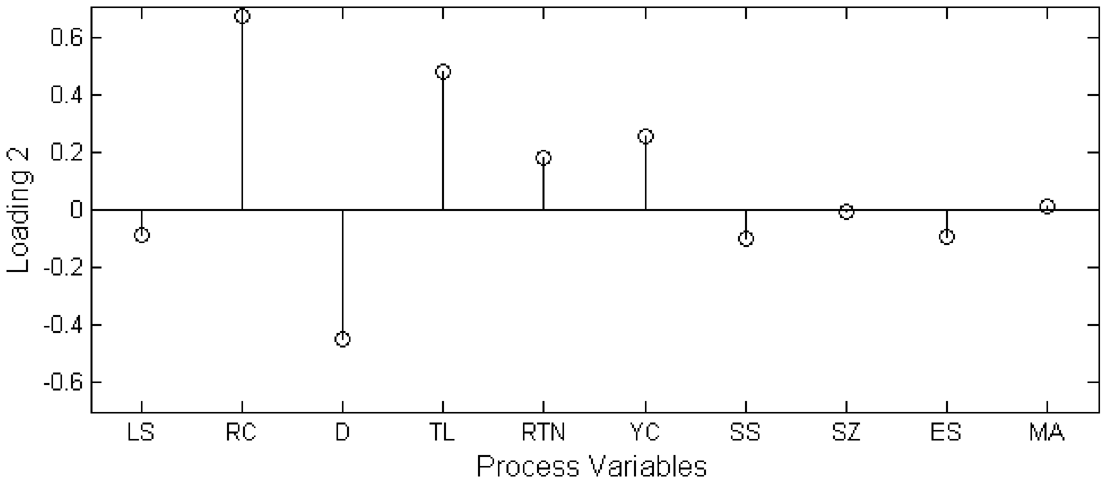

Figure 5.22. Loadings of PC 2.

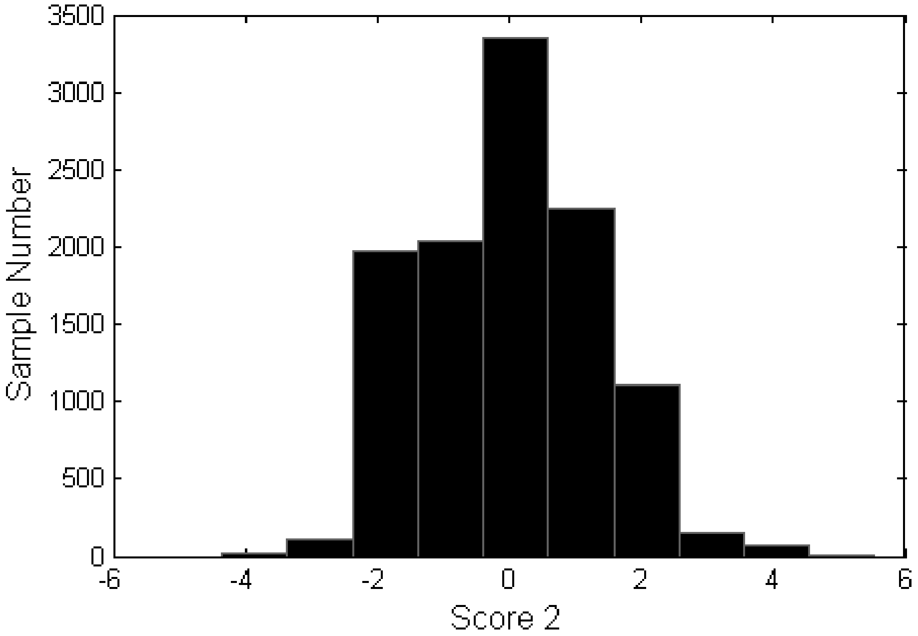

Figure 5.23. Distribution of Score 2.

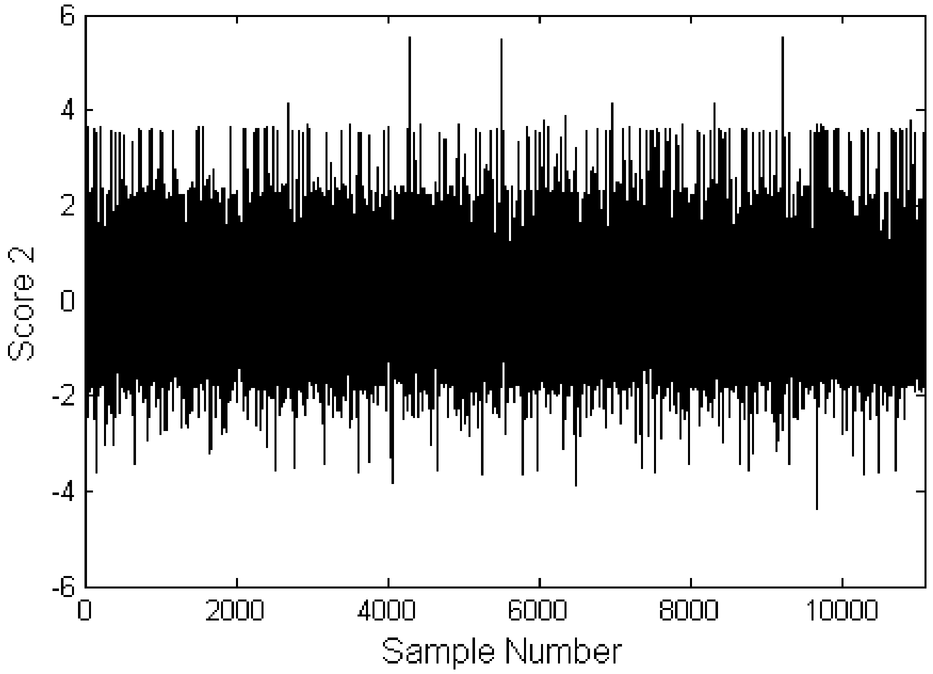

Figure 5.24. Change of process based on time according to Score 2.

5.3.3. Interpretation of PC 3

The third principle component (PC 3) explains 12% of the variance of the variables. This PC is dominated by lot size, draft, twist level and machine age, which are positively correlated (green in Figure 5.18). It is interesting what this PC indicates: draft and twist level set higher values and older machines are more likely to be used for higher lot sizes.

It is seen that while distributions of lot size and machine age are not symmetric (lot size is positively skewed), distributions of draft and twist level are close to symmetric (Figure 5.6, 5.7, 5.8 and 5.12). While lot size, draft and twist level have a tendency to get values of higher than their average values, majority number of machines is about 19 years old. Distribution of Score 3 can be seen from Figure 5.26. It is consistent with the distributions of lot size, draft, twist level and machine age.

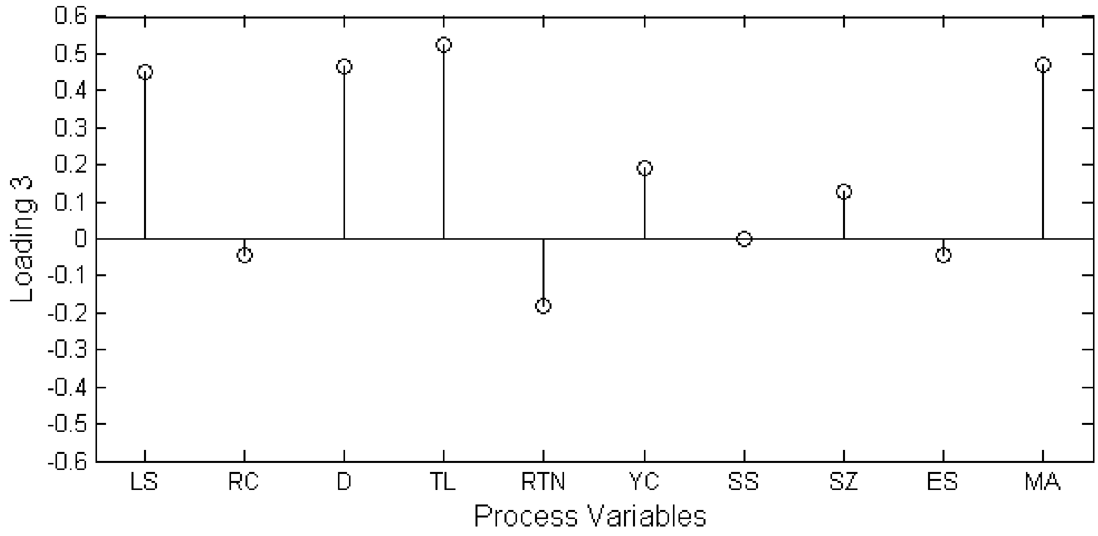

Figure 5.25. Loadings of PC 3.

As can be seen from Scores 3 in Figure 5.27, there is not change in the projection of process variables onto PC 3 with respect to time. Hence, the first three PCs show that the operating conditions of the process is stationary during the three years of operation.

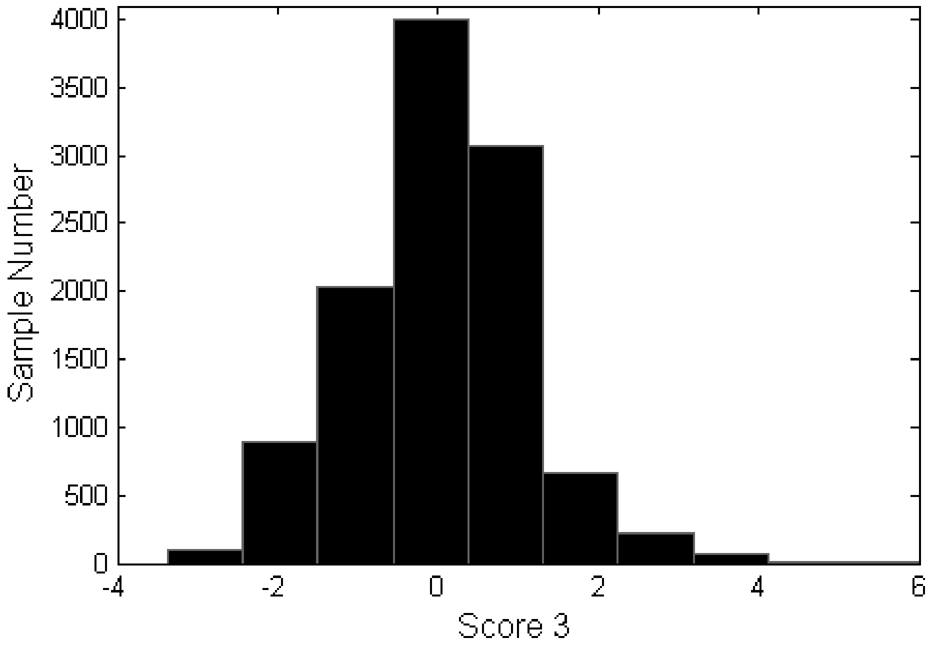

Figure 5.26. Distribution of Score 3.

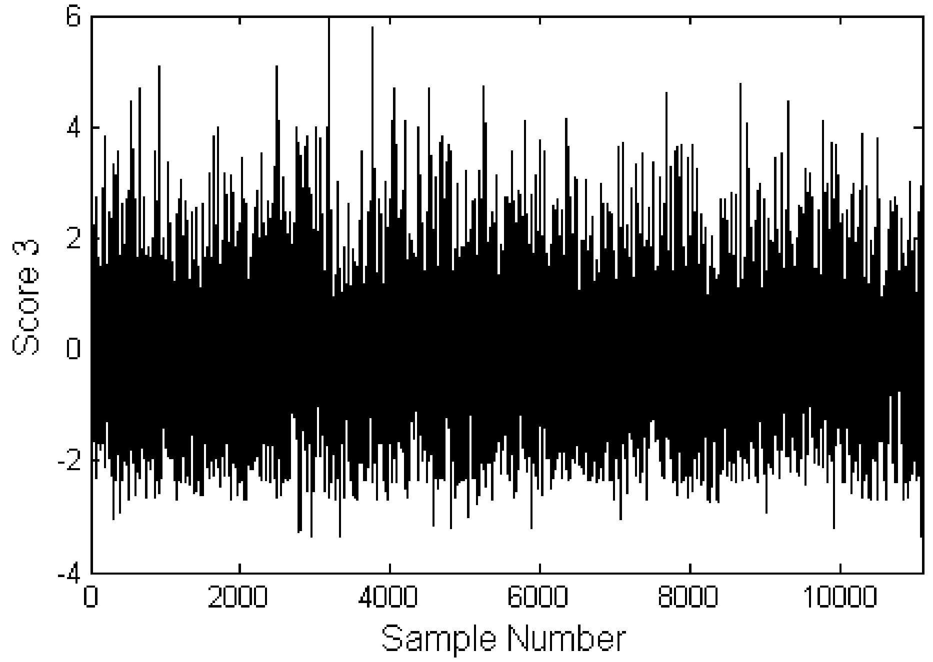

Figure 5.27. Change of process based on time according to Score 3.

5.4. CA of Ring Spinning Machines

Lot size is divided into six sub-groups, as 0-100 kg, 100-500 kg, 500-1000 kg, 1000-2000 kg, 2000-4000, 4000-10000 kg. A matrix consisting of the number of runs achieved on each machine with the (above) grouped lot size is formed and CA is employed on this matrix. The projection of results on the two-factor plane is shown in Figure 5.28. In the figure, blue, red and light green rectangels correspond to type I, II and III machines, respectively.

A number of cluster of machines can be seen. The first cluster of machines, which lie on the positive side of the first axis, contains thirteen type I ring spinning machines (2 to 4 and 6 to 15), four type II machines (16 to 20), and four type III machines (27 to 30). The second cluster may be taken to be composed of 23 machines that lie on the negative side of the first axis, from the origin to machine number 52. 15 ring spinning machines are of type I machines (1, 5, 31 to 37, 39, 43, 46 to 48, 52), two ring spinning machines are of type II (18 and 41), and six machines are of type III (21 to 26). Third, fourth and fifth clusters reside on the farthest negative side of the first axis and scattered over the second axis. Lot size is seen to increase as one moves along the first axis from positive to negative values. For low values of lot sizes (0 to 500 kg), runs are performed in the numbers of 2 to 4 and 6 to 15 (type I), 16, 17, 19, 20 (type II), and 27 to 30 (type III) ring spinning machines. As lot size gets values higher than 500 kg, runs are generally performed mainly by type I and type III ring spinning machines.

