DYEING PROCESS PARAMETER OPTIMIZATION AND QUALITY CHARACTERISTICS MODELING FOR VISCOSE BLENDED KNITTED FABRICS

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2016

UNIVERSITY OF MALAYA

ORIGINAL LITERARY WORK DECLARATION

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Registration/ Matric No: **KHA 120162**

Name of Degree: **DOCTOR OF PHILOSOPHY**

Title of Thesis

DYEING PROCESS PARAMETER OPTIMIZATION AND QUALITY CHARACTERISTICS MODELING FOR VISCOSE BLENDED KNITTED FABRICS

Field of Study: **Manufacturing Processes**

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ABSTRACT

The demand of viscose knitted fabrics is increasing rapidly due to its lower price and exclusive quality characteristics. In latest epoch of globalization, customers demand high quality products, lowest price and shorter lead time for product development and delivery. However, traditional knitting & dyeing process consists of trial and error approach which is time consuming, less efficient, cost ineffective and produces fabrics of inferior quality. Moreover, automatic control of knitting & dyeing process are developing slowly due to the complexity of that manufacturing process. Process optimization and quality characteristics modeling is one of the most viable and efficient alternative technique to meet the customers requirement.

Conventional trial-and-error approaches, full factorial experimental design as well as artificial neural network (ANN) and genetic algorithm for optimization did not succeed due to the large volume of works, longer experimental time and huge raw material availability. In this context, Taguchi method is an efficient tool for process optimization in quality engineering. Moreover, various factors affecting the quality characteristics of knitted fabrics are non-linear and interactive with each other's. In this background, Fuzzy logic (FL) is a scientific and engineering solution for quality modeling because FL model performs remarkably well in non-linear domain with smallest amount of experimental data.

The main objectives of this study were to optimize the dyeing process parameters and develop mathematical model for the prediction of color strength of viscose/lycra blended knitted fabrics through Taguchi method as well as develop intelligent prediction models for color strength of viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics and bursting strength of viscose/lycra blended knitted fabrics using fuzzy logic approach.

Further the aim was to build ANN prediction model to compare the fuzzy models performance and a resin finishing model for controlling the dimensional stability of viscose jersey knitted fabrics by fuzzy technique.

It was found from experimental study that viscose/lycra blended knitted fabrics color strength is approximately 60 % stronger while bursting strength is approximately 100 % weaker than that of cotton/lycra blended knitted fabrics. Further, color fastness of dyed fabrics depends more on the type of reactive dyes and dyeing method rather than washing parameters and type of fibers. The optimal factors in the viscose/lycra blended knitted fabrics dyeing process were found to be dye concentration 9 %, Time 60 minutes, temperature 75 ^{o}C, salt concentration 50 g/l, alkali concentration 14 g/l and liquor ratio 1:8. Further, coefficient of determination (R^2) and mean absolute error (MAE) between the experimental results and that predicted by the Taguchi mathematical model were found to be 0.921 and 3.48 %, respectively. It was concluded that Taguchi method was successful for optimization and prediction in complex dyeing. Furthermore, it was found that fuzzy models exhibit excellent prediction performance for viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics with less than 5 % MAE and coefficient of determination (R^2) more than 0.984. Additionally, ANN model showed superior prediction performance than fuzzy model and fuzzy resin finishing model was highly effective for maximum shrinkage control with minimum loss in bursting strength for viscose plain knitted fabrics.

ABSTRAK

Permintaan fabrik dikait KWS meningkat dengan cepat kerana harganya yang lebih rendah dan ciri-ciri kualiti yang eksklusif.Dalam zaman globalisasi terkini, pelanggan menuntut produk berkualiti tinggi, harga yang paling rendah dan masa memimpin pendek untuk pembangunan produk dan penghantaran. Walau bagaimanapun, mengait & pencelupan tradisional proses terdiri daripada percubaan dan kesilapan pendekatan yang memakan masa, kurang cekap, kos efektif dan menghasilkan fabrik berkualiti rendah. Selain itu, kawalan automatik mengait & pencelupan proses membangunkan perlahan-lahan kerana kerumitan proses pembuatan. Pengoptimuman proses dan kualiti ciri-ciri model adalah salah satu teknik alternatif yang paling berdaya maju dan berkesan untuk memenuhi keperluan pelanggan.

Pendekatan cuba-ralat konvensional, reka bentuk uji kaji faktorial lengkap serta rangkaian neural tiruan (ANN) dan algoritma genetik untuk pengoptimuman tidak berjaya disebabkan oleh jumlah besar kerja-kerja, lebih lama masa eksperimen dan besar ketersediaan bahan mentah. Dalam konteks ini, kaedah Taguchi adalah alat berkesan untuk pengoptimuman proses dalam bidang kejuruteraan yang berkualiti. Selain itu, pelbagai faktor yang mempengaruhi ciri-ciri kualiti fabrik dikait adalah bukan linear dan interaktif antara satu sama lain. Dalam latar belakang ini, logik kabur (FL) adalah penyelesaian saintifik dan kejuruteraan untuk pemodelan kualiti kerana model FL melakukan amat baik dalam domain bukan linear dengan jumlah yang paling kecil daripada data eksperimen.

Objektif utama kajian ini adalah untuk mengoptimumkan dan membangunkan model matematik bagi proses pencelupan melalui kaedah Taguchi serta membangunkan model ramalan untuk kekuatan warna KWS, kapas dan kain lyocell rajutan dan kekuatan penuh KWS rajutan kain yang menggunakan pendekatan logik kabur.

Lagi tujuannya adalah untuk membina ANN model ramalan untuk membandingkan prestasi model kabur dan model resin penamat untuk mengawal kestabilan dimensi KWS Jersi fabrik dikait dengan teknik kabur.

Ia didapati daripada kajian eksperimen bahawa kekuatan warna kain KWS adalah lebih kurang 60 % lebih kuat manakala penuh kekuatan adalah lebih kurang 100 % lebih lemah berbanding dengan kapas. Di samping itu, peningkatan kubu warna untuk kain dicelup didapati sangat kecil selepas tiga basuhan. Faktor-faktor yang optimum dalam proses pencelupan KWS didapati kepekatan pewarna 9 %, Masa 60 minit, suhu 75 ^{0}C, kepekatan garam 50 g /l, kepekatan alkali 14 g /l dan nisbah minuman keras 1: 8. Di samping itu, pekali penentuan (R^2) dan min ralat mutlak (*MAE*) antara keputusan eksperimen dan yang diramalkan oleh model matematik yang Taguchi didapati 0.921 dan 3.48 % masing-masing. Ia telah membuat kesimpulan bahawa kaedah Taguchi berjaya untuk pengoptimuman dan ramalan dalam pencelupan kompleks.

Tambahan pula, didapati bahawa model kabur mempamerkan prestasi ramalan yang sangat baik untuk KWS, kapas dan kain lyocell dikait dengan kurang daripada 5 % *MAE* dan pekali penentuan (R^2) lebih dari pada 0.984. Selain itu, model ANN menunjukkan prestasi lebih baik daripada ramalan model kabur dan kabur resin model kemasan adalah amat berkesan untuk mengawal pengecutan maksimum dengan kerugian minimum dalam penuh kekuatan untuk KWS fabrik dikait biasa.

ACKNOWLEDGEMENT

First of all, I would like to thank to almighty ALLAH (SWT)) who gave me the courage and determination for materializing my dream to complete this thesis successfully.

I would like to acknowledge my sincere gratitude and thank to my respected main supervisor Prof. Dr. Imtiaz Ahmed Choudhury for his constant inspiration, encouragement, support, advice and invaluable guidance towards write up of the thesis. Without his scholastic criticisms, enthusiastic assistance, trustworthy interest and valuable suggestions as well as above all continuous supervision throughout the period of this research, I could not conclude this thesis.

I would also like to express thanks to my second supervisor Dr. Azuddin Bin Mamat for his advice and valuable comments to make this thesis much more informative.

I would also like to express my deepest gratitude and indebtedness to my former main supervisor Dr. Md Altab Hossain for his untiring inspiration, encouragement, support, advice, wholehearted assistance and valuable direction throughout the period of this research.

I would also like to express my deepest gratitude and thanks to the Chairman Md Hasib Uddin and Managing Director Shamim Reza of Textile research laboratory APS, APS Group, Dhaka, Bangladesh for providing the laboratory facilities to conduct this research investigation.

My sincere thanks to the staff of Textile research laboratory APS, APS Group, Dhaka, Bangladesh, mainly Mr. Shahin, Mr. Sultan, Mr. Mohsin, Mr. Sattar, Mr. Mustafiz and Mr. Hafiz for their patience, help and kindly assistance during my studies.

There are many others people whom I would like to thank for their help and support during my study in University of Malaya, Malaysia especially Mr. Rakib, Mr. Morshed, Mr. Harizom, Mr. Sazzad, Mr. Saifullah, Mr. Enamul, Mr. Kader, Mr. Arafat, Mr. M.A Malek, Mr. Zia, Mr. Farhad and Mr. Wakil for their assistance.

I would like to thank to Associate Prof. Dr. Shamsuddin, Associate Prof. Dr. Abdush Shahid, Associate Prof. Abdul Hannan and Prof. Dr. Ayub Nabi Khan for their guidance, help and useful discussion during my studies.

Finally, I would like to give my best gratitude to my parents, wife and son for their love, patience and understanding support throughout my studies, especially to my wife Ferdousi Rahman and my son Md Yasir Arafat.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	:	Artificial Neural Network
ANFIS	:	Adaptive - Neuro Fuzzy Inference System
AC	:	Alkali Concentration
ANOVA	:	Analysis of Variance
BS	:	Bursting Strength
CS	:	Color Strength
CI	:	Confidence Interval
CT	:	Curing Time
CE	:	Confirmation Experiment
DC	:	Dye Concentration
DT	:	Dyeing Time
DOE	:	Design of Experiment
DP	:	Degree of Polymerization
FG	:	Fabric GSM
FL	:	Fuzzy Logic
GSM	:	Grams per Square Meter
H	:	High
HM	:	High Medium
L	:	Low
LR	:	Liquor Ratio
LS	:	Length way-Shrinkage
LM	:	Low Medium
M	:	Medium
MAE	:	Mean Absolute Error

MH	:	Medium High
OA	:	Orthogonal Array
PT	:	Process Temperature
RC	:	Resin Concentration
RMS	:	Root Mean Square
RSM	:	Response Surface Methodology
SL	:	Stitch Length
S/N	:	Signal to Noise Ratio
SC	:	Salt Concentration
S/J	:	Single Jersey
TDOE	:	Taguchi Design of Experiment
TM	:	Taguchi Method
VVL	:	Very Very Low
VL	:	Very Low
VH	:	Very High
VVH	:	Very Very High
WS	:	Width way Shrinkage
YC	:	Yarn Count
YT	:	Yarn Tenacity
K/S	:	Color Strength
K	:	Light absorption coefficient
S	:	Light scattering coefficient
R	:	Reflectance value of dyed material
Cell-OH	:	Cellulose
$D\text{-}SO_2\text{-}CH{=}CH_2$	:	Vinyl sulphone dye

R^2	:	Coefficient of determination
R	:	Correlation Coefficient
Avg	:	Average
SS_F	:	sum of square of a factor
SS_T	:	Total sum of square
DOF	:	Degree Of Freedom
n_m	:	Mean of total S/N ratio
P_F	:	Percentage contribution
μ_i	:	Membership function of i rule
b_i	:	Position of the singleton in the i^{th} universe
P_v	:	Predicted value
E_v	:	Experimental value

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The major copious fibers used in the world are the cellulose fiber. Cellulose fibers provide comfort, outstanding water absorbency, wide-ranging use, and are completely biodegradable (Agarwal, 2014; Siller et al., 2013; Yolacan, 2009). There are two sources of cellulosic fiber, one which is acquired directly from the natural resources such as cotton; and others which are regenerated from the wood of trees such as viscose, modal, cupramonium, and lyocell fiber. Wood pulp is a renewable resource and is not appropriate for food manufacturing (Agarwal, 2014).

The main starting material for viscose fiber is high grade wood pulp in the shape of pressed sheet which contain primarily cellulose with a logically high degree of polymerization (DP). Viscose fibers are manufactured using this pressed sheet with warm 18 % aqueous sodium hydroxide solution and about 10 % of their weight of carbon disulphide (Broadbent, 2001a; Yolacan, 2009). Now a day, viscose has found diversified usefulness particularly in apparel, high value application, household materials etc. because of its similar properties with cotton and in several cases better than cotton. Specifically, viscose fiber with advanced tenacity is often used in technical textiles. On the other hand, viscose is more absorbent and extremely reactive than others cellulosic fiber. Gorgeous, rich brilliant color can be dyed on viscose fiber fabric owing to its better absorbency (Bahtiyari et al., 2009; Broadbent, 2001a; Shaikh et al., 2012).The viscose fiber are renewable, sustainable, biodegradable, biopolymer, and have excellent moisture (more than cotton), moderate dry strength and abrasion resistance (Agarwal, 2014; Broadbent, 2001a; Roggenstein, 2011; Shaikh et al., 2012).

The replacement of cotton by viscose fiber can get better environmental friendliness. Viscose fiber reduces water consumption and has 10 times higher production than that of conventional cotton fiber. Additionally, for the cultivation of viscose fiber, no need pesticides and fertilizers which have toxic impact on the fresh water and soil, while it is necessary for cotton production (Agarwal, 2014).

Knitting is one of the major fabrics production methods among others two weaving and non-weaving methods (Hussain et al., 2015; Jamshaid et al., 2013). In recent time, the demand of knitted fabrics especially the knitted fabrics made of viscose is increasing rapidly owing to its lower price and extraordinary quality characteristics like rich brilliant color, superior moisture (greater than cotton), comfy to wear, spongy to the skin, elasticity, drape, wrinkle resistance and easy-care properties more than cotton knit and woven fabrics. Besides, due to their unique quality characteristics compared to woven fabrics and cotton knitted fabrics, viscose knitted fabrics are typically preferred for apparel wears such as T-shirts, shirts, sweaters, blouses, underwear, casual wear, active wear and sportswear (Degirmenci and Topalbekiroglu, 2010; Hussain et al., 2015; Hussain et al., 2013; Jamshaid et al., 2013). There have been various properties of knitted fabrics like physical, mechanical and color properties. The physical and mechanical properties comprise the fabric areal density as GSM (grams per meter square), loop density, tightness factor, thickness, drape, dimensional stability, air permeability and bursting strength. Further, color strength, color fastness and color difference values are the fundamental color properties (Murugesh and Selvadas, 2013).

Bursting strength (BS) is one of the significant physical and mechanical properties of the viscose plain knitted fabrics (Jamshaid et al., 2013; Pamuk, 2015). Knitted fabrics are not just rendering forces in the vertical and perpendicular directions but also they are exposed to multi axial forces during dyeing, finishing and their usage.

Testing tensile and tearing strength in the wale and course directions in knitted fabrics are not suitable because of the structural properties, hence testing bursting strength turns into extremely important particularly for knitted fabrics before manufacturing. Generally, the bursting strength test is performed to evaluate the fabric's capability to withstand multi axial stresses without breaking off (Jamshaid et al., 2013; Mavruz and Ogulata, 2010; Unal et al., 2012).

In addition, Dyeing is the third important but most complex process others than the weaving and spinning processes in the textile manufacturing which combines with science of chemistry, physics, mechanics, physical chemistry, fluid mechanics and thermodynamics (Hussain et al., 2005; Kuo and Pietras, 2010; Shaikh, 2010; Shamey and Nobbs, 1998; Zeydan and Toga, 2011).Viscose regenerated cellulosic fiber can be dyed by the same dye types as for other cellulosic fiber, such as cotton and lyocell. However, Reactive dyes are the most popular for dyeing of viscose fiber on the commercial scale due to their affordable prices, brilliancy of shades, good tinctorial value and plausibly good fastness properties (Agarwal, 2010).

The color strength and color fastness are the basic and most important color properties to the consumers among all the dyed knitted fabrics qualities. However, color strength/color shade variation in dyed fabrics is one of the most common reasons of second-grade fabrics quality and rejection in the textile dyeing industry, causing delay for delivery schedule and massive yearly losses in profits for shade correction and re-dyeing (Ashraf et al., 2014). Subsequently, it has been found from the past study that a shade correction and a re-dyeing raise the overall product costs at a dye house by approximately 30 % and 70 – 130 %, respectively (Kuo and Pietras, 2010). Additionally, based on many years of experience in the textile dyeing and apparel occupation, it has been seen that notwithstanding all other qualities within the acceptable limit, buyers do not accept any piece of export quality garment in a minor deviation of color shade and poor color fastness of their requirements. For this reason, control of color shade/color strength and color fastness is the important matter in the dyeing process.

Furthermore, poor dimensional stability has been familiar as a severe trouble in viscose knit wear even after decades of developments in modern manufacturing method (Agarwal et al., 2011). Although almost the entire single-knit structures have a large propensity to shrink but single-knit structures made of viscose fiber can shrink extremely, mainly in length direction, owing to its relatively lower crystalline and more amorphous structure than that of cotton fiber (Broadbent, 2001a; Hussain et al., 2013).

A lot of methods have been employed to overcome the poor dimensional stability of knitted fabrics. Among them decreasing the loop length of knitted fabrics, application of elastomeric yarns, tumble drying and mechanical compaction methods improve the dimensional stability. But all these processes limit their use for improving dimensional stability (Candan and Onal, 2003; Karmakar, 1999; Safdar et al., 2014). Application of resin finishing process in this regard is a further potential solution for improving and controlling the dimensional stability problem of the viscose jersey knits (Hussain et al., 2013; Lo et al., 2009). However, application of resin rigorously deteriorates the bursting strength of treated fabrics. Moreover, resins make the fabrics stiffer and harsh hand feel. Application of softening agent with polyethylene emulsion in this regard can help in retaining fabrics strength.

Conventional hit and trial experimental approach did not succeed in this regard due to huge loss of time and resources. Therefore; in such cases a critical balance has to be maintained to attain optimum dimensional stability in viscose knits, with minimum loss in fabric bursting strength (Hussain et al., 2013).

1.2 Problem Statement

The quality of fabrics is considered an especially big issue in many parts of the world in the today's textile and apparel market. In latest era of globalization; customers demand diversified and high quality fashionable products with minimum prices as well as shorter lead time for product development and delivery (Ngai et al., 2014). However, the traditional knitting & dyeing process consists of trial and error approach which is time consuming, less efficient, cost ineffective and produces fabrics of inferior quality (Kuo and Pietras, 2010). Moreover, automatic controls of knitting & dyeing processes are developing slowly because of the complexity of that manufacturing process (Hussain et al., 2005; Shamey and Nobs, 1998).

To meet the increasing demand for quality, fashion, marketability as well as reduce process time and production cost, the manufacturers are applying more competent machinery, new process technologies and new improved quality raw materials (Fazeli et al., 2012; Kuo and Pietras, 2010; Zavareh et al., 2010). Process optimization and quality characteristics modeling on the other hand is one of the most feasible and competent alternative technique for efficient control of the critical factors which has a substantial impact on the reduction of process time and production cost as well as productivity improvement (Fazeli et al., 2012; Kuo and Pietras, 2010; Kuo et al., 2008; Zavareh et al., 2010; Zeydan, 2008).

However, earlier researches were not professionally capable to optimize the dyeing process parameters and develop intelligent model for the prediction of quality characteristics of viscose/lycra blended knitted fabrics because of the high degree of variability in raw materials, multistage processing and a lack of precise control on process parameters among others (Guruprasad and Behera, 2010; Hatua et al., 2014; Vadood, 2014).

The literature review exposed a number of efforts concerning process optimization in the complex dyeing. Conventional trial-and-error approaches as well as single factor variable at a time for optimization did not succeed to present an in general design of parameters because of the large volume of works as well as very tough to find the interactive effects. Moreover, full factorial experimental design involves big number of experiments, longer experimental time and huge raw material availability which are expensive as well as hard to control (Chary and Dastidar, 2010; Fazeli et al., 2012; Kuo et al., 2008; Zavareh et al., 2010). In contrast, statistical models and intelligent models such as artificial neural network (ANN) and genetic algorithm (GA) need enormous amount of experiments for optimization (Fie et al., 2013; Jamshaid et al., 2013; Majumdar and Ghosh, 2008).

In this context, Taguchi method is the efficient tool for process optimization in quality engineering which uses a special design of orthogonal arrays to study the whole process parameters space with only a small number of experiments and provides an efficient, simple and systematic methodology for optimization in a faster and economic way as well as determines the main factors affecting the process response (Chary and Dastidar, 2010; Fazeli et al., 2012; Kumar and Karimi, 2014; Krishankant et al., 2012; Kuo et al., 2008; Mavruz and Ogulata, 2010; Pamuk, 2015; Su and Kuo, 2015). Taguchi optimization is faster and economic than GA. Taguchi method utilize statistical tool like ANOVA to analyze the results, whereas ANN and GA approaches have no such kind of statistical tool to scrutinize the results (Fie et al., 2013).

It has been found in the past study that the different factors affecting the fabrics physical and mechanical properties are yarn type, yarn count, yarn tenacity, yarn breaking elongation, yarn breaking strength, yarn twist, yarn evenness, fabric wale and courses, knitting stitch length, cover factor, tightness factors and relaxation treatment, fabrics GSM, number of feeders and gauge of knitting machine (Ertugrul and Ucar, 2000; Jamshaid et al., 2013; Mavruz and Ogulata, 2010; Pamuk, 2015; Unal et al., 2012).

In addition, various research have been reported on the factors affecting the color properties of knitted fabric including dye concentration, temperature, time, pH, salt concentration and material to liquor ratio (Fazeli et al., 2012; Zavareh et al., 2010; Zeydan and Toga, 2011). Further, factors involving with optimal shrinkage controlling with desired bursting strength are concentration of cross linking agent, concentration of softener and curing time in resin finishing process. Hence, control of the process parameters during diverse arena of knitting, dyeing and resin process is a significant issue in order to obtain the final products as per customers' requirement (Murugesh and Selvadass, 2013).

Moreover, all these factors perform non-linearly and interactive with one another, hence it is very challenging for scientists and engineers to control the knitting-dyeing processes and accordingly not easy to create an exact model as well as functional relationship between process parameters and quality characteristics (Ertugrul and Ucar, 2000; Huang and Yu, 1999; Jamshaid et al., 2013; Majumdar and Ghosh, 2008; Unal et al., 2012).

Over the past decades, a variety of models such as mathematical models, statistical models and intelligent models namely ANN and ANFIS models have been developed and applied for the prediction of fabric quality characteristics like color strength, fastness, levelness, pilling resistance, tensile strength, bursting strength and dimensional properties (Afzal et al., 2014; Ashraf et al., 2014; Fazeli et al., 2012; Hagighat et al., 2014; Hatua et al., 2014; Jamshaid et al., 2013; Moezzi et al., 2015; Unal et al., 2012).

The mathematical models developed by some researchers (Fazeli et al., 2012; Frydrych, 1992; Mavruz and Ogulata, 2010; Zavareh et al., 2010) in related studies have been based on the original theories of basic science and assumptions or simplifications. Hence, prediction accuracy of the mathematical model is not very encouraging (Majumdar and Ghosh, 2008).

The statistical models on the other hand, established by a number of investigators (Afzal et al., 2014; Ashraf et al., 2014; Hussain et al., 2013; Jamshaid et al., 2013; Kuo and Pietras, 2010; Quadir et al., 2014) have been used in similar research. However, statistical models limit the user by requiring a large amount of sample data (Hill et al., 1994) as well as prior information or estimation of any mathematical model in advance is important for developing a statistical model (Majumdar and Ghosh, 2008). Moreover, both the mathematical and statistical models are unable to capture the non-linear relationship between inputs and outputs (Hatua et al., 2014).

Alternatively, the intelligent techniques such as ANN and ANFIS models have the ability to model in non-linear domain have been applied by several researchers (Azimi et al., 2013; Hussain et al., 2015; Haghighat et al., 2014; Hatua et al., 2014; Kan et al., 2013; Moezzi etal., 2015) in areas linked to this study. Nevertheless, these ANN and ANFIS models are trained using massive amounts of noisy experimental data for parameters optimization which are labor intensive and time consuming process to accumulate from the knitting and dyeing industries (Jamshaid et al., 2013; Majumdar and Ghosh, 2008). In addition, ANN does not tell the core logic based on which decisions are taken (Hatua et al., 2014).

In this background, fuzzy logic (FL) is the scientific and engineering solution for quality modeling as fuzzy logic performs remarkably with small amounts of experimental data in non-linear, ill-defined, trial-error and complex textile domain (Hossain et al., 2011; Huang and Yu, 1999; Majumdar and Ghosh, 2008; Snehal et al, 2013; Vadood, 2014). Moreover, a fuzzy logic model is more reasonable, cheaper in design cost and frequently easier to apply in comparison to other models (Hatuaet al., 2014; Majumdar and Ghosh, 2008; Nasrullahzadeh and Basri, 2014; Snehal et al, 2013; Vadood, 2014).

Therefore, the main objectives of this study were to optimize the dyeing process parameters and develop mathematical model for the prediction of color strength of viscose/lycra blended knitted fabrics through Taguchi method as well as develop intelligent models for the prediction of color strength of viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics and bursting strength of viscose/lycra blended knitted fabrics by fuzzy logic approach**.** Further, the aim was to build ANN prediction model for the color strength of viscose/lycra blended knitted fabrics in order to investigate the fuzzy models performance and develop fuzzy resin finishing model for controlling the dimensional stability of viscose jersey knitted fabrics. The overall objectives of this research have been discussed in section 1.4.

1.3 Research Gap

Various studies from interdisciplinary areas of textile which describe to controller development as well as process optimization and modeling by mathematical, statistical, ANN and ANFIS methods for different textile materials. Despite lots of studies in textile manufacturing, there are still few gaps for research which are listed as follows:

I. A lot of study has been reported on process and properties of different textile materials like fiber, yarns and fabrics of cotton, polyester, acrylic, wool, lyocell, nylon and their blended woven and knitted fabrics. However, there is no literature available on studying the effects of different processing variables on the properties of viscose fabrics and compared with cotton fabrics.

II. In the past study, various mathematical models, statistical models as well as intelligent models such as ANN, ANFIS and genetic algorithm (GA) have been applied for process optimization and quality characteristics modeling of aforesaid textile materials.

III. In the literature, various efforts such as decreasing knitting loop length, tumble drying, mechanical compaction, application of resin finishing and elastomeric yarns as well as few statistical modeling technique have been reported to overcome the poor dimensional stability of viscose knitted fabrics.

However, it was seen from statement II and III that no work has been conducted on the optimization of the dyeing process parameters through Taguchi method and modeling quality characteristics by using fuzzy logic approach for viscose/lycra blended knitted fabrics.

1.4 Research Objective

The study is investigated on the optimization and modeling for viscose/lycra blended knitted fabrics. The main purpose of this study is to improve products quality with reduced process time in textile manufacturing industry. The precise objectives of the present work comprise:

(i) To study the effects of process variables on the fabric properties of viscose/lycra and compare with that of cotton/lycra blended knitted fabrics in textile manufacturing.

(ii) To optimize the dyeing process parameters and develop mathematical model for the prediction of color strength of viscose/lycra blended knitted fabric through Taguchi method.

(iii) To develop intelligent models for the prediction of color strength and bursting strength of viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics by Fuzzy logic approach and compare the models performance for viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics.

(iv) To develop ANN prediction model for color strength of viscose/lycra blended knitted fabrics for comparison of fuzzy model performance and fuzzy resin finishing model for controlling the dimensional properties of viscose jersey knitted fabric.

1.5 Research Methodology

The research is based on a theoretical analysis of different textile materials with the optimization of the dyeing process parameters, formulation of mathematical model, development of fuzzy intelligent and ANN prediction models as well as experimental investigation. The dyeing process parameter optimization and development of mathematical model has been based on the dye concentration, dyeing time, temperature, salt concentration, alkali concentration and liquor ratio through Taguchi approach. Further, fuzzy intelligent models have been developed for the prediction of color strength of viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics and bursting strength of viscose/lycra blended knitted fabrics. Additionally, an ANN prediction model has been built for the prediction of color strength of viscose/lycra blended knitted fabrics and compared with fuzzy model in terms of prediction accuracy as well as a resin finishing model has been constructed for controlling the dimensional properties of viscose jersey knitted fabrics via fuzzy technique. Finally, several experiments and prediction analysis have been conducted to investigate the models performance. Detailed methodology will be discussed in Chapter three. However, the overall research activities have been presented as flow chart in Figure 1.1

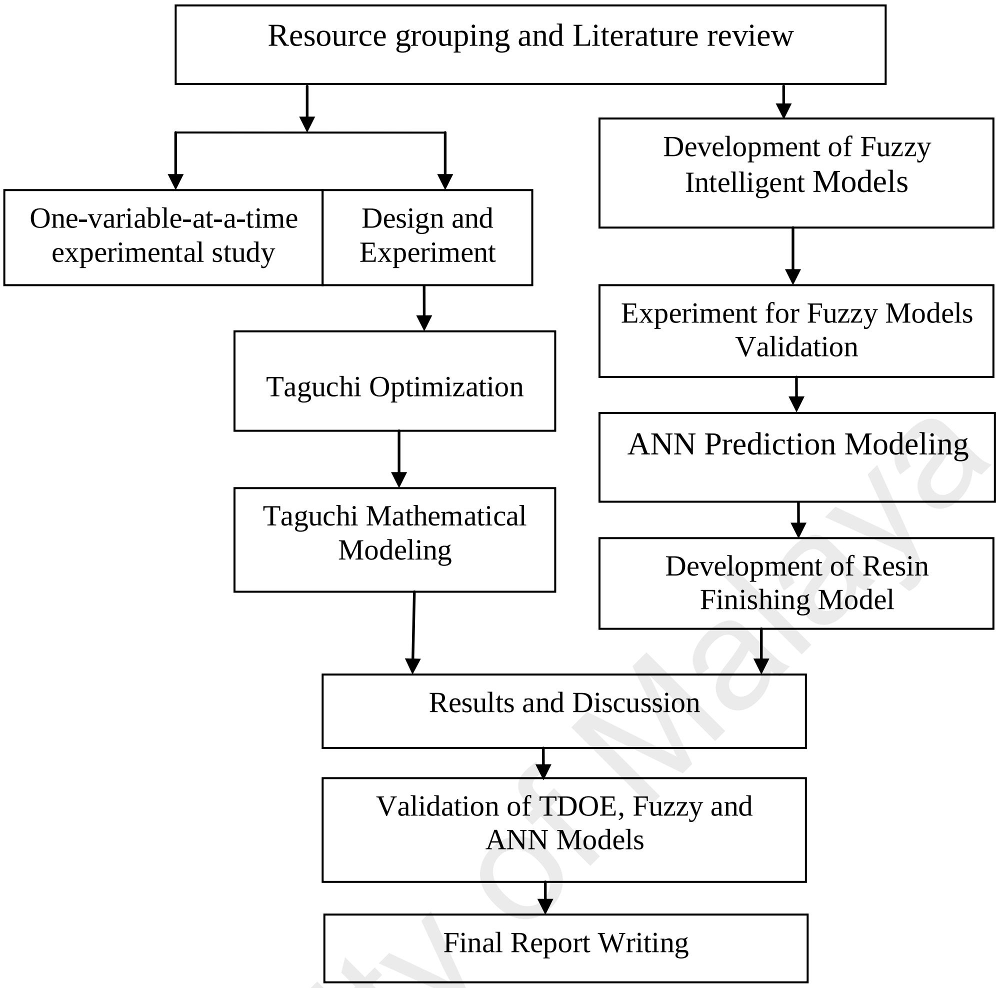


Figure 1.1: Flow chart of research work

1.6 Organization of the Thesis

In Chapter 1, Introduction, problems statement, research gap, objective, research methodology and organization of the Thesis have been discussed.

In Chapter 2, a brief discussion of viscose, knitted fabrics, fabric quality, knitting; different pre-treatment process, dyeing and Taguchi method, Response surface methodology, Fuzzy logic and ANN models are presented.

In Chapter 3, experimental set up used to study the effect of different process conditions. Taguchi design of experiment for optimization & mathematical modeling and development of Fuzzy intelligent models for viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics and ANN prediction model as well as resin finishing model have been discussed.

In Chapter 4, effects of the different process conditions have been discussed. The results and discussion of Taguchi optimization & mathematical model along with Fuzzy intelligent models for viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics as well as ANN prediction model and resin finishing models have been presented. The results are discussed in graphical formation as well as in tabular forms.

In Chapter 5, conclusions are reached; recommendations are made for future study into optimization and modeling of knitted fabric manufacturing.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The purpose of this literature review chapter is to provide previous information on the issues to be considered in this study and emphasize the relevance of the present study. This section reviews the history of viscose fiber, comparison of fiber properties with respect to cotton and lyocell fiber, knitting & knitted fabrics, quality characteristics of knitted fabrics, dyeing, development of Taguchi design of experiment, Fuzzy logic model and ANN prediction model as well as their application and limitations in Textile and dyeing**.** Subsequently, the aim of this literature survey is to find the suitable methodology for dyeing process parameters optimization and quality characteristics modeling for viscose/lycra blended knitted fabrics. At the end of this chapter, summary of the literature review are presented.

2.2 Viscose Fiber and Its History

Rayon is the fundamental name used for viscose fiber manufactured from regenerated cellulose (Shaikh et al., 2012). Primarily, the chronological augmentation of viscose was initiated by an "artificial silk" hypothesis. An English naturalist Robert Hook established first "Artificial Silk" theory in 1664. Subsequently, British scientist Cross and Bevan discovered the first viscose method for regenerated cellulose manufacturing in 1891. Afterward, Courtaulds Ltd manufactured the initial saleable viscose fiber in 1905. The American viscose company in 1910 firstly called rayon as "Artificial silk" and many others name. Finally, in 1924, a committee formed by the department of commerce of the government of America and various commercial organization decided upon the name "rayon" for "Artificial silk".