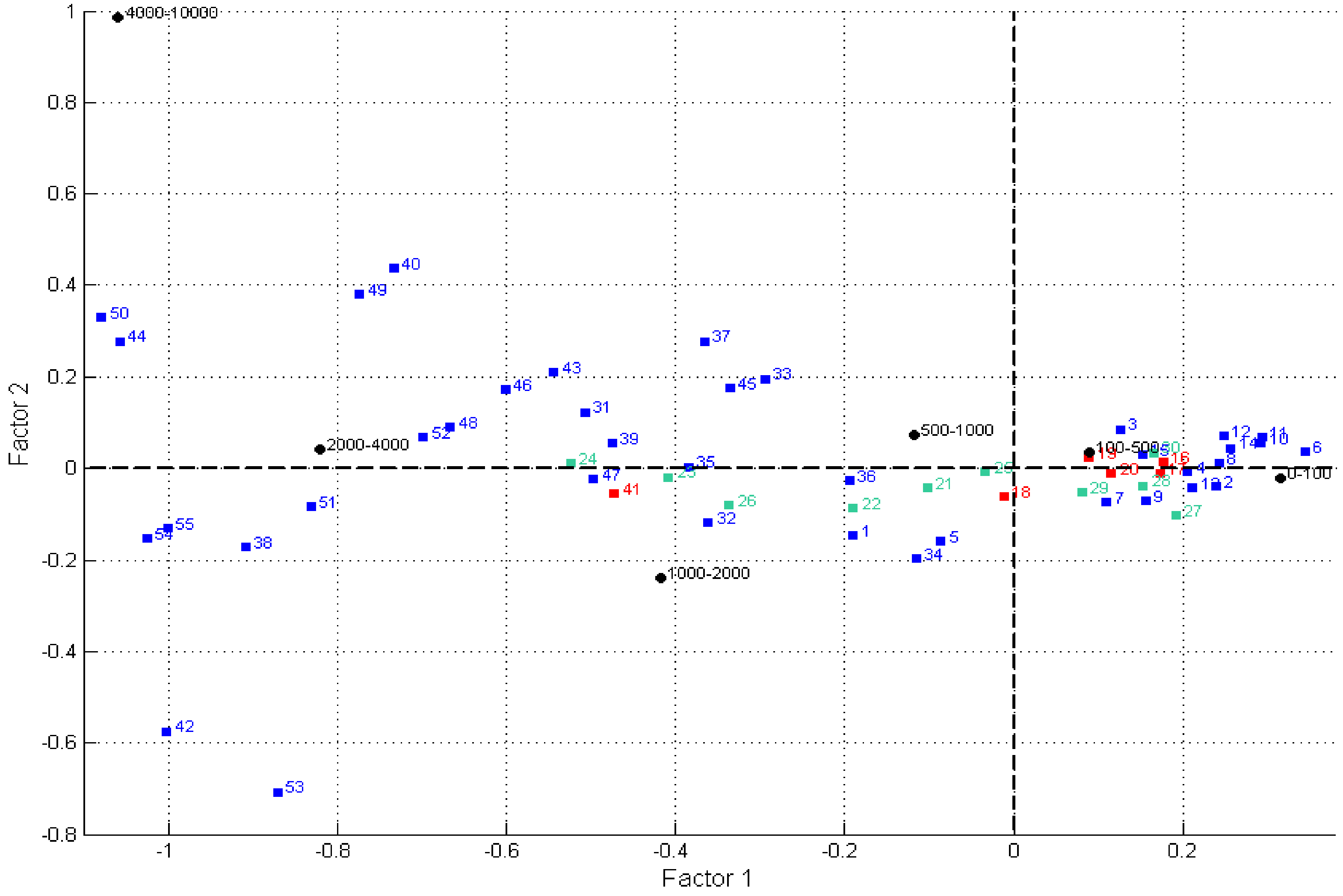

Figure 5.28. Factor 1 vs Factor 2 in correspondence analysis.

5.5. Logistic Regression Models for Ring Spinning Machines

Logistic regression models for ring spinning machines are constructed with respect to each machine type, Zinser, Suessen and Gaudino in YUNSA.

5.5.1. Model for Type I Machines

In the model for type I machines, colors and compositions are divided into various subgroups for increasing power of the model. Colors are divided into three subgroups such as Col_1, Col_2 and Col_3 which can be seen in Table 5.3. Compositions have two subgroups such as $Comp_1$ and $Comp_2$ (Table 5.4).

Table 5.3. Grouped colors in Model of Type I Machines.

Col_1	**Col_2**	**Col_3**
Ecru	Blue	Black
Brown	Dark Blue	Marengo
Grey	Other	Plucked ecru
Grey marl		

Logistic regression models were obtained by minimizing the deviance, individual parameter p-values, further evaluated by Hosmer-Lemeshow goodness of fit test (Hosmer *et al.*, 1997) and area under the receiver operating characteristic curve (ROC) (Zweig and Campbell, 1993). The best model is determined as follows, with the p-values of the estimated parameters in Table 5.5.

$$\begin{aligned}\log(p/1\text{-}p) = {} & 27.531 + 0.154Col_2 - 0.178Col_3 - 1.029Comp_2 + 0.928MSub_1 - 0.193LS \\ & - 0.015TL - 2.309RTN + 0.070YC + 0.001SS - 1.506RC + 0.031RC\times YC \\ & + 0.428Comp_2\times RC - 4.921\times 10^{-5}\times RTN\times SS + 0.060RTN^2 + 9.597\times 10^{-6}TL^2 \\ & - 0.002YC^2\end{aligned}$$

Table 5.4. Grouped compositions in Model of Type I Machines.

$Comp_1$	**$Comp_2$**
96/4 Wool/Lycra	100 Wool
85/15 Wool/Pagastic	85/15 Wool/Nylon
75/10/15 Wool/Nylon/Pagastic	70/30 Wool/Nylon
60/40 Wool/PES	75/10/15 Wool/Nylon/Lycra
50/50 Wool/PES	
45/55 Wool/PES	
58/38/4 Wool/PES/Lycra	
43/53/4 Wool/PES/Lycra	
Others	

Result of Hosmer-Lemeshow goodness of fit for observed and estimated faulty product probabilities is shown in Figure 5.29, and one can see a good match. Area under its ROC is found to be 0.66, with optimal true positive and false positive rates as 0.63 and 0.40, respectively (Figure 5.30). The higher this area, the better is the predictive capacity of the model.

While estimated coefficient of Col_2 has positive value, estimated coefficient of Col_3 has negative value. As it is seen from Figure 5.31, when color changes from Col_1 to Col_2, failure probability increases 0.04 (from 0.57 to 0.61). This indicates that in production of blue, dark blue and other colors, end break increases slightly. On the other hand, when color changes from Col_2 to Col_3, failure probability decreases 0.08 (from 0.61 to 0.53) in the conditions of other variables are at median and composition is in the position of $Comp_1$ that the production is mainly carried out. This shows that while black, marengo and plucked ecru produces, end breakage rate decreases. On the other hand, perturbation in faulty product probability due to color is found to be within the 95% prediction intervals (dashed lines), showing that the contribution of the different colors to faulty production may be statistically insignificant.

Table 5.5. P-values of the model parameters for Type I Machines.

Model parameters	**p-value**	**Model parameter**	**p-value**
Intercept	0.044	**SS**	0.081
$\mathbf{Col_2}$	0.015	**RC**	8.10×10^{-15}
$\mathbf{Col_3}$	0.008	**RC×YC**	1.20×10^{-10}
$\mathbf{Comp_2}$	0.0004	**$\mathbf{Comp_2}$×RC**	1.91×10^{-7}
$\mathbf{MSub_1}$	1.53×10^{-9}	**RTN×SS**	0.084
LS	1.24×10^{-20}	**$\mathbf{TL^2}$**	0.009
TL	0.005	**$\mathbf{RTN^2}$**	0.0003
RTN	0.013	**$\mathbf{YC^2}$**	8.04×10^{-10}
YC	0.001		

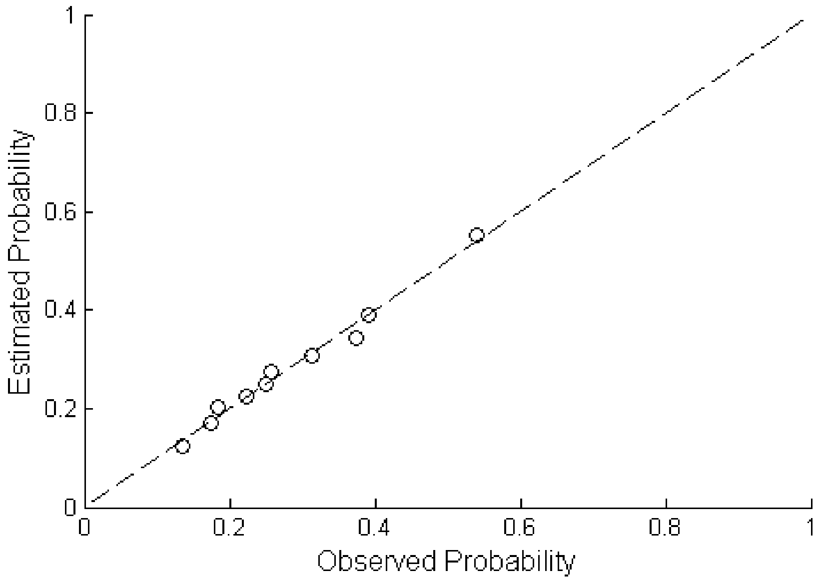

Figure 5.29. Observed probability vs estimated probability in Model of Type I Machines.

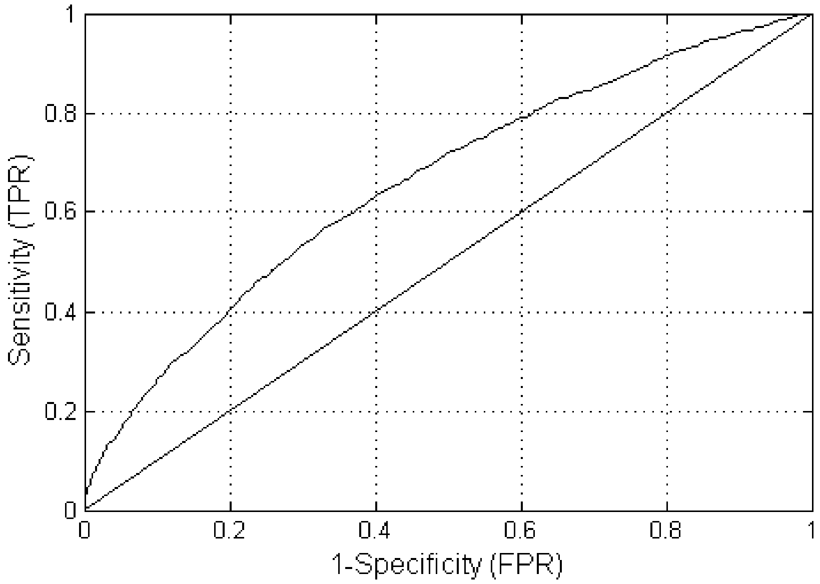

Figure 5.30. ROC in Model of Type I Machines.

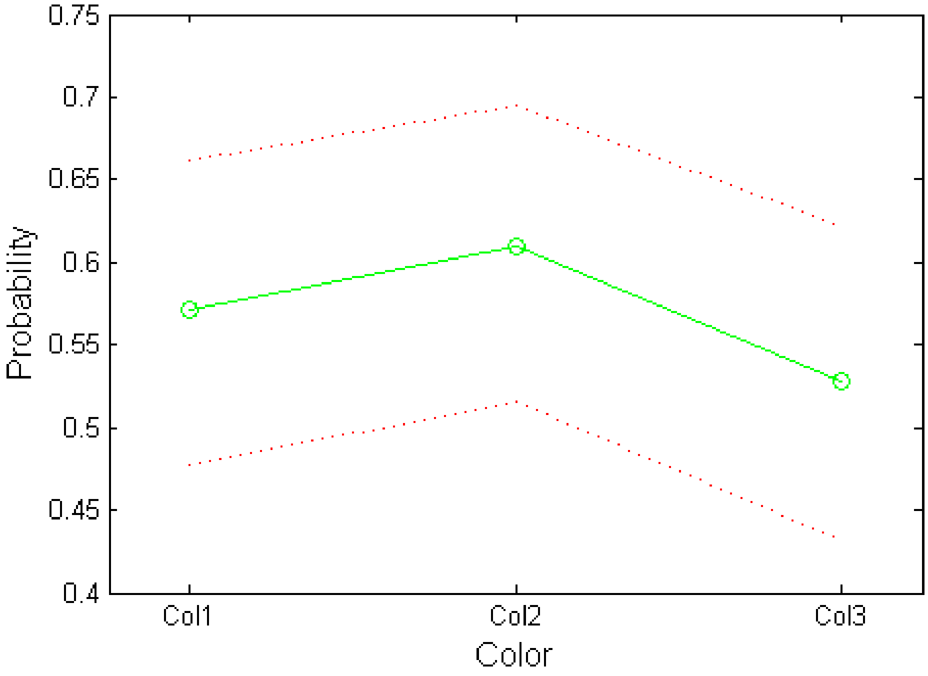

Figure 5.31. Effect of color on failure probability in Model of Type I Machines.

Estimated coefficient of $MSub_1$ is found to be positive. When all the other process conditions are taken at their median values, failure probability of the reference group, which includes all type I machines except machine number 36 is 0.38, while failure probability increases to 0.61 for of machine number 36 (Figure 5.32). The p-value for this coefficient is found to be $1.53x10^{-9}$ (Table 5.6), and the effect of machine 36 exceeds the prediction intervals, hence it may be suggested that end breakage rate is higher for the machine number 36 compared to other type I ring spinning machines.

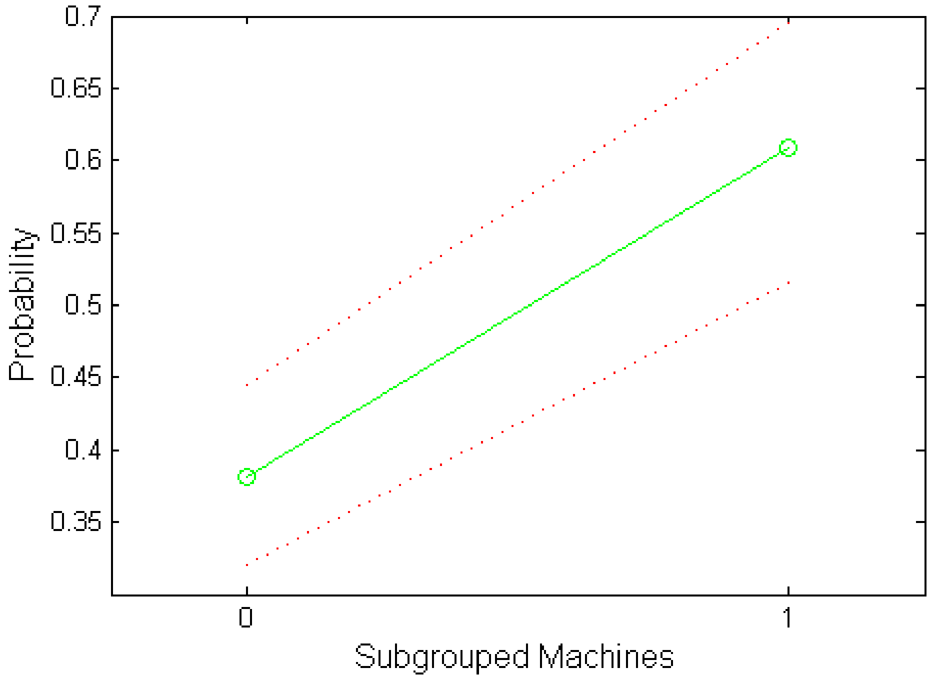

Figure 5.32. Effect of subgrouped machines on failure probability in Model of Type I Machines.

Failure probability according to lot size alters from 0.74 to 0.46. Since lot size has logaritmic values in the model, when lot size is increased from 100 kg to 500 kg, failure probability decreases from 0.65 to 0.57 (Figure 5.33). With a p-value of $1.24x10^{-20}$, this indicates that lot size has a statistically significant effect on fault probability; as lot size is increased, fault probability decreases for type I machines.

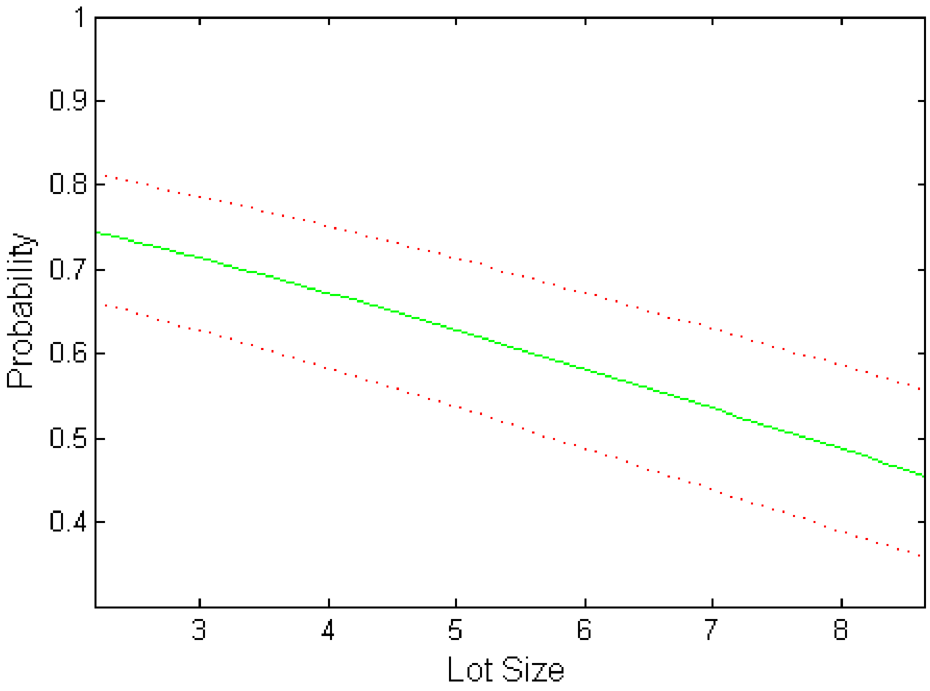

Figure 5.33. Effect of lot size on failure probability in Model of Type I Machines.

Roving count contributes to the logistic model via its main effect and interaction terms. To evaluate the effect of roving count on fault probability, each of its interaction is taken separately into consideration. Main effect of roving count has a negative coefficient (-1.506), but its interaction with $Comp_2$, i.e. 100 Wool, 85/15 Wool/Nylon, 70/30 Wool/Nylon, 75/10/15 Wool/Nylon/Lycra, has a positive coefficient (0.428). When roving count gets low values in production of $Comp_2$, failure probability decreases 0.09 (from 0.52 to 0.43). This demonstrates that when the low roving counts are fed to the ring spinning machine, the end breakage rate decreases from 0.52 to 0.43 (Figure 5.34). On the other hand, when roving count gets high values effect of $Comp_2$ on failure probability is positive (Figure 5.35). This indicates that when rovings has high counts for yarn production, the end breakage rate increases from 0.68 to 0.87, as seen in the historical data set. Roving count and yarn count has a positive interaction term in the model. For low count values of yarn, there is a parabolic relation between yarn count and end breakage: end breakage rate increases until yarn count is 36 Nm, and then decreases (Figure 5.36). For moderate values of roving count (around 3 Nm), relation between end breakage and yarn count is again a concave function (Figure 5.37).

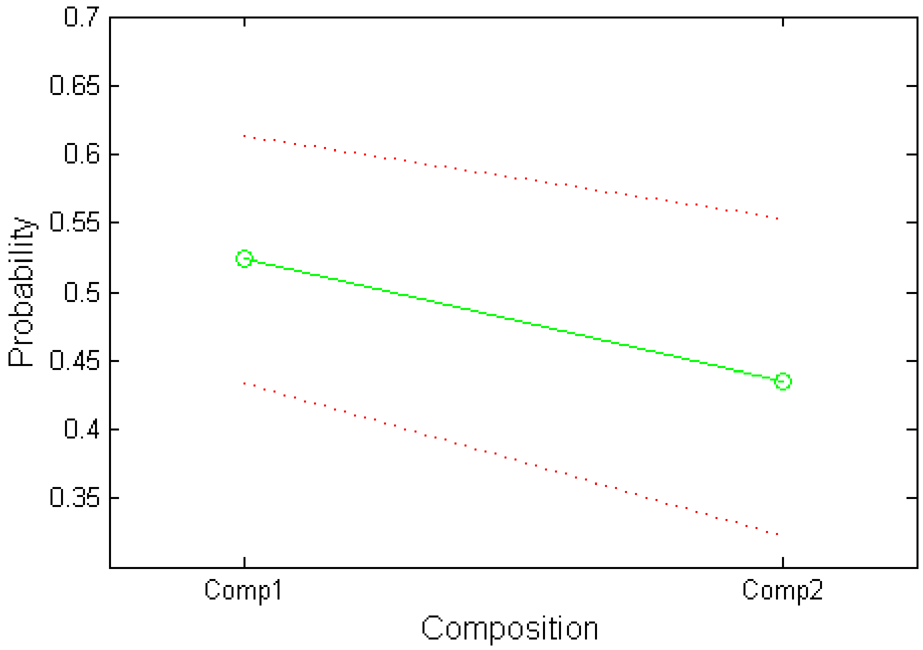

Figure 5.34. Effect of composition on failure probability at low values of roving count in Model of Type I Machines.

The same interaction term can be examined taking yarn count to be constant and roving count to be variable. For low values of yarn count, failure probability decreases from 0.60 to 0.05 as roving count is increased in its range (Figure 5.38). At the high values of yarn count gets relation between failure probability and roving count changes its character. Failure probability increases from 0.03 to 0.79 as roving count is increased in its range (Figure 5.39).

Ring traveler number and spindle speed has a negative interaction term in the model. For the high values of ring traveler number, failure probability is found to decrease as spindle speed is increased, albeit with large prediction intervals (Figure 5.40). When the spindle speed takes high values, failure probability of ring traveler number changes parabolically (Figure 5.41). Up to ring traveler number of 24.5, end breakage rate decreases from 0.82 to 0.58, and then increases to 0.89.

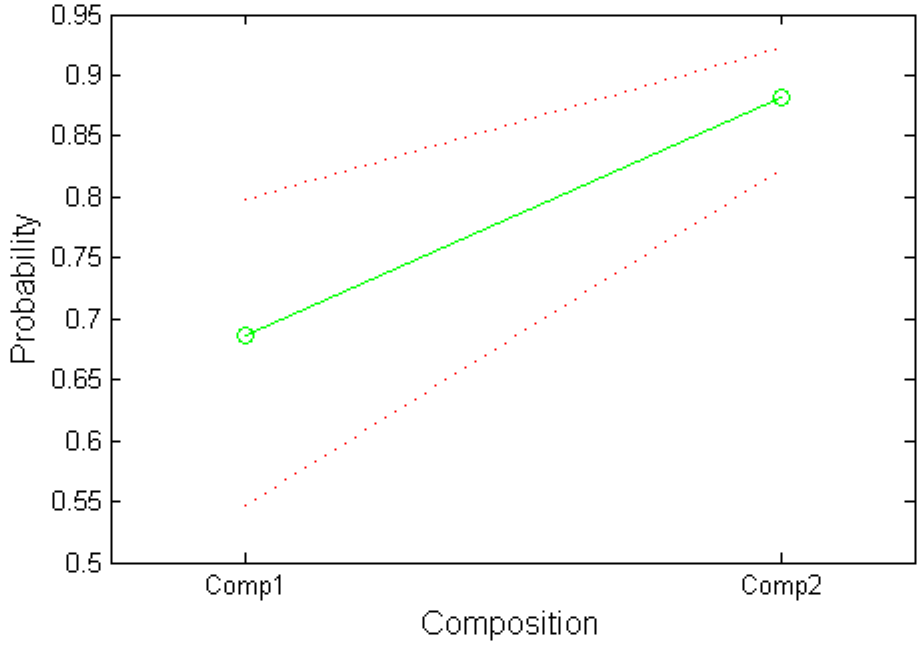

Figure 5.35. Effect of composition on failure probability at high values of roving count in Model of Type I Machines.

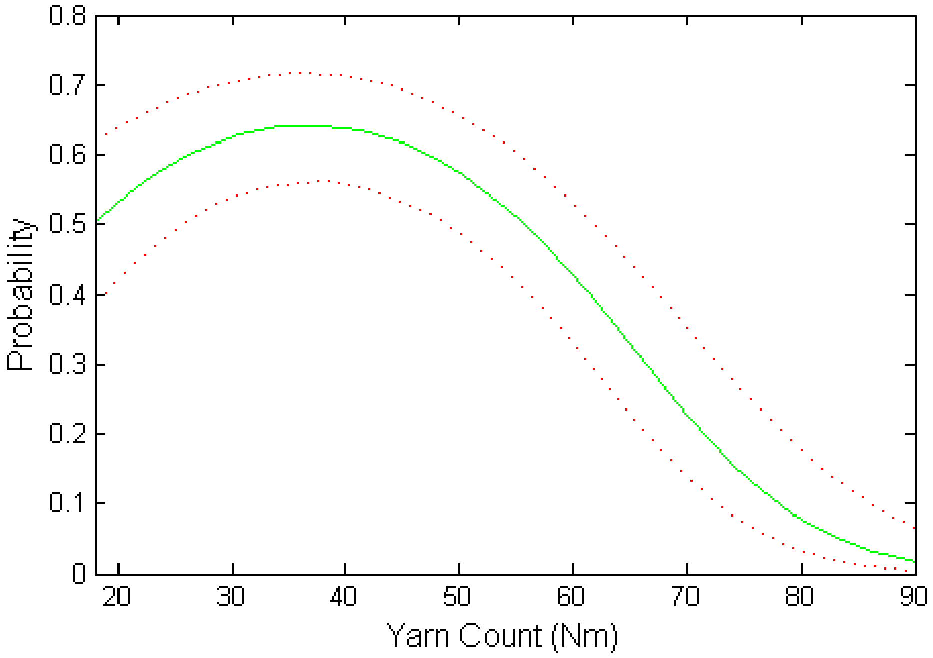

Figure 5.36. Effect of yarn count on failure probability at low values of roving count in Model of Type I Machines.

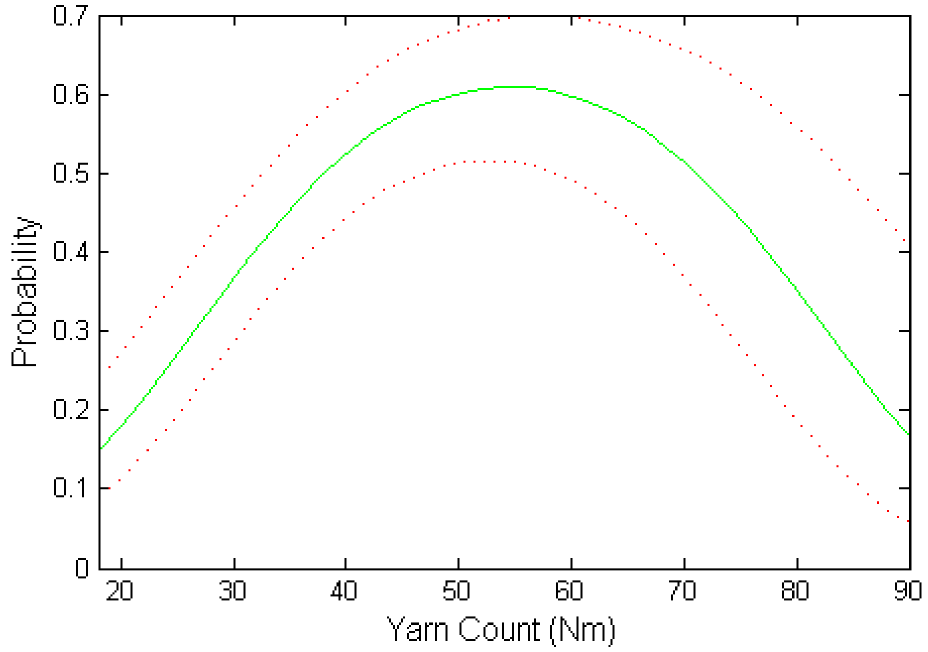

Figure 5.37. Effect of yarn count on failure probability at moderate values of roving count in Model of Type I Machines.