It was called rayon because of two reasons: either because of its brightness and similarity in structure with cotton (sun = ray, on = cotton). The name of viscose has been originated from the word “viscous”. As a consequence modern cellulose offshoot has acquired the current name of “Viscose rayon”. The main beginning substance used in order to manufacture the viscose fiber is good quality wood macerate in the structure of pressed pieces (Broadbent, 2001a; Howard, 1986; Misra, 2010; Shaikh et al., 2012).

2.2.1 Manufacturing of viscose fiber

The first in viscose manufacturing is isolation of cellulose from the wood. For this purpose, the logs are de-barked and then chipped into small pieces. The pulping process that is carried out next is designed to remove as much lignin, hemicelluloses and other extractable materials as possible, while avoiding degradation of cellulose, though some controlled degradation is allowed in order to produce cellulose of desired DP. The next step is bleaching to remove any residual lignin, which can be carried out by a process that avoids the uses of chlorine. The final products consisting of 90 - 94 % of α–cellulose and residual hemicellulose is formed into perfectly white sheet (Mather and Wardman, 2011). The overall manufacturing flow chart of viscose fiber has been presented in Figure 2.1.

(i) Soda –cellulose preparation

The high DP (Degree of Polymerization) purified wood pulp which restrains 90 – 94 % cellulose in the form of pressed sheet is the key initial material for viscose fiber manufacturing. The cellulose sheets are shredded and their moisture content is adjusted to 50 %. These pulp sheets are immersed in a big tank containing warm 18 % aqueous sodium hydroxide, where sheets swell as the alkali reacts chemically with the hydroxyl groups of the cellulose to form soda cellulose (Broadbent, 2001a; Mather and Wardman, 2011).

$$\mathrm{Cell-OH + NaOH \rightarrow Cell-O^{-}Na^{+} + H_2O} \qquad \text{Scheme (2.1)}$$

(ii) Xanthation

The soda cellulose is separated from the steeping lye by pressing and then shredded to obtain a bulky, reactive product. The shredded crumbs are next aged in air at ambient temperature for up to 24 hours. The soda celluloses are then fed into churns and rotated under vacuum, where carbon disulphide (CS_2) is gradually added. The CS_2 reacts with the soda cellulose to form soda cellulose xanthate, which is bright orange in color (Mather and Wardman, 2011).

$$\mathrm{Cell-O^{-}Na^{+} + CS_2 \rightarrow Cell-O-CS-S^{-}Na^{+}} \qquad \text{Scheme (2.2)}$$

Side reactions can also occur:

$$\mathrm{CS_2 \ + NaoH \rightarrow 2Na_2CS_3 + Na_2CO_3 + 3H_2O} \qquad \text{Scheme (2.3)}$$

$$\mathrm{Na_2CS_3 + 6NaoH \rightarrow 3Na_2S + Na_2CO_3 + 3H_2O} \qquad \text{Scheme (2.4)}$$

These side reactions are more significant at higher temperatures, whereas lower temperature require longer time to achieve complete Xanthation. As a compromise a temperatures between 25 – 37 ^{0}C is used, with times for 30 - 90 minutes.

(iii) **Ripening**

The sodium cellulose xanthate solution obtained is somewhat big in molecular size which is not simple to spin by a spinneret. Hence, this xanthate solution is dissolved in 1 – 2 % sodium hydroxide solution at 8 – 12 ^{0}C to give an orange - brown spinning solution, which is then aged for a further 1 - 3 days until it reaches the correct viscosity and "ripen index" for extrusion (Mather and Wardman, 2011).

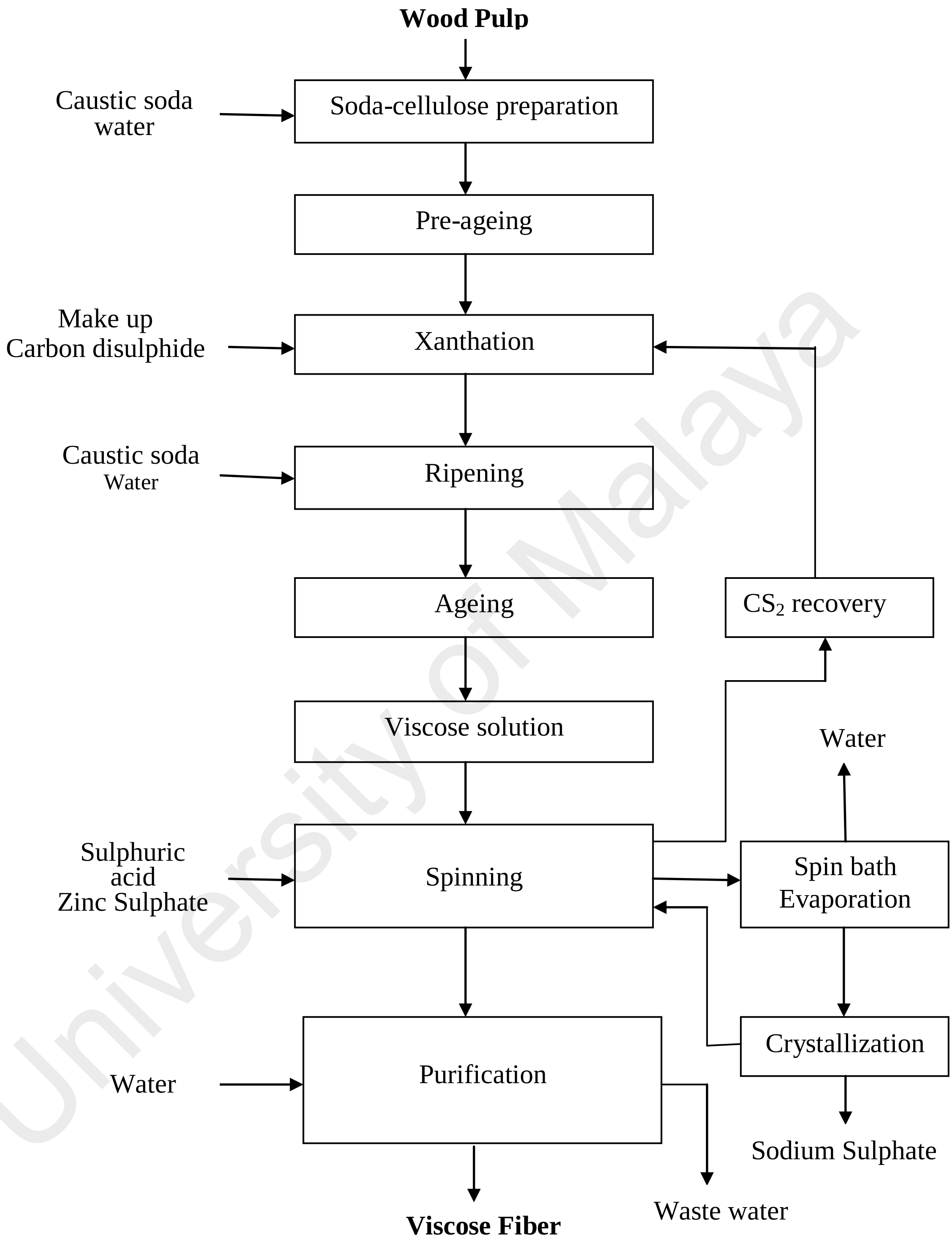


Figure 2.1: Process of viscose rayon regeneration

(iv) Spinning

The ripe viscose solution is at last degassed and filtered in preparation for wet spinning. Subsequently, the solutions of soda cellulose xanthate are extruded into a bath containing 10 % sulphuric acid, 18 % sodium sulphate and 1 % zinc sulphate to coagulate the cellulose xanthate, which followed by of hydrolyses to restructure cellulose. The chemical reactions take place in the coagulation bath can be represented as:

$$2\text{Cell} - \text{O} - \text{CS} - \text{S}^{-}\text{Na}^{+} \; + \; \text{H}_2 SO_4 \; \rightarrow 2\text{Cell} - \text{OH} + 2\text{CS}_2 \; + \; \text{Na}_2\text{SO}_4 \quad \text{Scheme (2.5)}$$

The existence of zinc sulphate support fiber strength and consequences in serrated cross section. The divalent zinc ion is considered to create a weak cross-link between adjacent cellulose xanthate anions:

$$\text{Cell} - \text{O} - \text{CS} - \text{S}^{-} \ldots \text{Zn}^{2+} \ldots {}^{-}\text{S} - \text{CS O} - \text{Cell} \qquad \text{Scheme (2.6)}$$

The still plastic filaments overtake around and are expanded in the middle of rotating pulleys. The careworn filaments may be congregate in a Topham box, or wound up on perforated tubes to form bobbins.

(v) Purification

The filaments produced lead to several after treatment to attain pure viscose fiber. It is systematically washed and treated with dilute sodium sulfide to remove any sulfur impurities (Broadbent, 2001a; Misra, 2010; Shaikh et al., 2012; Yolacan, 2009).

2.2.2 Types of viscose fiber

Basically, Viscose fibers are four types**:**

(i) Regular viscose:

It is classically found in apparels and home furnishing application. Usually, Viscose means regular viscose. Regular viscose becomes unstable and may stretch or shrink when wet due its low wet strength. The fabric made from regular viscose is recommended for dry cleaning to preserve the appearance. In case of machine washing, without treated regular viscose can shrink up to 10%. Among all the viscose's, regular viscose has the largest market share (Shaikh et al., 2012).

(ii) **High wet modulus (HWM) viscose:**

It is a modified viscose that has similar properties like regular viscose but only difference in high wet strength. High wet modulus viscose can be machine washed and tumble dried. It exhibits much similar end-use properties like cotton. It can be mercerized like cotton for increasing strength and lusture. In case of apparel, HWM viscose is frequently used as "Polynosic rayon" or the trade name MODAL^{TM} (Shaikh et al., 2012).

(iii) High tenacity viscose:

It is also a modified regular viscose to provide outstanding strength as two times that of HWM viscose. Its main application is in the tire cord and industrial end-use. High tenacity viscose may be finished by chemically coated or rubberized for protection from moisture and potential loss of dimensional stability and strength during use (Shaikh et al., 2012).

(iv) Cupramonium viscose:

It is another type modified viscose and its properties like regular viscose. There is some difference in the manufacturing process from regular viscose and it is fewer environments friendly. As a result, Cupramonium viscose production in the world market is no more (Shaikh et al., 2012).

2.2.3 Properties of viscose fiber

a) Physical properties

Viscose has superior stretchy properties at trivial elongations and greater luster as compared to cotton. It end to bloat very much in water and undergo greater elongation under tension in both the wet and dry states due to less crystalline and oriented than cotton. The moisture regain of viscose is notably superior in comparison to the cotton due to wide-ranging amorphous regions in viscose. In wet condition, viscose fiber enlarges equal to 5% in length and distends capable of twice its dimensions. The heat conductivity and electrical properties are identical as cotton. Viscose is chilly to handle, and static charges do not generate in the fiber at humidity's larger than 30%. The specific gravity of viscose is same as cotton and varies between 1.50 and 1.54 (Agarwal, 2014; Broadbent, 2001a; Shaikh et al., 2012). The overall comparison of physical properties of viscose and cotton are presented in Table 2.1 (Broadbent, 2001a; Shaikh et al., 2012).

Table 2.1: Comparison of physical properties of viscose and cotton

Property	Unit	Viscose			Cotton
		Regular viscose	Polynosic Rayon	HWM Rayon	
Degree of Polymerization		250-300	450-500	450-500	1500-3000
Cross section		Serrated	Round	N.A	Bean shaped
Moisture regain	(%)	11-14			6-8
Density	(gm/cc)	1.50			1.52
Diameter	microns	15,20,25			
Recovery from Stretch (2%)	(%)	85 Poor	95 Good	95 Good	98 Good

b) **Chemical properties**

The chemical properties of viscose are fundamentally identical to cotton. Cold dilute or concentrated alkali has no severe effect on viscose, but hot dilute acids and alkali have significant effect on viscose at a rate faster than cotton. Viscose is extensively assailed by hydrogen peroxide in larger concentration but resistant to oxidizing bleach agents. If viscose is exposed to sunlight for longer time causes degradation of cellulose chains and loss of strength of the fiber (Broadbent, 2001a; Shaikh et al., 2012).

c) **Mechanical properties**

The dry and wet tenacities of the viscose vary with tenacities of 18 to 54 g/tex dry and 9 to 36 g/tex wet. The great loss in strength of wet regular tenacity viscose makes it subject to scratch for the period of laundering. The percentage elongation at break varies from 10 to 30 % dry and 15 to 40 % wet. The recovery at 2 % elongation ranges from 70 to 100 %. In general, the viscose has significantly higher elongations at break than observed for cotton (Agarwal, 2014; Broadbent, 2001a; Roggenstein, 2011; Shaikh et al., 2012). The different cellulose fibers mechanical properties are demonstrated in Table 2.2 (Broadbent, 2001a; Shaikh et al., 2012).

Table 2.2: Comparison of different cellulose fibers mechanical properties

Property	Units	Lyocell	Viscose	Modal	Cotton
Titre	dtex	1.7	1.7	1.7	-
Dry tenacity	cN/tex	40-42	22-26	36-38	20-24
Elongation at break /dry	%	14-16	20-25	11-13	7-9
Wet tenacity	cN/tex	34-38	10-15	28-30	26-30
Elongation at break/ wet	%	16-18	25-30	12-14	12-14
Water imbibition	%	65	90	70	50
Cellulose DP		550-600	290-320	450-500	2-3000
Initial wet modulus	cN/tex (5% ext)	270	50	210	100
Moisture regain	%	11.5	13	12.5	8

2.2.4 Application of viscose fiber

After discovered in 1891, viscose was manufactured simply on a small scale for typically application of decorative purposes such as imitation flowers or small ornaments on the dresses. Afterward, it was used for domestic items. Nowadays, due to their similarity characteristics with cotton and some places superiority on cotton fiber are used in manufacturing various products, ranging from home furnishings to outwear and value addition applications purposes. Viscose is used both as 100% viscose fiber but is sometimes blended with other textile fiber such as cotton, polyester, wool, nylon, spandex lycra etc. The following are the application areas of viscose and its blended fabrics (Agarwal, 2014; Shaikh et al., 2012).

(i) Home furnishing

The marvelous moisture absorption and silk-like aesthetic with superb drape and feel so property of viscose fiber make it widely used in home furnishing items such as bed covers, mattresses, blankets, curtains, draperies, sheets, slip covers, tablecloths, and upholstery etc.

(ii) **Apparels**

Textile apparel from causal to office wear is made of Viscose fabric. Most of the textile apparel especially denim knitwear and woven fabric are composed of 100% Viscose and its blended materials. Viscose fabric is soft and comfortable. It has well drapes properties which is one of the desirable properties for an apparel fabric. There are many popular textile apparels which are made of viscose such as blouses, dresses, saris, jackets, lingerie, linings, millinery (hats), slacks, sport shirts, sportswear, suits, ties, work clothes.

(iii) **Nonwoven fabrics**

The most important use of viscose is in non-woven fabrics, where absorbency is important. Nonwoven fabric such as medical swabs and dressings, hygienic absorbents, wipes, coating bases, leather substitutes, filters, interlinings, diskette liners, battery separators, disposable and other semi-durable apparel are composed of viscose fiber. These disposable products are biodegradable.

(iv) **Technical textile**

A diversity of technical products are made of high-tenacity viscose fiber such as reinforcement to mechanical rubber goods, applications within the aerospace, agricultural and textile industries, braided cord, tapes, etc.

(v) Sports

Many sports wears are made of viscose fabric. Viscose fabric is ideal for sportswear because its individual nano-fibrils regulate the absorption and release of moisture (1.8 liter of water per hour). The space between the body and the performance textile remains dry. In addition, enjoyable coolness and smooth surface of the viscose prevent skin irritation

(vi) Hygienic fabrics

Viscose is the most absorbent of all cellulose fibers, even more so than cotton and linen (table 1). Because of this, viscose absorbs perspiration and allows it to evaporate away from the skin, making it an excellent summer fabric. Its high absorbency applies equally to dyes, allowing beautiful, deep, rich colors. Thus it is preferred for crepe, gabardine, suiting, lace, outer wear fabrics and linings for fur coats.

2.2.5 Advantages of viscose fiber

Viscose has a silk-like artistic with excellent swathe and feel and keep hold of its rich brilliant colors. Their cellulosic based provide many properties like those of cotton or other natural cellulosic fibers. The viscose fibers are renewable, sustainable, biodegradable, biopolymer, antibacterial, and have excellent moisture absorbent (higher than cotton), moderate dry strength and abrasion resistance (Agarwal, 2014; Broadbent, 2001a; Roggenstein, 2011; Shaikh et al., 2012). The replacement of cotton fiber by Viscose fiber can develop the environmental friendliness. Viscose fibers diminish water consumption and have 10 times higher production than that of conventional cotton fiber. Additionally, for the cultivation of Viscose fiber, no need pesticides and fertilizers, which have toxic impact on the fresh water and soil; while it is essential for cotton production (Agarwal, 2014).Viscose is breathable, comfortable to wear, and simply dyed in vivid colors. It does not make static electricity, nor will it pill if not the fabric is made from short, low-twist yarns. Viscose is comfy, soft to the skin. Akin to other cellulosic fibers, it is not elastic, which implies that it will crumple. Viscose withstands ironing temperatures slightly less than those of cotton. It may be attacked by silverfish and termites, however usually defies insect damage. It will mildew, although that normally is not a trouble. One of viscose's strengths is its adaptability and aptitude to blend simply with a lot of fibers—now and then to decrease cost, further times for lusture, softness, or absorbency and consequential comfort. Viscose has moderate resistance to acids and alkalis and usually the fiber itself is not damaged by bleaches; however, dyes used in the fabric may experience color change. As a cellulosic fiber, viscose will burn, yet flame retardant finishes can be applied. Accordingly viscose's properties are more comparable to those of natural cellulosic fibers like cotton (Shaikh et al., 2012).

2.2.6 Blending of viscose fiber

As demand for comfortable and adaptable clothing has burgeoned in recent decades, the use of incorporated elastane in knitted fabrics has increased. Fabrics incorporating elastane exhibit increased extensibility, elasticity, a high degree of recovery, good dimensional stability and require only simple care. Further, blending makes it possible to build in a combination of potential properties. In blends of viscose fiber with synthetic fiber like lycra, the synthetic component provides crease recovery, dimensional stability, tensile strength, bursting strength, abrasion resistance and easy care properties, whilst the viscose cellulose fiber contribute moisture absorption, antistatic characteristics and reduced pilling. Rayon has been used more and more in blends with synthetic fibers, since rayon undergoes less degradation than cotton with durable press and wash-and-wear finishes (Cuden et al., 2013; Gokarneshan and Thangamani, 2013; Howard, 1986;Shilpa et al., 2007).

2.3 Concept of Knitting and Knitted Fabrics

2.3.1 Knitting

Knitting is one of the major fabrics production methods among others two weaving and non- weaving methods (Jamshaid et al., 2013; Mavruz and Ogulata, 2010). Knitting technology includes all processes that are necessary to manufacture knitted fabrics. Knitting is produced by a series of loops, intermeshing in rows and every one hanging from the last. In a knit structure, every loop is called as a stitch; a vertical row of stitches is called wale and a horizontal row of stitches is called course. Knitted fabrics are produced by two general methods such as weft knitting and warp knitting (Shahbaz et al., 2005).

(a) Weft knitting method

(b) Warp knitting method

(a) Weft knitting method:

Continuous yarn is used in weft knitting for forming courses and rows of loops (Mavruz and Ogulata, 2010). Weft knitting comes in three basic stitches such as plain knit, rib knit, and purl knit. Weft knitting produces both circular in addition to flat fabrics. Weft is a yarn that runs back and onward. Weft knitting, each needle loops into its thread. With this loop, the weft knitting produces parallel rows, and the loops are also interlocked as shown in Figure 2.2.The fabrics having weft knitting are highly draped able and elastic. Weft knitting fabric produces in tubular or flat form is not that easy to untie. In weft knitting, needles just knit in a series for each yarn. Weft knitted fabric produced yardage as well as shaped garment (Spencer, 2001).

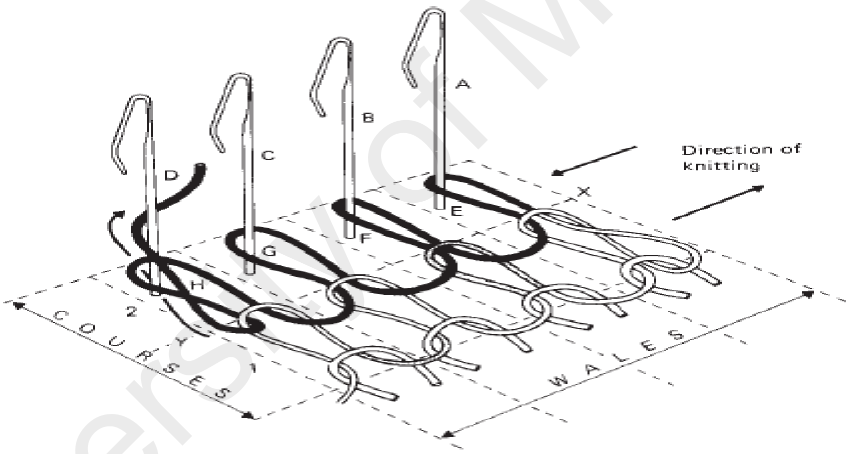


Figure 2.2: Weft knitting method (Spencer, 2001)

(b) Warp knitting method:

In wrap knitting yarn used are laid side by side upon one or more wrap (Shahbaz et al., 2005).The warp knitting comes in six stitches like: Tricot Knit, Milanese Knit, Simplex Knit, Raschel Knit, Ketten Raschel Knit, and Crochet Knit. A warp is that which run up and down are depicted in Figure 2.3. In warp knitting, the needles knit simultaneously for yarns. Warp knitting produces only yardage and considered as fastest knitting (Spencer, 2001).

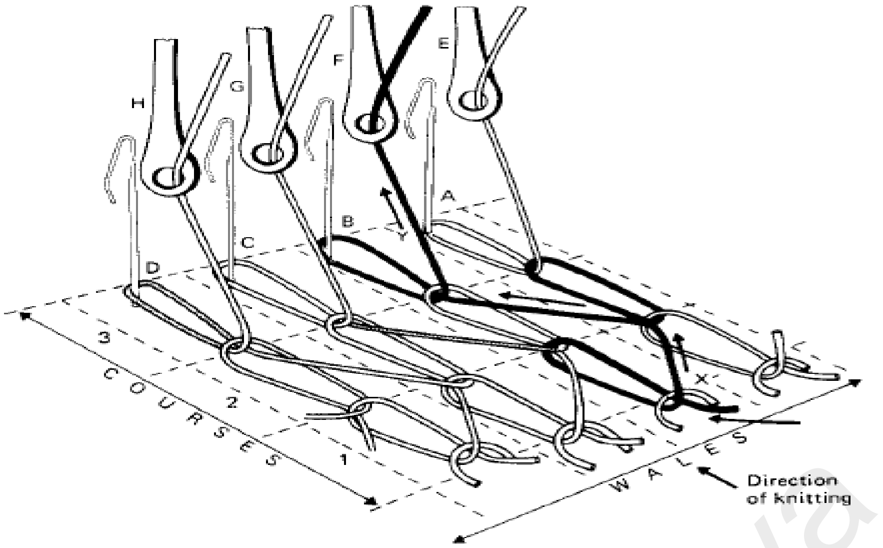


Figure 2.3: Warp knitting method (Spencer, 2001)

2.3.2 Knitted fabrics

Basically, Knitted fabrics are formed by intermeshing/ interlocking yarn loops with each other's in wale and course directions by means of needles (Shahbaz et al., 2005). Knitted fabrics can be made much more quickly and easily than woven fabrics at comparatively less cost. Knitted fabrics are generally light in weight, comfortable in wear even during travel, but yet require little care to keep their neat appearance. The tendency of knits to resist wrinkling is another factor to boost up their popularity. Knitted fabrics are used for designing active clothing such as sports clothing. Their elastic nature permits for abundant physical activity. They are made as flat or tubular fabrics depending on the end use. Tubular fabrics may not have any seams at the sides whereas flat fabrics are treated just like woven fabrics (Babor et al., 2005; Mavruz and Ogulata, 2010). Based on the fabric structure, knitted fabrics are Jersey knit, Rib knit, Double knit.

(a) Jersey knit: These fabrics are weft knitted and are distinguished by discrete other than flat vertical lines on the face and leading horizontal ribs on the reverse side. Fancy varieties are also produced. They are used in making hosiery sweaters, sportswear etc.

(b) Rib knit: These fabrics are made by using rib stitch with two sets of needles. These fabrics are used where stretch is desired as they show excellent degree of elasticity. Rib knits are warm to wear. They are used as apparels such as shirts, blouses, body stockings etc.

(c) Double knit: Double knits are produced by the interlock stitch. The fabric is riblike in appearance on both the sides. Decorative fabrics are also produced by jacquard attachment. These fabrics show good dimensional stability and are easy to cut and sew. They do not require any seam finishes as the fabric does not ravel. They are firm, heavier, less stretchable and more resilient. Double knits are commonly made from polyester, acetate or wool fiber. These fabrics are used as very durable apparel.

Example: Single jersey, Rib, Interlock, Pique and Fleece.

2.3.3 Quality characteristics of knitted fabrics

(i) Fabric GSM/Fabric areal density

The Fabric areal density in grams per square meter (GSM) is one of the most important physical properties among all the qualities of viscose knitted fabrics. Basically, GSM (gm/m^2) is the weight per unit area of fabrics and GSM is directly related to the fabric weight. For readymade garments, costing of a garment depends on the fabrics weight or fabrics GSM. Fabric GSM has great impact on the bursting strength, spirality, Air permeability, color strength etc. (Afzal et al., 2014; Jamshaid et al., 2013).

(ii) Bursting strength

The bursting strength is one of the most important physical and mechanical properties among all the viscose plain knitted fabrics qualities (Jamshaid et al., 2013). Fabrics are not only exposed to forces in the vertical and perpendicular directions but also they are exposed to multi axial forces during dyeing, finishing and usage. As a result, bursting strength is extremely important for plain knitted fabrics. Thus, it is further essential to predict the bursting strength of the knitted fabrics before its manufacturing. Generally, the bursting strength test is conducted to assess the fabric's ability to withstand multi axial stresses without breaking off (Ertugrul and Ucar, 2000; Jamshaid et al., 2013; Mavruz and Ogulata, 2010; Unal et al., 2012).

(iii) Dimensional properties

Dimensional stability is one of the important physical properties of plain jersey knitted fabrics especially made of cotton or viscose. It includes shrinkage and spirality of knitted jersey fabrics. Basically, shrinkage occurs in jersey knitted fabrics due to fiber properties, yarn properties and knit fabrics structure. In addition, the main problem of the single jersey construction is fabric spirality due to their unstable constructions and yarn twist liveliness, which affects all the fabric and produces huge troubles through the clothing stage as it affects the garment by displacing side seams (Safdar et al., 2014; Sreenivasan and Raj, 2009).

(iv) Air permeability (AP)

AP is a significant characteristic of clothing comfort which is defined as the rate of volume of air conceded vertically through a unit area of fabric at some pressure gradient over a unit time (Bedek et al., 2011). In other words, AP has been described as a function of porosity of the knitted fabrics. Basically, AP controls the thermal balance of the wearer by allowing the air to pass through the clothing, especially after exercise.

Subsequently, a variety of research have been reported on the parameters affecting the AP of knitted fabrics comprising fiber type, fiber fineness, fiber surface characteristics, yarn geometry, yarn count, yarn hairiness, loop or stitch length, tightness factor, fabric thickness, areal density, fabric porosity, size and shape of the fabric pores, environmental humidity, and laundering (Afzal et al., 2014; Bedek et al., 2011).

(v) Color strength (K/S)

The color strength is the depth of color of a dyeing per unit amount of dye in the material. Quantitative assessment is possible from measurement of the reflection spectrum of a sample of the dyeing and percentage of the dye (Broadbent, 2001). This value is material dependent and it varies between 0 to 30. Kubelka-Munk theory was established in 1930s, and most commonly used in the coloration engineering. Subsequently, the color strength (*K/S*) of dyed fabric can be calculated using Kubelka-Munk theory as shown in Equation 2.7 (Baumann et al., 1987):

$$\frac{K}{S} = \frac{(1-R)^2}{2R} \tag{2.7}$$

where, *K* is the light absorption coefficient, *S* is the light scattering coefficient and *R* is the reflectance value of dyed fabric.

In case of textile fabrics, it is supposed that the absorption (*K*) takes place by means of the dyes merely moreover scattering (*S*) due to the textile fiber. The rays of light are not simply reflected at the colored layer surface however some are refracted and internally reflected. The *K/S* value is proportional to the concentration of the dye and it is calculated in the visible spectrum. The *K/S* value at highest wavelength symbolizes the maximum color strength of the dyed sample. Since color strength is the ratio of light absorption coefficient *(K)* and light scattering coefficient (*S*), hence it is dimension less.

2.4 Pre-Treatment of Cellulosic Fabrics

Viscose and other cellulosic fabrics are pre-treated using diverse chemicals and process to increase the dye ability. Pre-treatment was carried out before the dyeing to eliminate the non-cellulosic impurities and boost the dye uptake. There are four general pre-treatment methods:

In textile wet processing, there are four general pre-treatment methods:

- Cationic fixing agent
- Plasma treatment
- Enzymatic treatment
- Alkaline treatment

2.4.1 Cationic fixing agent

Cationic fixing agents develop the quality of fixation and fastness of cationic dyed fabrics (Sharif et al., 2007; Wei et al., 2005). Cationic fixing agents include amines, quaternary ammonium, phosphonium and tertiary sulphonium salts are applied as dye fixing agents. The quaternary ammonium salt is one of the most frequently used cationic fixing agents among them. Depending on the type of dyes, fixing agents can be used before or after dyeing (Blackburn et al., 1998). It has been seen that reactive dyes provide superior results for cotton fabric pre-treated with 3-chloro-2 hydroxy propyltrimethyl ammonium chloride (CMAC) or its derivatives (triethyl, tripropyl, tripentyl and tetradecyl ammonium chloride) than an after treatment (Sharif et al., 2007).

2.4.2 Plasma treatment

In most cases, plasma treatments of textile substances alter the surface of the fiber in order to boost their surface wet ability, dye ability, fiber cohesion, dimensional stability, flame resistance, adhesive bonding, printability, electromagnetic radiation reflection, and surface hardness, hydrophilic and hydrophobic propensity (Cai et al., 2003; Devetak et al., 2012). In general, plasmas have free electrons, ions, radicals and neutral particles. Moreover, distinguishingly, plasmas are quasi-neutrality of the complete gas and be short of thermal equilibrium ensuing from the leading energy giving to the free electrons. Further, plasma treatments do not entail huge amount of chemicals and water. Plasma treatment is an ionized gas contains highly dynamic negative (electrons) and positive (proton) ions.

The treatment by plasma is incredibly strong to crash the organic bonds by using vacuum ultraviolet photons and by physical bombardment with active particles. For this reason, it provides effect of crackdown, ablation or engraving, cross-linking, and surface chemical modification at control parameters. Plasma treatment working at atmospheric pressure using air as reagent gas forms polar groups by controlled surface oxidation with air or oxygen. These polar groups, carboxyl and hydroxyl groups, boost the surface energy of the polymer, enhancing the wet ability of the textiles such as fabric, (by liquid and adhesive) and improves the bond strength and dye uptake. Plasma treatment of viscose fabric by means of oxygen and argon conveyed a negative effect, damaging the fabric for both longer (60 minutes) and short (5 minutes) duration. But, 5 minutes plasma treatment progress the wet ability of fabric (Mak et al., 2006).

2.4.3 Enzymatic treatment

A lot of most modern R and D studies have been paying attention for boosting up the quality characteristics of cellulosic substance based on cotton, linen, viscose, lyocel and their mixtures and blends with synthetic fiber with enzymatic treatment like pectinase, lipase and cellulase. The purpose of enzymatic treatment to cellulosic object is to eliminate all impurities such as waxes, pectin and hemicelluloses and individual loose fiber ends that projected from the fabric surface, concurrently, improve the wetting properties in order to keep hold of the strength of fabric at a satisfactory point. In case of viscose fabrics, enzymatic treatment lets flat of the surface of viscose fabric and develops wetting properties by the elimination of impurities and individual loose fiber ends that project from the surface of the untreated fabric (Ciechańska et al., 2002; Hartzell et al., 1998; Hsieh and Lisa, 1998; Koo et al., 1994).

2.4.4 Alkali treatment

Alkali treatments enhance lustre, dye ability, uniformity and dimensional stability of the fabric by the swelling action within the cellulose structure and the associated re-organization of yarn and weave geometry (Holme, 1986). They cause changes in the structure, morphology, accessibility and reactivity of cellulosic fiber, depending upon the concentration, treatment temperature, physical state of the material and the degree of polymerization of cellulosic fiber (Crawshaw, et al., 2001). The change in the chemical structure and physical properties of cellulose fiber due to the caustic treatment was first introduced by Mercer in 1844. Lowe discovered the industrial use of alkali cellulose fiber, which makes it more lustrous (Bahtiyari, 2009; Blackwell, 1971)

2.5 Dyes

Dyes are the most important materials in Dyeing. Dyes are color unsaturated natural particles should have attraction for fiber to be efficiently used. The dyes on fiber are actually jump to the fiber by one or more corporal forces comprising hydrogen bonding, Vander Waals, or ionic forces and in definite cases chemically bound by covalent bonds. Regenerated viscose cellulose fiber is generally dyed with the dye types that are also compatible with cotton and lyocell fiber, such as direct, reactive, vat, sulphur, and pre metalized acid dyes. Direct and sulphur dyes are favored because of their low cost. Reactive and vat dyes are favored for high quality fabrics with excellent fastness properties (Agarwal, 2010; Christie, 2001; Rys and Zollinger, 1975).