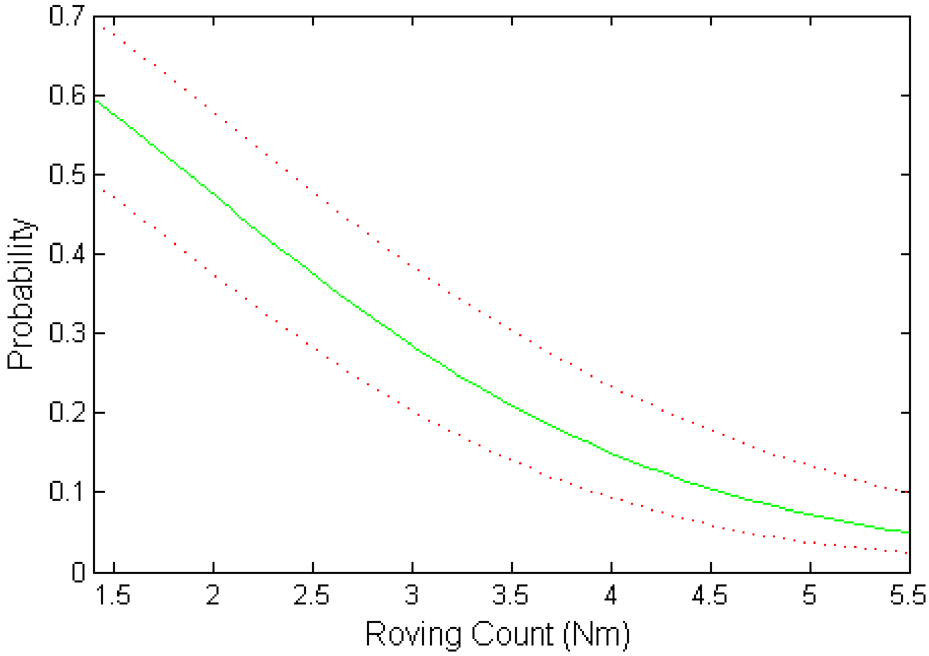

Figure 5.38. Effect of roving count on failure probability at low values of yarn count in Model of Type I Machines.

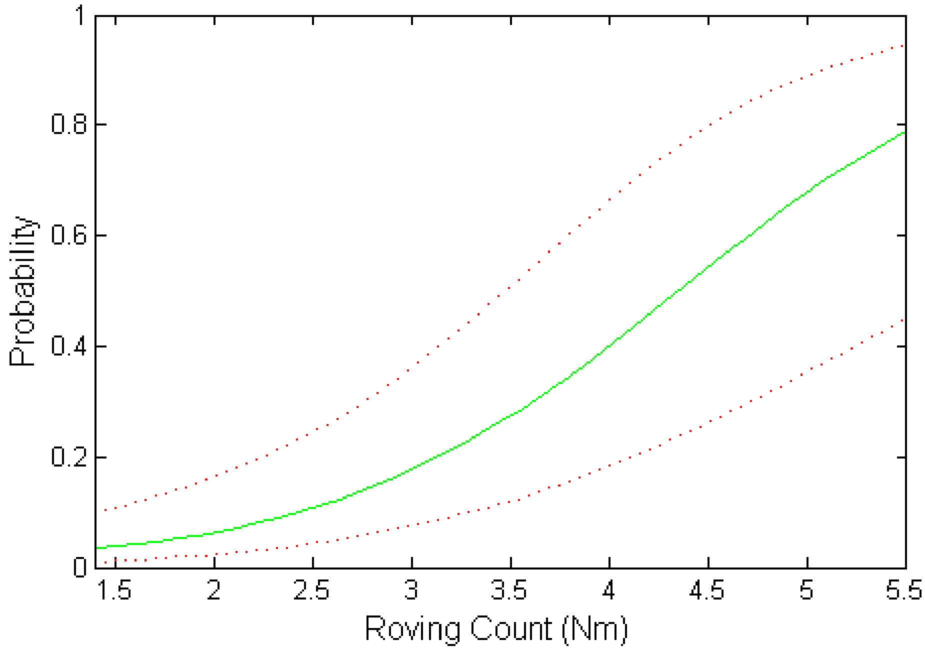

Figure 5.39. Effect of roving count on failure probability at high values of yarn count in Model of Type I Machines.

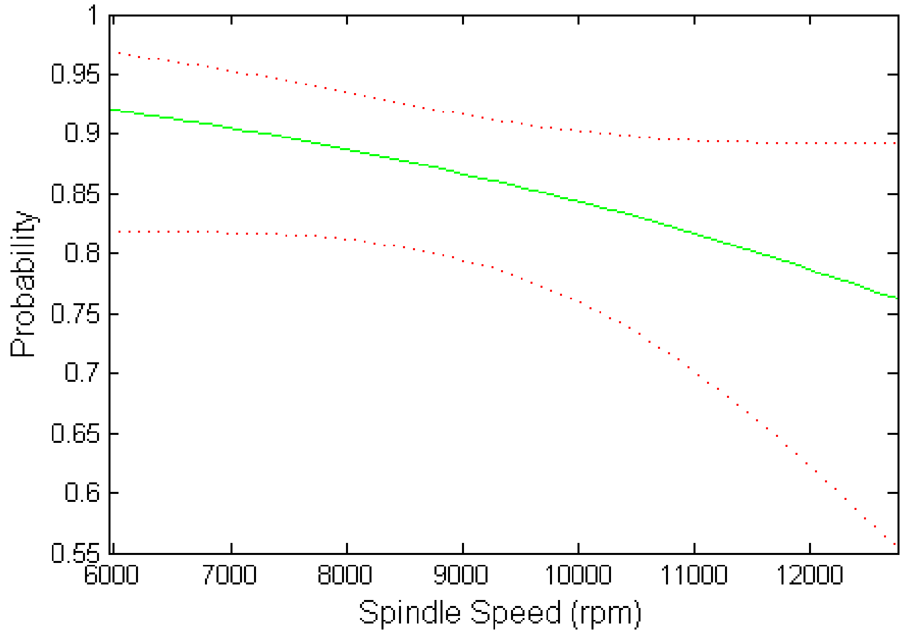

Figure 5.40. Effect of spindle speed on failure probability at high values of ring traveler number in Model of Type I Machines.

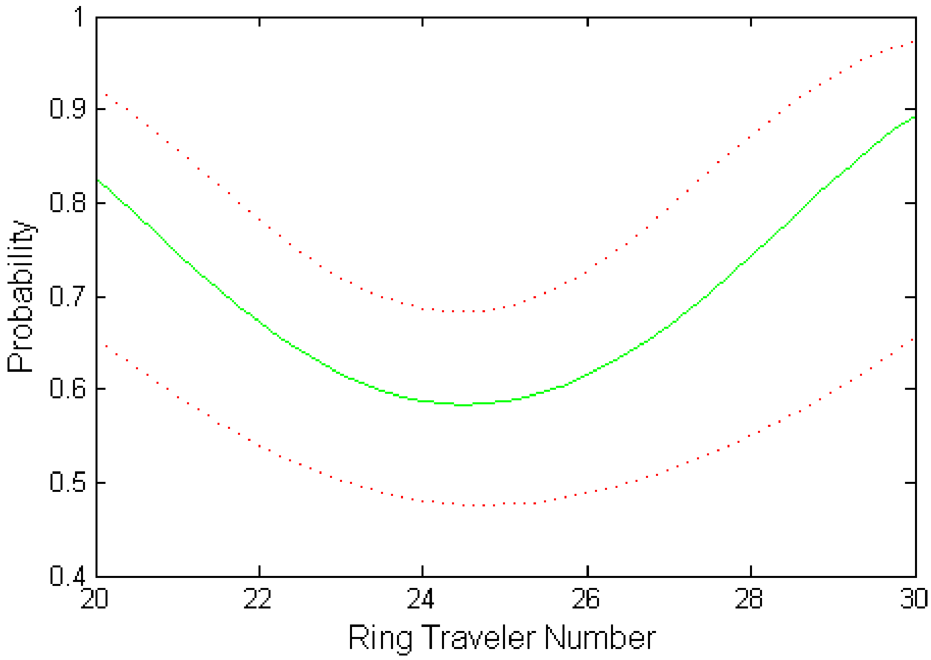

Figure 5.41. Effect of spindle speed on failure probability at high values of spindle speed in Model of Type I Machines.

5.5.2. Model for Type II Machines

Colors and compositions in the model for type II machines are divided into various subgroups in order to increase predictive power of the model. Colors are divided into two subgroups such as Col_1 and Col_2 (Table 5.6). As it is seen from Table 5.7, compositions are split into three subgroups such as $Comp_1$, $Comp_2$ and $Comp_3$.

The best model for type II machines is obtained as follows with the p-values of the estimated parameters in Table 5.8:

$$\begin{aligned}\log(p/1\text{-}p) = {} & 197.550 + 0.584\mathrm{Col}_2 - 0.354\mathrm{Comp}_2 + 0.717\mathrm{Comp}_3 + 0.339\mathrm{MSub}_1 \\ & - 0.228\mathrm{MSub}_2 - 0.129\mathrm{LS} - 0.003\mathrm{TL} - 0.861\mathrm{RC} - 2.853\mathrm{YC} + 0.025\mathrm{RC}\times\mathrm{YC} \\ & - 0.076\mathrm{D} + 0.001\mathrm{D}^2 - 15.747\mathrm{RTN} + 0.320\mathrm{RTN2} + 0.230\mathrm{RTN}\times\mathrm{YC} \\ & - 0.005\mathrm{RTN2}\times\mathrm{YC}\end{aligned}$$

To evaluate the predictive power of the regression model constructed for type II machines, area under its ROC is found to be 0.70, with optimal true positive and false positive rates as 0.67 and 0.40, respectively (Figure 5.42).

Table 5.6. Grouped colours in Model of Type II Machines.

Col_1	**Col_2**
Ecru	Blue
Plucked ecru	Dark Blue
Marengo	
Grey	
Grey marl	
Brown	
Black	
Other	

Table 5.7. Grouped compositions in Model of Type II Machines.

$Comp_1$	**$Comp_2$**	**$Comp_2$**
96/4 Wool/Lycra	60/40 Wool/PES	70/30 Wool/Nylon
85/15 Wool/Pagastic	50/50 Wool/PES	
43/53/4 Wool/PES/Lycra	45/55 Wool/PES	
	85/15 Wool/Nylon	
	75/10/15 Wool/Nylon/Pagastic	
	Other	

As seen from Figure 5.43, when color changes from Col_1 to Col_2 group, failure probability increases by 0.14, from 0.37 to 0.51 when other variables are taken at their median values, and composition is taken to be equal to $Comp_2$. This indicates that end breaks are likely to increase for the blue and dark blue colored yarns.

Table 5.8. P-values of the model parameters for Type II Machines.

Model parameters	**p-value**	**Model parameter**	**p-value**
Intercept	4.96×10^{-6}	**YC**	0.0008
$\mathbf{Col_2}$	0.0015	**D**	0.17
$\mathbf{Comp_2}$	0.054	**RTN**	5.03×10^{-6}
$\mathbf{Comp_3}$	0.044	$\mathbf{RC\times YC}$	0.026
$\mathbf{MSub_1}$	0.030	$\mathbf{RTN\times YC}$	0.0005
$\mathbf{MSub_2}$	0.145	$\mathbf{RTN^2\times YC}$	0.0003
LS	0.0045	$\mathbf{D^2}$	0.095
TL	0.0035	$\mathbf{RTN^2}$	3.28×10^{-6}
RC	0.089		

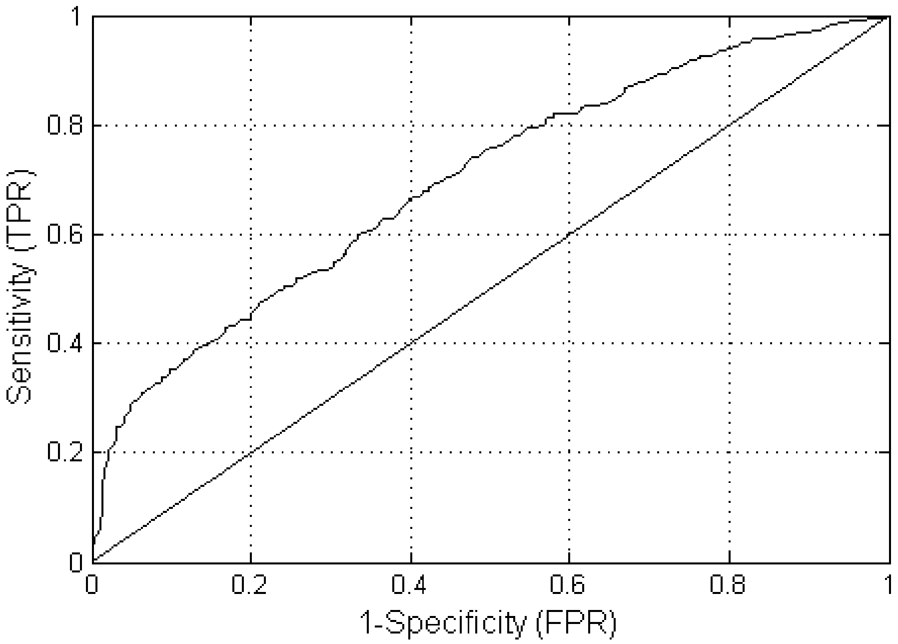

Figure 5.42. ROC in Model of Type II Machines.

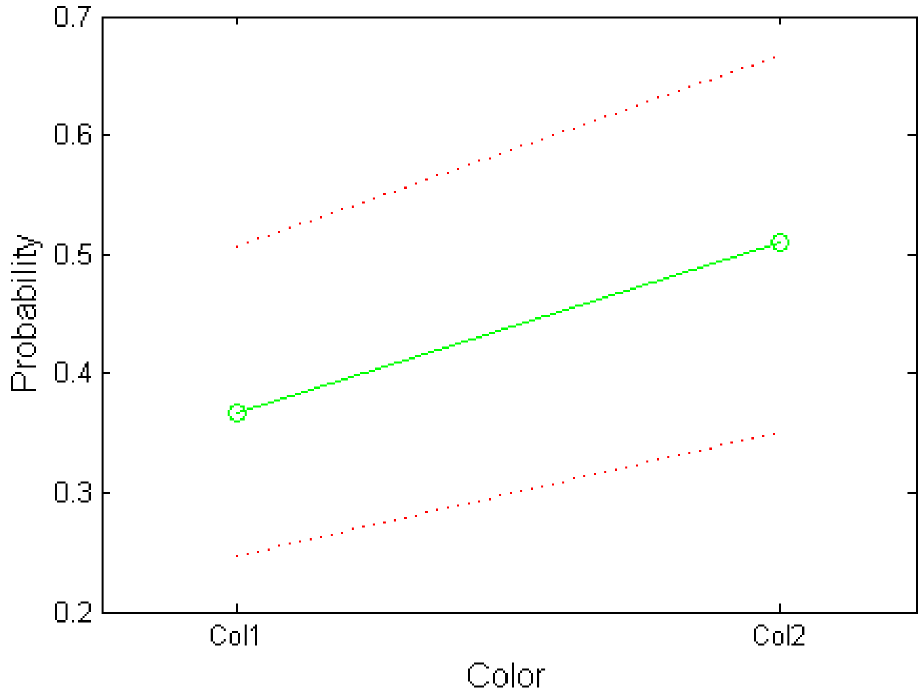

Figure 5.43. Effect of color on failure probability in Model of Type II Machines.

While the estimated coefficient of $Comp_2$ has a negative value, the estimated coefficient of $Comp_3$ has positive value. There is no production of the compositions of 58/38/4 Wool/PES/Lycra and 75/10/15 Wool/Nylon/Lycra in the type II machines. Failure probability of reference subgroup ($Comp_1$) is 0.45 and failure probabilities of $Comp_2$ and $Comp_3$ are 0.37 and 0.63, respectively (Figure 5.44). Decrease in failure probability switching from reference set to $Comp_2$ shows that end breakage is low while manufacturing of blends in group of $Comp_2$. In production of $Comp_3$ (70/30 Wool/Nylon) blends in type II machines have highest failure probability compared to other composition groups. Nevertheless, large prediction intervals shows that one should be cautious in generalizing these results.

While estimated coefficient of $MSub_1$ has positive value, estimated coefficient of $MSub_2$ has negative value. Failure probability of reference subgroup is 0.29, failure probabilities of subgroup 1 and subgroup 2 of machines are 0.37 and 0.25, respectively (Figure 5.45).

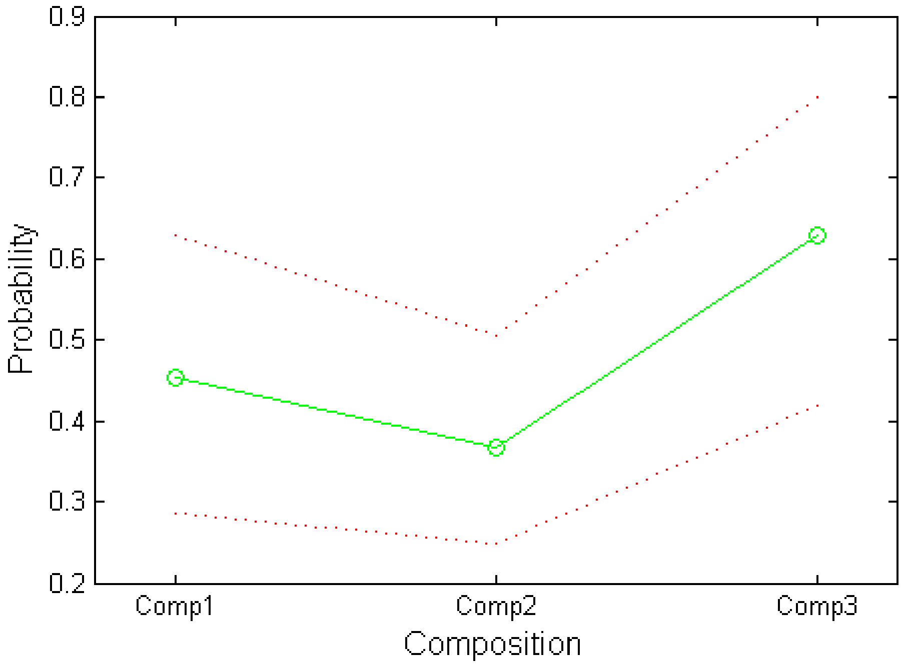

Figure 5.44. Effect of composition on failure probability in Model of Type II Machines.

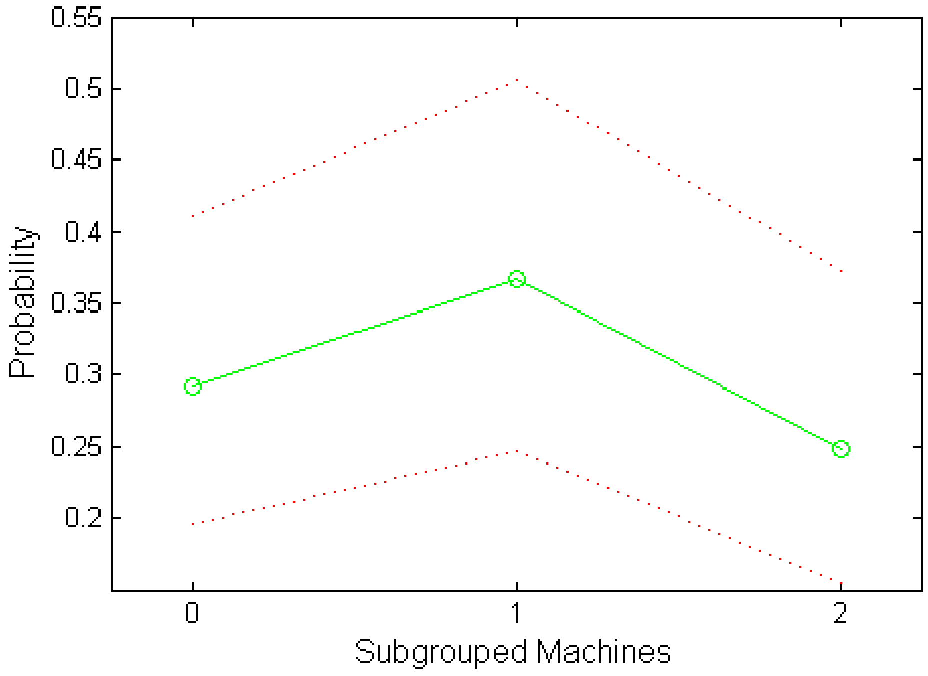

Figure 5.45. Effect of subgrouped machines on failure probability in Model of Type II Machines.

As lot size is increased, failure probability drops down from 0.46 to 0.28. Since lot size has logaritmic values in the model, when lot size is increased from 100 kg to 500 kg, failure probability decreases from 0.39 to 0.34 (Figure 5.46). Compared to Figure 5.33, the effect of lot size in both types of machines is in the same direction, but significantly at different magnitudes.

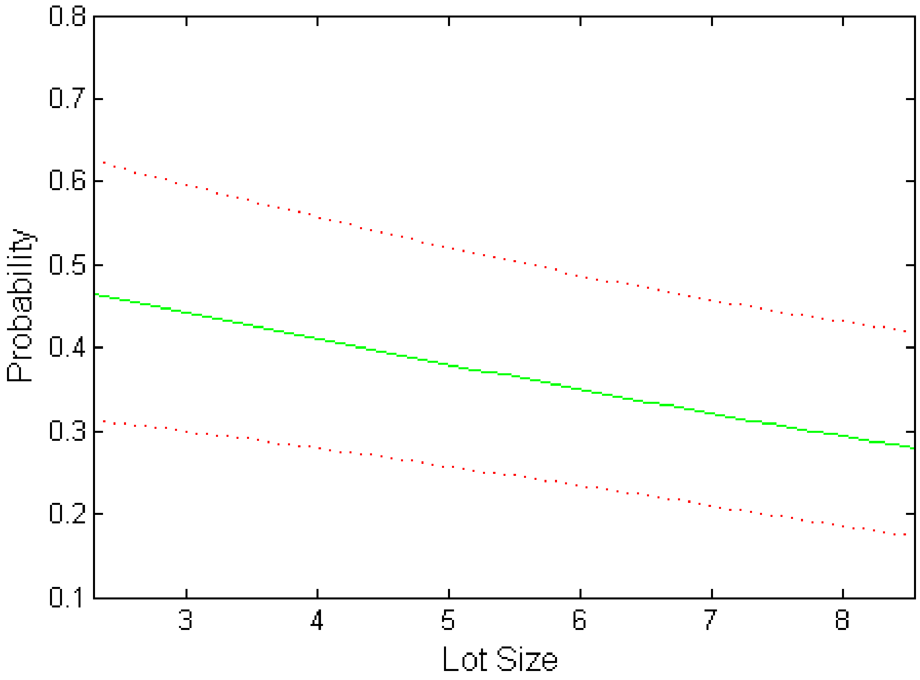

Figure 5.46. Effect of twist level on failure probability in Model of Type II Machines.

Figure 5.47 shows that increase in twist level has positive impact on end breakage, similar to the findings of Huang *et al.* (1994). They correlated twist level and breaking strength, and found that when twist level increased, breaking strength increased. Huang and Oxenham (1994) indicated that breaking strength of yarn was inversely proportional to end breakage rate.

Failure probability changes between 0.49 to 0.70 in a parabolic fashion as draft is changed between its operating ranges. However, prediction interval is quite wide to deep significance to the parabolic relation (Figure 5.48).

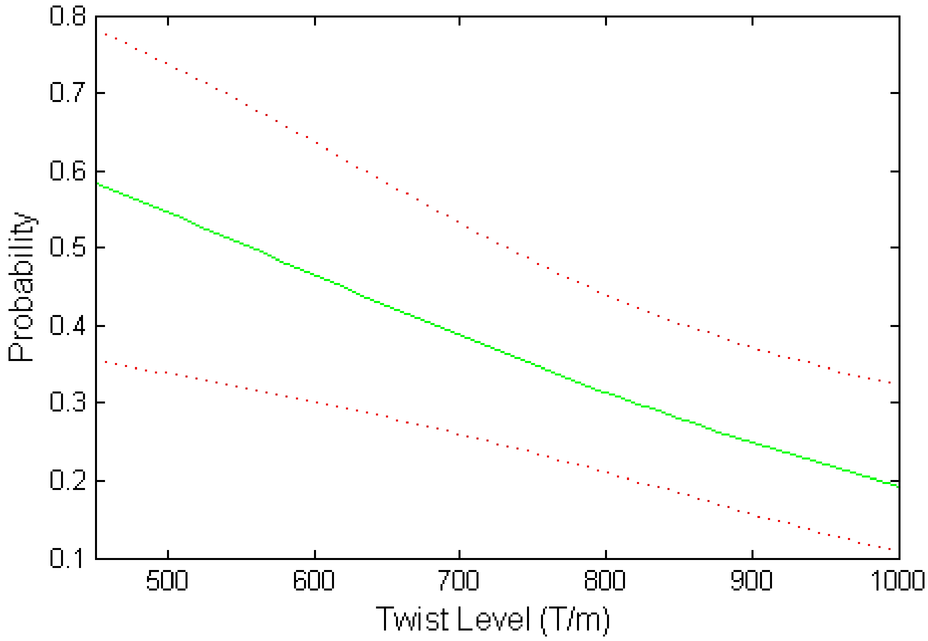

Figure 5.47. Effect of twist level on failure probability in Model of Type II Machines.

Yarn count contributes to the logistic model via its main effect and interaction terms. The effect of yarn count on fault probability is determined as taking each of its interactions separately into consideration. Main effect of yarn count has a negative coefficient (-2.853), but its interaction with roving count has a positive coefficient (0.025). At high values of roving number, yarn count increases. When yarn count is getting thinner, end breakage dramatically increases from 0.08 to 0.90 (Figure 5.49). The study of prediction of end breakage rate performed by Huang *et al.* (1994) showed that end breakages increase as yarn count increases. Their result is compatible to this results. Furthermore, Prendzova (2000) examined the effect of cotton yarn properties on end breakage and found the similar result that yarn count and end breakage are directly proportional to each other. When ring traveler number is about its median value, end breakage probability increases from 0.14 to 0.68 when yarn count increases (Figure 5.50). In addition, when yarn count gets lower values, end breakage probability has a parabolic relation with ring traveler number. The end breakage rate decreases up to ring traveler number of 24.7 and then starts to increase (Figure 5.51), similar to the behavior seen for Type I machines (Figure 5.41).

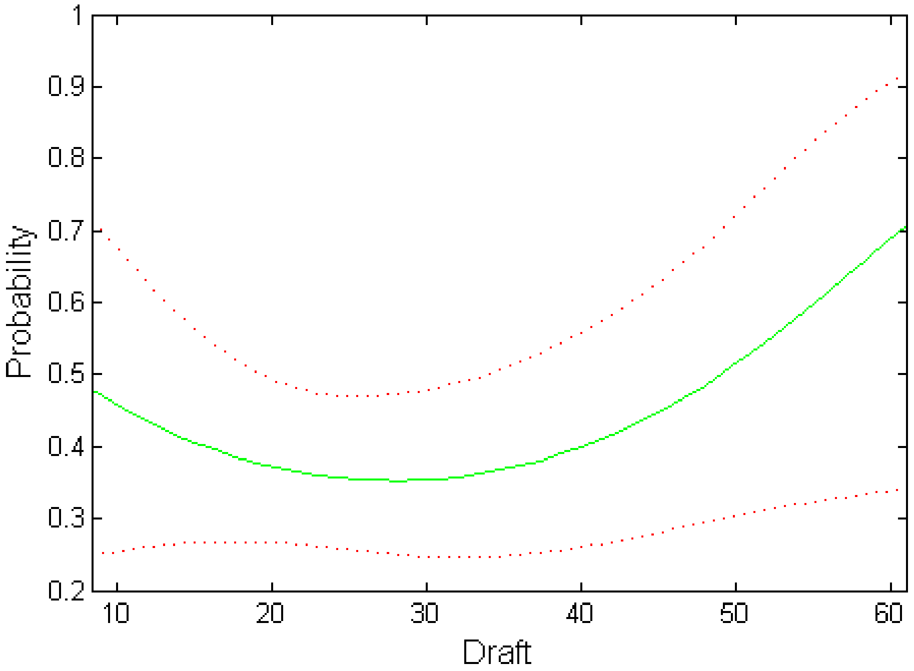

Figure 5.48. Effect of draft on failure probability in Model of Type II Machines.