2.6 Dyeing

Dyeing is a process to apply color in to fiber, yarns or fabrics for imparting a particular hue to a substance in the presence of an application medium (Kuo and Fang, 2008). As well, most of the proficient dyers/dyeing engineers claim that dyeing is more an art than a science because of the superficially innumerable variables that are complicated to monitor but must be dealt with to attain high quality products. It is noted that dyeing represent the third important step in textile manufacturing (Kuo and Pietras, 2010; Kuo and Fang, 2008; Shaikh, 2010; Zeydan and Toga, 2011).

2.7 Theory of Dyeing with Reactive Dyes

Reactive dyes cover a full range of bright shades, with good to excellent wash fastness, moderate to good light fastness (Agarwal, 2010; Aspland, 1992). This class of dye is mostly used to dye the cellulosic fiber; however, suitable functional group of reactive dyes is used for wool and man- made fiber. Dye containing a triazine or vinyle sulphone group could form covalent bond with the hydroxyl group of cellulose fibers at proper pH and at reasonable temperature between 20 – 100 ^{0}C (Cegarra et al., 1992).

The overall dyeing mechanism for the creation of covalent bond between the dye molecules of reactive dyes and cellulose polymer basically depend on three processes namely absorption, diffusion, and chemical reaction/fixation as shown in Figure 2.4 (Trotman, 2010).

Absorption: Absorption is the movement of the dye from the solution phase to the fiber phase, at the fiber surface. Basically, reactive dyes and cellulose fibers show negative charge in dye bath and repel each other reducing substantivity of dye. Once salt is added in the dye bath to reduce the negative charge by decreasing its zeta potential difference between the fiber phase and dye molecule resulting better absorption (Broadbent, 2001b). In fact, salt acts as exhaustion agent and assist in movement of dye molecules from dye bath on to the fiber surfaces. The rate of absorption depends on dye concentration, salt concentration and liquor ration of the dye bath (Trotman, 2010).

Diffusion: The diffusion of the dye means movement of dye molecules from the fiber surface to the interior of the fiber. Moreover, rate of diffusion of the dye molecules depend on temperature of the bath and size of dye molecules. Higher the temperature better is the rate of diffusion for dye molecules of lower size.

Fixation/Chemical reaction: Finally, the formation of covalent bonds between dye and fiber represent the fixation or the chemical reaction. The good fastness to washing of dyeing with reactive dyes on the cellulose fibers is a result of the stable covalent bond formed between the dye molecules and cellulose polymer. The covalent bond can be formed between the dye and cellulose fiber by substitution reaction with heterocyclic ring of triazine dyes (scheme 2.7) and by addition reaction with vinyl sulphone dyes (scheme 2.9). But both dyes are hydrolyzed if they react with water (scheme 2.8 and 2.10). These three segments of reactive dyeing determine the dye levelness, dye penetration and dye uptake (Rys and Zollinger, 1975).

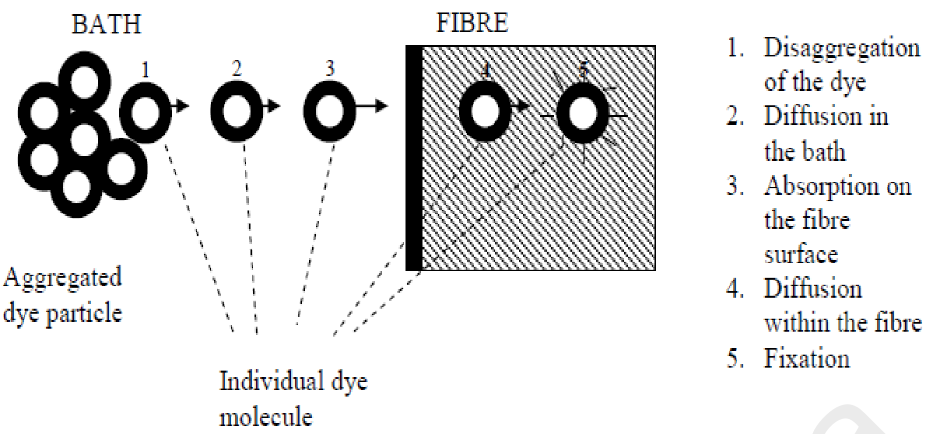
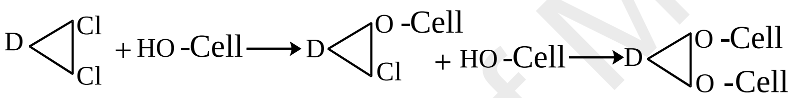
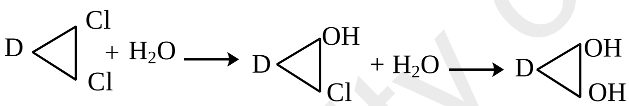


Figure 2.4: The dyeing mechanism with reactive dyes (Syed, 2010)



Scheme 2.7

(Complete fixation)



Scheme 2.8

(Hydrolyzed dye)

$D\text{-}SO_{2}\text{-}\ CH = CH_2 + HO - Cell \rightarrow D\text{-}SO_2\text{-}CH_2\text{-}CH_2\text{-}O\text{-}Cell$ Scheme 2.9

(Complete fixation)

$D\text{-}SO_{2}\text{-}\ CH = CH_2 + H_2O \longrightarrow D\text{-}SO_2\text{-}CH_2\text{-}CH_2\text{-}OH$ Scheme 2.10

(Hydrolyzed dye)

2.8 Dyeing Method

There are two methods mainly used for dyeing textiles materials as listed below;

- Exhaust dyeing or discontinuous dyeing.
- Continuous dyeing.

Raw fibers and yarns are dyed through the exhaust dyeing method, while fabric can be dyed by either the exhaust or the continuous dyeing methods. The selection of dyeing method depends on the volume of the material to be dyed, particular shade, type of dye, dye reactivity, substantivity and cost.

2.8.1 Exhaust dyeing

Exhaust dyeing is expressed the weight of dye to be used in term of the percentage of dye on the weight of materials and the weight of dye bath in term of liquor-to-goods/materials ratio and the dye molecules slowly transferred from a comparatively large volume dye bath to the materials and exhausted with longer time in this methods (Aspland, 1997; Broadbent, 2001b). Exhaust dyeing process is more economical due to its versatility, ease of control and short run capability as compared to continuous dyeing and it is a common popular dyeing method in textile dyeing industries (CHO, 2004). There are few exhaust dyeing machines such as Winch, Jet, Jigs, Beam Package dyeing machines which can function at temperatures up to 140^{0}C and lower temperature. Conversely, exhaust dyeing processed fabrics are used for casual wear, leisure wear and sport swear due to its satisfactory levels of color fastness to washing, rubbing and light, combined with attractive aesthetics (Burdett et al., 1999; CHO, 2004).

In exhaust/batch dyeing systems, the dye reacts with fiber while dye is absorbed into the cellulose substance. In cellulose substrate dyeing with reactive dye, the efficiency of fixation depends on the rate of absorption of dye into the textile material. Further, the factors affecting the dye-fiber reaction are reactivity rario, substantivity, and dye diffusion, liquor ratio and surface area of the substrate available. There are three valuable types of reactive dyeing methods based on the factors to be control to uptake of reactive dyes for level dyeing (Shore, 1995).

- Alkali-controllable reactive dyeing.
- Salt-controllable reactive dyeing.
- Temperature-controllable reactive dyeing

❖ ***Alkali-controllable Reactive Dyeing***

- Most favorable fixation temperature ranging from 40 – 60 ^{0}C.
- Relatively lower exhaustion in neutral salt solution before alkali addition.
- Care is essential during alkali addition to attain level dyeing because of its high reactivity.
- Examples: dichlorotriazine, chlorodifluoropyrimidine, dichloroquinoxaline or vinylsulphone reactive systems.

❖ ***Salt-controllable Reactive Dyeing***

- The suitable fixation happens at temperatures between 80 ºC and 100 °C.
- Moderately high exhaustion at neutral p^{H}.
- Care is essential during salt dosing to make sure level dyeing due to its low reactivity. It is preferable to add electrolytes portion wise.
- Examples: trichloropyrimidine, aminochlorotriazine or bis (aminochlorotriazine). Aminofluorotriazine.

❖ ***Temperature-controllable Reactive Dyeing***

- In this dyeing method, the dye-fiber bond is formed at temperatures ranging from 80 ^{0}C to more than 100 ^{0}C, in the absence of alkali.
- This method has self-leveling characteristics, hence no need any dye bath auxiliary to make possible level dyeing.
- Controlled temperature is necessary to attain good dyeing results.
- Examples: bis (aminonicotinotriazine), Kayacelon react (KYK).

2.8.2 Continuous dyeing

In continuous dyeing process, the textile substrates are passed continuously in to a small bath containing dye range with varying speed between 50 to 250 meters per minute. Continuous dyeing process sequence as follows: (a) pad -dry-chemical pad-steam, (b) pad-steam, (c) pad-chemical pad-steam. In this process, Padding dyeing, fixation and washing remain continuously. Continuous dyeing is a popular and most economic dyeing method for single color large lot production. Continuous dyeing process is predominant for woven fabrics especially for cotton, polyester and their blended woven fabrics. But, sometimes Nylon carpets are also dyed in continuous processes. Continuous dyeing of carpet is quite popular in USA. Due to the increasing cost of energy and labor and environment issues over the past several decades has forced the textile industry to consider continuous processes over batch processes (Aspland, 1997; Broadbent, 2001b, Shaikh, 2010).

2.9 Previous study on the Optimization and Modeling in Textile and Dyeing

In the past century, there are many numbers optimizing and predictive models have been developed and applied by many researcher to optimize the process parameters and predict the quality characteristic of textile materials like fabric GSM, bursting strength, dimensional properties, color strength, color fastness, color levelness, pilling resistance etc. There are mainly two types of modeling methodology namely deterministic model and nondeterministic model. Principally, Deterministic model include mathematical model and statistical model. Moreover, mathematical model and statistical model include Taguchi method and Response surface methodology (RSM). In contrast, non-deterministic models based on genetic methods and intelligent methods which include artificial neural network (ANN), Fuzzy logic expert system (FLES) and Genetic Algorithm (GA) (Guruprasad, 2010; Majumdar and Ghosh, 2008).

2.9.1 Taguchi Method

In the past few years, Taguchi method has been applied to optimize the interactive process parameters in the several textile and dyeing processes.

Fazeli et al., (2012) applied Taguchi method to model the color yield of 100 % cotton fabric with six selected direct dyes. The influence of dye concentration, electrolyte concentration, dyeing temperature and dyeing time on the color Yield has been investigated. They found that values of R^2 and R^2_{adj} from the obtained models are fit for all cases as well as stated that electrolyte concentration and dyeing temperature are the most important factors for color Yield in cotton fabrics dyeing with direct dyes.

Mavruz and Ogulata, (2010) used Taguchi approach to optimize the bursting strength of 1x 1 rib cotton knitted fabrics as a function of relaxation treatment, yarn type and loop length.

From this investigation, they concluded that Taguchi method is able to maximize the bursting strength of knitted fabrics with simple experiments as well as is efficient on the optimization and prediction in textile domain.

Kuo et al., (2008) studied Taguchi method to find the optimal dyeing process parameters for PET and Lycra blended fabrics dyeing where color strength is a function of machine working temperature, dyeing time, dye concentration and material to liquor ratio with disperse dyes using one bath two section dyeing method. They identified optimal dyeing condition as dyeing working temperature 140 ^{0}C, dyeing time 30 min, dye concentration 1 % and bath ratio 1:20 and from ANOVA it was found that dye concentration is the most significant factors for color strength in PET and Lycra blended fabrics dyeing. In addition, color strength of dyed fabric is found to be very much closer to the target value.

Engin et al., (2008) presented Taguchi method as an experimental design to determine the optimal process conditions in color removal from textile dye bath house effluents in a zeolite fixed bed reactor. They investigate the influence of HTAB concentration, zeolite bed height and wastewater flow rate and found that HTAB is the most significant factors in the zeolite bed reactor in color removal from textile dye bath house effluents.

Zeydan, (2008) reported the use of Taguchi design of experiment (TDOE) to model the strength of jacquard woven fabric. The effects of fiber, yarns and fabrics properties on the strength of woven fabric have been investigated through TDOE methodology. The results obtained from the TDOE were also compared with experimental results. It was found that strength of the woven fabric improves approximately 1 % while optimum processing conditions deduce from TDOE in the manufacturing stage.

Kuo and Fang, (2006) applied Taguchi quality method for parameters design to determine the optimal dyeing conditions for Nylon and lycra blended fabrics dyeing with acid dyes using one bath two section dyeing method. In this experiment, they studied the effect of dyeing working temperature, dyeing time, dye concentration and bath ratio on color strength of Nylon fabrics. They found optimal dyeing condition as dyeing working temperature 100 ^{0}C, dyeing time 50 min, dye concentration 0.6 % and material to liquor ratio 1:20. Further, from analysis of variance (ANOVA), they obtained the significant factors in the Nylon and Lycra blended fabrics dyeing are dye concentration and material to liquor ratio. Additionally, it was found that color strength of dyed fabric is very much closer with the target value.

Chen, (1997) applied Taguchi method to find optimal dyeing condition for polyester fiber dyeing with disperse dyes under normal pressure to achieve optimal color strength.

It was found that application of Taguchi method for optimization study can play a vital role in quality engineering. However, major problem in the Taguchi mathematical model is that it cannot always find out the interactions effects like some of the other design of experiment techniques (Kumar and Ishtiaque, 2009). Additionally, since, Taguchi mathematical models are developed on the basis of fundamental theories of basic sciences and assumption or simplification; hence, the prediction accuracy of mathematical model is not very encouraging (Majumdar and Ghosh, 2008).

2.9.2 Response Surface Methodology

Response surface methodology (RSM) investigates the relationship between two or more variables. Many researcher's proposed RSM for process parameters optimization and quality characteristics modeling that are summarized as follows:

Afzal et al., (2014) developed response surface regression model to investigate the effects of blend fiber ratio, yarn count, knitting loop length, fabric thickness and areal density on the air permeability (AP) of polyester/cotton blended interlock knitted fabrics. They found that blend fiber ratio did not significantly affect the AP of inter-lock knitted fabrics. They also found that AP decreases with increasing in yarn linear density, fabric thickness and areal density however AP increases with increasing in knitting loop length. The results obtained from the response surface regression model were compared with experimental results. The absolute error was found to be 2.54%, which explained good agreement by the presented model.

Quadir et al., (2014) reported statistical regression model to study the effect of elastane linear density and draft ratio on the physical and mechanical properties of core spun cotton yarns. It was found that core-spun yarn tenacity; elongation and hairiness are affected not only by the overall yarn linear density but also by the elastane linear density and the draft ratio.

Ashraf et al., (2014) examined the effect of cotton fiber and yarn characteristics on color variation in woven fabric dyed with vat dyes using statistical regression method. They found that the fabric containing weft yarns made from cotton with higher reflectance (Rd) values gave poor color strength as compared to that of lower Rd values. Fabric comprising combed weft yarns showed better color depth (*K/S*) values as compared to that comprising carded weft yarns made from the same raw cotton. Furthermore, the fabric comprising finer- or lower-twist weft yarns gave higher color depth as compared to that with coarser or higher-twist weft yarns.

It was concluded that slight variations in the cotton or yarn characteristics in the weft yarns could result in significant shade variations in the vat-dyed fabric.

Jamshaid et al., (2013) addressed response surface regression model to predict the bursting strength of plain knitted fabrics by taking yarn tenacity, knitting stitch length and fabric GSM as predictor variables. They showed that the effect of stitch length and fabric GSM is not linear on the fabric bursting strength and surface regression model have ability on the prediction with good accuracy.

Hussain et al., (2013) presented response surface methodology with central composite experimental design for modeling and optimization of the shrinkage control and bursting strength of Lacoste Pique cotton knitted fabrics after application of cross linking agent and softener.

Kuo and Pietras, (2010) used regression based statistical method for controlling pH in open beck dyeing to improve its process quality. They showed that a dyer should set the p^H of solution in the beck before the dyes are added for best coloring results.

Asim et al., (2012) applied desirability function to find the optimal quality such as color strength (K/S,) color fastness to washing, light and rubbing, resistance to abrasion and pilling, of fixation of reactive printing and crease resistant finishing.

Zavareh et al., (2010) designed and developed a RSM model based on central composite design (CCD) to find optimal dye bath condition in exhaust dyeing of cotton fabric with six diazo direct dyes as a function of dye concentration, electrolyte concentration, dyeing temperature, dyeing time and liquor ratio. The models showed a good fit.

Zeydan and Toga, (2011) suggested RSM based GRA methodology to find the optimal and robust dyeing process condition for acrylic fiber dyeing with Basic dye for obtaining even quality products and maximum customer satisfaction.

However, prior information or estimation of any mathematical model in advance is important for developing a statistical regression model. Moreover, statistical models are unable to capture the non-linear relationship between inputs and outputs (Ertuğrul and Uçar, 2000; Hatua et al., 2014).

2.9.3 Artificial Intelligence in Textile and Dyeing

The Textile and dyeing industries involve the interaction of a large number of variables with extremely non-linear relations and the quality of the final products directly depends on them (Jamshaid et al., 2013; Majumdar and Ghosh, 2008; Unal et al., 2012; Vadood, 2014).

Moreover, conventional mathematical, statistical and empirical models often fail to create exact functional relationship between the non-linear input variables and quality characteristics due to high degree of variability in raw materials, multistage processing and a lack of precise control on process parameters among others (Guruprasad and Behera, 2010; Hatua et al., 2014; Majumdar and Ghosh, 2008; Vadood, 2014;).

In contrast, artificial intelligences have been received a great attention from the researchers as alternative modeling methods in almost every field of human activity, including engineering, science, medicine, agriculture and manufacturing which are difficult to simulate by the above-mentioned methods (Guruprasad and Behera, 2010; Hatua et al., 2014; Vadood, 2014). The soft computing technique artificial intelligences are capable of capturing any kind of functional relationship from input-output data as well as mimic the behavior of biological system like human brain (Hatua et al., 2014; Jamshaid et al., 2013). By using existing information technologies, artificial intelligences for performing difficult and important tasks can be developed quickly, maintained cheaply, used effectively at many sites, improved easily, and refined during operation to accommodate new situations and facts (Vadood, 2014).

The earlier applications of artificial intelligence in the dyeing and textile fields included fuzzy logic and artificial neural networks. This section reviews some of the major applications of artificial intelligence in different sectors of the dyeing and textile industries.

2.9.3.1 Fuzzy Logic

The artificial intelligence fuzzy logic is one of the most successful system and efficient modeling tool which focus on the various research investigations by mathematicians, scientists and engineers from around the world (Gopal, 2009).There are few publications on fuzzy logic application in the textile and dyeing related to this research has been reported as follows:

Haghighat et al., (2014) presented fuzzy logic model for the prediction of needle penetration force in woven denim fabrics as a function of needle size, number of fabric layer and fabric weight. The results show that the needle penetration force in diverse denim fabrics can be predicted with high accuracy using fuzzy logic model. In another study, Haghighat et al., (2012a) developed fuzzy logic intelligent model for predicting the yarn hairiness of polyester-viscose blended yarn based on spindle speed, traveller count and yarn count as input variables.

Mule et al., (2013) presented fuzzy logic controller for the simulation of color strength of printed fabrics as a function of fabric GSM, number of stroke and viscosity. They found that fuzzy controller is satisfactory to handle any non-linear system with good accuracy.

Radhia et al., (2013) proposed fuzzy sensitivity criterion method to select the most relevant input parameters of plasma process to be used to develop neural network models for predicting fabric surface properties in plasma fabric surface treatment.

Singha et al., (2013) applied fuzzy logic interface to control the hot/cold oil flow, temperature and pressure and predict the best energy saving model for nylon 6 polymerization spinning process.

Thi et al., (2010) used fuzzy systems for predicting seam pucker based on fabric structure and mechanical properties. Experimental results showed that designed fuzzy systems are efficient for predicting seam pucker grades in clothing manufacturing.

Majumdar and Ghosh, (2008) discover fuzzy expert model for modeling of yarn strength by means of fiber tenacity, mean length, micronaire value and short fiber content. Authors showed that yarn tenacity increases with increasing in fiber tenacity and mean length but decreases with increasing in short fiber content.

Sarna et al., (2008) pointed on the application of fuzzy set theory to find the maturity degree of cotton fiber based on the examination of cotton fractures using the scanning electron microscope (SEM) system. They found that the method of analyzing of SEM images with the application of a fuzzy set enables to perform quantitative analysis of cotton fracture images.

Ceven and Ozdemir, (2007) applied fuzzy logic model to investigate the influence of yarn counts, pile length and twist level on the boiling shrinkage behavior of chenille- yarns and found that the relation between the experimental and fuzz model predicted shrinkage is linear.

Tavanai et al., (2005) investigate the application of two fuzzy regression models to model the color yield in PET dyeing with disperse dyes as a function of dye concentration, time and temperature. From the investigation, they found that fuzzy regression with triangular coefficients is preferred than the exponential fuzzy coefficient model.

Jahmeerbacusa et al., (2004) developed fuzzy controller in order to control dye bath p^H and achieve optimum color yield and levelness in exhaust dyeing. Results of the control system simulation showed very satisfactory tracking performances of the pH profiles.

Kuo et al., (2004) suggested mathematical model based on fuzzy theory for the prediction of properties of melt spinning system taking input parameters as extruder screw speed, gear pump speed and winder speed.

Kayacan et al., (2004) applied fuzzy logic model to investigate the effects of yarn linear density and twist factor on the yarn speed in air jet weaving looms. They confirmed that yarn speed could be found out in relation to the twist factor and yarn count by fuzzy logic.

Hung and Yu, (1999) developed fuzzy logic controller for controlling dye concentration, p^H and temperature in cotton fabric dyeing with direct dyes. Subsequent to experimental study, authors found that fuzzy logic controller is able to control the dye concentration, p^H and temperature as the desired values to obtain target shade and coloration uniformity in final products.

2.9.3.2 Artificial Neural Network

Artificial neural network **(**ANN) is a computational powerful data modeling tool in artificial intelligence (Hatua et al., 2014; Hussain et al., 2015; Ngai et al., 2014) that has been applied successfully to various disciplines including textile and dyeing area for different working conditions. The application of ANN related to the subject of this work can be summarizes as follows:

Hussain et al., (2015) applied ANN model to predict the wrinkle recovery of polyester/cotton blended woven fabrics by taking input variables as warp and weft yarn linear densities, ends/25 mm and picks/25 mm.

Moreover, authors compared the ANN model performance with ANFIS model in terms of prediction accuracy and found that ANN model exhibits slightly better performance than the ANFIS Model.

Moezzi et al., (2015) established ANN model to predict the tensile properties of UV degraded nylon66/polyester woven fabric at different levels of exposure time. The results obtained from the ANN model were then compared with the experimental results. Authors proved that developed ANN model performs excellent in prediction.

Haghighat et al., (2014) developed ANN model to investigate the influence of sewing needle size, number of fabric layer and fabric weight on the needle penetration force in woven denim fabrics. The results signify that the needle penetration force in various denim fabrics can be predicted with high accuracy using ANN model. In addition, authors showed that the effects of number of fabric layer and fabric weight on the needle penetration force are much more profound than needle size. In another study, Haghighat et al., (2012b) discovered ANN prediction model to study the hairiness of polyester-viscose blended yarn. Authors further stated that ANN model can be applied as a decision making support tool for the production engineer to select and adjust the appropriate spinning process parameters for the production of high quality yarn.

Hatua et al., (2014) developed ANN model for the prediction of ultraviolet protection factor of polyester-cotton blended woven fabrics by taking proportion of polyester in weft yarn, weft count and pick density as input variables. Further, author compared the developed ANN model with ANFIS model in terms of prediction accuracy and found that both models have ability in prediction with high accuracy.

Jamshaid et al., (2013) presented ANFIS model to predict the bursting strength of plain knitted fabrics based on the yarn tenacity, knitting stitch length and fabric GSM as input variables. In this study, they explained that the effect of stitch length and fabric GSM is not linear on the fabric bursting strength.

Kan et al., (2013) used ANN model to predict the color propperties of 100% cotton denim fabric taking input variables treatment temperature, treatment time, p^H, mechanical agitation and fabrics yarn twist level. The results obtained from ANN model were then compared with experimental results and found that color properties could be predicted perfectly with the aid of ANN model.

Azimi et al., (2013) discovered ANN methodology to predict the effect of first heater temperature, setting overfeed and D/Y on the tenacity of set yarns and effect of twist texturing speed and first heater temperature on the crimp stability of stretch yarn.

Unal et al., (2012) applied ANN prediction model to investigate the effects of yarn count, yarn tenacity, yarn unevenness, number of wales and coreses on the single jersey cotton knit fabrics bursting strength and air permeabilty. In the same study, authors develop regression model to compare the ANN model performance and found that ANN model is superiorto regression model.

Shams- Nateri, (2011) investigated the effects of types and number of membership function on the performance of digital camera based ANFIS technique to measure the color properties of polyester fabrics.

Khataee et al., (2011) reported an ANN model to predict the performance of biological process and investigate effect of temperature, p^H, initial dye concentration, reaction time amount of algae on biological de-coloration efficiency.

Rolich et al., (2010) applied ANN model to investigate the effects of weft yarn density, warp yarn density, mass per unit area and thickness of fabrics on the tensile properties of woven fabrics.

Furferi and Gelli, (2010) discovered ANN model for predicting the yarn strength based on fiber properties such as length, strength and fineness. Authors proved that developed ANN model may be considered a practical method for assessing the yarn strength comparison with linear regression model.

Yuen et al., (2009) developed and design a new novel method for three layers BP neural network to investigate and classify fabrics stitching defects automatically.

Ertugrul and Ucar, (2000) applied ANN and ANFIS intelligent models for the prediction of bursting strength of cotton plain knitted fabrics by taking fabric weight, yarn breaking strength and yarn breaking elongation as input parameters.

The ANN and ANFIS models execute superior prediction accuracy in non-linear complex ground. Nevertheless, these ANN and ANFIS models are trained using massive amounts of noisy experimental data for parameters optimization which are labor intensive and time consuming process to accumulate from the textile and dyeing industries. Further, ANN and ANFIS models work as black box and there is no precise amplification of the nature of non-linearity between input-outputs (Jamshaid et al., 2013; Majumdar and Ghosh, 2008). In addition, ANN does not tell the core logic based on which decisions are taken (Hatua et al., 2014). Comparison between Taguchi method, statistical method, ANN and Genetic algorithm (GA) optimization methods and techniques has been presented in Table 2.3.

2.10 Previous Study on Dimensional Stability of Knitted Fabrics.

A lot of studies have been reported to improve the poor dimensional stability of knitted fabrics. Reeves and Frank (1962), propose that shrinkage of cotton knitted fabrics could be reduced by any treatment that prevents cotton fiber swelling on wetting. Candan and Onal (2003), reported that knitted fabrics made from open-end rotor yarns exhibit better dimensional stability than those made from ring spun yarn. However, open-end rotor yarns are not usually available in higher fineness and results in lower bursting strength than ring spun yarn, thus limiting their use in knitted fabrics (Ramesh et al. 2008).

In another study, Candan and Onal, (2003) and Karmakar (1999), reported that dimensional stability can be improved by decreasing the loop length of knitted fabrics. However, decreasing loop length in knitted fabrics is impractical after a certain limit because further than which knitting machines may not work correctly. In the same study, Candan and Onal (2003), and Karmakar (1999), proposed that application of elastomeric yarns may be a good solution to the poor dimensional stability. But such option is not always economical because of cost considerations of the elastane and supplementary heat-setting process. Moghassem and Tayebi, (2009) mentioned that mercerization is one of the method to improve dimensional stability of cotton knits. Apart from the cost, limited availability of proper mercerization method for knits and quality control issues limit the mercerization process (Karmakar, 1999).

Safdar et al. (2014), mentioned that mechanical compaction via compactors machine is a successful method for improving dimensional stability, but with limited shrinkage control, which may not last after 4-5 washes. In addition, tumble drying is the competent for controlling the dimensional stability of knitted garments (Somashekar and Elder, 1976; Fong and Knapton, 1970). However, lesser production and batch to batch quality variations of tumble drying method limit their use for improving dimensional stability (Safdar et al., 2014).

Lo et al., (2009) developed resin finishing technique as a potential solution for controlling the dimensional stability problem of the viscose knits. On the other hand, application of resin rigorously deteriorates the bursting strength of treated fabrics and resins make the fabrics stiffer and harsh hand feel. Hence, application of softening agent with polyethylene emulsion can help in retaining fabrics strength (Hussain et al., 2013).

2.11 Summary of Literature Review

The present study review the literature on the application of different textile materials, optimization of dyeing processing parameters and modeling quality characteristics for viscose blended knitted fabrics. Viscose fibers are renewable, sustainable, biodegradable and comfortable to wear, squashy to the skin, excellent moisture absorbent and moderate dry strength. Hence, demands of the viscose knitted fabrics are increasing rapidly. Various studies have been reported in the past century on the properties of different textiles materials such as fibers, yarns and fabrics of cotton, polyester, acrylic, wool, lyocell, nylon and their blends woven and knitted fabrics. However, no work has been reported to study the effects of different processing variables on the properties of viscose fabrics and compared with cotton fabrics. Further, it was observed from literature survey that a number of research based on various methods, including Taguchi method, RSM, ANN, ANFIS and Fuzzy logic approaches have been developed and applied for process optimization and quality characteristics modeling for aforementioned textile materials. Conversely, no study has been conducted on the process optimization through Taguchi methodology and quality characteristics modeling by using fuzzy logic approach for viscose/lycra blended knitted fabrics. Furthermore, various techniques have been proposed in the past study to improve the poor dimensional stability of viscose knitted fabrics which include decreasing the loop length of knitted fabrics, tumbles drying, mechanical compaction as well as application of elastomeric yarns and resin finishing methods. Using fuzzy technique in this regards can improve poor dimensional properties of viscose fabrics with minimum experimental data. In conclusion, it is not a complete summery of all applications but just to deliver some perception to understand how different optimization and modeling techniques can be applied to resolve textile and dyeing problems.

CHAPTER 3

MATERIALS AND METHODS

3.1 Introduction

The different materials and equipment used in the present study include fabric, chemicals, dyes and laboratory equipment. There are various experiments have been conducted to study the effects of different process variables on the properties of viscose knitted and cotton knitted fabrics. Further, the Taguchi design of optimization has been applied to investigate the optimal factors and their main effects in the dyeing process as well as develop mathematical model for the prediction of color strength of viscose knitted fabrics. Furthermore, Fuzzy intelligent models have been created for the prediction of color strength of viscose/lycra, cotton/lycra, lyocell/lycra blended knitted fabrics and bursting strength of viscose/lycra blended knitted fabrics. Finally, ANN prediction model has been developed for color strength of viscose/lycra blended knitted fabrics to compare the fuzzy model performance and also fuzzy resin finishing model has been developed to control the dimensional properties of viscose knitted fabrics.

3.2 Materials and Equipment

Materials used in the present study include fabric, chemicals, dyes and laboratory equipment.

3.2.1 Fabrics

Viscose knitted fabric having grams per square meter (GSM) weight in the ranges of 140 -200 grams was used. Fabric was mostly single Jersey with open width construction. However, another two types of cotton and lyocell knitted fabric with two different structure 1x1 rib and pique were also used with open width construction. The different types of fabrics are presented in Table 3.1.

Table 3.1: Lists of fabrics.

Fabrics type	Fiber type	Fiber Composition	Fabric GSM
Single Jersey	Viscose	100%	140
Single Jersey	Viscose/Lycra	(90/10)%, (95/5)%	180, 190, 200
Single Jersey, Pique and 1x1 rib	Cotton/Lycra	(90/10)%, (95/5)%	
Single Jersey and 1x1 rib	Lyocell /Lycra	(95/5)%	

The photographs of different knitted grey fabrics (Before treated) are depicted in Figure 3.1.

(a) Viscose grey fabric

(b) Cotton grey fabric

(c) Lyocell grey fabric

Figure 3.1: Photograph of grey fabrics (Before pre-treatment).

3.2.2 Dyes and Chemicals

The reactive dyestuff with different brand and classes were used in lab scale experimentation. Reactive dyes were predominantly used because of their common application in cellulosic textile materials dyeing due to the advantages such as easy application, better color brightness and color fastness. The detailed of these dyes with their supplier and function are shown in Table 3.2. The main chemicals like Feloson NOF was used as wetting agent, Kappavon CL as anti -creasing agent, hydrogen peroxide as bleaching agent, sodium carbonate as alkai, G/salt as exhaustion agent. The entire chemical with their function and supplier are presented Table 3.3.

Table 3.2: Lists of dyes.

Name of the items	Functions	Supplier	Origin
Remazol Blue RR	Dye	Dystar	Germany
Remazol Yellow RR	Dye	Dystar	Germany
Remazol Red RR	Dye	Dystar	Germany
Livafix Blue CA	Dye	Dystar	Germany
Livafix Red CA	Dye	Dystar	Germany
Sunfix Navy Blue MFD	Dye	Ohyoung	Korea

Table 3.3: Lists of chemicals.