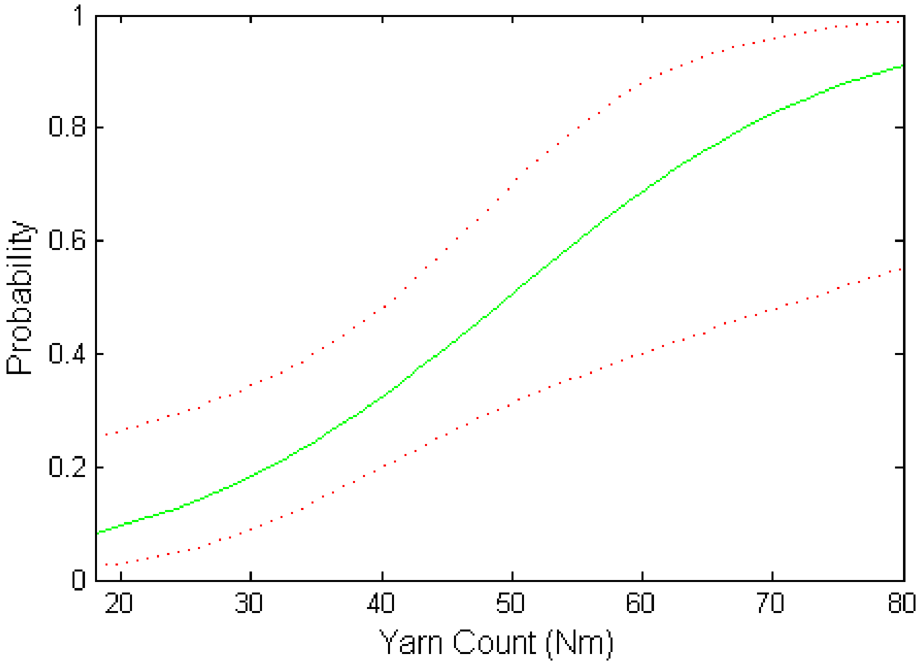

Figure 5.49. Effect of yarn count on failure probability at high values of roving count in Model of Type II Machines.

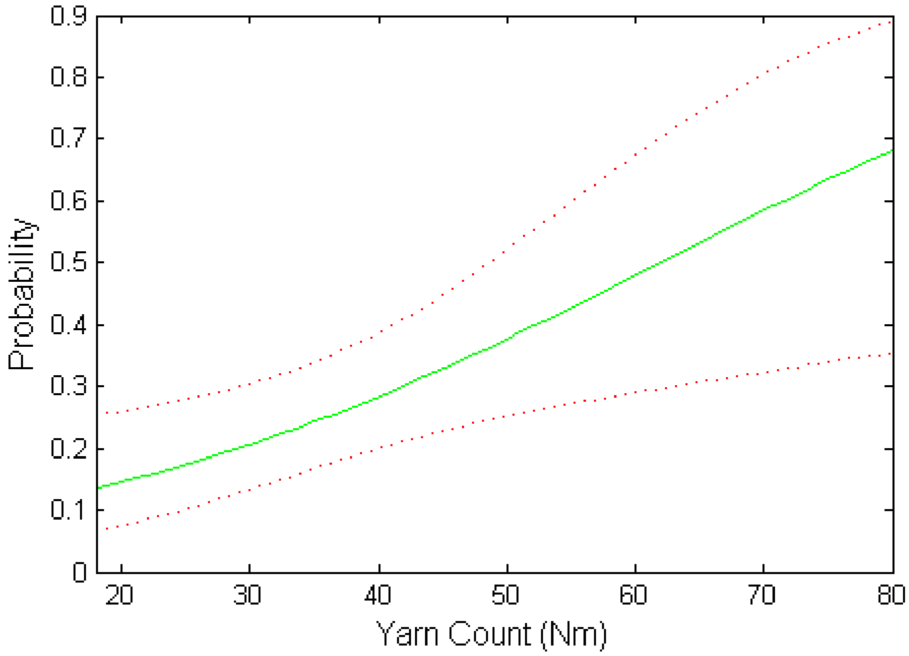

Figure 5.50. Effect of yarn count on failure probability at moderate values of ring traveler number in Model of Type II Machines.

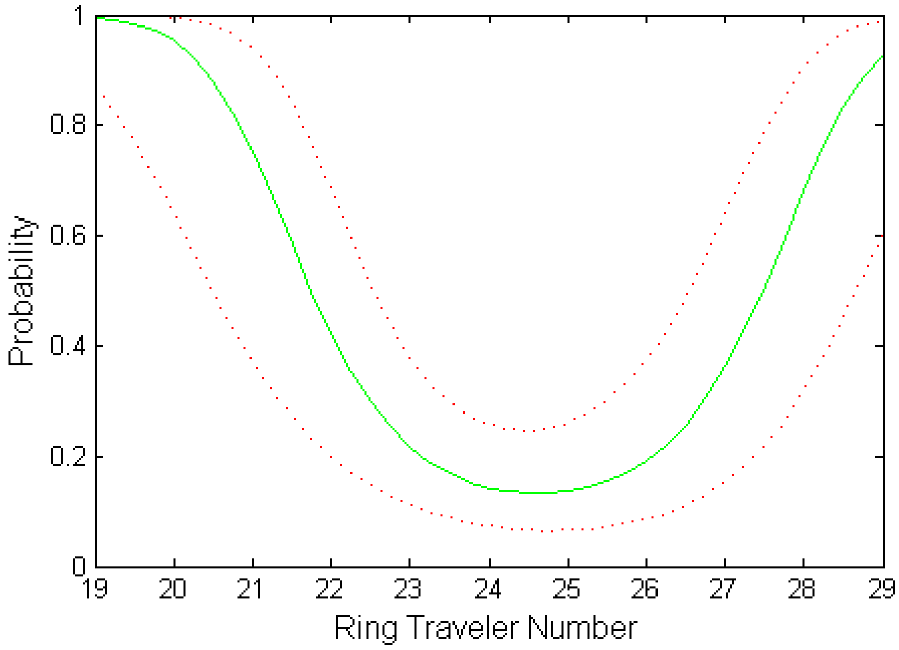

Figure 5.51. Effect of ring traveler number on failure probability at low values of yarn count in Model of Type II Machines.

5.5.3. Model for Type III Machines

Colors and compositions in the model for type III machines are divided into two subgroups such as Col_1 and Col_2 (Table 5.9) and $Comp_1$ and $Comp_2$ (Table 5.10), respectively.

Table 5.9. Grouped colours in Model of Type III Machines.

Col_1	**Col_2**
Ecru	Blue
Plucked ecru	Dark Blue
Marengo	Others
Grey	
Grey marl	
Brown	
Black	

Table 5.10. Grouped Compositions in Model of Type III Machines.

$Comp_1$	**$Comp_2$**
100 Wool	85/15 Wool/Nylon
60/40 Wool/PES	70/30 Wool/Nylon
50/50 Wool/PES	
45/55 Wool/PES	
Others	

The best model for type III machines is obtained with the p-values of the estimated parameters in Table 5.11 as follows:

$$\begin{aligned}\log(p/1\text{-}p) = {} & 10.194 + 0.414Col_2 + 0.778Comp_3 + 0.628MSub_1 - 0.294LS + 0.026MA \\ & - 0.003TL - 5.746RC + 0.795RC2 - 0.176YC + 0.115RC\times YC \\ & - 0.015RC^2\times YC\end{aligned}$$

Table 5.11. P-values of the model parameters for type III machines.

Model parameters	**p-value**	**Model parameter**	**p-value**
Intercept	0.0003	**TL**	0.0047
Col_2	0.0042	**YC**	0.0002
$Comp_3$	0.0002	**MA**	0.0565
$MSub_1$	2.56×10^{-7}	**RC×YC**	0.0001
LS	6.51×10^{-10}	**RC^2**	0.0057
RC	0.0017	**$RC^2\times YC$**	0.0011

To evaluate the predictive power of the regression model constructed for type III machines, area under its ROC is found to be 0.75, with optimal true positive and false positive rates as 0.65 and 0.28, respectively (Figure 5.52).

As seen in Figure 5.53, when color changes from Col_1 to Col_2, failure probability increases from 0.53 to 0.63 when other variables are taken at their median values, and composition is taken to be equal to $Comp_1$. Models with alternative grouped colors, such as ecru + plucked ecru and other colors; ecru + plucked ecru + black and other colors, are studied, but minimum sum of deviance of subgroups is found by this formulation.

There is no production of the compositions of 43/53/4 Wool/PES/Lycra, 58/38/4 Wool/PES/Lycra, 75/10/15 Wool/Nylon/Lycra, 75/10/15 Wool/Nylon/Pagastic, 85/15 Wool/Pagastic and 96/4 Wool/Lycra in the type III machines. As can be seen in the Figure 5.54 below, when composition changes from $Comp_1$ to $Comp_2$, failure probability increases from 0.53 to 0.71. Estimated coefficient of lot size has originally negative value. Failure probability according to lot size alters from 0.75 to 0.29. Since lot size has logaritmic values in the model, when lot size is increased from 100 kg to 500 kg, failure probability decreases from 0.67 to 0.55 (Figure 5.55). This finding shows that in all three types of machines (see also Figures 5.33 and 5.46), there is a negative relation between lot size and failure probability.

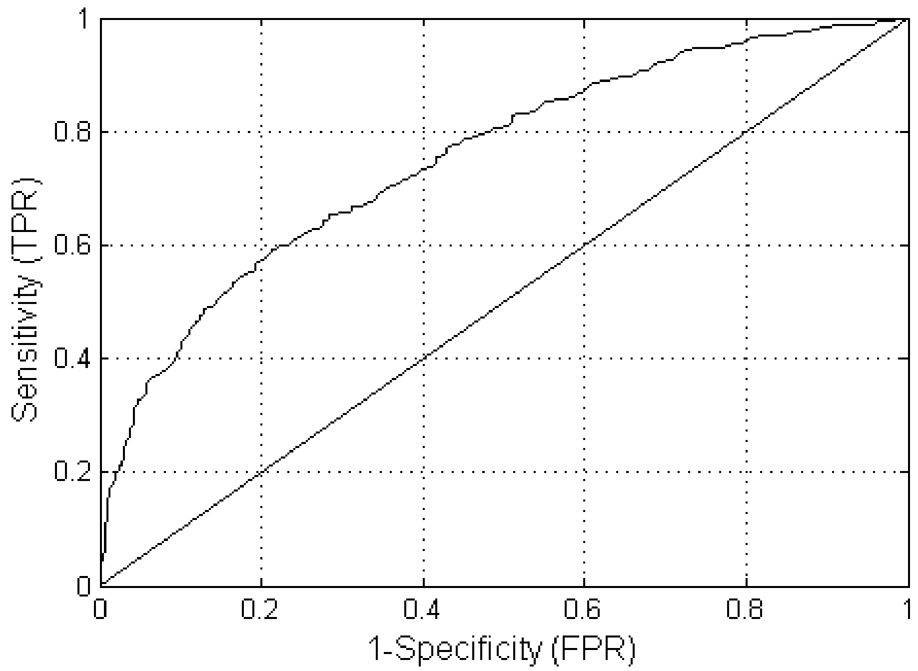

Figure 5.52. ROC in Model of Type III Machines.

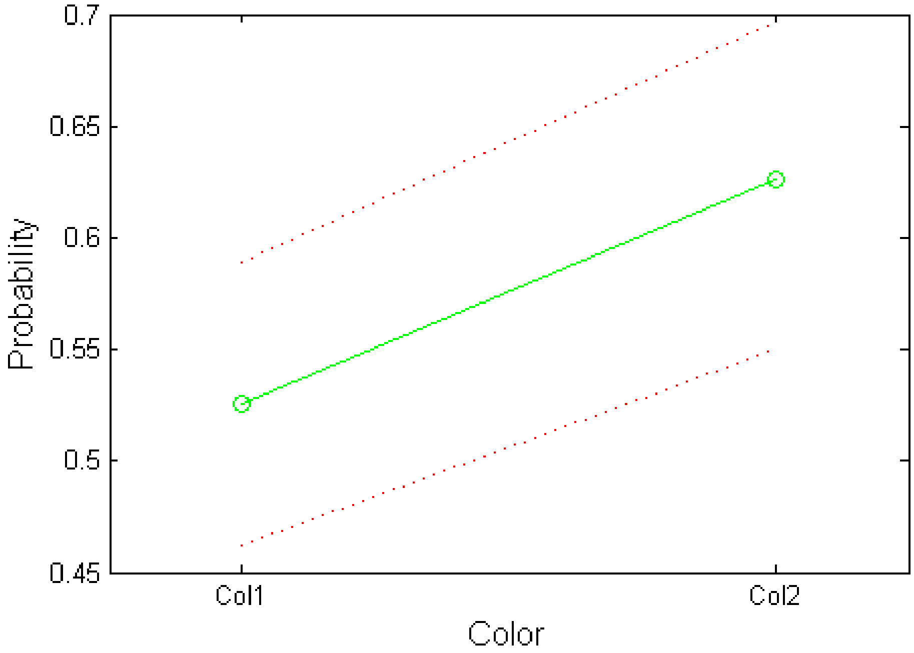

Figure 5.53. Effect of color on failure probability in Model of Type III Machines.