Name of the items	**Function**	**Supplier**	**Origin**
Feloson NOF	Wetting agent	CHT Bangladesh	Germany
Kappavon CL	Anti-creasing agent	Kapp-chemie Bangladesh	Germany
Sirrix 2UD	Sequestering agent	Archoma Bangladesh	Thailand
Kappazon H-53	Peroxide stabilizer	Kapp-chemie Bangladesh	Germany
Kappazyme AP	Peroxide killer	Kapp-chemie Bangladesh	Germany
Kappacom E-12	Leveling agent	Kapp-chemie Bangladesh	Germany
Ispon- PSR	Soaping agent	Bozzeetto Bangladesh	Italy
Glauber salt	Electrolyte	Tread Asia	China
Sodium carbonate	Alkali	Shodesh chemical itd	China
Hydrogen peroxide	Bleaching agent	HP Chemical Bangladesh	Bangladesh
Acetic acid	Neutralizing agent	HP Chemical Bangladesh	Bangladesh
Cellusoft CR	Cellulase enzyme	Novozyme, Bangladesh	Denmark
Reaknit FF	Crosslinking agent	CHT, Bangladesh	Germany
Polysiligen	Silicon softener	CHT, Bangladesh	Germany
ECE Detergent	Wash off agent	SDC	UK
Sodium perborate	Alkali	Merck	Germany

3.2.3 Machinery and Equipment

A variety of machinery and equipment including lab dyeing equipment, sample dyeing machine, Spectrophotometer, Pneumatic Bursting tester, Rubbing tester, Knitting machine, Washing machine, Stenter, Compactor etc. were used to conduct experiment and analysis. The list of machinery and equipment with their function and supplier are shown in Table 3.4.

Table 3.4: Lists of Machinery and Equipment.

Name of the Machine	Functions	Brand	Supplier	Origin
Knitting machine	To knit fabrics	Pailung	Pacific associates, Bangladesh	Taiwan
Stenter	Heat setting, drying and width controlling	Ehwa suntex platinum	Texlink, Bangldesh	Korea
Lab dyeing machine	dyeing	Ugolini	Ugolini SPA	Italy
Dyeing machine	Dyeing	Sclavos	Sclavos corporation	Greece
Spectrophotometer	Assess color strength/shade	Datacolor SF 650 TM	Data color International	USA
Pneumatic Bursting tester	Test bursting strength	SDL Atlas	SDL Atlas	England
Compactor	To control fabrics width and dimensional stability	Lafer	SE Ltd.	Italy
Woven and incubator	Laboratory drying	SDL Atlas	SDL Atlas	England
Laboratory padder	padding	Labtec	SDL Atlas	Taiwan
Washing machine	To wash fabrics	Wascator	SDL Atlas	England
Color fastness to wash	Color fastness testing	Rotawash	SDL Atlas	England
Rubbing tester	Test rubbing	Crockmeter	SDL Atlas	England

3.3 Textile Manufacturing

Textile manufacturing begins with the production of fiber, which can be harvested from natural sources (cotton, linen, jute), manufactured from regenerative cellulosic materials (viscose, acetate), or may be entirely synthetic (nylon, polyester). Fibers then pass through four main stages of processing, including i) yarn production, ii) fabric production, iii) dyeing, and iv) apparel production (Yang and McGarrahan, 2005).The entire manufacturing sequence can be presented as a flowchart in Figure 3.2.

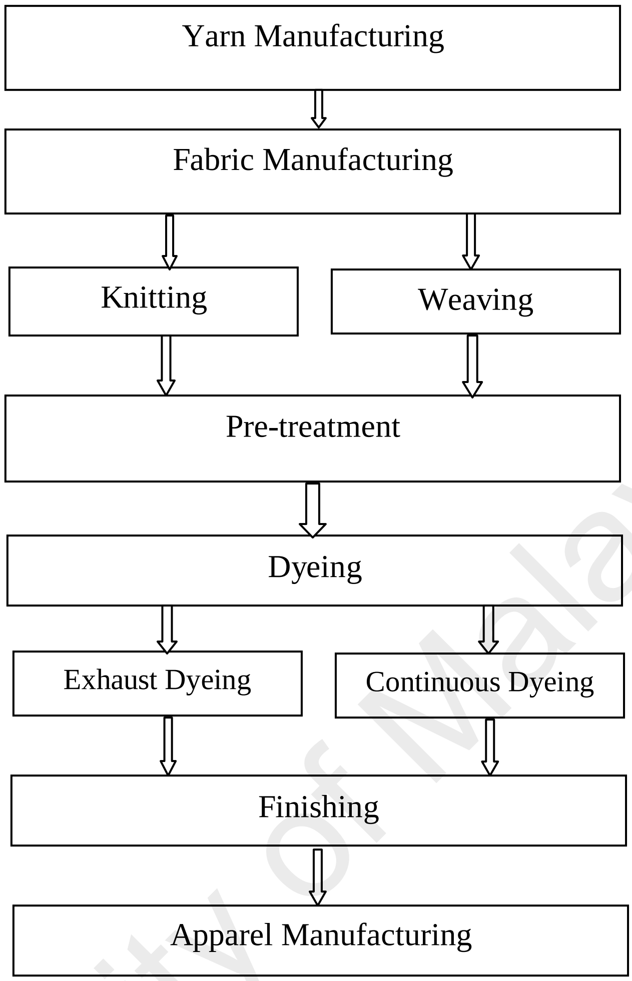


Figure 3.2: Flow Chart of Textile Manufacturing.

3.4 Experiments, Design, Optimization and Mathematical Modeling

3.4.1 Pre-treatment of cellulosic knitted fabrics

Textile pre-treatment is the series of cleaning operations and proper setting for subsequent processes. Textile pre-treatment processes consist of chemical process and mechanical process. Chemical pre-treatment process may be broadly defined as a procedure mainly concerned with the removal of all impurities such as hemi-cellulose, pectin, wax, fat and oil from the cellulosic knitted fabrics to a level necessary for good whiteness and absorbency by utilizing minimum time, energy and chemicals as well as water.

Chemical pre-treatment process for cellulosic knitted fabric includes scouring and bleaching which is done in one bath. In addition, mechanical pre-treatment process defined as a heat treatment process to achieve best dimensional stability with correct finished fabric GSM in case of blended knitted fabrics with lycra fiber. Viscose and other cellulosic knitted fabrics are pre-treated using diverse chemicals and mechanical process to increase the dye ability and boost the dye uptake. Pre-treatment was carried out before the dyeing.

Purpose of pretreatment:

- To remove hemi-cellulose, pectin, wax, fat, oil from the cellulosic fabrics.
- To increase the lusture of the treated materials.
- To increase the absorbency of the treated materials.
- To increase the dye ability of the treated materials.
- To pre-set the knitted fabric width for required GSM and dimensional stability.

There are following common pre-treatment processes are conducted for Cellulosic knitted fabrics to achieve uniform water absorbency with white index more than 70% as well as dimensional stability within 5%.

a) Heat-setting

Heat-setting is the first and important step to achieve best dimensional stability and correct finished GSM in case of blended knitted fabrics manufacturing with lycra fiber**.** In case of jersey knit, it is essential to apply lowest possible length wise tension to give optimum dimensional stability. Firstly, the fabric is pre-wetted on the stenter padding mangle (Figure 3.3) using 2g/l wetting detergent (Feloson NOF, CHT Germany) and 1 g/l lubricating agent (Kappavon CL). After that, the padded fabric was subjected to heat-setting in the pin stenter.

Depending on the number of chamber of stenter, heat – setting temperature and curing time were adjusted. Normally, in 7- 8 chamber stenter, heat-setting is performed at temperature of 190 - 200 ^{0}C for 45-60 second curing time. Further, for jersey knit, heat-setting width were maintained approximately 5 – 10 % wider than the desired finished width and overfeed as high as possible.

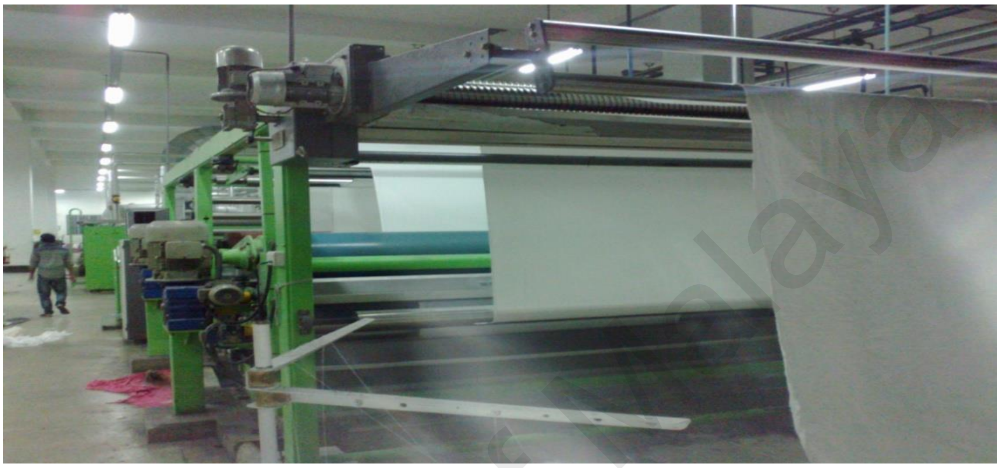


Figure 3.3: Stenter machine (APS Textile, Bangladesh).

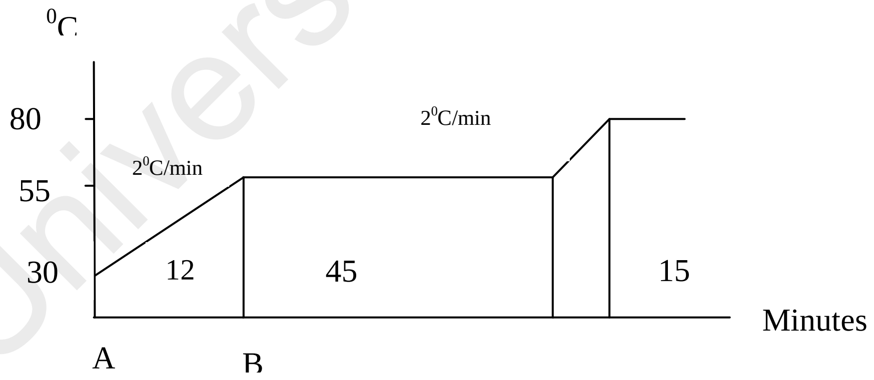
b) Enzymatic treatment

The purpose of enzymatic treatment for cellulosic textile material is to eliminate all impurities such as waxes, pectin and hemicelluloses and individual loose fiber ends that project/float from the fabric surface. Simultaneously, it improves their cleaner surface conferring cooler feel, brightens luminosity of colors, soften feel and increases resistance to pilling. Pill is the projected/floated fibre on the fabric surface that may form due to wash and wear. Enzymes are bio-catalyst and accelerate the degradation of longer cellulose chains on the surface of the cellulosic textile materials in to smaller ones by catalytic action mechanism. The cellulase enzyme Cellusoft CR was kindly supplied by Novozyme (Bangladesh). Cellusoft CR was applied as per Table 3.5 conditions for viscose and cotton by exhaust method.

In exhaust method, enzyme and others chemical auxiliaries are added in one bath vessel with required material to liquor ratio and run for a specified time and temperature. The pH 5.5 of the enzyme bath was adjusted using acetic acid. Then, temperature is raised at 80 ^{0}C and run for 15 min. Subsequent to cold rinse, the fabric was dried. The method of enzymatic treatment by exhaust is shown in Figure 3.4. After conditioning, pilling test was conducted for this fabric. Basically pilling is formed on fabric surface during washing and wearing of the textile garment due to poor quality yarn properties. Hence, in textile dyeing industries, pilling test means abrasion is conducted in a testing lab by ICI or Martindale pilling tester machine for 100 to 2000 revolutions on the fabric surface. Then pilling resistance is assessed by grey scale in unit less numerical value.

Table 3.5: Enzyme treatment conditions.

Process parameters	Unit	Levels		
Cellusoft CR	g/l	0	0.5	1.0
Acetic acid (p^H=4.5-5.5)	g/l	0.1		
Time	minutes	50		
Temperature	^{0}C	55		



A= Water,   B = Cellusoft CR (0.5 g/l and 1 g/l) at p^H = 4.5-5.5

Figure 3.4: Enzymatic treatment by exhaust method.

c) Alkali treatment

Pre-treatment of viscose and cotton knitted fabrics are actually done in a combined scouring and bleaching bath. Since, viscose is the pure cellulose, pre-treatment need to be mild in nature due to remove any residual sulfur and spinning lubricant that were used in viscose manufacturing stage. This residual sulfur may cause to prevent dye uptake as well as uneven dyeing. Moreover, spinning lubricant used on viscose has tendency to yellowish with heat and cause dye uneven should be removed through pre-treatment process. Further, viscose processing needs a little higher liquor ratio than cotton because of high water retention and high swelling. Similarly, lyocell is also pure cellulose fiber, thus pre-treatment is done like viscose fiber. On the other hand, cotton is natural cellulose fiber which contains impurities (hemi-cellulose, pectin, wax, fat etc) that have to be removed before dyeing and printing process. The viscose/lycra, lyocell/lycra and cotton/lycra knitted fabrics were then performed one bath scouring and bleaching in industrial scale sample winch dyeing machine (Figure 3.5) according to Table 3.6 pre-treatment conditions. Finally, the fabrics were cold rinsed followed by hot washing and neutralized by acetic acid and dried. The pre-treated fabrics samples are shown in Figure 3.6.

Table 3.6: Pre-treatment conditions.

<table>
<tr><th rowspan="3">Parameters</th><th rowspan="3">Unit</th><th colspan="3">Viscose and lyocell</th><th colspan="3">Cotton</th></tr>
<tr><th rowspan="2">Levels</th><th>time</th><th>Temp.</th><th rowspan="2">Levels</th><th>time</th><th>Temp.</th></tr>
<tr><th>min</th><th>^0C</th><th>min</th><th>^0C</th></tr>
<tr><td>Detergent</td><td>(g/l)</td><td>1.0</td><td rowspan="7">30</td><td rowspan="7">90</td><td>1.0</td><td rowspan="7">60</td><td rowspan="7">98</td></tr>
<tr><td>Sequestering agent</td><td>(g/l)</td><td>1.0</td><td>1.0</td></tr>
<tr><td>Hydrogen peroxide</td><td>(g/l)</td><td>1.0</td><td>2.5</td></tr>
<tr><td>Soda ash</td><td>(g/l)</td><td>2.0</td><td>6.0</td></tr>
<tr><td>Anti-creasing agent</td><td>(g/l)</td><td>1.5</td><td>1.5</td></tr>
<tr><td>Peroxide stabilizer</td><td>(g/l)</td><td>0.2</td><td>0.2</td></tr>
<tr><td>Acetic acid</td><td>(g/l)</td><td>1.0</td><td>1.0</td></tr>
</table>

Figure 3.5: Sclavos winch dyeing machine (APS Textile, Bangladesh).

(a) Viscose pretreated fabric

(b) Cotton pretreated fabric

(c) Lyocell pretreated fabric

Figure 3.6: Photographs of pre-treated fabrics.

3.4.2 Effects of Process Variables on Fabrics Properties

The effects of different process variables on the fabric properties of viscose knitted fabrics were studied and compared with those of cotton knitted fabrics.

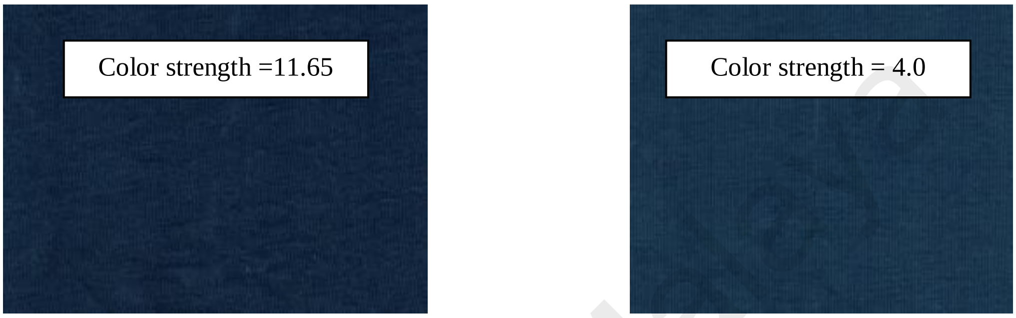
a) Effects of dyeing conditions on color strength

In a laboratory dyeing machine (Figure 3.7), viscose/lycra and cotton/lycra blended knitted bleached fabric samples (each 5gm) were dyed using exhaust dyeing methods with Remazol Blue RR reactive dyes (Dystar, Germany) according to a set of values for dye concentration (1- 9) %, salt concentration (20-60) g/l, alkali concentration (3-16) g/l, dyeing time (30-90) minutes, dyeing temperature (30-90) ^{0}C and material to liquor ratio (1:4 to 1: 20) as shown in Table 3.7. These dyeing conditions have been chosen based on color concept and recommendation of dyes manufacturers. After dyeing all samples were cold rinsed and then hot washed at 90 ^{0}C for 10 minutes to remove salt, alkali and unfixed dyes. Next, the dyed samples were dried and conditioned for 2 hours at (65±2) % RH (relative humidity) and (20±2) ^{0}C temperature. In this experiment, as an example, photograph of dyed sample of viscose and cotton fabrics are shown in Figure 3.8.

Figure 3.7: Laboratory dyeing machine (APS Textile, Bangladesh).

Table 3.7: Dyeing conditions.

Parameters	Unit	Levels				
Dye concentration	%	1	3	5	7	9
Time	Minute	30	45	60	75	90
Temperature	^{0}C	30	45	60	75	90
Material: Liquor		1:4	1:8	1:12	1:16	1:20
Salt	g/l	20	30	40	50	60
Soda	g/l	3	7	10	13	16



(a) Photograph of dyed viscose fabric (b) Photograph of dyed cotton fabric

Figure 3.8: Photograph of dyed fabrics.

Subsequent to conditioning, reflectance values (R) of all dyed samples were measured using the spectrophotometer (Figure 3.9), in a visible region with wavelength ranges of 400 nm - 700 nm with an interval of 10 nm, Diaphragm 30 mm, D_{65} illuminant and 10^0 observer settings. The average reflectance value of 4 readings was taken for each sample. Lastly, the color strength (K/S) of each sample was calculated using the Kubelka-Munk Equation 3.1(Baumann et al., 1987):

$$\frac{K}{S} = \frac{(1-R)^2}{2R} \tag{3.1}$$

Where, *K* is the light absorption coefficient, *S* is the light scattering coefficient and *R* is the reflectance of dyed fabric. Finally, effects of different dyeing conditions on color strength are studied.

Figure 3.9: Spectrophotometer (APS Textile, Bangladesh).

b) Effects of different brand and classes of dyes on color strength

The dyeing process was performed in a laboratory dyeing machine (Figure 3.7) for four different dyestuff classes according to a set of values for dye concentration (2% and 4%), salt concentration (40 - 60) g/l, alkali concentration (10 - 15) g/l, dyeing time (60) minutes, dyeing temperature (60) ^{0}C and material to liquor ratio (1:10) as shown in Table 3. 8 for viscose and cotton fabrics (each 2.5gm) by exhaust /batch method. In exhaust /batch method, all the processes are done in one bath taking all dyes, chemicals and fabrics. Firstly, dye bath is set at 40 ^{0}C and then auxiliaries + dyes (A), salt (B) and alkali (C) are added to bath at this temperature. Subsequently, dye bath temperature is raised 2 ^{0}C per minute up to 60 ^{0}C and the dyeing process is continued for 60 minutes. In this study, the overall dyeing process is presented graphically in Figure 3.10. After dyeing all samples were cold rinsed and then hot washed at 90 ^{0}C for 10 minutes and dried. After conditioning in a laboratory atmosphere at (65±2) % RH (relative humidity) and (20±2) ^{0}C temperature for 2 hours, the reflectance values of all dyed samples were measured using the spectrophotometer in a visible wavelength ranges of 400 nm - 700 nm with an interval of 10 nm, 30 mm Diaphragm, D_{65} illuminant and 10^0 observer settings. The average of reflectance values for each sample was taken. As a final point, the color strength (*K/S*) was computed by the Kubelka-Munk Equation 3.1.

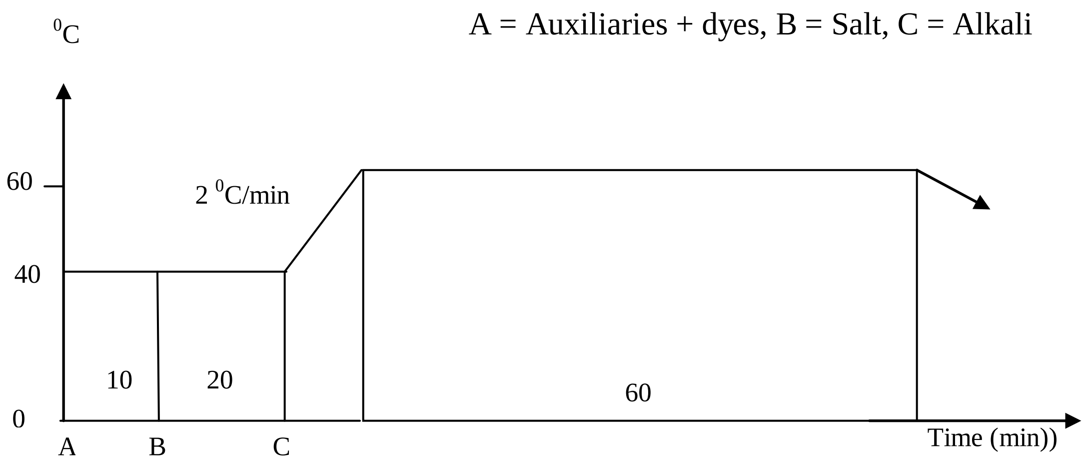


Figure 3.10: Dyeing procedure of different dyes.

Table 3.8: Dyeing conditions of different dyes class.

Parameters	unit	level	
Remazol Blue RR	%	2	4
Remazol Red RR	%	2	4
Livafix Blue CA	%	2	4
Livafix Red CA	%	2	4
Dyeing time	minute	60	
Dyeing temperature	^{0}C	60	
Material to liquor ratio		1:10	
Salt	g/l	40	60
Soda ash	g/l	10	15

c) Effects of fabric GSM on color strength

The cotton and viscose fabrics bleached sample having areal density 160, 190 and 220 (g/m^2) were dyed in a lab dyeing machine using dye concentration 3 %, salt 40 g/l, soda 10 g/l at 60 ^{0}C for 60 minutes. Subsequently dyeing all samples were cold rinsed and next hot washed at 90 ^{0}C for 10 minutes and dried. Afterward, reflectance values of all dyed samples were calculated by the spectrophotometer. To this end, the color strength was computed by means of Equation 3.1.

d) Effects of fiber blend ratio and fabric GSM on bursting strength

The fabrics samples with 5% and 10 % Lycra and areal density 190, 220 and 240 (g/m^2) are obtained from production are put down on flat surface for 24 hours at atmospheric conditions. Then the areal density (g/m^2) of each sample was measured according to the BS EN 12127 ISO 3801 standard and bursting strength (kPa) of each sample was tested using SDL ATLAS Pneumatic bursting tester (Figure 3.11) (Model 229P) with a specimen of 30 mm in diameter according to ISO-139388-1 test method.

Figure 3.11: Pneumatic Bursting tester (APS Textile, Bangladesh).

e) Effects of washing conditions on the color fastness to washing and rubbing

i. Dyeing:

The cotton and viscose fabrics/lycra blended bleached sample having GSM 190 are dyed in a lab dyeing machine using dye concentration 4 % (Remazol Blue RR), G/salt 60 g/l, soda ash 15 g/l at 60 ^{0}C for 60 minutes. After dyeing all samples were cold rinsed and hot washed according to washing conditions as shown Table 3.9.

After dyeing, dyed samples were cold rinses and hot washed at 90 ^{0}C for 10 minutes with 0.5 % soaping agent followed by neutralizing. Next the samples were dried and conditioned at lab atmospheric conditions for color fastness testing. Finally, color fastness to washing and rubbing are tested according ISO test method and assessed by grey scale as per rating 1-5 for color change and color staining. Grey scale rating value 1 means poor color fastness and 5 means excellent color fastness that are internationally quality standard.

Table 3.9: Washing conditions.

Parameters	Unit	level		
Washing time	min	10	20	40
Wash temperature	^{0}C	80	95	110
Soaping agent	g/l	0	0.5	1

ii. Fastness to rubbing

Rubbing fastness was performed according to the BS EN ISO 105 x 12: 2002 (Standard, 2002) on crock meter. The dyed fabric was measured in both warp and weft directions separately. The test specimen of 10 cm x 4 cm was taken both of the knitted fabric and held on the crock tester. Cotton bleached fabric of 5 x 5 cm was taken and gripped with the help of wire on the finger having a size 1.4 cm. The cotton fabric was rubbed 10 times to and fro against the test specimen. The bleached fabric was rubbed both in dry and wet state separately.

iii. **Fastness to washing**

Washing fastness tests were carried out on a Rota Wash, SDL Atlas according to the BS EN ISO 105 C06: 2010(Standard, 2010). The specimen dyed sample was cut to 4 x 10 cm, and the same size of multi-fiber (secondary cellulose acetate, bleached un-mercerized cotton, nylon, polyester, acrylic, wool) society of dyers and colorists (SDC) standard specimen was taken. The dyed sample and standard was then stitched together from the face (one side). The washing liquor was prepared at liquor to goods ratio 50:1, containing SDC standard ECE Reference Detergent 4 g/l and Sodium Perborate 1 g/l With 10 Steel Balls. The dyed and standard samples were placed in the Rota wash pot and then run for 30 min at a temperature of 40 ^{0}C. After washing, the specimens were taken out, un-stitched and washed again with cold water in a beaker for 5 minutes. The fabric is simply dipped in water in the beaker. This static wash is followed by running tap water continuous wash for further 5 minutes to remove unfixed and hydrolyzed dyes from the fabric and then dried in an open air or oven. After drying the fabric was rated by using grey scale and staining scale from rating (1 to 5). Each multi-fiber was rated separately.

3.4.3 Taguchi Optimization and Mathematical Modeling

3.4.3.1 Taguchi Methods

Taguchi's methods developed by Japanese Engineer Prof Taguchi in 1950 emphasize the efficient utilization of engineering approach rather than advanced statistical scheme. The Taguchi method utilizes orthogonal array (OA), signal-to-noise (S/N) ratios, main effects, and analysis of variance (ANOVA) which make it different than classical methods.

Taguchi's OA allows the user to perform far fewer experiments than the factorial design; however it still finds the best combination of all of the possible combinations (Engin et al., 2008; Fie et al., 2013; Mavruz and Ogulata, 2010; Zeydan, 2008). For example, if we have a process with seven parameters and each parameter has two levels, then we can apply an orthogonal array chosen *L*8, which specifies performing eight experiments. Conversely, if we utilize the factorial design of experiments for the same process, in that case, we have to carry out $2^7 = 128$ experiments (Fie et al., 2013; Krishankant et al., 2012; Z; Kumar and Ishtiaque, 2009; Kuo et al., 2008; Pamuk, 2015). Taguchi design of experiments is easy to adopt and apply for users with limited knowledge of statistics (Krishankant et al., 2012).

In addition, Taguchi approach separately determine the individual or main effects of the independent variables on performance parameters whilst other designs provide collective effect of variable in terms of equations or three dimensional curves or contour diagrams, which are frequently not easy to understand and interpret (Kumar and Ishtiaque, 2009). Taguchi method does not need enormous amount of experimental data for parameters optimization (Chary and Dastidar, 2010; Fie et al., 2013; Fazeli et al., 2012; Kuo et al., 2008; Mavruz and Ogulata, 2010). In addition, Taguchi optimization is faster and economic than genetic algorithm (GA). Taguchi method utilizes statistical tool like ANOVA to analyze the results, whereas ANN and GA approaches have no such kind of statistical tool to scrutinize the results (Fie et al., 2013). A basic configuration of Taguchi tactic for successful optimization comprises six main steps such as (i) Identification of control factors and their level on the performance characteristics (ii) Designing suitable and economic Experiment (iii) Conducting experiment (iv) Analysis of Experimental data (v) Analysis of variance (ANOVA) and (vi) Confirmation Experiment (Engin et al., 2008; Mavruz and Ogulata, 2010; Zeydan, 2008). The Taguchi methodology for optimization is shown in Figure 3.12.

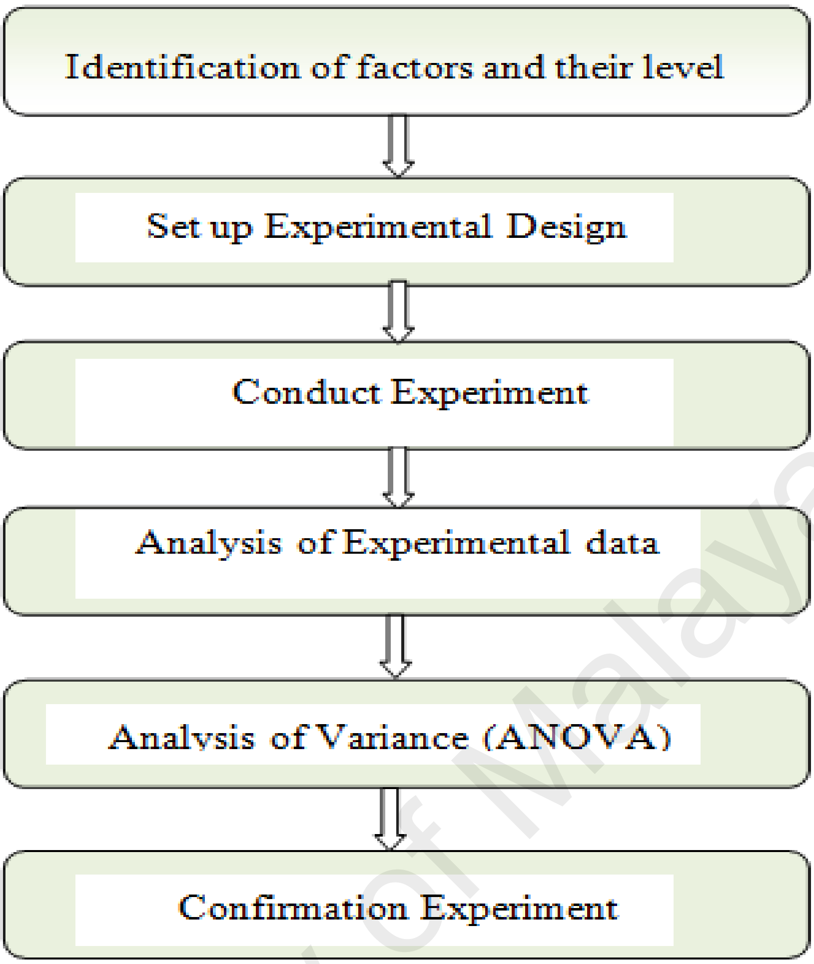


Figure 3.12: Taguchi optimization flow chart.

The key objective of The Taguchi methodology for optimization is to maintain the variance at a minimum level in the response, even in the existence of noise inputs. Therefore, the processes/ products are prepared in good physical shape against all variations. Taguchi defines the S/N ratio (η) as a performance criterion or quality index and expressed in decibels (dB).Theoretically, the S/N ratio (η) is the ratio of signal to noise in terms of power and alternatively represents the ratio of sensitivity to variability. The higher S/N ratio represents the better product quality. The concept is to maximize the S/N ratio by minimizing the effect of random noise factors, which have an important impact on the process performance (Fazeli et al., 2012; Mavruz and Ogulata, 2010; Zeydan M., 2008).

Therefore, the method of calculating the S/N ratio depends on whether the quality characteristic is (i) Smaller-the-better, (ii) Larger-the-better, or(iii) nominal-the-best (Chary and Dastidar, 2010; Fazeli et al., 2012; Mavruz and Ogulata, 2010; Tascan, 2014; Zeydan, 2008).

(i) Smaller is better (Yarn hairiness, abrasion, etc.)

$$S/N = -10log(\sum_{i=1}^{n} y_i^2) \quad (3.2)$$

(ii) Larger is better (Strength, Air permeability, Efficiency etc.).

$$S/N = -10log\left(\frac{1}{n}\sum_{i=1}^{n} 1/y_i^2\right) \quad (3.3)$$

Where, n is the number of repetitions for an experimental combination, i is a numerator, and y_i is the experimental value of i^{th} experiment.

(iii) Nominal is the best (dimension, humidity etc.).

$$S/N = -10log\left(\sum_{i=1}^{n} \frac{y^{-2}}{s^2}\right) \quad (3.4)$$

Where, y^{-2} is the average of data observed and s^2 the variance.

3.4.3.2 Experimental design

In the present study, six control factors namely dye concentration, dyeing time, temperature, salt concentration, alkali concentration, liquor ratio and five levels for each parameter were selected for Taguchi design as shown in Table 3.10. A Taguchi L25 (5^6) orthogonal array experimental design has been chosen for these factors with their levels and are presented in Table 3.11.

Table 3.10: Experimental parameters and their levels.

Process parameters	Unit	Level 1	Level 2	Level 3	Level 4	Level 5
A Dye concentration	%	1	3	5	7	9
B Time	Min	30	45	60	75	90
C Temperature	^{0}C	30	45	60	75	90
D Salt concentration	g/l	40	50	60	70	80
E Alkali concentration	g/l	10	12	14	16	18
F Liquor ratio		1:6	1:8	1:10	1:12	1:14

Table 3.11: Taguchi L25 (5^6) orthogonal array design.

Run No.	Coded factors value					
	A	B	C	D	E	F
1	1	1	1	1	1	1
2	1	2	2	2	2	2
3	1	3	3	3	3	3
4	1	4	4	4	4	4
5	1	5	5	5	5	5
6	2	1	2	3	4	5
7	2	2	3	4	5	1
8	2	3	4	5	1	2
9	2	4	5	1	2	3
10	2	5	1	2	3	4
11	3	1	3	5	2	4
12	3	2	4	1	3	5
13	3	3	5	2	4	1
14	3	4	1	3	5	2
15	3	5	2	4	1	3
16	4	1	4	2	5	3
17	4	2	5	3	1	4
18	4	3	1	4	2	5
19	4	4	2	5	3	1
20	4	5	3	1	4	2
21	5	1	5	4	3	2
22	5	2	1	5	4	3
23	5	3	2	1	5	4
24	5	4	3	2	1	5
25	5	5	4	3	2	1

3.4.3.3 Experimental procedure

After experimental set up, a total 25 viscose/lycra blended knitted samples were dyed with each experiment three runs according to the Taguchi L_{25} orthogonal array (Table 3.11) in a laboratory dyeing machine. At the end of dyeing, the samples were hot washed at 90 ^{0}C for 10 minutes to remove salt, alkali and unfixed dyes. Finally dyed samples were dried and conditioned. In this experiment, color strength of viscose/lycra knitted fabrics was chosen as the quality characteristic. The color strength of the samples was measured by spectrophotometer according to Kubelka-Munk theory as shown in Equation 3.1:

3.4.3.4 Determination of optimal factors level

Since, color strength of the fabrics has been selected as the quality characteristic in the present study, thus the "larger is better" mode is found to be suitable for this experimental design. After conducting experiment, the S/N ratio is then calculated for each group of experimental data according equation (3.3) as shown in Table 3.12, can be employed in calculating main effect of each control factor. Then, the response table and response graph were created for each control factor using Minitab 16 software as demonstrated in chapter 4 in Table 4.3 and Figure 4.13, respectively. Response table shows average response value over various levels for each factor. In response table, the delta value calculation of a factor can be expressed by the formula mentioned below:

$$\text{Delta value} = N_H - N_L \qquad (3.5)$$

Where, N_H = Highest S/N ratio value of a factor,

N_L = Lowest S/N ratio value of same factor.

Further, as per Taguchi analysis, highest delta value of factors is considered as highest ranking of a factor that is 1. Finally, main effects or optimal parameters of the control factors are determined through the delta values and ranking analysis from the response table and response graph.

Table 3.12: The L_{25} orthogonal array with the average color strength (CS) and S/N ratio.

Exp. N0.	A	B	C	D	E	F	Experimental results			Avg CS	Actual S/N ratio	Predicted S/N ratio
1	1	30	30	40	10	6	7.85	7.50	8.12	7.82	17.8641	17.8775
2	1	45	45	50	12	8	9.23	8.55	9.44	9.07	19.1521	19.1575
3	1	60	60	60	14	10	9.40	9.23	8.64	9.09	19.1713	19.1775
4	1	75	75	70	16	12	9.27	8.99	9.55	9.27	19.3416	19.3375
5	1	90	90	80	18	14	9.15	9.44	8.29	8.96	19.0462	19.075
6	3	30	45	60	16	14	10.65	10.39	10.79	10.61	20.5143	20.5175
7	3	45	60	70	18	6	11.16	11.22	10.79	11.05	20.8672	20.8675
8	3	60	75	80	10	8	11.37	11.52	10.93	11.27	21.0385	21.0475
9	3	75	90	40	12	10	10.57	11.07	10.65	10.76	20.6362	20.6375
10	3	90	30	50	14	12	10.21	10.01	10.39	10.20	20.1720	20.1775
11	5	30	60	80	12	12	11.71	12.18	11.07	11.65	21.3265	21.3175
12	5	45	75	40	14	14	11.55	12.01	11.22	11.59	21.2817	21.2775
13	5	60	90	50	16	6	11.68	11.84	11.37	11.63	21.3116	21.3175
14	5	75	30	60	18	8	10.49	10.65	10.26	10.47	20.3989	20.3975
15	5	90	45	70	10	10	11.61	11.16	10.65	11.14	20.9377	20.9375
16	7	30	75	50	18	10	12.35	12.53	11.84	12.24	21.7556	21.7575
17	7	45	90	60	10	12	12.07	11.43	11.68	11.73	21.3860	21.3675
18	7	60	30	70	12	14	10.36	10.13	11.52	10.67	20.5633	20.5675
19	7	75	45	80	14	6	11.84	12.91	11.52	12.09	21.6485	21.6475
20	7	90	60	40	16	8	11.91	11.68	12.72	12.10	21.6557	21.6575
21	9	30	90	70	14	8	12.50	12.90	11.80	12.40	21.8684	21.9875
22	9	45	30	80	16	10	10.16	10.79	9.55	10.16	20.1379	20.1375
23	9	60	45	40	18	12	11.94	13.10	11.84	12.29	21.7910	21.7975
24	9	75	60	50	10	14	12.28	11.58	12.61	12.16	21.6987	21.6875
25	9	90	75	60	12	6	12.83	12.18	11.84	12.28	21.7840	20.5775
C.E.	9	60	75	50	14	8	12.42	12.46	12.53	12.47	21.9186	22.3275

Avg = Average, C.E = Confirmation Experiment

3.4.3.5 Analysis of variance

Subsequently, the data obtained from the Taguchi design of experiment needs to analyze by the analysis of variance (ANOVA) to determine the significant factors and their percentage contribution to the response. Typically, there are few terms used in ANOVA can be calculated as follows (Kuo et al., 2008):

Sum of square (SS_F): The sum of square for a factor (SS_F) can be calculated as:

$$SS_F = \frac{mn}{L}\sum_{k=1}^{L}\left(\bar{y}_k - \bar{y}\right)^2 \qquad (3.6)$$

Where, m is the number of experiment, n is the repeat time for an experiment; L is the factor level, $\overline{y}_k$ is the average experiment results for a certain factor at k^{th} level and $\overline{y}$ is the average experiment results for all experiments.

Total sum of square (SS_T): it can be calculated as follows:

$$SS_T = \sum_{j=1}^{m}\left(\sum_{i=1}^{n} y_i^2\right)_j - mn(\overline{Y})^2 \quad (3.7)$$

Where, y_i is the experimental value for each experimental session.

Sum of square error (SS_{Error}):

$$SS_{Error} = SS_T - SS_{Factors} \quad (3.8)$$

Degree of freedom (DOF): The Degree of freedom of a factor can be determined as follows:

$$DOF_F = L-1 \quad (3.9)$$

Degree of freedom Error (DOF_{Error}):

$$DOF_{Error} = m \times (n-1) \quad (3.10)$$

Variance (V_F):

$$V_F = \frac{SS_F}{DOF_F} x\ 100 \quad (3.11)$$

V_F is the variance of factor

Variance of Error (V_{Er}):

$$V_{Er} = \frac{SS_{Error}}{DOF_{Error}} \quad (3.12)$$

Significant test (F-Test):

Significance of individual factors for the experiment can be determined by means of relationship between variance for experimental error (V_{Error}) and variance for individual factors (V_F) that is called as F- Test, defined as follows**:**

$$F = \frac{V_F}{V_{Error}} \tag{3.13}$$

Percentage contribution (P_F):

$$P_F = \frac{SS_F}{SS_T} \text{x } 100 \tag{3.14}$$

3.4.3.6 Confirmation experiment for TDOE

Confirmation experiment is an essential and important step in the Taguchi method at the end of the optimization study. The predicted value of total S/N ratio under optimal conditions is calculated using an additive model as follows (Kuo et al., 2008):

$$\frac{S}{N} = n_m + \sum_{i=1}^{n}(n_i - n_m) \tag{3.15}$$

where, n_m is mean of total *S/N* ratio, *i* is number of factors, and n_i denotes the S/N ratio for optimum factor level.

Therefore, the optimal conditions that will improve the process can be predicted and will then be validated by the confirmation experiment. Further, the result shall fall within the confidence interval. The difference between the predicted value and experimental value will be presented as the standard deviation *S*. The confidence interval (*CI*) under $1\text{-}\alpha$ confidence level can be expressed as follows:

$$CI = \left| \left(N_{\frac{\alpha}{2}} \text{x} \frac{S}{\sqrt{m_e}} \right) \right| \tag{3.16}$$

where, *N* is the total experiment number, m_e is the ratio of total experiment number and the degree of freedom in the equation for calculating the predicted value. This will ascertain that predicted values for the factors will develop the quality of the outcome and achieve the target quality.

3.4.3.7 Taguchi mathematical model development

Since, Taguchi method provides an efficient and systematic methodology for prediction with maximum number of input variables in a faster and economic way, hence six dyeing process parameters such as dye concentration, time, temperature, salt concentration, alkali concentration and liquor ratio have been taken for developing the Taguchi mathematical model (Mavruz and Ogulata, 2010). Taguchi mathematical model has been developed based on the Taguchi DOE data given in Table 3.12 by using Minitab 16 software. The model equation of color strength developed is given by the following equation:

$$Y = 8.185 + 0.354 * A + 0.001 * B + 0.019 * C - 0.003 * D + 0.011 * E - 0.021 * F \tag{3.17}$$

where, *A* = Dye concentration, *B* = Time, *C* = Temperature, *D* = Salt concentration, *E* = Alkali concentration, *F* = Liquor ratio and *Y* = fabric color strength.

If input values of *A*, *B*, *C*, *D*, *E* and *F* are given in Equation 3.17, the output value of color strength (*Y*) can be obtained. The prediction performance of the developed Taguchi mathematical model was statistically evaluated by calculating coefficient of determination (R^2) and mean absolute error (*MAE*) % from the actual and predicted fabric color strength obtained as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{pi} - y_{ei}\right)^2}{\sum_{i=1}^{n}\left(y_{ei} - y_m\right)^2} \tag{3.18}$$

$$MAE = \frac{1}{n}\left\{\left(\frac{y_{ei} - y_{pi}}{y_{ei}}\right) \text{x } 100\right\} \tag{3.19}$$

Where y_{ei} is the experimental value, y_{pi} is the predicted value, y_m is the mean of the experimental data and *n* is the number of experiments.

3.5 Development of Fuzzy Intelligent Models

The main objective of this study was to develop the fuzzy intelligent model for the prediction of color strength of viscose/lycra blended knitted fabric. However, another two intelligent models have been developed in this study for two cellulosic textile materials such as cotton/lycra and lyocell/lycra blended knitted fabrics in order to compare fuzzy model performance in terms of prediction accuracy as well as to prove that the developed fuzzy model is applicable for all cellulosic textile materials. For fuzzy modeling, different input variables were used for different fiber blend based on the effect of input variables on the color strength. Generally more number of inputs and ranges of input variables will require more fuzzy rules to be developed and the complexity of the expert system will be increased (Majumdar and Ghosh, 2008). Therefore, to simplify the fuzzy expert system, only the most significant dyeing input variables have been taken for fuzzy model developing. Further, ANN prediction model has been developed for color strength of viscose/lycra blended knitted fabric. In addition, Taguchi mathematical model has been developed for color strength of viscose/lycra knitted fabric taking maximum number of input variables because of Taguchi's advantages. In fact, ANN and Taguchi model have been developed in this study only for viscose/lycra knitted fabric to compare the fuzzy model performance.

3.5.1 Fuzzy Logic

The artificial intelligence fuzzy logic is a structure of multi-valued logic and an extension of crisp logic derived from fuzzy mathematical set theory developed by Zadeh (Haghighat et al., 2014; Majumdar and Ghosh, 2008; Ngai et al., 2014; Nasrullahzadeh and Basri, 2014; Vadood, 2014; Zadeh, 1965). Moreover, a fuzzy logic model is more reasonable, cheaper in design cost and frequently easier to apply than other models and gives better explanation of the nature of non-linearity among the input and output variables (Hatua et al., 2014; Majumdar and Ghosh, 2008; Nasrullahzadeh and Basri, 2014; Vadood, 2014).

In addition, in fuzzy logic system, non-linearity is coped by rules, membership functions, and the inference process which consequence in better accomplishment, simpler functioning and cheap design cost (Snehal et al, 2013). Furthermore, fuzzy logic simulates the decision making activities like experienced expert and uses a logical scheme to deduce control actions (Huang and Yu, 1999). Some limitations of ANN, ANFIS and statistical models on the contrary, can be overcome by fuzzy logic which can successfully translate the knowledge of a manufacturer into a set of expert system rules (Majundar and Ghosh, 2008). Unlike statistical regression model, fuzzy logic no needs information or prior assessment of any mathematical models in advance (Ertuğrul and Uçar, 2000**;** Majundar and Ghosh, 2008)**.** Besides, unlike ANN and ANFIS models, fuzzy logic does not require massive amounts of input-output data (Jamshaid et al., 2013; Majumdar and Ghosh, 2008). Furthermore, fuzzy logic is used to resolve problems in which descriptions of behavior and observations are imprecise, vague and uncertain (Majumdar and Ghosh, 2008). The term fuzzy refers to circumstances where there are no well-defined boundaries or explanation for the set of activities (Majumdar and Ghosh, 2008; Vadood, 2014). For instance, in textile and dyeing industries, a production engineer often uses terms such as high or low, strong or weak, for assessing the fabrics qualities such as bursting strength, fabric GSM, spirality, fabrics diameters, color strength, color fastness, levelness etc. Further, a production engineer knows the approximate interaction between knitting & dyeing process parameters and quality characteristics from his knowledge and experience (Majumdar and Ghosh, 2008).

In fuzzy logic, a fuzzy set has elements with only partial membership ranging from 0 to 1 to define uncertainty of classes that do not have obviously defined boundaries. For each input and output variable of a fuzzy logic intelligent system, the fuzzy sets are created by dividing the universe of discourse into a number of sub-regions, named in linguistic terms (*high*, *medium*, *low* etc.).

If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs as

$A = \{x, \mu_A(\mathrm{x}) / x \in X\}$, where, $\mu_A(\mathrm{x})$ is the membership function of x in A.

All properties of crisp set are also pertinent for fuzzy sets apart from the excluded-middle laws. In fuzzy set theory, the union of fuzzy set with its complement does not yield the universe and the intersection of fuzzy set and its complement is not null. This difference can be exposed as follows:

$A \cup A^{c'} = X$	Crisp sets	$A \cup A^{f'} \neq X$	Fuzzy sets
$A \cap A^{c'} = \emptyset$		$A \cap A^{f'} \neq \emptyset$	

A fundamental structure of fuzzy logic expert system consists of four primary units as shown in Figure 3.13 (Gopal, 2009; Hossain et al., 2012a; Su and Kuo, 2015). The four principal components are as follows:

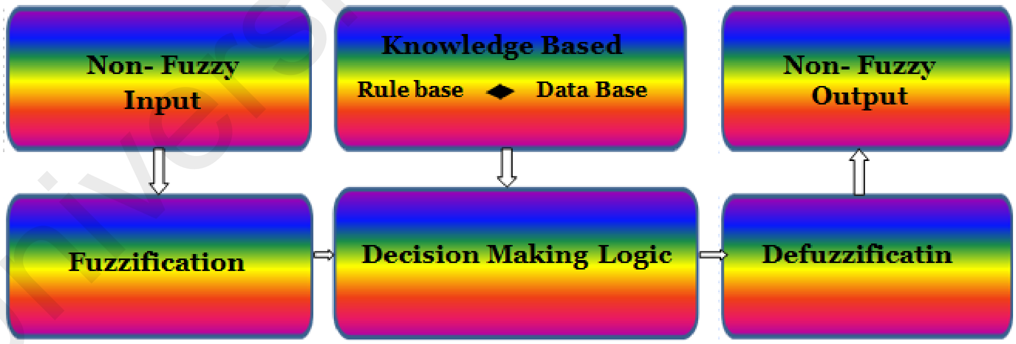


Figure 3.13: Basic structure of the fuzzy logic system (Gopal, 2009).

3.5.1.1 Fuzzification

Fuzzification module converts all numeric input and output variables into linguistic fuzzy sets such as low, medium, high and so on by membership functions (Haghighat et al., 2014). Moreover, membership functions is the central concept of fuzzy set theory and it is a typical curve that converts the crisp numerical value of input

–output variables into the fuzzy number within a range from 0 to 1, indicating the belongingness of the input to a fuzzy set (Su and Kuo, 2015). There are different forms of membership functions such as triangle, trapezoid, and Gaussian functions. Among these the triangular shaped membership function is the simplest and most often used due to its accuracy (Marakoglu and Carman, 2010). Ivanov et al., (2010) has stated that if there is minimal information for a particular variable and this variable is a quick to respond pointer, the range of value is divided into numerous identical triangular membership functions which defined as follows:

$$\mu_A(x,a,b,c)=\begin{cases}\dfrac{x-a}{b-a}; & a\le x\le b\\ \dfrac{c-x}{c-b}; & b\le x\le c\\ 0; & otherwise\end{cases} \tag{3.20}$$

In this case, the edge of the variable's interval may be represented with linear S-shaped and Z-shaped membership functions described respectively as:

(i) S-shaped membership functions

$$\mu_S(x,a,b)=\begin{cases}1; & x\le a\\ \dfrac{b-x}{b-a}; & a\le x\le b\\ 0; & x\ge b\end{cases} \tag{3.21}$$

(ii) Z-shaped membership functions

$$\mu_Z(x,a,b)=\begin{cases}0; & x\le a\\ \dfrac{x-a}{b-a}; & a\le x\le b\\ 1; & x\ge b\end{cases} \tag{3.22}$$

In Equations (3.20 -3.22), *x* is the input and output variables, *a, b,* and *c* are the coefficient of membership functions for the explained input and output variables. Further, the trapezoidal membership curve has a flat top and is simply a truncated triangle producing $\mu A(x)$ = 1 in large regions of universe of discourse. The trapezoidal curve is a function of a vector *x* and depends on four scalar parameters *a*, *b*, *c*, and *d*, as shown below:

$$\mu_A(x) = \begin{Bmatrix} 0; & d \le x \le a \\ \dfrac{x-a}{b-a}; & a \le x \le b \\ 1; & b \le x \le c \\ \dfrac{d-x}{d-c}; & c \le x \le d \end{Bmatrix} \tag{3.23}$$

Furthermore, the Gaussian membership functions depends on two factors, that is standard deviation (σ) and mean (μ) and it is expressed according to below Equation (3.24).

$$\mu_A(x) \;=\; e^{\frac{(\mu-x)^2}{2\sigma^2}} \tag{3.24}$$

The selection of different number and ranges of membership functions and their formations is based on system knowledge, expert's appraisals, experimental conditions and arbitrary choice. The values of input and output variables were given in such a way that they were equally spaced and covered the whole input and output space. Basically, a small number of parameters and more membership functions provide greater accuracy when using a fuzzy model. However, more membership functions require more fuzzy rules, which increase the complexity of the system (Gopal, 2009; Hossain et al., 2012a; Huang and Yu, 1999; Majumdar and Ghosh, 2008). In this study, different number and ranges of membership functions have been selected for developing fuzzy models based on expert knowledge, expert's appraisals and experimental conditions to find better prediction accuracy from the fuzzy models.

3.5.1.2 Knowledge base

The second important task of fuzzy modeling is the rule base formation. Besides, fuzzy rules are the heart of the fuzzy logic that decides the relationship among input and output variables of the model (Hatua et al., 2014; Majumdar and Ghosh, 2008). Furthermore, it contains a data base and a rule base. In the fuzzy knowledge base system, knowledge is expressed by if-then statement (Herva et al., 2012; Nasrullahzadeh and Basri, 2014).

Fuzzy rules consist of two parts: an antecedent part stating conditions on the input variables and a consequent part describing the corresponding values of output variables (Gopal M., 2009; Herva et al., 2012; Hossain et al., 2012a; Huang and Yu, 1999; Majumdar and Ghosh, 2008).The fuzzy rule base can be divided into two classes, namely the **Mamdani and Sugeno (**Herva et al., 2012; Vadood, 2014).

Mamdani models: In Mamdani models, both of the antecedent and consequence parts are in fuzzy set form.

Sugeno model: In Sugeno model**,** the antecedent part is in the form of a fuzzy set and the consequence part is made up by a linear equation or constant.

As an expression, when a fuzzy model with two inputs and one output involves, then development of fuzzy inference rules can be presented as follows:

Mamdani rule: If x_1 is A_1 and x_2 is A_2, then y is C_1; (3.25)

Sugeno rule: If x_1 is A_1 and x_2 is A_2, then $y = b_0 + b_1x_1 + b_2x_2$; (3.26)

Where, x_1, x_2, and y are linguistic variables, A_1, A_2, and C_1 are the consequent fuzzy numbers that represent the linguistic states and b_0, b_1, and b_2 are linear equation parameters (Haghighat et al., 2014; Vadood, 2014).

3.5.1.3 Decision making logic

It plays a central role like computer in a fuzzy logic model due to its ability to create human decision making and deduce fuzzy control actions as per the information provided by the fuzzification module by applying knowledge about how to control best process. Most commonly, Mamdani max-min fuzzy inference mechanism is used because it assures a linear interpolation of the output between the rules (Herva et al., 2012).

Mamdani suggested the application of a minimum operation rule as a fuzzy inference function. For two-inputs and single-output, fuzzy inference method is mathematically expressed as follows (Huang and Yu, 1999):

$$\alpha_i = \mu_{Ai}(I_1) \wedge \mu_{Bi}(I_2) \qquad i = 1, 2 \ldots n. \tag{3.27}$$

and

$$\mu_C(O_1) = \bigcup_{i=1}^{n} [\alpha_i \wedge \mu_{Ci}(O_1)] \tag{3.28}$$

where I_1, I_2 and O_1 input-output variables respectively, α_i is the weighting factor as a measure of the contribution of i^{th} rule to the fuzzy control action, and μ_{Ai}, μ_{Bi},μ_{Ci} ,and μ_C are the membership functions associated with fuzzy sets A_i, B_i, C_i and C, respectively.

Further, in case of three-input and two-output fuzzy system, fuzzy inference mechanisms can be shown graphically as below (Figure 3.14), where, *A*, *B* and *C* are inputs side and *Y* and Z are output side (Carman, 2008; Hossain et al., 2012a).

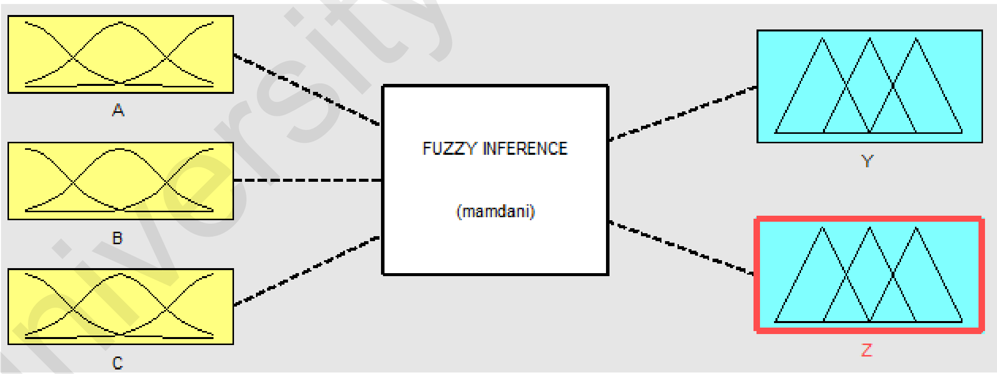


Figure 3.14: Fuzzy inference mechanisms (Mamdani).

3.5.1.4 Defuzzification

The defuzzification module converts the fuzzy output into non-fuzzy numeric value (Z) as control actions. The purpose of the defuzzification is to convert the fuzzy output into a precise crisp value because in various pragmatic circumstances the crisp control action is essential (Huang and Yu,1999; Rajasekaran and Vijayalakshmi, 2007).

There are various methods of defuzzification such as centroid, Centre of sum, mean of maxima and left-right maxima (Haghighat et al., 2014). Among various methods, center of gravity defuzzification method assures a linear interpolation of the output between the rules, hence most commonly this defuzzification method is used to convert the fuzzy inference output into a non-fuzzy value z in the following form for the distinct case (Haghighat et al., 2014; Huang and Yu,1999; Hossain et al., 2012a; Majumdar and Ghosh, 2008):

$$z = \frac{\sum_{i=1}^{n}(\mu_i * b_i)}{\sum_{i=1}^{n}\mu_i} \tag{3.29}$$

Where, bi is the position of the singleton in the i^{th} universe, and μ_i is the membership function of i rule.

3.5.1.5 Prediction performance measure

The prediction ability and accuracy of the developed system has been investigated according to the global prediction error such as mean absolute error (*MAE*) and coefficient of determination (R^2). The formulae of those accuracy measures are given below:

$$\text{MAE} = \frac{1}{\text{N}}\sum_{i=1}^{i=N}\left(\frac{\left|E_a - E_p\right|}{E_a}\times 100\right) \tag{3.30}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N}(E_a - E_p)^2}{\sum_{I=1}^{I=N}\left(E_a - E_M\right)^2}\right) \tag{3.31}$$

Where, E_a- Actual result, E_p-Predicted result, E_M- Mean value, N-Number of pattern

The coefficient of determinations (R^2) compares the accuracy of the model to the accuracy of a trivial benchmark model. The mean absolute error (*MAE*) gives the deviation between the predicted and experimental values and it is required to reach zero (Carman, 2008).

3.5.2 Fuzzy modeling for color strength of viscose/lycra knitted fabrics

Dye concentration (*DC*), salt concentration (*SC*) and alkali concentration (*AC*) have been applied in this study as input parameters for the development of intelligent model for color strength (*CS*) of viscose/lycra knitted fabrics by fuzzy logic. Dye concentration is the main contributor factor for color strength of viscose/lycra knitted fabrics. Further, since, zeta potential (negative ionic nature in water) values of viscose knitted fabrics are lower than the cotton knitted fabric, salt and alkali concentration affect more in uniform coloration. Therefore, these three dyeing process parameters have been chosen entirely for the modeling of color strength of the viscose/lycra knitted fabrics.

For fuzzification, the input variable *DC* was given four possible fuzzy sets, namely very low (VL), low (L), medium (M), and high (H) and three fuzzy numbers, low (L), medium (M), and high (H) were used for the input variables *SC* and *AC*. The values were given in such a way that they were equally spaced and covered the whole input space. In this study, four membership functions for *DC* and three membership functions for *SC* and *AC* have been selected based on system knowledge and experimental conditions and arbitrary choice. From previous experience, it has been found that dye concentration has the most effect on color strength compared to salt and alkali concentration, hence four membership functions were chosen for *DC*. Six fuzzy sets, namely very low (VL), low (L), low medium (LM), medium (M), high (H) and very high (VH), were used for the output variable *CS*, so that fuzzy logic system could map small variations in color strength with changes in the input variables. Overall linguistic fuzzy set for input-output parameters are shown in Table 3.13.

Table 3.13: Linguistic fuzzy sets for input-output parameters.

Parameters	Unit	Value Range	Linguistic fuzzy sets
Dye concentration (DC)	(%)	1-5	very low, low, medium, high
Salt concentration (SC)	(g/l)	15-35	low, medium, high
Alkali concentration (AC)	(g/l)	4-12	low, medium, high
Color strength (CS)		4-28	Very low, low, low medium, medium, high, very high

In the present research, triangular shaped membership functions have been used for both input and output variables owing to their suitability (Marakoglu and Carman, 2010). The units for the input and output variables are: *DC* (%), *SC* (g/l), *AC* (g/l) and *CS* (dimension less). There is a level of membership for each of the linguistic values that were applied to each variable. Fuzzifications of the used factors were made by aid of the following functions. These formulas are found out by using measurement values.

$$DC(i_1) = \begin{Bmatrix} i_1; & 1 \le i_1 \le 5 \\ 0; & otherwise \end{Bmatrix} \tag{3.32}$$

$$SC(i_2) = \begin{Bmatrix} i_2; & 15 \le i_2 \le 35 \\ 0; & otherwise \end{Bmatrix} \tag{3.33}$$

$$AC(i_3) = \begin{Bmatrix} i_3; & 4 \le i_3 \le 12 \\ 0; & otherwise \end{Bmatrix} \tag{3.34}$$

$$CS(o_1) = \begin{Bmatrix} o_1; & 4 \le o_1 \le 28 \\ 0; & otherwise \end{Bmatrix} \tag{3.35}$$

Where, i_1 is the first input variable (*DC*), i_2 is the second input variable (SC), i_3 is the third input variable (*AC*) and o_1 is the output variable (*CS*) as shown in Equations (3.32-3.35).

The degree of *DC* is calculated in percentage (%) from 1-5, *SC* is calculated in g/l from 15-35, *AC* is calculated in g/l from 4-12 and *CS* is calculated in (dimensionless) from 4-28, respectively. Prototype triangular fuzzy sets for the fuzzy variables, such as DC, SC, AC and CS were set up using MATLAB® Fuzzy Toolbox (version 7.10.0). The membership values obtained from the above formulae are shown in the Figures 3.15-3.18. These membership functions help in converting numeric variables of input and output into linguistic terms. Within this structure of the current research work, the subsequent rules are used to form the input and output membership functions.

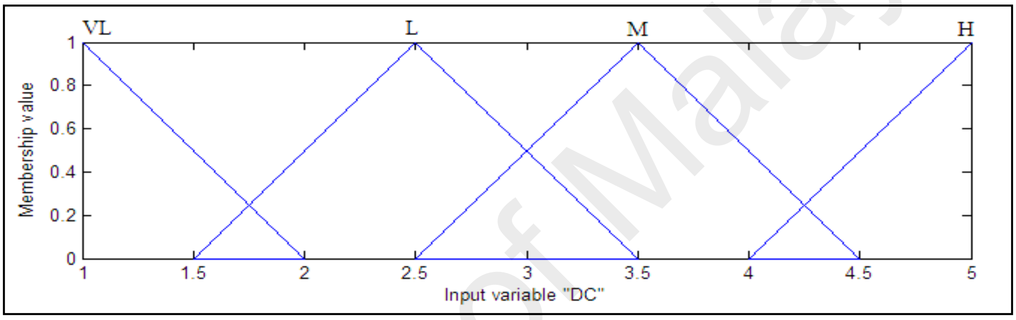


Figure 3.15: Membership functions of input variable DC.

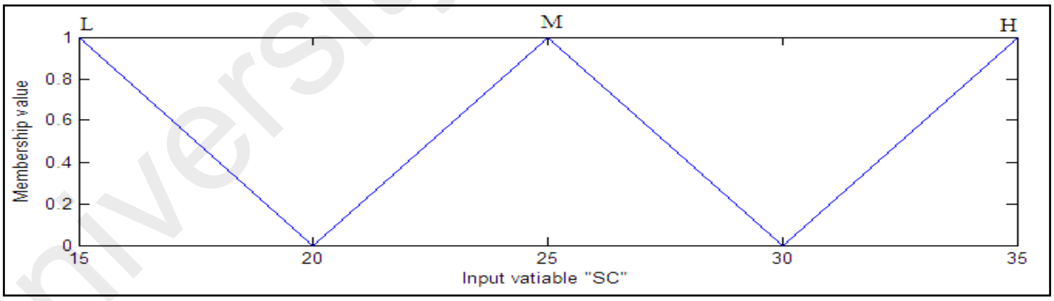


Figure 3.16: Membership functions of input variable SC.

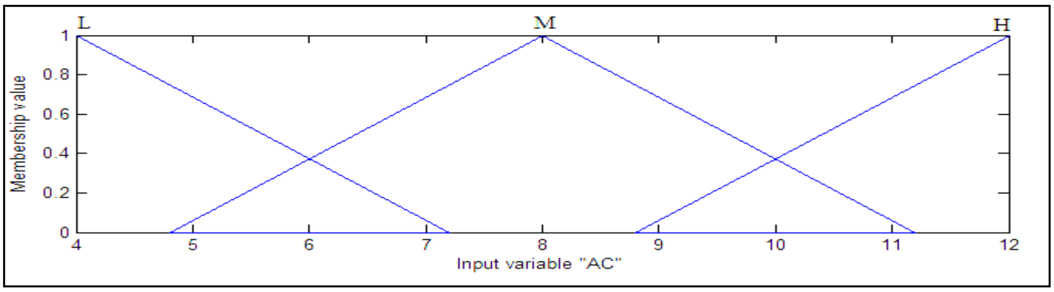


Figure 3.17: Membership functions of input variable AC.

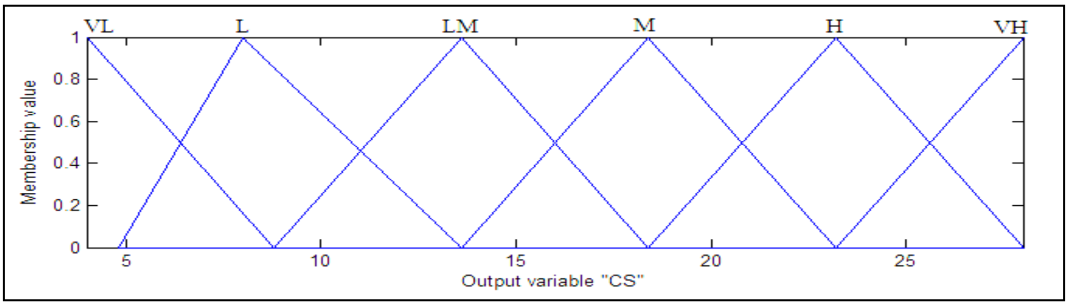


Figure 3.18: Membership functions of output variable CS.

The coefficients of membership functions for the fuzzy inference system (FIS) parameters are shown in Tables 3.14 - 3.17.

Table 3.14: Coefficients of membership functions for FIS parameter of DC.

Linguistic variables	Type	Coefficients (%)		
		a	*b*	*c*
Very low	S-shaped	1	2	-
Low	Triangular	1.5	2.5	3.5
Medium	Triangular	2.5	3.5	4.5
High	Z-shaped	4	5	-

Table 3.15: Coefficients of membership functions for FIS parameter of SC.