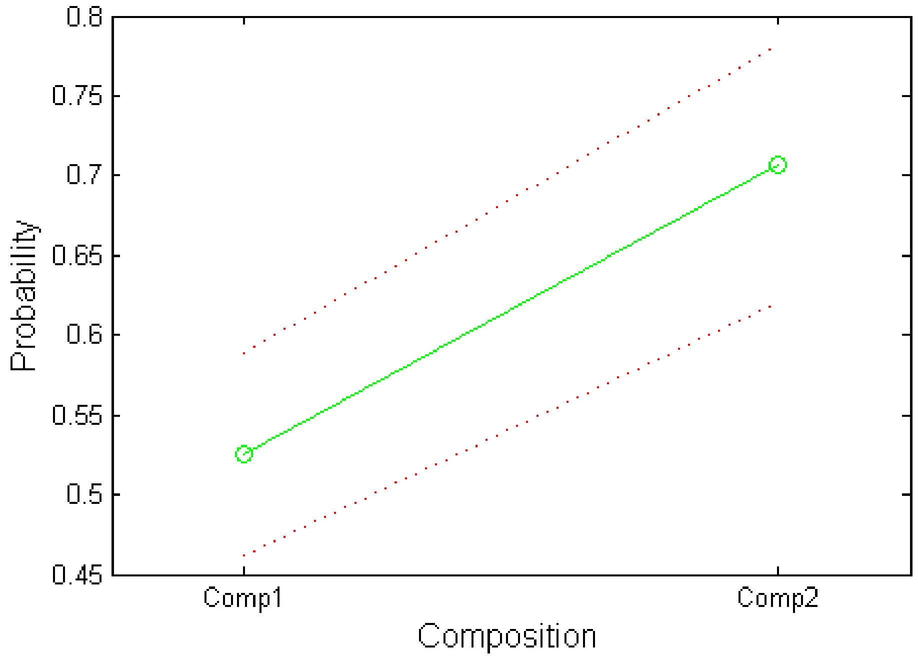

Figure 5.54. Effect of composition on failure probability in Model of Type III Machines.

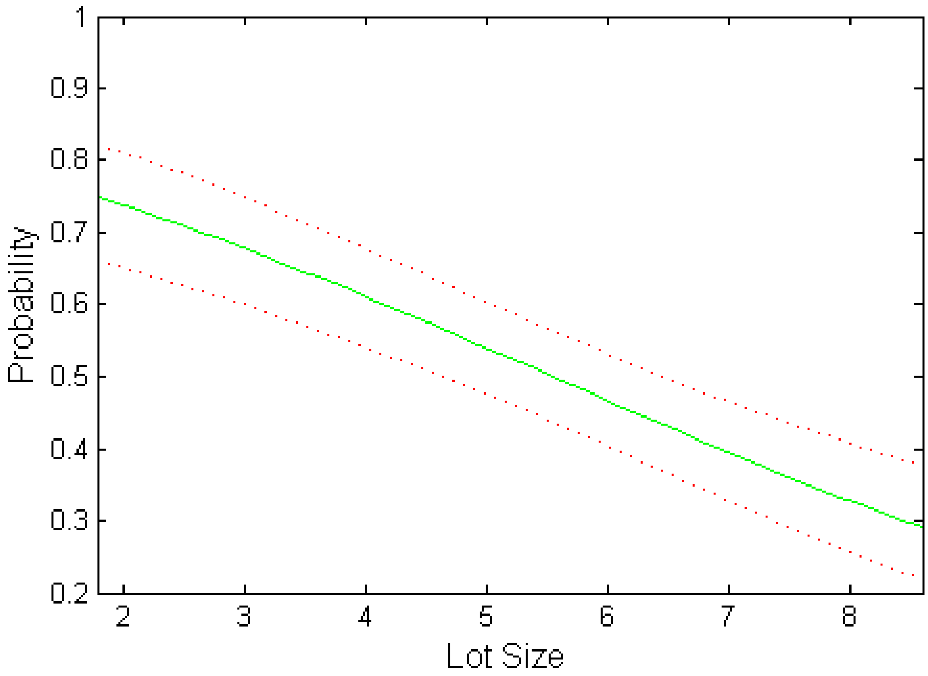

Figure 5.55. Effect of lot size on failure probability in Model of Type III Machines.

Failure probability decreases from 0.68 to 0.37 as twist level is increased (Figure 5.56). This result is almost identical to that seen for type II machines (Figure 5.47). At the same time, this result is similar to the results of the studies conducted by Huang and Oxenham (1994) and Huang *et al.* (1994).

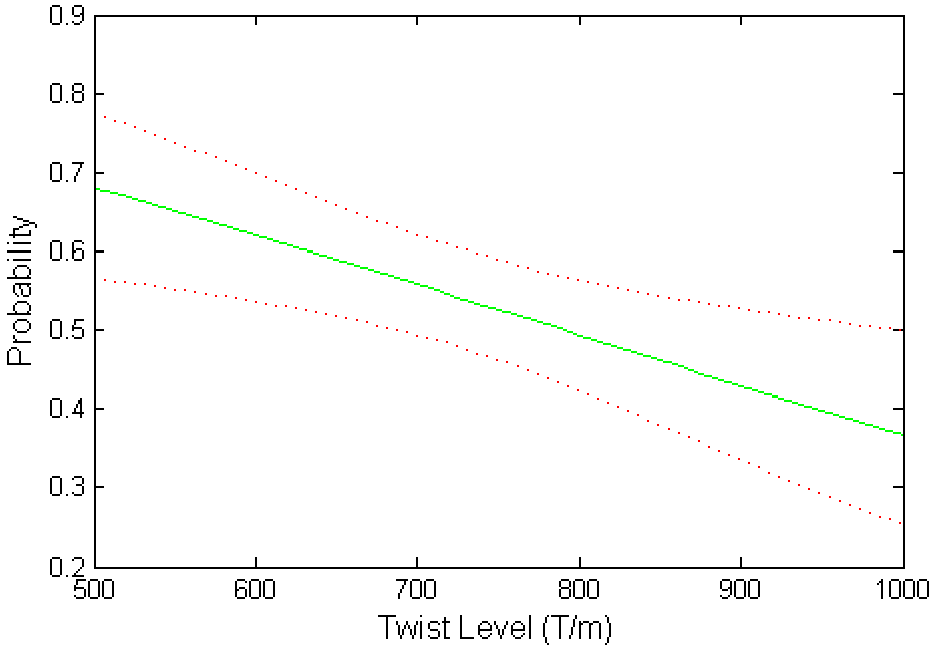

Figure 5.56. Effect of twist level on failure probability in Model of Type III Machines.

Estimated coefficient of $MSub_1$ has originally positive values. While failure probability of reference subgroup is 0.37, failure probability of subgroup 1 is 0.53 (Figure 5.57). Switching from reference to subgroup 1 of machines, end breakage increases 0.16. Taking also the prediction intervals into consideration, this is a significantly large value, showing that spinning quality of subgroup 1 machines is significantly lower than those of the rest of the machines. In Figure 5.58, failure probability increases from 0.48 to 0.57 as machine age is increased. Even if machine age does not cause a dramatic change, it still has an effect in the model. Estimated coefficients of main effects of roving count and yarn count are negative, but coefficient of their interaction term is positive. When roving count gets values between 1.4 and 2.1 Nm, yarn count is inversely proportional to probability of end breakage (Figure 5.59). If roving count gets values higher than 2.1, yarn count is directly proportional to probability of end breakage (Figure 5.60). This means that as feed roving gets thinner, i.e. roving count has high values, yarn count also increases, i.e. probability of end breakage drastically increases from 0.19 to 0.90. The studies conducted by Huang *et al.* (1994) and Prendzova (2000) show the similar results in relationship of yarn count and end breakage.

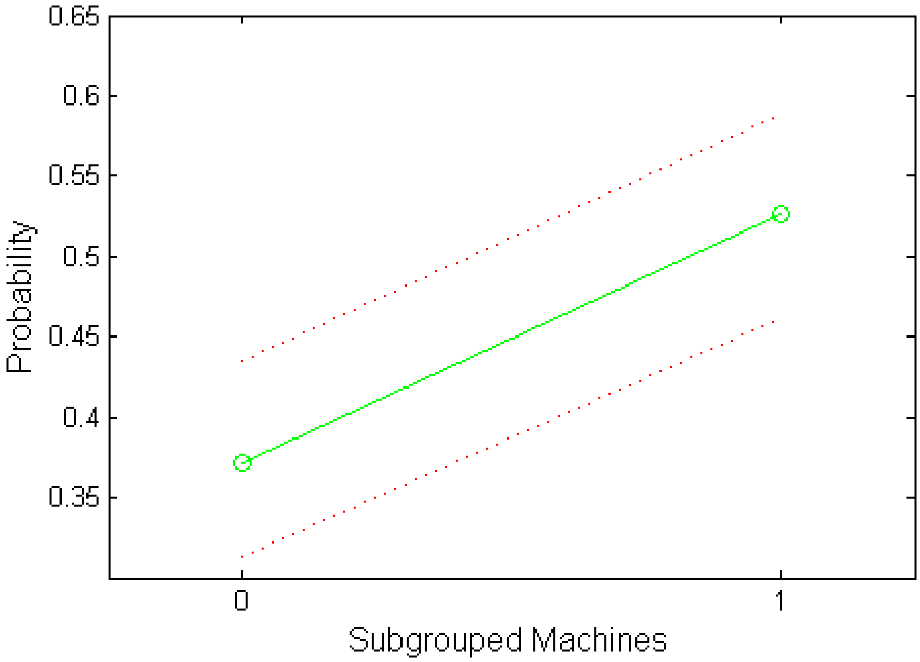

Figure 5.57. Effect of subgrouped machines on failure probability in Model of Type III Machines.

When yarn count gets values lower than 49 Nm, roving count is inversely proportional to failure probability until its median value (Figure 5.61). At values higher than median of roving count, confidence interval is too wide to safely interpret the resulting positive trend. When it is aimed to produce thick yarns, i.e. yarns have low counts, rovings with low roving count are fed and failure probability decreases. If yarn count gets values around 60 Nm, roving count is directly proportional to yarn count until its median value (Figure 5.62). When yarn count gets thinner, roving count increases and probability of end breakage increases. Furthermore, when yarn count gets high values, roving count increases until median and then decreases (Figure 5.63). However, this decrease is not reliable because of width of confidence interval. To produce a very thin yarn, high number of rovings is fed but in this situation, end breakage probability increases.

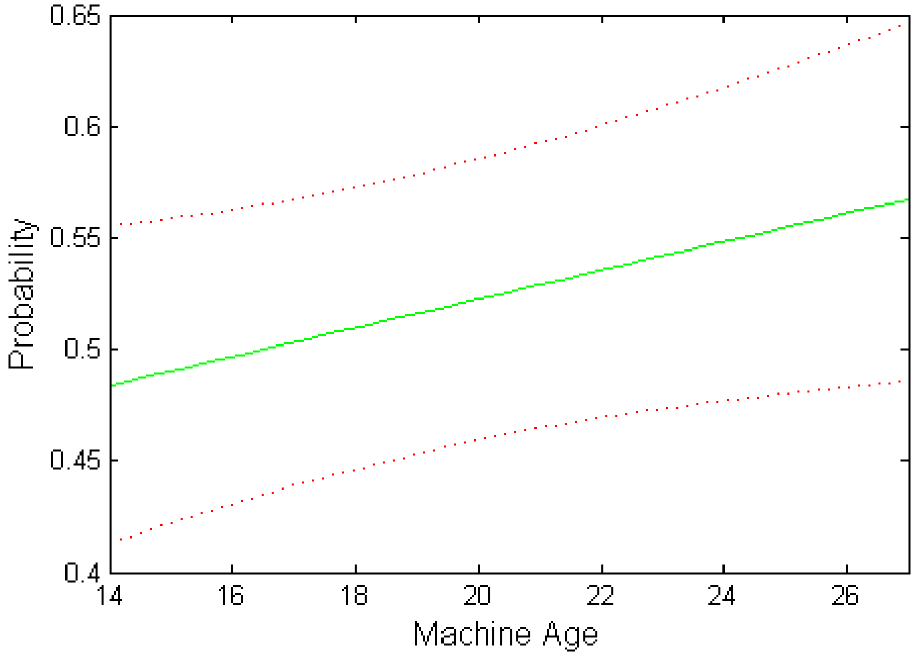

Figure 5.58. Effect of machine age on failure probability in Model of Type III Machines.

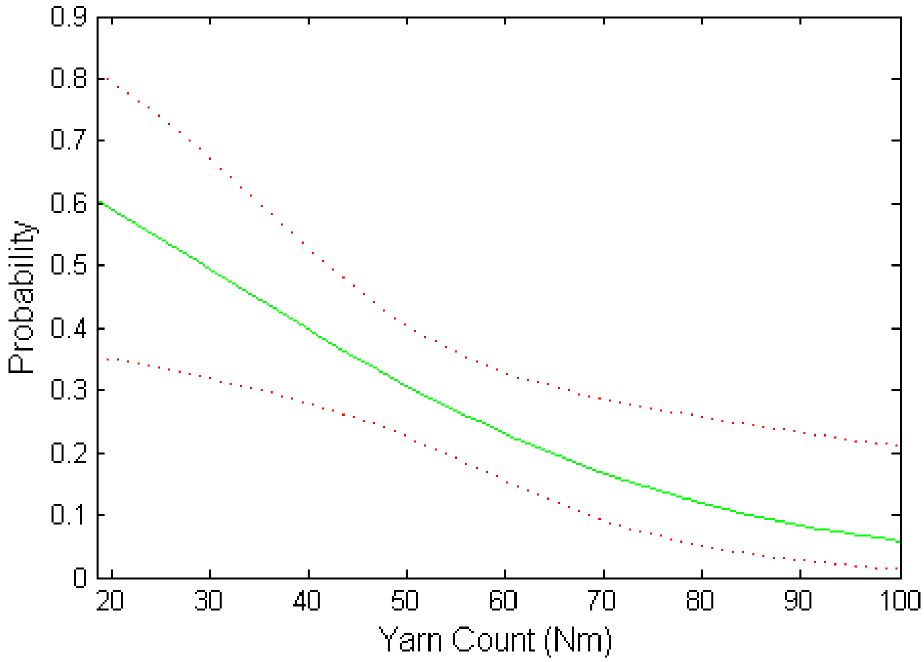

Figure 5.59. Effect of yarn count on failure probability at low values of roving count in Model of Type III Machines.