Linguistic variables	Type	Coefficients (g/l)		
		a	*b*	*c*
Low	S-shaped	15	20	-
Medium	Triangular	20	25	30
High	Z-shaped	30	35	-

Table 3.16: Coefficients of membership functions for FIS parameter of AC.

Linguistic variables	Type	Coefficients (g/l)		
		a	*b*	*c*
Low	S-shaped	4	7.2	-
Medium	Triangular	4.8	8	11.2
High	Z-shaped	8.8	12	-

Table 3.17: Coefficients of membership functions for FIS parameter of CS.

Linguistic variables	Type	Coefficients ()		
		a	*b*	*c*
Very low	S-shaped	4	4.8	-
Low	Triangular	4	8.8	13.6
Low medium	Triangular	8.8	13.6	18.4
Medium	Triangular	13.6	18.4	23.2
High	Triangular	18.4	23.2	28
Very high	Z-shaped	23.2	28	-

After fuzzification, total 36 rules were formed for dye concentration (*DC*), salt concentration (*SC*), alkali concentration (*AC*) and color strength (*CS*) by using Fuzzy logic tool box from MATLAB software (version 7.10.0) based on expert knowledge and previous practice are shown in Table 3.18. To exemplify how the values in the last column of the fuzzy inference rules (Table 3.18) are determined the following rules have been explained.

Rule 1: If input dye concentration (*DC*) is very low (VL), and salt concentration (*SC*) is low (L), and alkali concentration (*AC*) is low (L), then color strength (*CS*) is very low (VL).

Rule 16: If input dye concentration (*DC*) is high (H), and salt concentration (*SC*) is low (L), and alkali concentration (*AC*) is medium (M), then output *CS* is high (H).

The overall fuzzy intelligent modeling for color strength of viscose/lycra knitted fabrics has been presented schematically in Figure 3.19. In the present study, a mamdani max-min inference mechanism was used as these operators guarantee a linear exclamation of the output between the rules. Lastly, center of gravity defuzzification method has been used to convert the fuzzy output into non-fuzzy single crisp number value as per Equation 3.29 (Haghighat et al., 2014).

Table 3.18: Fuzzy inference rules for color strength model of viscose/lycra.

Rules	Input variables			Output variables
	DC	*SC*	*AC*	*CS*
1	VL	L	L	VL
2	L	L	L	VL
3	M	L	L	LM
4	H	L	L	M
5	VL	M	L	VL
6	L	M	L	VL
7	M	M	L	M
8	H	M	L	H
9	VL	H	L	VL
10	L	H	L	L
11	M	H	L	M
12	H	H	L	H
13	VL	M	L	VL
14	L	L	M	L
15	M	L	M	M
16	H	M	L	H
17	VL	M	M	VL
18	L	M	M	LM
19	M	M	M	M
20	H	M	M	H
21	VL	H	M	VL
22	L	H	M	L
23	M	H	M	H
24	H	H	M	VH
25	VL	L	H	VL
26	L	L	H	L
27	M	L	H	L
28	H	L	H	LM
29	VL	M	H	VL
30	L	M	H	L
31	M	M	H	H
32	H	M	H	VH
33	VL	H	H	VL
34	L	H	H	VL
35	M	H	H	H
36	H	H	H	VH

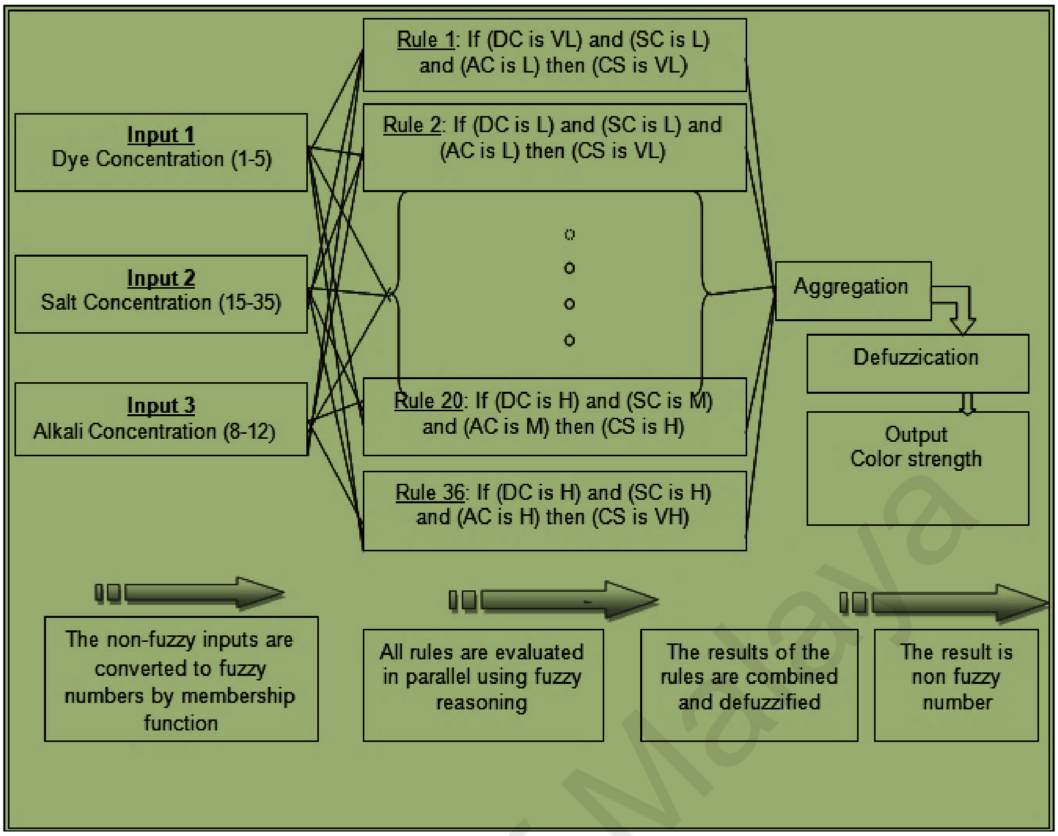


Figure 3.19: Schematic diagram of fuzzy logic modeling for color strength.

To demonstrate the fuzzification process, linguistic expressions and membership functions of *DC*, *SC* and *AC* obtained from the developed rules and above formulae (Equations 3.32 -3.35) are presented analytically. The membership functions value can be calculated for all fuzzy sets as follows:

$$\mu_L(DC) = \begin{Bmatrix} \dfrac{i_1 - 1.5}{2.5 - 1.5}; & 1.5 \le i_1 \le 2.5 \\ \dfrac{3.5 - i_1}{3.5 - 2.5}; & 2.5 \le i_1 \le 3.5 \\ 0; & i_1 \ge 3.5 \end{Bmatrix} \quad (3.36)$$

$$\mu_L(DC) = \{0/1.5 + 0.5/2 + 1/2.5 + ...+ 0.5/3 + 0/3.5\} \quad (3.36a)$$

$$\mu_M(DC) = \begin{Bmatrix} \dfrac{i_1 - 2.5}{3.5 - 2.5}; & 2.5 \le i_1 \le 3.5 \\ \dfrac{4.5 - i_1}{4.5 - 3.5}; & 3.5 \le i_1 \le 4.5 \\ 0; & i_1 \ge 4.5 \end{Bmatrix} \quad (3.37)$$

$$\mu_M(DC) = \{0/2.5 + 0.5/3 + 1/3.5 + ... + 0.5/4 + 0/4.5\} \quad (3.37a)$$

$$\mu_M(SC) = \begin{Bmatrix} \frac{i_2 - 20}{25 - 20}; & 20 \le i_2 \le 25 \\ \frac{30 - i_2}{30 - 25}; & 25 \le i_2 \le 30 \\ 0; & i_2 \ge 30 \end{Bmatrix} \quad (3.38)$$

$$\mu_M(SC) = \{0/20 + 0.4/22 + 1/25 + ... + 0/30\} \quad (3.38a)$$

$$\mu_M(AC) = \begin{Bmatrix} \frac{i_3 - 4.8}{8 - 4.8}; & 4.8 \le i_3 \le 8 \\ \frac{11.2 - i_3}{11.2 - 8}; & 8 \le i_3 \le 11.2 \\ 0; & i_3 \ge 11.2 \end{Bmatrix} \quad (3.39)$$

$$\mu_M(AC) = \{0/4.8 + 0.375/6 + ... + 1/8\} \quad (3.39a)$$

Similarly, the linguistic expressions and membership functions of other could be calculated. In the defuzzification stage, truth degrees (μ) of the rules are calculated for each rule by aid of the min and then by taking the max between working rules. To comprehend fuzzification, consider this example. For crisp input *DC* = 3 %, *SC* = 25 g/l and *AC* = 8 g/l, the rules 18 and 19 are fired. The firing strength (truth values) α of the two rules are obtained as:

$$\alpha_{18} = \min\{(\mu_L(DC), \mu_M(SC)), \mu_M(AC)\} = 0.5$$

$$\alpha_{19} = \min\{(\mu_M(DC), \mu_M(SC)), \mu_M(AC)\} = 0.5$$

Consequently, the membership functions for the conclusion reached by rules (18) and (19) are obtained as follows.

$$\mu_{18}(CS) = \min\{0.5, \mu_L(CS)\}$$

$$\mu_{19}(CS) = \min\{0.5, \mu_H(CS)\}$$

Haghighat et al., (2014) have cited that in many circumstances, for a system whose output is a fuzzy set, it is essential to aggregate the fuzzy sets in to a single fuzzy set by aggregation method. Finally, using Equation 3.29, Figure 3.18 and Table 3.17, the crisp output of color strength is obtained as 16.

3.5.3 Fuzzy modeling for color strength of cotton/lycra knitted fabric

From practical experience of working in textile dyeing industry, the dyeing process parameters namely dye concentration (*DC*), dyeing time *(DT*) and process temperature (*PT*) influence the color strength of cotton/lycra knitted fabric considerably. Hence these three dyeing process have been used as the input variables to the fuzzy color strength modeling of cotton/lycra knitted fabric. A MATLAB Fuzzy Toolbox (version 7.10.0) was used to develop the fuzzy intelligent model of color strength. Six possible fuzzy number namely very low (VL), low (L), medium (M), medium high (MH), high (H) and very high (VH) were chosen for the input variable DT, four possible linguistic variables namely very low (VL), low (L), medium (M) and high (H) was used for the input variable DT and three possible linguistic variables namely low (L), medium (M) and high (H) was used for the input variable PT. The values were specified in such a way that they were equally spaced and covered the whole input space. In this study, six membership functions for DC, four membership functions for DT and three membership functions for PT have been selected based on system knowledge and previous experience. It has been seen from past experience in dyeing that dye concentration has the most effect on the color strength compared to dyeing time and process temperature, hence six membership functions were chosen for DC. Seven linguistic variables, namely very low (VL), low (L), low medium (LM), medium (M), high medium (HM), high (H) and very high (VH), were considered for the output variable CS, so that the expert system could map small changes in color strength with changes in the input variables.

In the present study, triangular shaped membership functions have been used for both input and output variables due to their accuracy (Marakoglu and Carman, 2010). There is a level of membership for each linguistic word that applies to that input variable. Fuzzifications of the used factors namely dye concentration (*DC*), dyeing time (*DT*), process temperature (*PT*) and color strength (*CS*) are made by aid follows functions:

$$DC(i_1) = \begin{cases} i_1; & 0.5 \le i_1 \le 7 \\ 0; & otherwise \end{cases} \tag{3.40}$$

$$DT(i_2) = \begin{cases} i_2; & 40 \le i_2 \le 70 \\ 0; & otherwise \end{cases} \tag{3.41}$$

$$PT(i_3) = \begin{cases} i_3; & 50 \le i_3 \le 70 \\ 0; & otherwise \end{cases} \tag{3.42}$$

$$CS(o_1) = \begin{cases} o_1; & 1 \le o_1 \le 22 \\ 0; & otherwise \end{cases} \tag{3.43}$$

In Equations (3.40 - 3.43), i_1 is the first input variable (*DC*), i_2 is the second input variable (*DT*) and i_3 is the third input variable (*PT*) and o_1 is the output variable (*CS*). The amount of *DC* is computed in percentage (%) from 0.5 - 7, *DT* is calculated in second from 40 - 70, *PT* is determined in degree Celsius (^{0}C) from 50 - 70 and *CS* is calculated in (dimensionless) from 1- 22, respectively.

The creation of membership functions for the input variables DC, DT, PT and output variable CS are shown in Figures 3.20 - 3.23. These membership functions facilitate in converting numeric variables of input and output into linguistic fuzzy sets. Within this structure of the current research work, the subsequent rules are used to form the input and output membership functions.

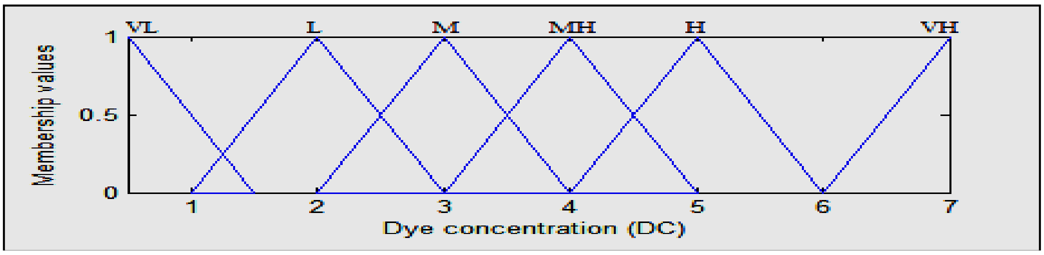


Figure 3.20: Membership functions of input variable DC.

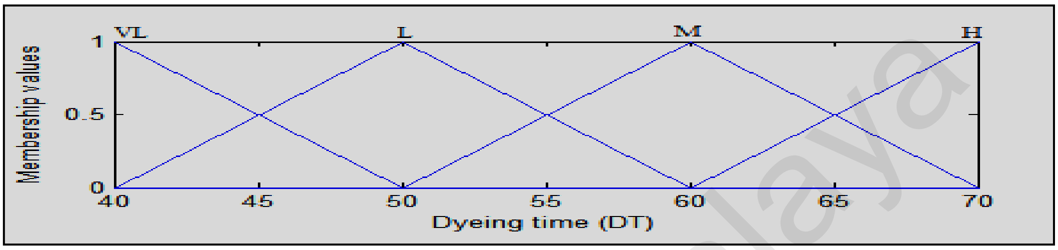


Figure 3.21: Membership functions of input variable DT.

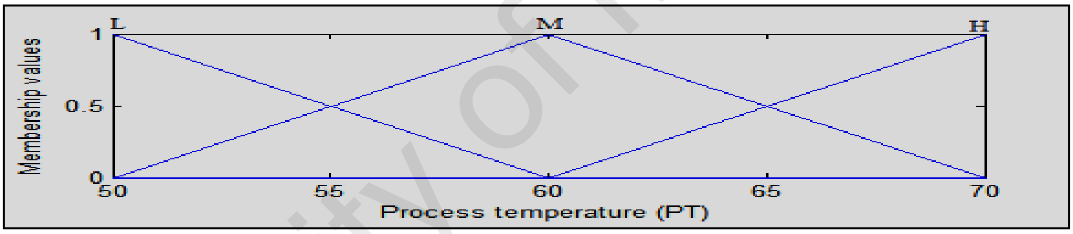


Figure 3.22: Membership functions of input variable PT.

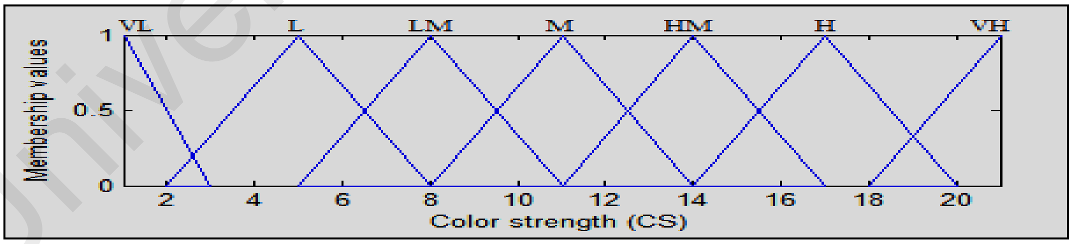


Figure 3.23: Membership functions of output variable CS.

The coefficients of membership functions for the input and output parameters of color strength model of cotton knitted fabrics have been presented in Appendix A. Subsequent to fuzzification, total 72 fuzzy rules were created for the input and output parameters based on expert knowledge and previous experience. A number of rules are presented in Table 3.19.

In this study, a mamdani max-min inference approach has been used since these operators assure a linear interpolation of the output between the rules. Finally, the center of gravity defuzzification method has been applied in the present investigation in order to transfer the fuzzy output into non-fuzzy crisp numeric value according to Equation 3.29 (Haghighat et al., 2014). The linguistic expressions and membership functions of input parameters of dye concentration (*DC*), dyeing time (*DT*), and dyeing process temperature (*PT*) could be calculated and are presented Appendix B.

Table 3.19: Fuzzy inference rules for color strength model of cotton/lycra.

Rules	Input variables			Output variables
	DC	*DT*	*PT*	*CS*
1	VL	VL	L	VL
-----	-----	-----	-----	-----
2	L	VL	L	L
-----	-----	-----	-----	-----
16	MH	M	L	M
-----	-----	-----	-----	-----
18	H	M	L	MH
-----	-----	-----	-----	-----
36	M	M	H	H
-----	-----	-----	-----	-----
72	H	H	H	VH

3.5.4 Fuzzy modeling for color strength of lyocell/lycra knitted fabric

For the development of color strength model of lyocell/lycra knitted fabrics, three dyeing process parameters namely dye concentration (DC), dyeing temperature (DT) and liquor ratio (LR) have been used as input variables and color strength (CS) of the dyed fabrics as the output variable. These process parameters have been found to affect significantly on the color strength of lyocell/lycra knitted fabric. Six possible linguistic variables namely very low (VL), low (L), medium (M), medium high (MH), high (H) and very high (VH) were chosen for the input variable DC and three probable fuzzy variables that is low (L), medium (M) and high (H) were used for the input variables DT and LR. In this study, six membership functions for DC, three membership functions for DT and LR have been selected based on system knowledge, experimental conditions and arbitrary choice. Fourteen output fuzzy sets (level 1 to level 14) have been regarded for color strength, in order that the fuzzy expert system might map little changes in color strength with changes in the input variables. In the current investigation triangular shaped membership functions have been applied for both input and output variables because of their accurateness (Carman, 2008). The units for the input and output variables are: DC (%), DT (^{0}C), LR (dimension less) and CS (dimension less). There is a level of membership for each linguistic word that applies to that input variable. Fuzzification of the dye concentration (DC), process temperature (PT), Liquor ratio (LR) and color strength (CS) are made by aid follows functions:

$$DC(i_1) = \begin{Bmatrix} i_1; & 1 \le i_1 \le 9 \\ 0; & otherwise \end{Bmatrix} \tag{3.44}$$

$$PT(i_2) = \begin{Bmatrix} i_2; & 45 \le i_2 \le 75 \\ 0; & otherwise \end{Bmatrix} \tag{3.45}$$

$$LR(i_3) = \begin{Bmatrix} i_3; & 4 \le i_3 \le 12 \\ 0; & otherwise \end{Bmatrix} \tag{3.46}$$

$$CS(o_1) = \begin{Bmatrix} o_1; & 1.5 \le o_1 \le 21 \\ 0; & otherwise \end{Bmatrix} \tag{3.47}$$

In these Equations (3.44 - 3.47), i_1 is the first input variable (*DC*), i_2 is the second input variable (*PT*) and i_3 is the third input variable (*LR*) and o_1 is the output variable (*CS*).

The value of *DC* is computed in percentage (%) from 1 - 9, *PT* is determined in degree Celsius (^{0}C) from 45 – 75, *LR* is computed in (dimension less) from 4 - 12 and *CS* is calculated in (dimensionless) from 1.5 – 21, respectively. The triangular formed membership functions for the fuzzy variables, namely, DC, DT, LR and CS have been developed using MATLAB Fuzzy Toolbox as depicted in Figures 3.24 - 3.27.

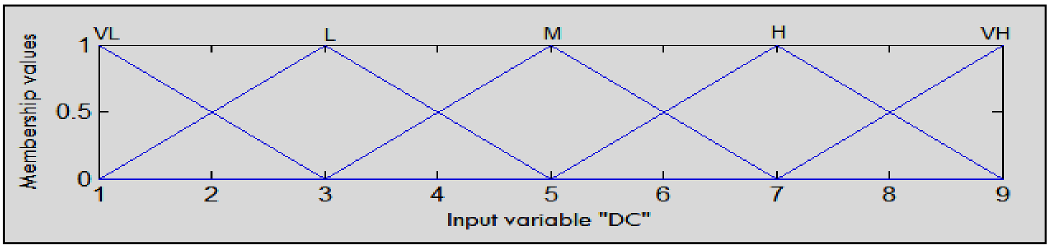


Figure 3.24: Membership functions of input variable DC.

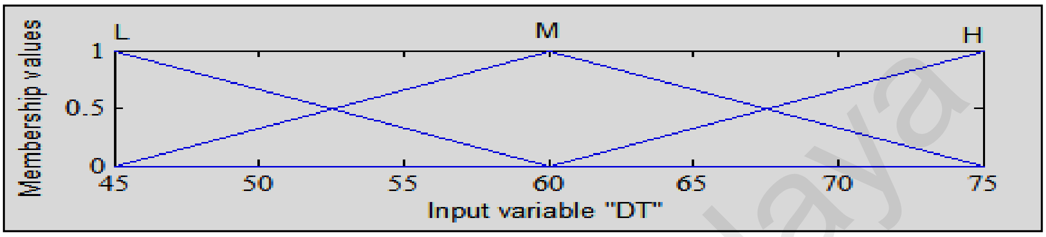


Figure 3.25: Membership functions of input variable DT.

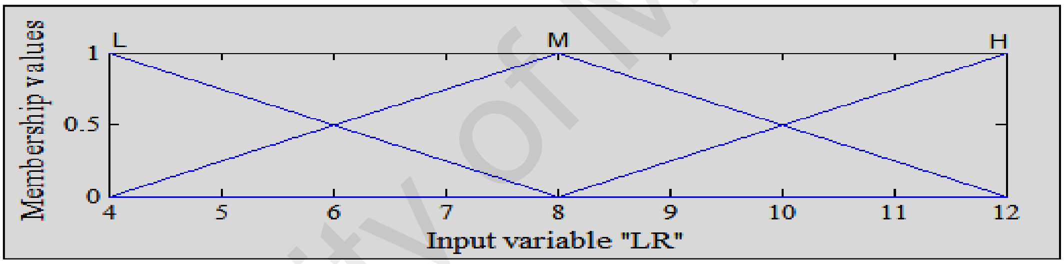


Figure 3.26: Membership functions of input variable LR.

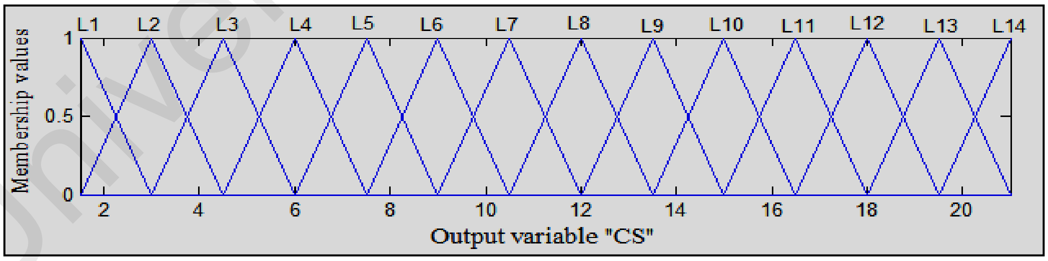


Figure 3.27: Membership functions of output variable CS.

The coefficients of membership functions for the input variables dye concentration, dyeing time, liquor ratio and output parameters of color strength model of lyocell/lycra knitted fabrics have been presented in Appendix C. Since, input variable DC has five, DT and LR have three linguistic levels, and hence total 5 x 3 x 3 = 45 fuzzy rules were created. Some rules are shown in Table 3.20.

Further, a mamdani max-min inference mechanism and the center of gravity defuzzification method have been used in this modeling to convert the fuzzy output into non-fuzzy numeric value as per Equation 3.29 (Haghighat et al., 2014). The linguistic expressions and membership functions of input parameters of dye concentration (DC), dyeing process temperature (DT), and liquor ratio (LR) could be computed and are presented Appendix D.

Table 3.20: Fuzzy inference rules for color strength model of lyocell.

Rules	Input variables			Output variables
	DC	*DT*	*LR*	*CS*
1	VL	L	L	L1
-----	-----	-----	-----	-----
2	L	L	L	L4
-----	-----	-----	-----	-----
16	VL	L	M	L2
-----	-----	-----	-----	-----
30	VH	H	M	L12
-----	-----	-----	-----	-----
40	VH	M	H	L12
-----	-----	-----	-----	-----
45	VH	H	H	13

3.5.5 Fuzzy modeling for bursting strength of viscose/lycra knitted fabrics

For development of fuzzy logic model, three knitting variables such as knitting stitch length (*SL*), yarn count (*YC*) and yarn tenacity (*YT*) have been used as input variables and bursting strength (*BS)* of knitted fabrics as output variable. These knitting variables have been exclusively selected as they influence the fabric bursting strength considerably. A Fuzzy logic Toolbox from MATLAB (version 7.10.0) was used to develop the proposed fuzzy model of bursting strength. For fuzzification, four possible linguistic subsets namely very low (VL), low (L), medium (M), and high (H) for input variables *SL* and *YC* as well as three convenient linguistic subsets namely low (L), medium (M) and high (H) for input variable *YT* were chosen in such a way that they are evenly spaced and cover up the entire input spaces.

Ten output fuzzy sets (Level 1 to 10) (where, L = Level) were considered for fabric bursting strength (BS), so that the fuzzy logic system can map small changes in bursting strength with the changes in input variables. In this study, the triangular shaped membership functions are used for input-output variables because of their accuracy (Marakoglu and Carman, 2010). Selection of the number of membership functions and their initial values is based on the system knowledge and experimental conditions. There is a level of membership for each linguistic word that applies to that input variable. Fuzzification of the stitch length (SL), yarn count (YC), yarn tenacity (YT) and bursting strength (BS) are made by aid following functions:

$$SL(i_1) = \begin{Bmatrix} i_1; & 2.7 \le i_1 \le 3.0 \\ 0; & otherwise \end{Bmatrix} \tag{3.48}$$

$$YC(i_2) = \begin{Bmatrix} i_2; & 24 \le i_2 \le 36 \\ 0; & otherwise \end{Bmatrix} \tag{3.49}$$

$$YT(i_3) = \begin{Bmatrix} i_3; & 15.25 \le i_3 \le 15.75 \\ 0; & otherwise \end{Bmatrix} \tag{3.50}$$

$$BS(o_1) = \begin{Bmatrix} o_1; & 270 \le o_1 \le 460 \\ 0; & otherwise \end{Bmatrix} \tag{3.51}$$

In these Equations (3.48 - 3.51), i_1 is the first input variable (*SL*), i_2 is the second input variable (*YC*) and i_3 is the third input variable (*YT*) and o_1 is the output variable (B*S*).

The value of SL is computed in mm from 2.7 – 3.0, *YC* is determined in Ne from 24 – 36, *YT* is computed in g/tex from 15.25 – 15.75 and *BS* is calculated in kPa from 270 - 460, respectively. Triangular shaped membership functions for the fuzzy variables namely, stitch length (*SL*), yarn count (*YC*) and yarn tenacity (*YT*) and bursting strength (*BS*) have been created using Fuzzy Toolbox from MATLAB and are shown in the Figures 3.28 - 3.31.

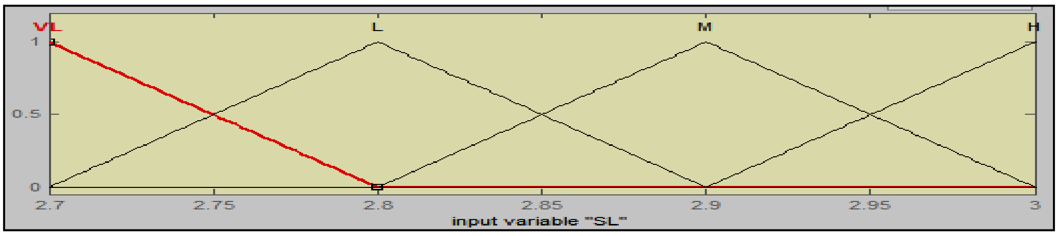


Figure 3.28: Membership function of input variable SL.

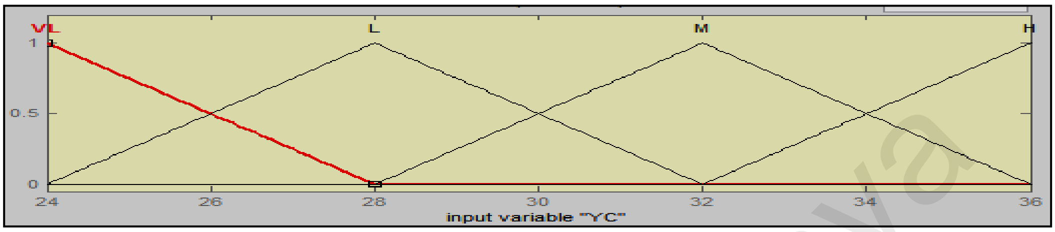


Figure 3.29: Membership function of input variable YC.

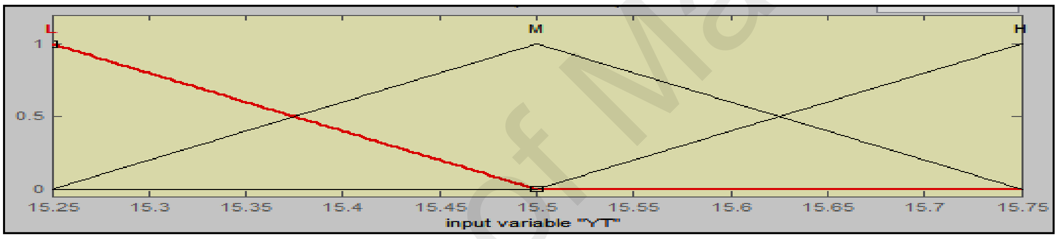


Figure 3.30: Membership function of input variable YT.

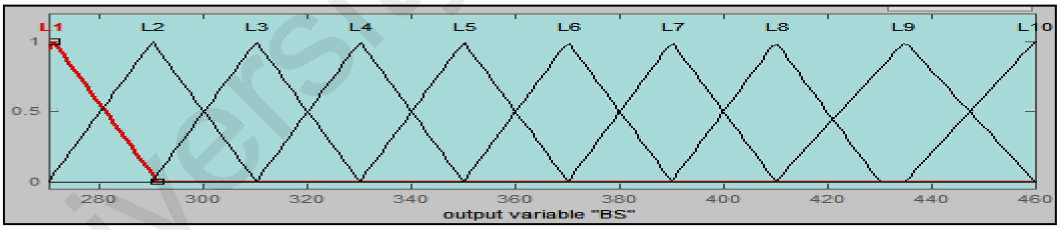


Figure 3.31: Membership function of output variable BS.

The coefficients of membership functions for the input variable, stitch length (*SL*), yarn count (*YC*), yarn tenacity (*YT*) and output variables of bursting strength (BS) of lyocell knitted fabrics have been presented in Appendix E. Conceptually, there could be 4 x 4 x 3 = 48 fuzzy rules, as input variable *SL* having 4 linguistic levels, *YC* having 4 linguistic levels and *YT* having 3 linguistic levels. However, to make simpler the fuzzy logic system only 24 fuzzy rules have been formed based on expert knowledge and previous experience (Majumdar and Ghosh, 2008). Some of the rules are presented in Table 3.21. Further, a Mamdani max-min inference approach and the center of gravity defuzzification method have been applied in this work to aggregate and defuzzification. The linguistic expressions and calculation of membership functions values of input parameters of stitch length (*SL*), yarn count (*YC*) and yarn tenacity (*YT*) are demonstrated in Appendix F.

Table 3.21: Fuzzy inference rules for bursting strength model of viscose.

Rules no.	Input variables			Output variable
	SL	*YC*	*YT*	*BS*
1	VL	H	L	Level 3
2	L	H	L	Level 2
…..	…..		…..	…..
10	L	L	M	Level 5
11	M	L	M	Level 6
…..	…..		…..	…..
23	M	VL	M	Level 9
24	H	M	H	Level 6

3.6 Experiments for the Validation of Fuzzy Intelligent Models

3.6.1 Experiment for color strength of viscose/lycra knitted fabrics

Dyeing process was conducted for bleached viscose/lycra blended knitted fabric samples (each 5gm) via exhaust dyeing methods with Remazol Blue RR reactive dyes in a laboratory dyeing machine (Figure 3.6) according to dyeing conditions as shown in Table 3.22. Subsequent to dyeing all samples were cold rinsed and then hot washed at 90 ^{0}C for 15 minutes to remove the electrolyte, alkali and unfixed dyes. Next, the samples were dried and conditioned. The photograph of viscose single jersey (S/J) dyed fabric sample is showed in Figure 3.32. Following conditioning, reflectance values of all dyed samples were measured using the spectrophotometer (Figure 3.8), in a visible region with wavelength ranges of 550 nm, 600 nm and 650 nm.

The average of three reflectance values for each sample was taken. Finally, Color strength was calculated using the Equation 3.1.

Table 3.22: Dyeing conditions for viscose knitted fabric.

Process Parameters	Unit	Values				
Dye concentration	%	1	2	3	4	5
Salt concentration	g/l	15		25		35
Alkali concentration	g/l	4		8		12
Time	minute	60				
Temperature	^0C	60				
Material to Liquor ratio		1:12				

Figure 3.32: Photograph of viscose dyed fabric.

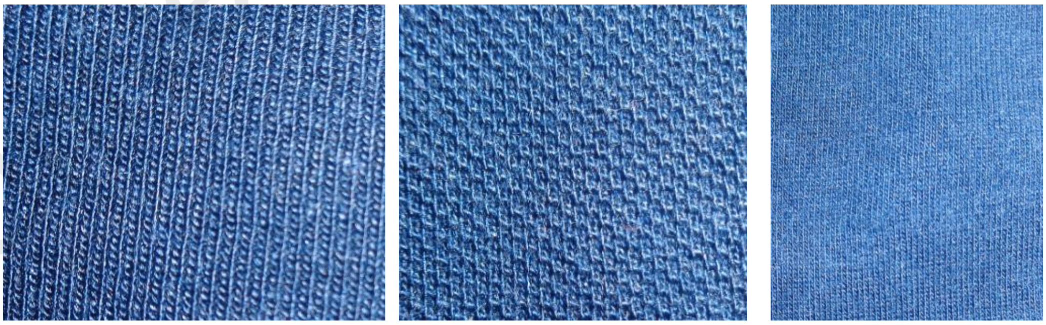
3.6.2 Experiment for color strength of cotton/lycra knitted fabrics

In this study, three different structures of bleached cotton knitted fabrics such as 95 % cotton with 5 % lycra single jersey, 100 % cotton 1x1 rib and 100 % cotton pique were (each 5gm) dyed using exhaust dyeing methods with Remazol Blue RR reactive dyes in a laboratory dyeing machine according to a set of values for dye concentration (%), salt concentration (g/l, alkali concentration (g/l), dyeing time (min), process temperature (0^0C) and material: liquor ratio as shown in Table 3.23. Commonly, dye concentration, dyeing time and process temperature are the most important factors affecting the color strength of cotton/lycra blended knitted fabrics.

After dyeing all the samples were cold rinsed and hot washed at 90 ^{0}C for 10 minutes remove salt and unfixed dyes. Then, the samples were dried and conditioned for 2 hours at (65±2) % relative humidity and (20±2) ^{0}C temperature. For example, the photograph of cotton dyed samples with three knitted structure such as 1x1rib, Pique and S/J are displayed in Figure 3.33. After conditioning, reflectance values of all dyed samples were measured using the spectrophotometer (Data Color 650 TM), in a visible region with wavelength ranges of 550 nm, 600 nm and 650 nm and average of three reflectance values for each samples are taken. Finally, the color strength (K/S) was calculated using Kubelka- Munk Equation 3.1.

Table 3.23: Dyeing conditions for cotton knitted fabric.

Process parameters	Unit	Values				
Dye concentration	%	0.5	2.5	4.5	5.5	7
Dyeing Time	minutes	40	50	60	70	
Dyeing Temperature	^{0}C	50	60	70		
Salt concentration	g/l	45				
Alkali concentration	g/l	12				
Material: Liquor ratio		1 :10				



(a) 1x1 RIB fabric (b) Pique fabric (c) S/J fabric

Figure 3.33: Photograph of cotton dyed fabrics, (a) 1x1 RIB fabric, (b) Pique fabric, (c) S/J fabric.

3.6.3 Experiment for color strength of lyocell/lycra knitted fabrics

In this investigation, two diverse constructions of bleached lyocell knitted fabrics such as 95 % lyocell with 5 % lycra single jersey and 100 % lyocell 1x1 rib were (each 5gm) dyed using exhaust dyeing methods with Remazol Blue RR reactive dyes in a laboratory dyeing machine according to a set of values as shown in Table 3.24. After dyeing all the samples were cold rinsed and hot washed at 90 ^{0}C for 10 minutes with 0.5 g/l soaping agent. Subsequently, the samples were dried and conditioned for 2 hours at (65±2) % relative humidity and (20±2) ^{0}C temperature. The photograph of lyocell dyed samples with two knitted structure such as S/J and 1x1rib are demonstrated in Figure 3.34. After conditioning, reflectance values of all dyed samples were measured using the spectrophotometer in a visible region with wavelength ranges of 400 -700 nm and average of three reflectance values for each samples are taken. At the end, the color strength (K/S) was calculated using Kubelka- Munk Equation 3.1. The experimental results for lyocell/lycra knitted fabrics are presented in Appendix G.

Table 3.24: Dyeing conditions for lyocell.

Process parameters	Unit	Values				
Dye concentration	%	1	3	5	7	9
Dyeing Temperature	^{0}C		45	60	75	
Material: Liquor ratio			4	8	12	
Time	minutes	50				
Salt concentration	g/l	50				
Alkali concentration	g/l	14				

(a) S/J fabric (b) 1x1 rib fabric

Figure 3.34: Photograph of (a) S/J, (b) 1x1 rib lyocell knitted dyed fabrics.

3.6.4 Experiments for bursting strength of viscose/lycra knitted fabric

3.6.4.1 Fabric knitting and heat setting

In this research, total 20 viscose/lycra blended plain fabrics samples were knitted according to Table 3.25 knitted fabric variables on Pailung single jersey circular knitting machine (Figure 3.35), having 30 inches diameter, 20 gauges (needles/inch) and 90 yarn feeders. The jersey knitted fabric was pre-wetted on the padding mangle using 2 g/l wetting detergent (Feloson NOF, CHT Bangladesh) and 1 g/l lubricating agent (Kappavon CL, Kappe-chemie, Bangladesh) and then heat setting was conducted on the pin stenter finishing machine at a temperature of 200 ^{0}C for 45 second of curing time.

Table 3.25: Knitted fabric variables and their level.

Process Parameters	Unit	Level			
		1	2	3	4
Stitch length	mm	2.7	2.8	2.9	3.0
Yarn count	Ne	24	30	34	
Yarn tenacity	g/tex	15.25	15.5	15.75	

Figure 3.35: Circular knitting machine (APS Textile, Bangladesh).

3.6.4.2 Fabric processing and testing

The fabrics samples were subjected to semi-bleached at 90 ^{0}C for 40 minutes in a sample dyeing machine using anti creasing agent 1 g/l (Kappavon CL), sequestering agent 0.5 g/l (Kappquest FE), wetting agent 1 g/l (Feloson NOF), soda ash 2.5 g/l, hydrogen peroxide (50%) 1g/l, stabilizing agent 0.2 g/l (Kappazon H53). Then the fabrics samples were washed with proper rinsing and finally treated with acetic acid (1g/l) and peroxide killing agent 0.2 g/l (Kappazyme AP) for neutralizing and peroxide killing respectively. After bleaching, the fabric samples were dried and compacting properly with Lafer compactor machine (Figure 3.36).

After production, all the fabrics samples were conditioned firstly on a flat surface for at least 24 hours prior to testing under standard laboratory conditioned [RH (65±2) % and (20±2) ^{0}C temperature]. Then the fabric bursting strength (kPa) of each sample was tested using Pneumatic Bursting tester (Figure 3.9) with a specimen of 30 mm in diameter according to ISO-139388-1 test method. The experimental results of fabric bursting strength are shown in Appendix H.

Figure 3.36: Lafer compacting machine (APS Textile, Bangladesh).

3.7 A NN Prediction Model Development

3.7.1 Artificial neural network

Artificial neural network (ANN) is a computational powerful data modeling tool that is inspired by the structure of biological networks able to capture and represent each kind of input - output relationship which are unknown or hard to describe (Haghighat et al., 2014; Moezzi et al., 2015; Nohut et al. 2015; Ngai et al., 2014). Currently, ANNs are being used for a wide variety of tasks in many different fields of engineering, science, medicine, agriculture, manufacturing, especially in the field of textile manufacturing (Haghighat, 2014; Hussain et al., 2015; Vadood, 2014). One major application area of ANN is prediction. A most broadly used artificial neural network that is based on the multi-layer perceptron (MLP) has been shown in Figure 3.37 (Azimi et al., 2013).

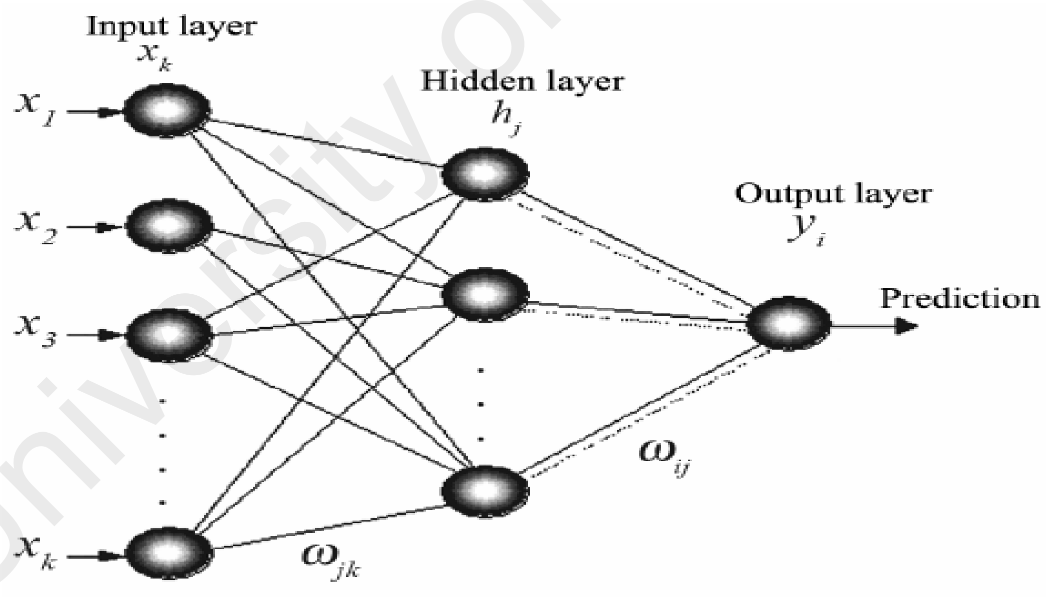


Figure 3.37: Basic structure of ANN (Azimi et al., 2013).

Despite the many satisfactory characteristics of ANN construction a neural network predictor for a meticulous prediction problem is a nontrivial job. Modeling issues that affect the performance of an ANN is considered carefully.

The basic and most important task in the ANN modeling is to determine the appropriate network architecture that is the number of hidden layers, number of neurons in each layer and the number of arcs which inter-connect with the neurons. Other network design decisions include the selection of activation functions of the hidden and output nodes, the training algorithm, data transformation or normalization methods, training and test sets, and performance are measured (Hussain et al., 2015).

3.7.1.1 The network architecture

In general, a multi-layer feed forward neural is parallel interconnected structure consisting of: (i) input layer (independent variables), (ii) hidden layers, (iii) and output layer (dependent variables) (Hossain et al., 2012; Moezzi et al., 2015; Nohut et al., 2015). The input layer receives and distributes the input signals. The number of neurons in the input and output layers in ANN prediction model is directly related to the number of problem parameters under study and there is no order to exactly determine it. In the hidden layers, the relation between the input and output layers is created and the output layer gives the output value. The hidden layer and nodes play very important roles for many successful applications of neural networks. The hidden nodes in the hidden layer allow neural networks to detect the feature, to capture the pattern in the data, and to perform complication nonlinear mapping between input and output variables (Moezzi et al., 2015; Nohut et al., 2015). From the theoretical results, most of the researchers use only one hidden layer for prediction purpose and show that a single hidden layer is sufficient for ANNs to approximate any complex nonlinear function with any desired accuracy. However, one hidden layer networks may require a very large number of hidden nodes. The activated function is also called the transfer function. It determines the relationship between input and outputs of the node and a network.

In general, the activation function introduces a degree of nonlinearity that is valuable for most ANN application. In practice, only small numbers of "well-behaved" functions are used. Generally, a network may have different activation function for different nodes in the same or different layers. Majority of researcher use logistic transfer functions for hidden nodes for prediction study. The logarithm sigmoid (logsig) transfer function can be shown as per Equation (3.52) (Moezzi et al., 2015).

$$f(x) = \frac{1}{1+ e^{-x}} \tag{3.52}$$

3.7.1.2 ANN training algorithm

A neural network is generally trained so that a particular input leads to specific output. The process of training is adjusting the weight and bias values to minimize the overall mean or total squared error between the desired and actual output values (Guruprasad and Behera, 2010; Haghighat et al., 2012). There are many training algorithms are used to optimize the performance of neural networks. Among them most popular used training method is the feed forward back propagation with Levenberg-Marquardnt learning algorithm (Hussain et al., 2015; Nohut et al., 2015). This is more efficient nonlinear optimization method and is used in most prediction models (Azimi et al., 2013; Guruprasad and Behera, 2010; Haghighat et al., 2012).

3.7.1.3 Data normalizations

Nonlinear activation functions such the logistic function typically have the squashing role in restricting or squashing the possible output from a node to, typically (0.1, 0.9), (0, 1) or (-1, 1). Data normalization is often performed before the training process begins. When nonlinear transfer function is used at the output nodes, the desired output values must be transformed to the range of the actual outputs of the network.

Even if a linear output transfer function is used, it may still be advantageous to standardize the outputs as well as the input to avoid computational problems, to meet algorithm requirement, and to facilitate network learning (Sanjoy and Jyothi, 2006). There are two potential normalization equations to be used to normalize the input and output data are presented below Equations 3.53 and 3.54 (Zain et al., 2010). Equation 3.54 has been chosen for data normalization in this study.

$$\frac{2}{d_{\max} - d_{\min}} \times (d_i - d_{\min}) - 1 \tag{3.53}$$

$$\frac{0.8}{d_{\max} - d_{\min}} \times (d_i - d_{\min}) + 0.1 \tag{3.54}$$

where, *di* is the i^{th} input/output data,

d_{max} is the maximum value of input/output data and

d_{min} is the minimum value of input/output data.

3.7.1.4 Training and test sample

Typically, training and test sample are required for building an ANN prediction models. The training sample is used for ANN model development and the test sample adopted for evaluating the prediction ability of the model. Sometimes a third one called validation sample is also utilized to avoid the over fitting problem or to determine the stopping point of the training process. But it is common to use one test set for both validation and testing purpose particularly with small data sets. Sample size is closely related with the prediction performance of ANN models. It is evident that the larger the sample size, the more accurate the result will be. Sartori and Antsaklis, (1991) reported that the ANN prediction performance increases with increasing in training sample size.

Further, it was seen from the published journal that there is no exact guideline for the ratio of training and testing data.

But it is common that most of the researchers use smaller number of testing samples than training samples and suggested the ratio of training and test samples as percent such as 90 %: 10 %; 85 %: 15 % and 80 %: 20 % with a total of 100 % for the combined ratio (Zain et al., 2010).

3.7.1.5 Prediction performance measure

After the successful training of the network, the network is tested with the test data. Using the results produced the network; statistical methods have been used to make comparison. In the present study, the prediction performance in terms of the global prediction error such as mean absolute error percentage (*MAPE*), root-mean squared (*RMS*) and coefficient of determination (R^2) are used to assessed and compare Fuzzy logic and ANN models. The formulae of those accuracy measures are given below:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{\sum_{I=1}^{I=N} (E_a - E_M)^2} \right) \tag{3.55}$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{N}} \tag{3.56}$$

$$\text{MAEP} = \frac{1}{\text{N}} \sum_{i=1}^{i=N} \left(\frac{|E_a - E_p|}{E_a} \times 100 \right) \tag{3.57}$$

Where, E_a = Actual result, E_p = Predicted result, E_m = Mean value, N = Number of pattern.

The coefficient of determinations (R^2) compares the accuracy of the model to the accuracy of a trivial benchmark model. *RMS* should be small as close as zero for good accuracy of prediction. The mean absolute error percentage (*MAPE*) gives the deviation between the predicted and experimental values and it is required to reach zero.

3.7.2 ANN modeling for color strength of viscose/lycra knitted fabrics

In the present study, ANN prediction model has been developed to predict the color strength of viscose knitted fabrics in textile dyeing industry using NN tool box from MATLAB (version 7.10.0). Input variables to the feed forward neural network are DC (dye concentration) (1-5 %), SC (salt concentration) (15-35 g/l) and AC (alkali concentration) (4-12 g/l) in input layer. The color strength (CS) of dyed sample is chosen as the output variable in output layer for developing ANN model. In this study, ANN model is developed based on 3- 6 -1 network structure, meaning that it has three nodes for input layer, six nodes for hidden layer and one node for output layer as shown in Figure 3.38.

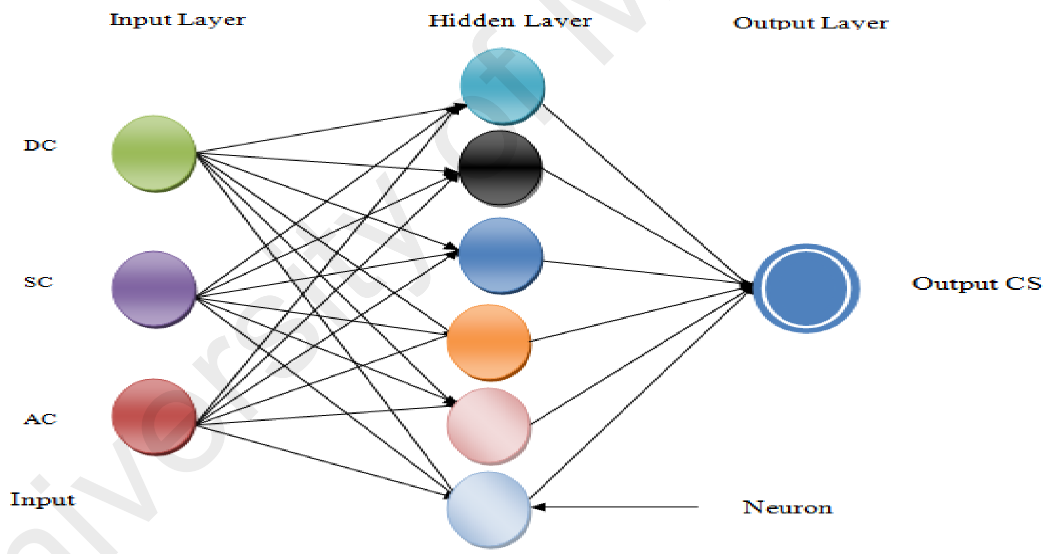


Figure 3.38: Single hidden-layer ANN for color strength (CS) model.

The number of nodes in hidden layer is chosen double with the number of input nodes in all prediction models. In this investigation, no transfer function in the input layer, while logistic sigmoid (logsig) transfer function in hidden layer and purelinear (pureln) transfer function in the output layer have been used to develop ANN prediction model.

A total 45 experimental data sets were used to feed ANN structure. Out of 45 data sets, 36 data sets were applied to train ANN and 9 data sets were used for test and validation the ANN model. Data normalization is often performed before the training process begins. In the present study, Equation 3.54 is used for data normalization of both input and output values between 0.1 and 0.9. Subsequent to data normalization, neural network is trained so that a particular input leads to specific output by minimizing the overall mean or total squared error between the desired and actual output values (Guruprasad and Behera, 2010; Haghighat et al., 2012). Among various training algorithm, the feed forward back propagation with Levenberg-Marquardt learning algorithm is the most popular training method used to train the ANN. After successful training of ANN, the prediction formulas of dyeing performance are obtained as a function of dye concentration, salt concentration and alkali concentration. Weights and bias value of input to hidden layer and hidden to output layer is obtained from MATLAB neural network toolbox. In order to test ANN models, nine experiments are designed randomly. The experimental values for training and coded values for training ANN models are shown in Appendix I and Appendix J, respectively. During training period one dataset is needed to avoid overtraining of ANN model by early stopping. In this study, testing data set of ANN is also used for validating neural networks during training. It is reduced the number of experiments of the present study. It is also saved the time and cost of project without affecting the performance the prediction model.

3.8 Development of Resin Finishing Model.

3.8.1 Fabric pretreatment and dyeing

The pre-treatment of the fabric was done in industrial-scale winch dyeing machine at 90 ^{0}C for 40 min using anti creasing agent (Kappavon CL 1 g/l), sequestering agent (Kappquest FE, 0.5g/l), wetting agent (Felosan NOF 1 g/l), soda ash

(2.5 g/l), Hydrogen peroxide 50% (2.5 g/l), stabilizing agent (Kappazon H53 0.0.3 g/l). Then 0.1 % syno white 4BK was added in bath to make the sample white shade. Finally, the dyed fabric was hot washed, rinsed and neutralized by using 1.0 g/l acetic acid.

3.8.2 Resin finishing

The resin finishing treatments were conducted according to the experimental conditions given in Table 3.26. The recipes were prepared with the specified amount of the resin, softener and $MgCl_2$ catalyst (20 % of the amount of resin used as recommended by resin manufacturer). The application of the recipes was done on the laboratory padder at 75 % pick-up, followed by drying and curing at 170 °C for the times specified in the experimental conditions.

Table 3.26: Experimental conditions for resin treatment.

Parameters	Unit	Level		
Resin concentration	g/l	25	75	125
Softener concentration	g/l	15	45	75
Curing time	second	45	135	225

3.8.3 Measurement of shrinkage and bursting strength

Subsequent to production, all the fabrics samples were subjected to conditioning firstly on a flat surface for at least 24 hours prior to testing under standard atmospheric conditions at relative humidity (65 ± 2) % and temperature (20 ± 2) °C. The length and width-way shrinkage of the samples was calculated as per equation (3.58) and (3.59) after washing the samples according to AATCC TM-135. The test sample with length and width way marking is depicted in Figure 3.39. Then the bursting strength (kPa) of each resin treated sample was measured using Pneumatic Bursting tester (Figure 3.11) with a specimen of 30 mm in diameter according to ISO-139388-1 test method.

The experimental results for shrinkage and bursting strength are shown in Table 3.27.

$$Length\ \ way\ Shrinkage = \frac{Lb-La}{Lb}\ \text{x}\ 100 \tag{3.58}$$

$$Width\ \ way\ Shrinkage = \frac{Wb-Wa}{Wb}\ \text{x}\ 100 \tag{3.59}$$

Where, *Lb* = Length before wash, *La* = Length after wash (Figure 3.39)

Wb = Width before wash, *Wa* = Width after wash (Figure 3.39)

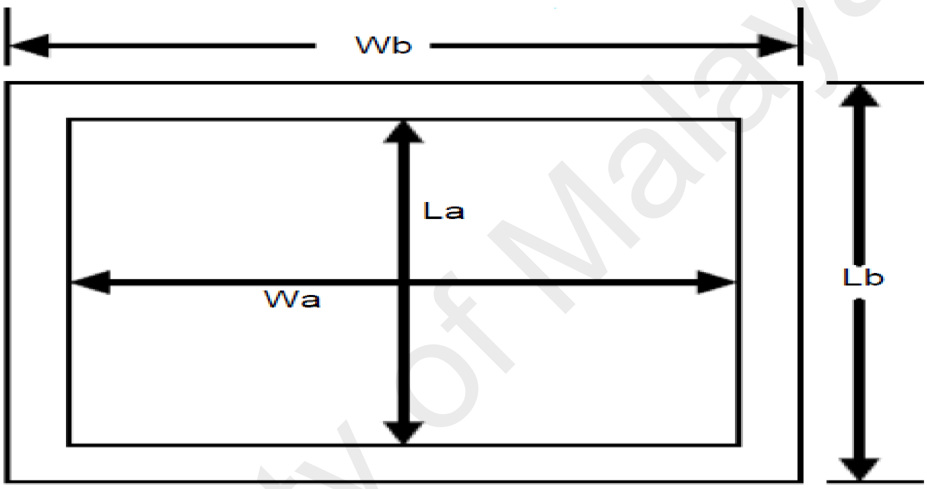


Figure 3.39: Test sample with length and width way marking.

Table 3.27: The experimental results for shrinkage and bursting strength.

Exp No.	Resin	Softener	Curing time	Shrinkage		Bursting strength
	g/l	g/l	sec	LS	WS	BS
1	25	15	45	-4.27	-0.67	273.80
2	25	45	135	-3.73	-1.47	314.40
3	25	75	225	-5.50	-1.87	281.00
4	75	15	135	-1.60	-2.00	317.70
5	75	45	225	-6.13	0.27	311.40
6	75	75	45	-5.50	-0.93	271.60
7	125	15	225	-2.93	-0.80	299.00
8	125	45	45	-6.53	0.20	286.30
9	125	75	135	-6.70	-0.23	307.40

3.8.4 Fuzzy prediction model development

For the development of resin finishing model of viscose knitted fabrics, resin concentration (RC), softener concentration (SC) and curing time (CT) has been used as input variables and length-way shrinkage (LS), width-way shrinkage (WS) and bursting strength (BS) as the output variables. Three possible linguistic fuzzy sets namely low (L), medium (M), and high (H) were chosen for the input variables RC, SC and CT. Nine output fuzzy sets (level 1 to level 9) have been considered for LS,WS and BS. These linguistic fuzzy sets are able to properly cover the ranges of inputs and outputs parameters.

In the present study triangular shaped membership functions have been used for both input and output variables due to their accuracy (Marakoglu and Carman, 2010). The membership functions for resin concentration (RC), softener concentration (SC), curing time (CT), length-way shrinkage (LS), width-way shrinkage (WS) and bursting strength (BS) have been shown in Figures 3.40 - 3.45.

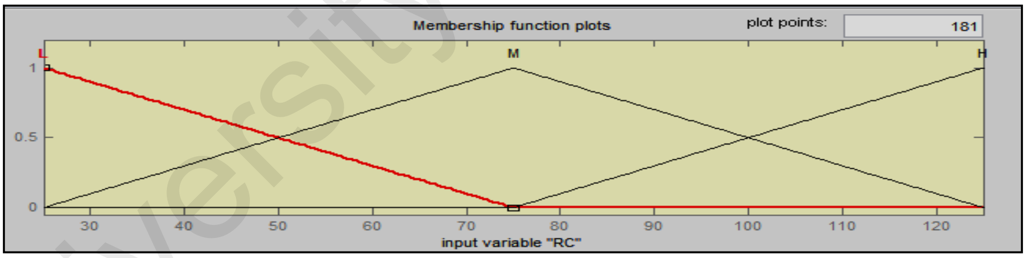


Figure 3.40: Membership function of RC.

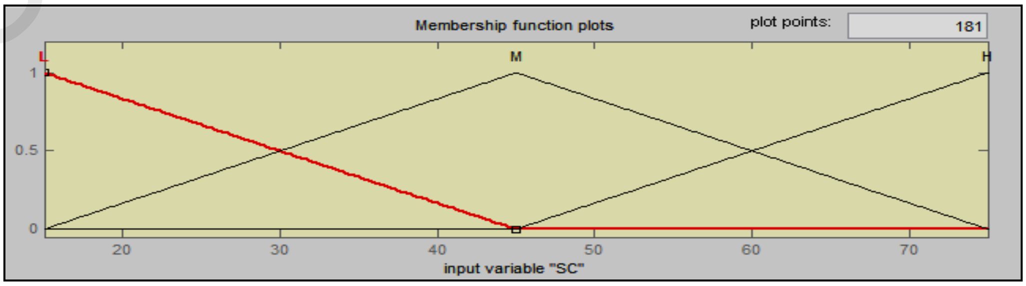


Figure 3.41: Membership function of SC.

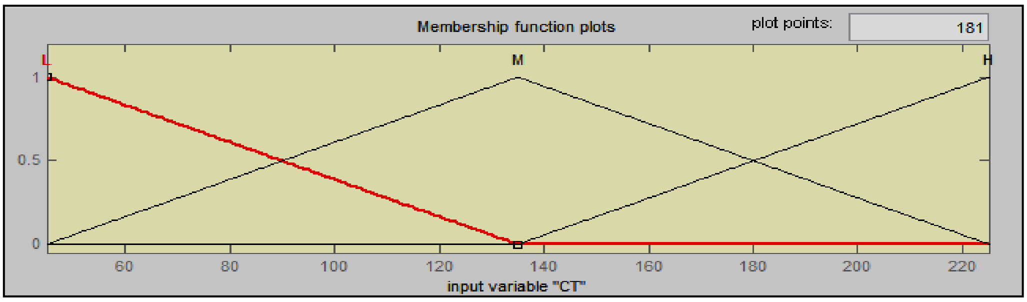


Figure 3.42: Membership function of CT.

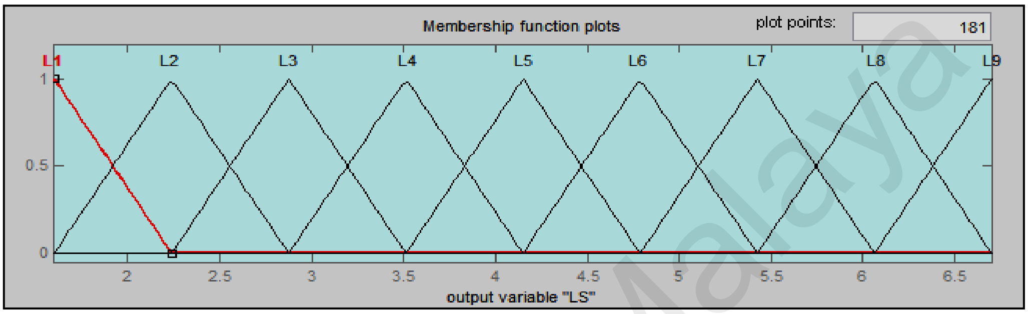


Figure 3.43: Membership function of LS.

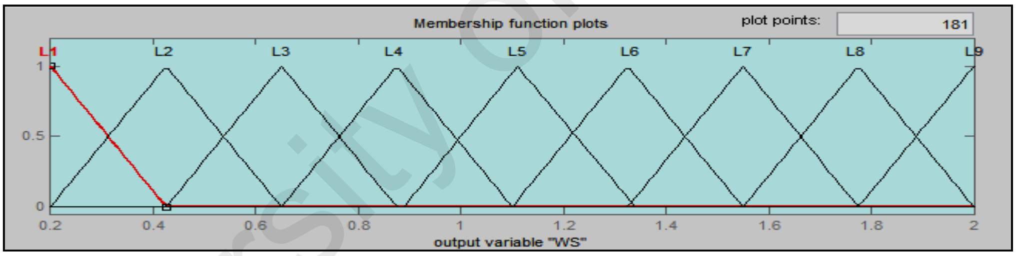


Figure 3.44: Membership function of WS.

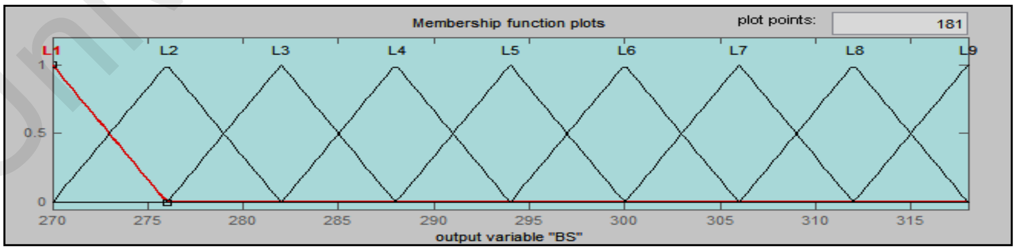


Figure 3.45: Membership function of BS.

After fuzzification, total 9 fuzzy rules were created based on expert knowledge and previous experience as presented in Table 3.28. In these rules, 'AND' operation was used. The function '*Minimum*' of the two values was selected for 'AND' operator.

Finally, a mamdani max-min inference mechanism and center of gravity defuzzification method have been applied in this study to convert fuzzy output into non-fuzzy crisp numeric value (Hghighat et al., 2014).

Table 3.28: Fuzzy inference rules for shrinkage.

Rules no.	Input variables			Output variables		
	RC	*SC*	*CT*	*LS*	*WS*	*BS*
1	L	L	L	L1	L7	L2
2	L	M	M	L4	L7	L8
3	L	H	H	L7	L8	L3
4	M	H	L	L7	L4	L1
5	M	L	M	L1	L9	L9
6	M	M	H	L8	L1	L8
7	H	M	L	L9	L1	L4
8	H	H	M	L9	L1	L7
9	H	L	H	L3	L4	L6

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

The effects of the different process variables have been studied experimentally for viscose/lycra knitted fabrics and also results are discussed as well as compared with cotton/lycra knitted fabrics. The results and discussion of Taguchi optimization study & mathematical model for the prediction of color strength of viscose/lycra knitted fabrics are presented. Further, results of Fuzzy intelligent prediction model for color strength of viscose/lycra blended knitted fabrics have been discussed and compared with the Fuzzy color strength model of cotton/lycra and lyocell/lycra blended knitted fabrics. Also a prediction performance result of Fuzzy intelligent model has been compared with Taguchi mathematical model and ANN prediction model. In addition, performance of fuzzy resin finishing model has been discussed and presented. The results are discussed in graphical formation as well as in tabular forms.

4.2 Effects of Process Variables on Fabric Properties

4.2.1 Effects of dye concentration on color strength

The color strength (CS) of cotton/lycra and viscose/lycra knitted fabrics in different dye concentration (DC) are depicted in Figure 4.1. Figure illustrates that color strength increases with increasing in dye concentration (DC) for both fabrics because of more absorptions of dyes. However, color strength increases rapidly for viscose /lycra knitted fabrics while increases slightly for cotton /lycra knitted fabrics. The reason for rapid increasing in color strength for viscose /lycra as compared to cotton /lycra knitted fabrics is due to the high absorbency and reactivity of viscose fiber (Broadbent, 2001; Shaikh et al., 2012).