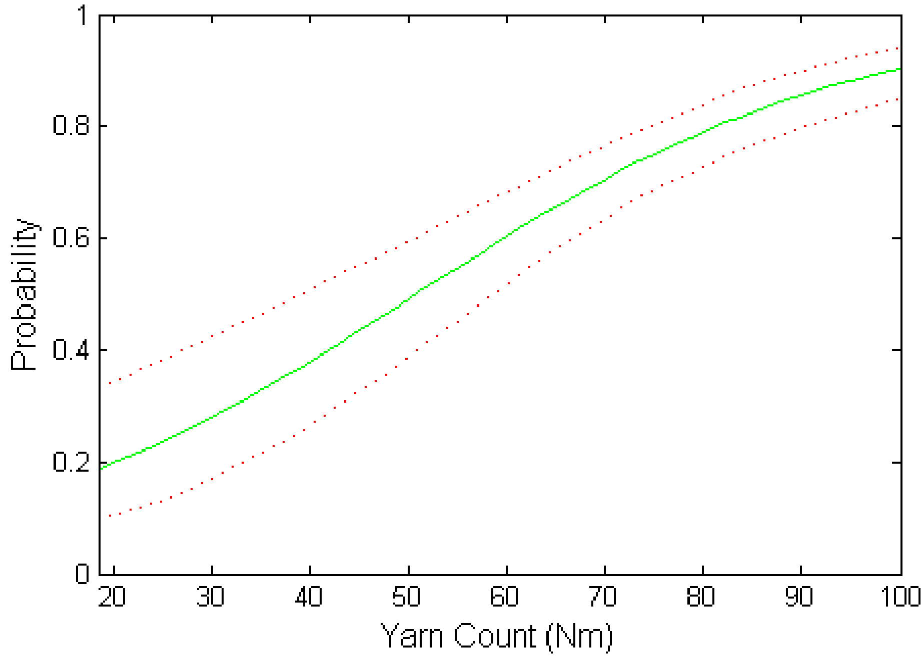

Figure 5.60. Effect of yarn count on failure probability at high values of roving count in Model of Type III Machines.

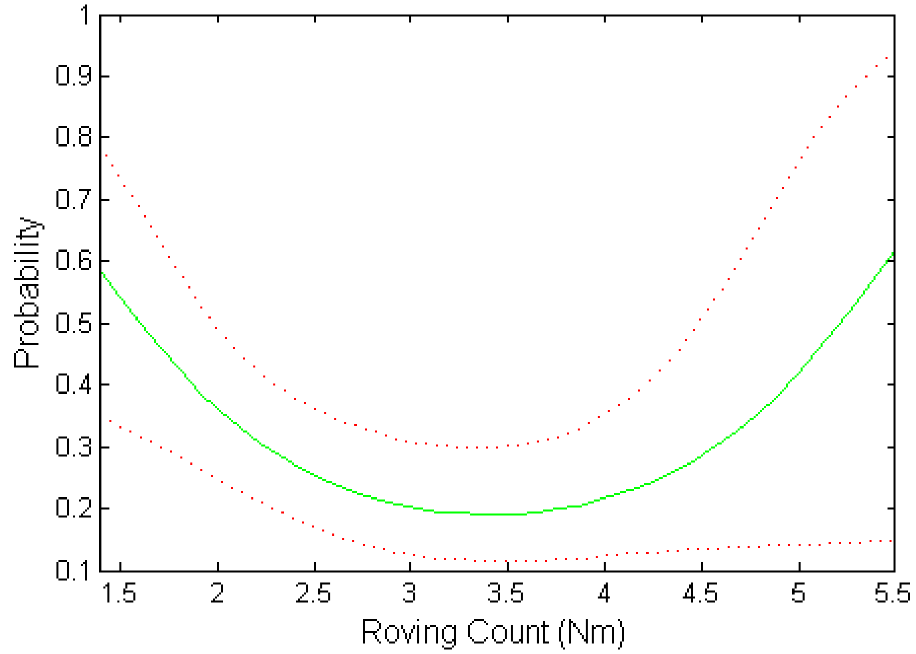

Figure 5.61. Effect of roving count on failure probability at low values of yarn count in Model of Type III Machines.

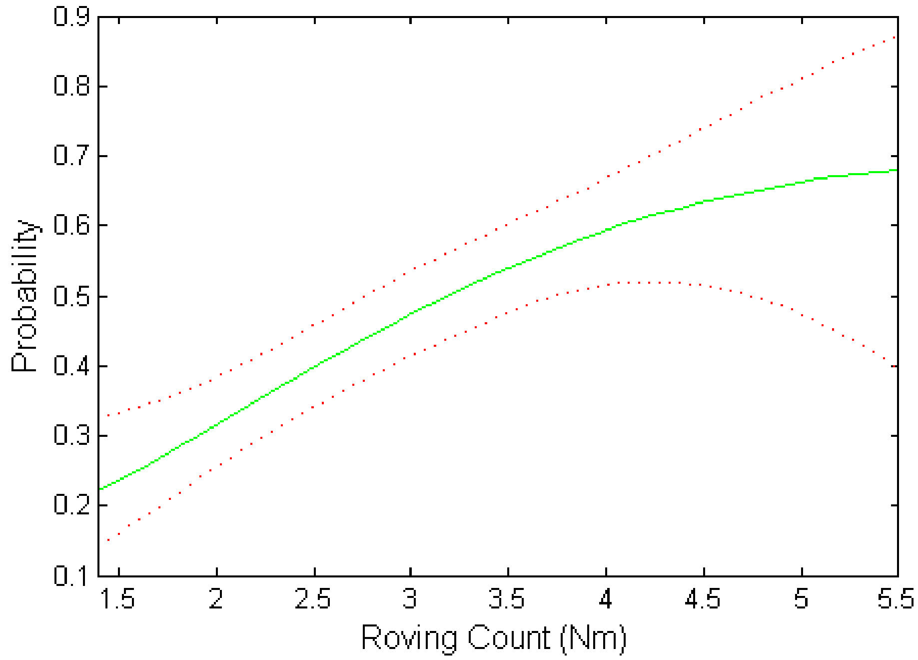

Figure 5.62. Effect of roving count on failure probability at moderate values of yarn count in Model of Type III Machines.

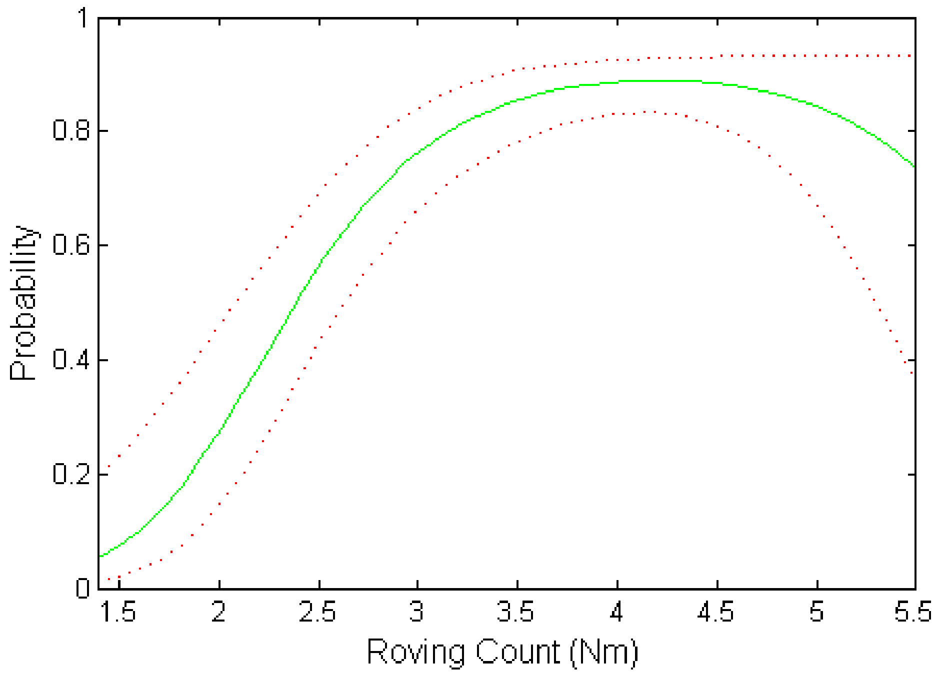

Figure 5.63. Effect of roving count on failure probability at high values of yarn count in Model of Type III Machines.

6. CONCLUSIONS AND RECOMMENDATIONS

The ring spinning process data from YUNSA are sampled from 2012 to 2014. Principal component analysis and correspondence analysis are used to describe the ring spinning process characteristics on reduced dimensions, while logistic regression analysis is used to model how failure (end breakage) probability changes with respect to process conditions.

Yarn production is mainly carried out in colors of ecru, black and dark blue and in compositions of 100% Wool and 43/53/4 Wool/PES/Lycra in type I machines (Zinser), which formed the majority of the machines. Doubled yarn (E-Siro) production rate is found higher than singled yarn production, while S and Z-twist directions rate of produced yarns were almost same. CA shows that for low values of lot sizes (0 to 500 kg), type I machines 2 to 4, and 6 to 15, type II machines 16, 17, 19, 20, and type III machines 27 to 30 were preferred. For lot sizes higher than 500 kg, runs were performed mainly in type I ring spinning machines 1, 5, 31 to 40, and 42 to 55, and type III machines 21 to 26. PCA shows that PC 1 accounts for the operation with high yarn counts (higher than 42 Nm), single yarns, Z direction of twist, high ring traveler number (greater than 24) and low spindle speed (lower than 9702) and PC 2 represents a collective change of roving count and twist level in the same direction but draft in the opposite direction. This results suggest that it is needed to decrease spindle speed and use high ring traveler number to produce thin yarns, and this enables ring spinning process to work safely. Twist direction is determined according to the intended use of the yarns and affects the handle of the fabric. If the aim is to produce fabric for men's suits, single yarns and Z direction of twist are preferred. Furthermore, if high roving counts are fed into ring spinning machines, it is essential to impart high level of twist and give low values of draft in order to transform fibers into yarn. Lot size does not contribute to the lowest indexed PCs, showing that continuous process conditions are adjusted independently of the ordered lot sizes.

Models for ring spinning machines are constructed based on machine types in spinning mill using logistic regression. Hence, three models were obtained in order to predict the end breakages. The predictive powers of the regression model constructed for the first, second and third types of machines, area under its ROC was found to be 0.66, 0.70 and 0.75 with optimal true positive and false positive rates as 0.64 and 0.40, 0.67 and 0.40, and 0.65 and 0.28, respectively. In recent years, various researchers (Beltran *et al.*, 2004; Beltran *et al.*, 2006; Majumdar and Majumdar, 2004; Majumdar and Sarkar, 2005; Ureyen and Gurkan, 2008; Dayik, 2009; Furferi and Gelli, 2010) have indicated an interest in the use of ANN in order to predict the relationships between yarn properties. The relation of ring spinning process variables with number of end breakage is highly nonlinear; for this reason, the prediction performance of ANN models was found superior than that from regression models in these studies. On the other hand, it should be noted that ANN does not give an explicit functional representation between input and the output variables. Furthermore, instead of a high-resolution model on the number of end breakages, a low-resolution model on a simpler quality control variable, i.e. whether the spun ring meets the demands or not, may be more practical both for industrial applications, and for modeling, since this model would eliminate the need to estimate the whole nonlinear manifold. Hence, in the current study, logistic regression on the probability of faulty products is preferred over ANN models and linear regression models on the number of end breakages.

In all logistic models, lot size, roving count, yarn count, and color are significant and common. The probability of faulty products increases especially in the production of the colors of blue and dark blue in all machines. In the production of Wool/Nylon blends in type II and III of ring spinning machines, end breakage probability is higher compared to the blends of Wool/PES. In all machines, end breakages decreases with increasing the lot size. Since lot sizes are not correlated with the process variables, one may say that during of a spinning process run is proportional to the lot size i.e. the higher the lot size, the longer is the duration of the run. From this perspective, decreasing of the probability of end breakages for higher lot sizes may be explained by referring to “warming up” of the machines, i.e. when the lot sizes are higher, machines are operated for a longer time, decreasing the probability of end breakage.

Draft is found significant only for type II machines. Even if machine age does not cause a dramatic change in the failure probability, there is a subtle effect of type III machines, which vary between 14 to 27 years of age: fault probability increases for "older" machines. Relation between ring traveler number and yarn count is found to be significant for type II machines. When ring traveler number is around median, yarn count increases so end breakage probability increases from 0.17 to 0.68. Moreover, if ring traveler number gets values higher than 27.6, yarn count decreases so end breakage probability decreases from 0.80 to 0.48.

Roving count and yarn count affect failure probabilities not only via main effect terms, but also through interaction and quadratic terms. Furthermore, directions and magnitudes of these effects may change for different types of machines, showing that the relation of roving count and yarn count with end breakages may be highly nonlinear. In type II and III of machines, as yarns get thinner, end breakage probability may increase even more than 0.7. This result is compatible with the study of prediction of end breakage rate performed by Huang *et al.* (1994), which showed that end breakages increase as yarn count increases. Furthermore, Prendzova (2000) examined the effect of cotton yarn properties on end breakage and found the similar result that yarn count and end breakage are directly proportional to each other.

Failure probability decreases (from 0.58 to 0.19 in second type of machines, from 0.68 to 0.37 in third type of machines) according to twist level changes. The results indicate that increase in twist level has positive impact on end breakage due to enable strength to the yarn. Huang *et al.* (1994) found similar results in their study. They correlated twist and breaking strength and found that when twist level increased, breaking strength increased. Huang and Oxenham (1994) indicated that breaking strength of yarn was inversely proportional to end breakage rate.

Ring spinning machines are divided into various subgroups in all models. It is found that some machines have higher failure probability compared to others which can be referred as problematic machines. The problematic machines are identified as following: type I machine 36, type II machines 18, 19, 41, and type III machines 24, 27.

In the current study, a descriptive analysis method to summarize operating conditions of a multivariate yarn spinning process, consisting of quantitative and nominal operating variables, and a logistic regression method to predict the quality of the product from the process variables are proposed. Descriptive analysis may be extended using multiple correspondence analysis (Abdi and Valentin, 2007), the multivariate version of correspondence analysis, on multiple nominal variables. Using these proposed methods in textile industry, overall manufacturing trend can be evaluated and revised, if necessary, and the end breakage rates may be reduced via examining the process conditions and machines, for which failure probability is higher. Future study is required to improve the prediction performance of the model via including other of process variables in the logistic regression model. Furthermore, there are other quality variables such as breaking strength and breaking elongation of yarns, yarn tenacity, unevenness, thin and thick places, important for establishing the yarn quality; logistic regression models may also be constructed for these variables.

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