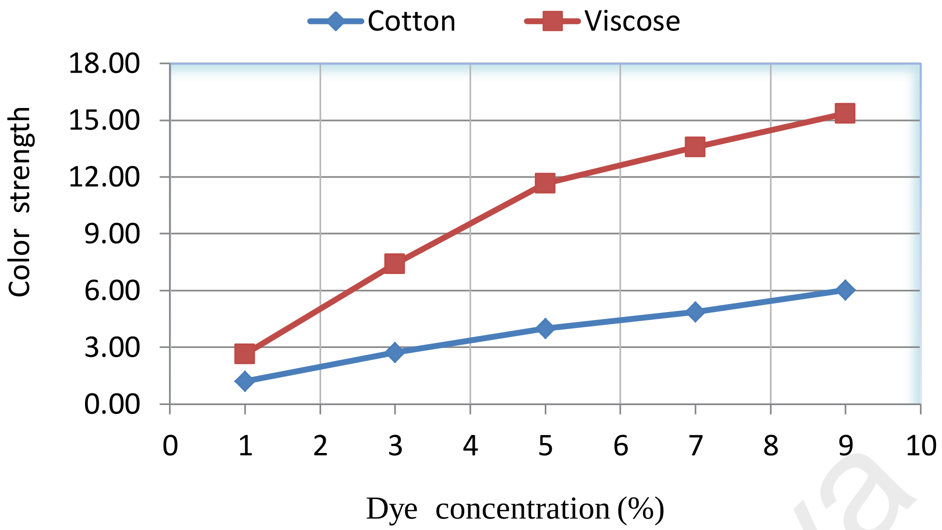


Figure 4.1: Effects of dye concentration on color strength at dyeing time 60 min, temperature 60 ^{0}C, salt concentration 60 g/l, alkali concentration 15 g/l and M:L ratio 1:12.

4.2.2 Effects of dyeing time on color strength

Figure 4.2 depicts that the effects of dyeing time on color strength (CS) is not linear for cotton/lycra and viscose/lycra knitted fabrics. Firstly, for viscose/lycra knitted fabrics, the color strength increases sharply with the increases of time from 30 minutes to 75 minutes due to more absorption of dye, but it decreases when the time increases from 75 minutes to 90 minutes because of hydrolysis of dyes for prolonged time. A similar pattern has been observed for cotton/lycra knitted fabrics also but an effect of time on color strength is not pronounced as viscose.

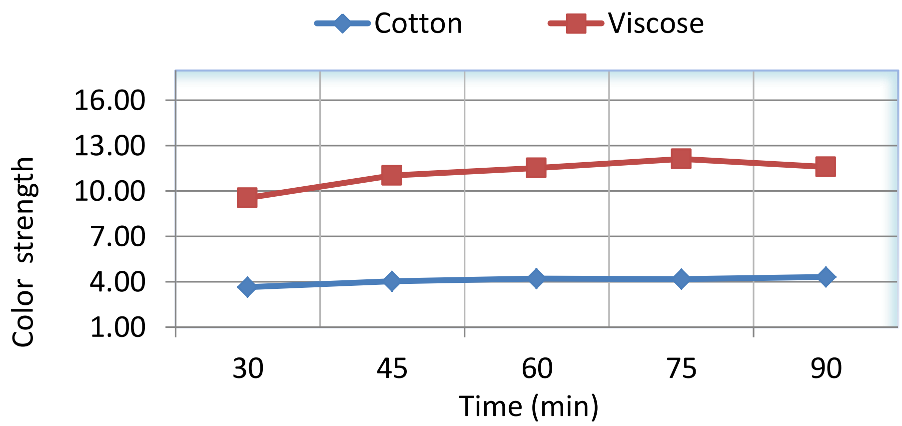


Figure 4.2: Effects of dyeing time on Color strength at dye concentration 5 %, temperature 60 ^{0}C, salt concentration 60 g/l, alkali concentration 15 g/l and M:L ratio 1:12.

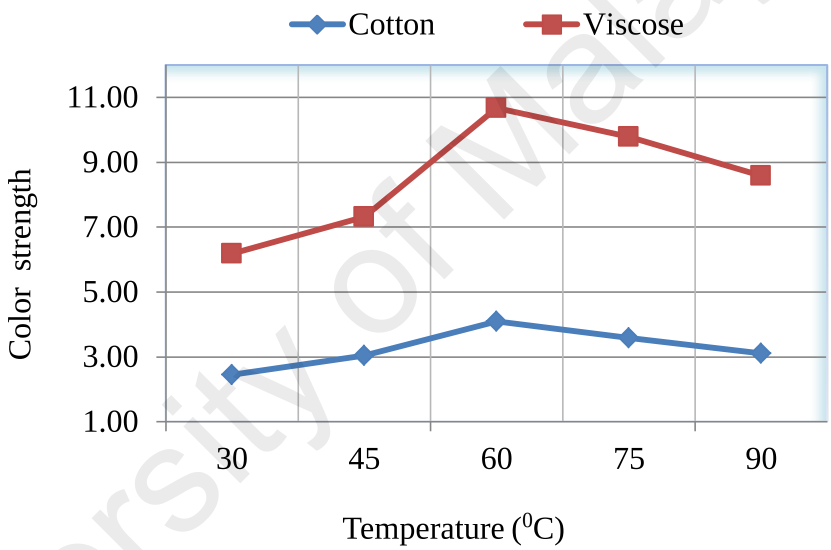


Figure 4.3: Effects of dyeing temperature on color strength at dye concentration 5 %, time 60 min, salt concentration 60 g/l, alkali concentration 15 g/l and M:L ratio 1:12.

4.2.3 Effects of dyeing temperature on color strength

It is obvious from Figure 4.3 that the effect of dyeing temperature on color strength is not linear for cotton/lycra and viscose/lycra knitted fabrics. The color strength increases remarkably for both fabrics with the increases in dyeing temperature from 30 ^{0}C to 60 ^{0}C due to more exhaustion and fixation, however it decreases while dyeing temperature increases from 60 ^{0}C to 90 ^{0}C owing to hydrolysis of dyes in a higher dyeing temperature.

4.2.4 Effects of salt concentration on color strength

The color strength increases with increases in salt concentration for viscose /lycra and cotton knitted fabrics as shown in Figure 4.4. These is because salt represses negative charge by decreasing its zeta potential from the fabric surface and boost up rapid dye absorption and exhaustion, leading to higher color strength for viscose /lycra knitted fabrics. It is clear from Figure 4.4 that the increasing in color strength for viscose is higher than the cotton fabrics with increasing in salt concentration due to higher amorphous region in viscose.

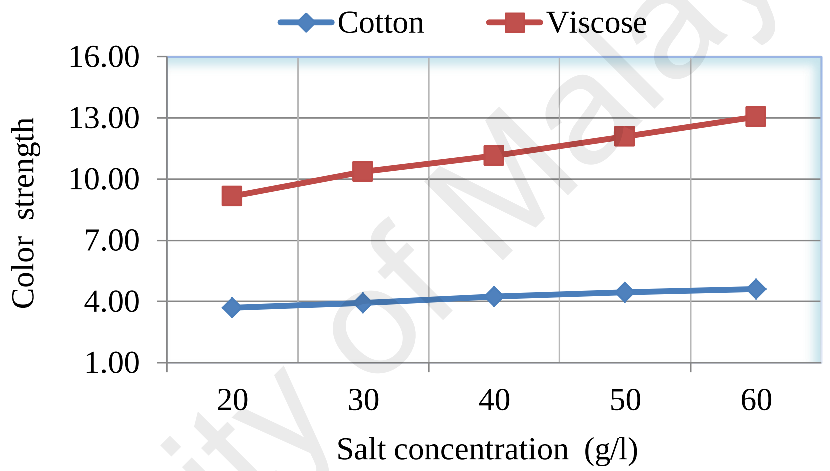


Figure 4.4:Effects of salt concentration on color strength at dye concentration 5 %, time 60 min, temperature 60 ^{0}C, alkali concentration 15 g/l and M:L ratio 1:12.

4.2.5 Effects of alkali concentration on color strength

The effects of alkali concentration on the color strength for viscose /lycra and cotton knitted fabrics as shown in Figure 4.5. Figure exemplify that the effects of alkali concentration on color strength is not much more profound for both fabrics.

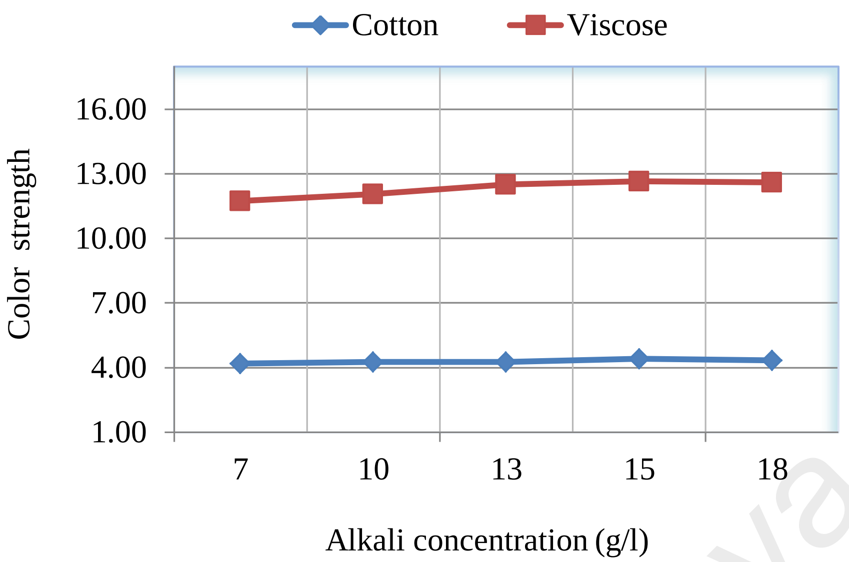


Figure 4.5: Effects of alkali concentration on color strength at dye concentration 5 %, time 60 min, temperature 60 ^{0}C, salt concentration 60 g/l, and M: L ratio 1:12.

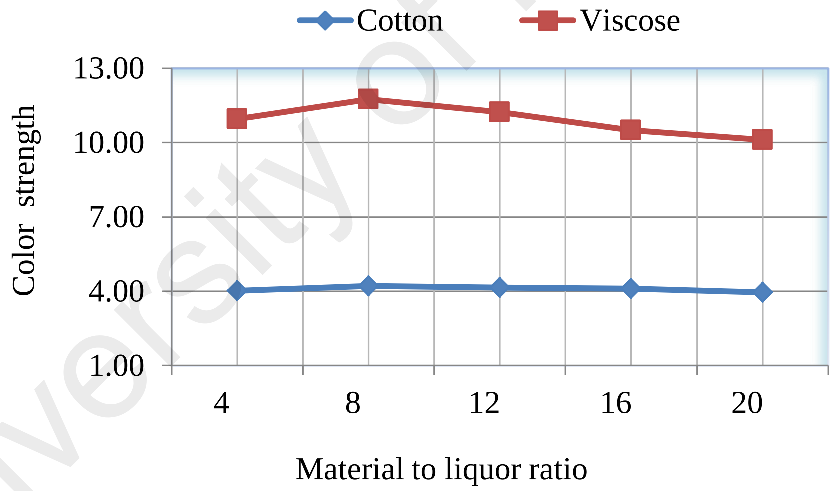


Figure 4.6: Effects of Material to liquor ratio on color strength at dye concentration 5 %, time 60 min, temperature 60 ^{0}C, salt concentration 60 g/l, and alkali concentration 15 g/l.

4.2.6 Effects of liquor ratio on color strength

Figure 4.6 depicts that the effects of liquor ratio on color strength is not linear for cotton/ lycra and viscose /lycra knitted fabrics. The color strength increases for both fabrics up to liquor ratio 1:8, however it shows downward trend whilst liquor ratio increases from 1:8 to 1:20 owing to lower concentration of dye bath.

4.2.7 Effects of alkali bleaching on color strength

The effects of alkali bleaching on color strength of viscose and cotton fabrics have been demonstrated in Figure 4.7. Figure shows that alkali bleaching has more influence on the color strength for cotton fabric than that of viscose fabrics due to changes in the chemical and structural properties of cotton fiber during the combined scouring bleaching process. The reason for that the unwanted impurities in cotton fiber is removed by alkali bleaching which facilitates the dye uptake while viscose is pure cellulose, hence effect is very minor (Murugesh and Selvadass, 2013).

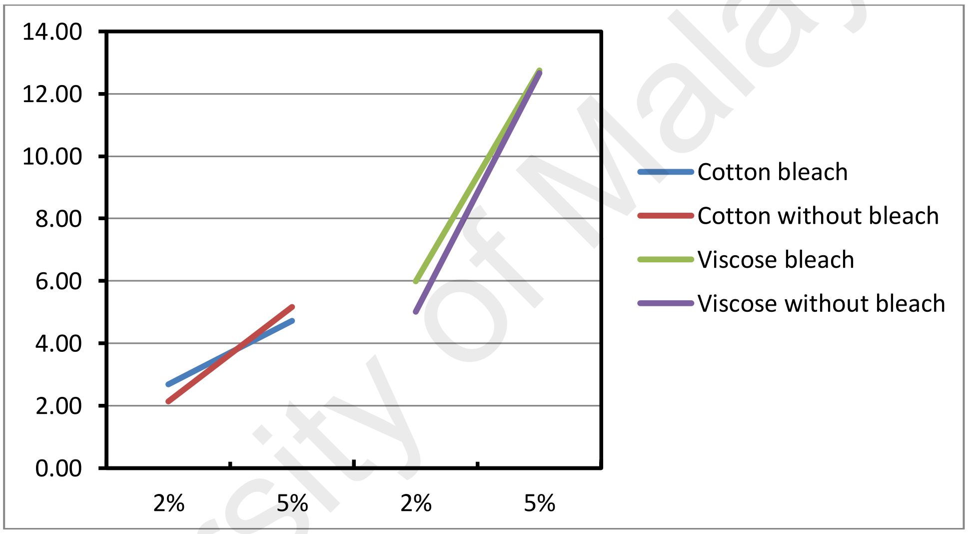
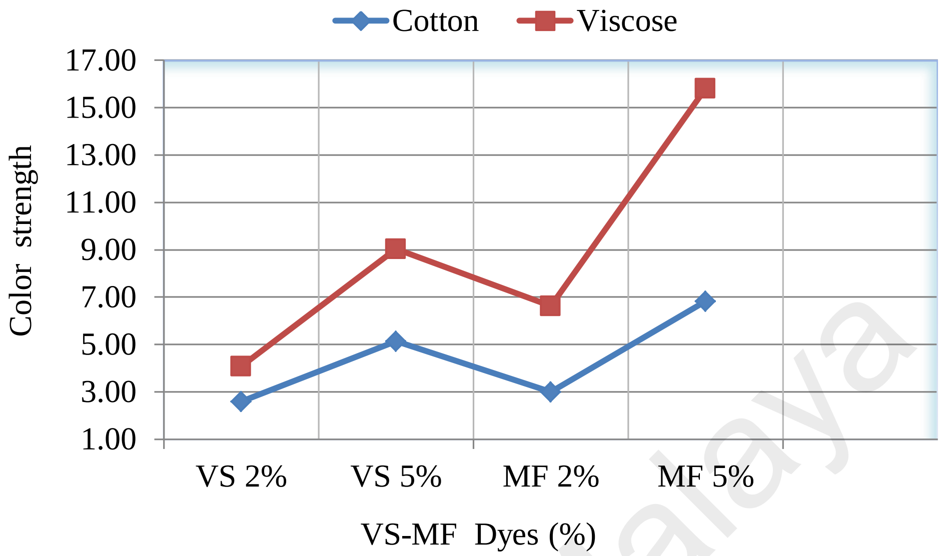


Figure 4.7: Effects of alkali bleaching on color strength at time 60 min, temperature 60 ^{0}C and M: L ratio 1:12.

4.2.8 Effects of different dyes class on color strength

(i) ***Vinyl sulphone (VS) and Multi-functional (MF) dyes***

Color strength of VS dyes (Remazol Blue RR) and MF dyes (Sunfix Navy Blue MFD) for viscose and cotton fabrics have been exposed in Figure 4.8. MF dyes because of high substantivity shows higher color strength as compared to VS dyes for both fabrics. However, color strength of viscose is more than to 120 % (In case of 2% MF dyes) and more than to 130% (In case of 5% MF dyes) higher than the cotton fabric (Aspland, 1997; Bates, et al., 2008). This is because viscose fabric is more absorbent than the cotton fabric.



VS = Vinyle sunphone and MF = Multifunctional

Figure 4.8: Effects of VS and MF dyes on color strength.

(ii) ***Remazol RR and Livafix CA dyes***

It is evident from Figure 4.9 and Figure 4.10 that color strength increases with increasing in Remazol Blue RR and Livafix Blue CA dye concentration except Remazol Red RR and Livafix Red CA dyes. Moreover, color strength obtained for viscose fabrics at dye concentration 2 % and 4 % are 50 % higher than the cotton fabrics.

This is owing to difference in fiber composition and dye chemistry. The amorphous region in viscose fiber fabrics are greater extent as compared to the cotton, which allow dye molecules penetrating rapidly to reacts with the accessible site of the viscose fiber and formed covalent bond.

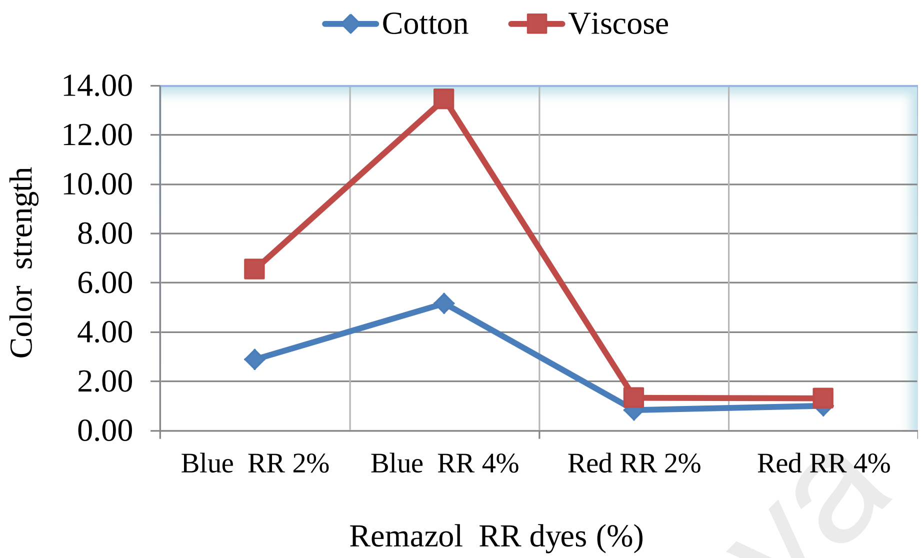


Figure 4.9: Color strength of Remazol RR dyes.

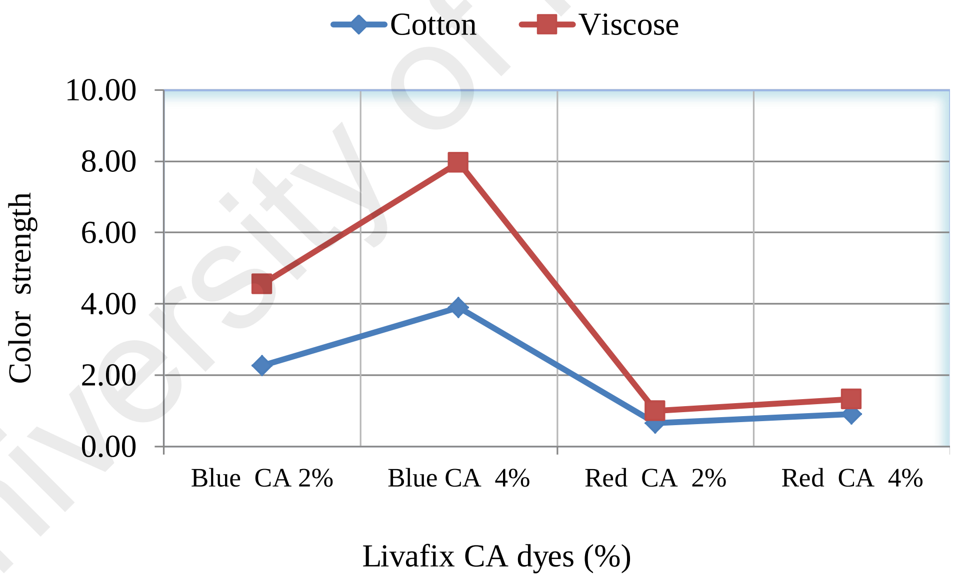


Figure 4.10: Color strength of Livafix CA dyes.

4.2.9 Effects of knitted fabric GSM on color strength

The effects of fabric GSM on the color strength for viscose /lycra and cotton/lycra knitted fabrics as shown in Figure 4.11. Figure shows that color strength increases with the decreasing in fabric GSM for both fabrics.

Basically, fabric GSM decreases due to decreases in yarn linear density. Further, if yarn linear density decreases then number of loops per unit area will be increased, hence fabric porosity will be increased which enables dye liquor to penetrate easily throughout the fabric structure (Afzal et al., 2014; Ashraf et al., 2014; Riza and Kerim, 2007).

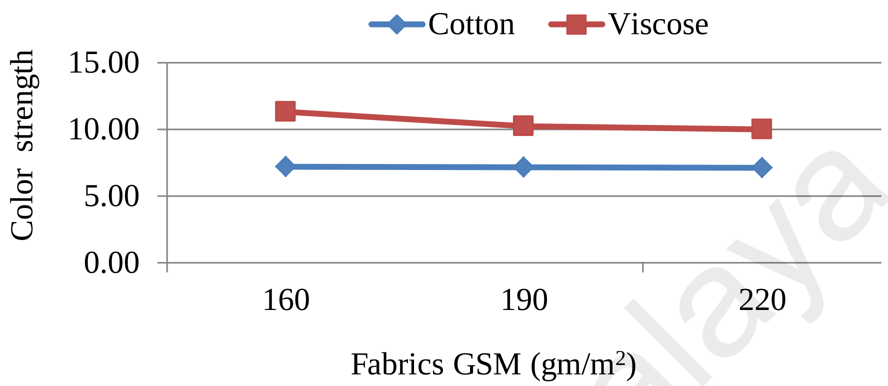


Figure 4.11: Effects of fabrics GSM on color strength.

4.2.10 Effects of knitted fabric GSM on bursting strength

The bursting strength (BS) of cotton/lycra and viscose/lycra knitted fabrics are given in Figure 4.12. Figure shows that bursting strength increases with the increasing in fabric GSM for cotton/lycra knitted fabrics and viscose/lycra knitted fabrics due to increase in number of loops per inch which bear the multidirectional force. It is apparent that the increasing in bursting strength for cotton/lycra is severe with the increase in fabric GSM due to higher DP (Degree of polymerization) and higher crystallinity of cotton than viscose fabrics, which leading to privileged bursting strength (Jamshaid et al., 2013).

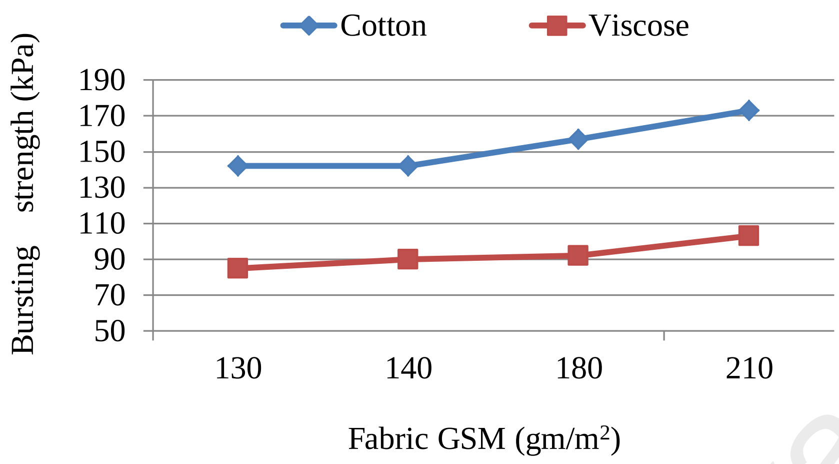


Figure 4.12: Effects of fabric GSM on bursting strength.

4.2.11 Effects of Lycra % on bursting strength

The effects of lycra percentages (%) on the bursting strength has been depicted in Figure 4.13. It is noticeable from the Figure 4.13 that bursting strength decreases with the increases in lycra percentages (%) for cotton/lycra and viscose/lycra both knitted fabrics due to decrease in number of loops per inch which bear the multidirectional force.

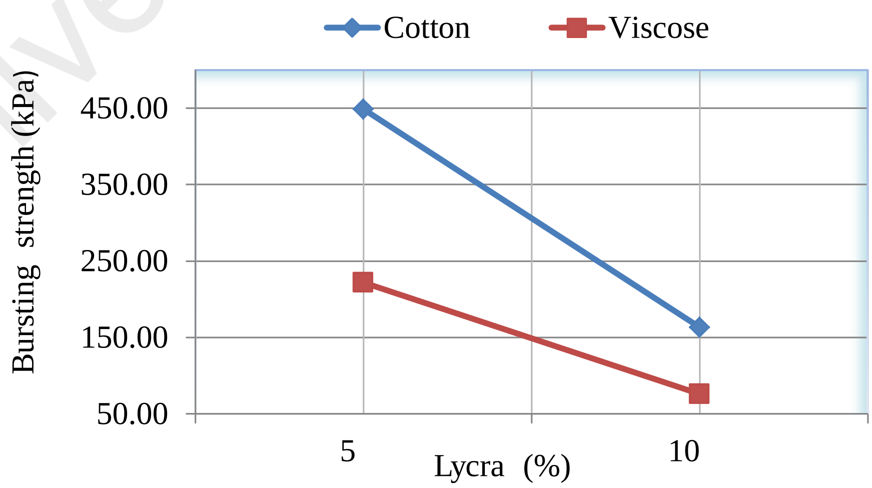


Figure 4.13: Effects of lycra % on bursting strength.

4.2.12 Effects of enzymatic treatment on pilling resistance

The pilling grades of cotton/lycra and viscose/lycra knitted fabrics are shown in Figure 4.14. It can be observed from Figure 4.14 that the pilling grades of viscose/lycra knitted fabrics are very poor in all cases. Alternatively, the pilling grades of cotton/lycra knitted fabric are good for enzyme dosing of 0.5 g/l to 1 g/l and poor for without enzyme dosing. Therefore, it can be concluded that the pilling grades of cotton/lycra knitted fabric increased with the increasing of enzyme dosing, whereas no enzyme effects on the pilling grades of viscose/lycra knitted fabrics.

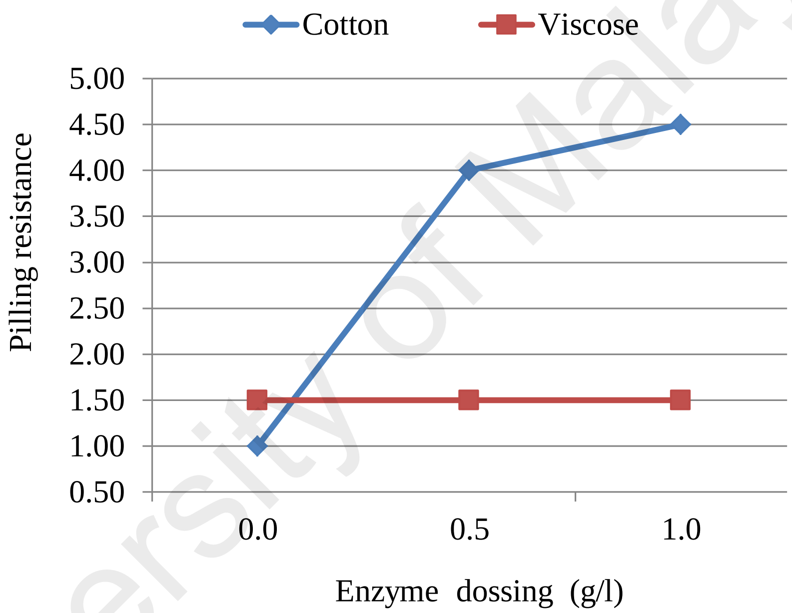


Figure 4.14: Effects of enzyme on pilling resistance.

4.2.13 Effects of washing time and temperature on color fastness to wash and rubbing

Table 4.1 shows that the color fastness to washing and rubbing under various washing times is similar for both cotton and viscose fabrics. However, Table 4.1 also reveals that the rubbing fastness of viscose fabric is slightly higher than that of cotton fabrics. Table 4.2 shows that the color fastness to washing and rubbing under various washing temperature are identical for both cotton and viscose fabrics.

However, Table 4.2 also reveals that the rubbing fastness of viscose fabric is a little greater than that of cotton fabrics. It was observed from the Table 4.1 and 4.2 that the fastness, especially wash fastness depends more on the reactive dye type and dyeing method rather than type of fiber. Intrinsically, the wet rub fastness for viscose is rather better than cotton fiber.

Table 4.1: Effects of washing time on color fastness to wash and rubbing.

Exp. No.		washing time (min)	Wash fastness				Rubbing fastness	
			Color staining			Color Change	Dry	Wet
			Cotton	Nylon	Polyester			
1	cotton	10	4.5	4.5	4.5	4.5	4.5	2.5
	viscose		4.5	4.5	4.5	4.5	4.5	3.5
2	cotton	20	4.5	4.5	4.5	4.5	4.5	2.5
	viscose		4.5	4.5	4.5	4.5	4.5	3.5
3	cotton	40	4.5	4.5	4.5	4.5	4.5	2.5
	viscose		4.5	4.5	4.5	4.5	4.5	3.5

Table 4.2: Effects of washing temperature on color fastness to wash and rubbing.

Exp. No.		wash temperature (^{0}C)	Wash fastness				Rubbing fastness	
			Color staining			Color Change	Dry	Wet
			Cotton	Nylon	Polyester			
1	cotton	80	4.5	4.5	4.5	4.5	4.5	2.5
	viscose		4.5	4.5	4.5	4.5	4.5	3.5
2	cotton	95	4.5	4.5	4.5	4.5	4.5	2.5
	viscose		4.5	4.5	4.5	4.5	4.5	3.5
3	cotton	110	4.5	4.5	4.5	4.5	4.5	2.5
	viscose		4.5	4.5	4.5	4.5	4.5	3.5

4.3 Taguchi Optimization and Mathematical Model

4.3.1 Taguchi optimization study

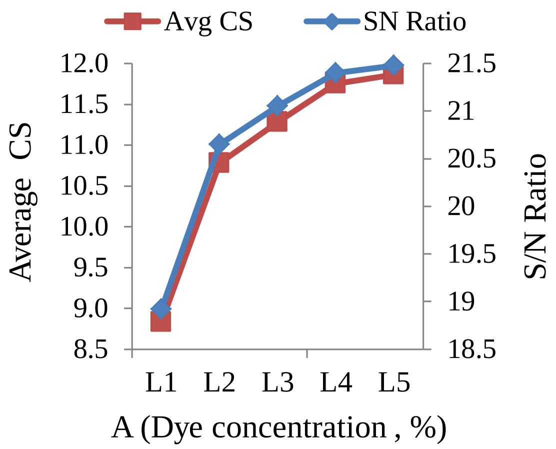
Based on Taguchi design of Experiment explained in section 3.2.3, results have been analyzed and presented as follows:

4.3.1.1 Analysis of experimental results

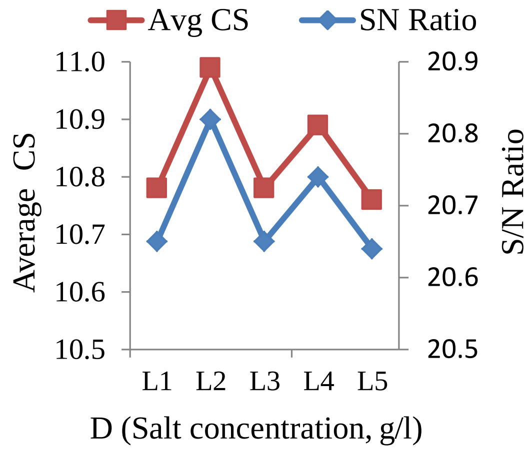
Figure 4.15(a) illustrates that color strength increases with increases in dye concentration. A possible explanation for this may be the increases in dye concentration results in increases dye bath concentration which leading to higher dye absorption as well as increase in color strength due to dye concentration is directly proportional to the dye absorption.

Figure 4.15(b) depicts that the effects of dyeing time on color strength is not linear. Firstly, the color strength increases sharply with the increases in time from 30 minutes to 60 minutes due to more exhaustion of dye, but it decreases while time increases from 60 minutes to 90 minutes because of hydrolysis of dyes for prolonged time.

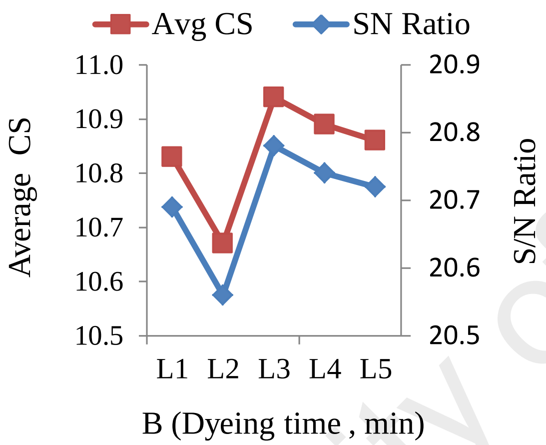
From Figure 4.15(c), it is obvious that the effect of dyeing temperature on color strength (CS) is not linear. The CS increases remarkably with the increases in dyeing temperature from 30 ^{0}C to 75 ^{0}C.This is because the dye solubility as well as number and volume of voids in viscose polymer chain increases at higher temperature, resulting faster diffusion of dye molecules inside the fiber, leading to higher color strength. However, dye solubility and viscose fiber reach its equilibrium state after 75 ^{0}C temperature, resulting dye hydrolysis, leading to lower color strength.



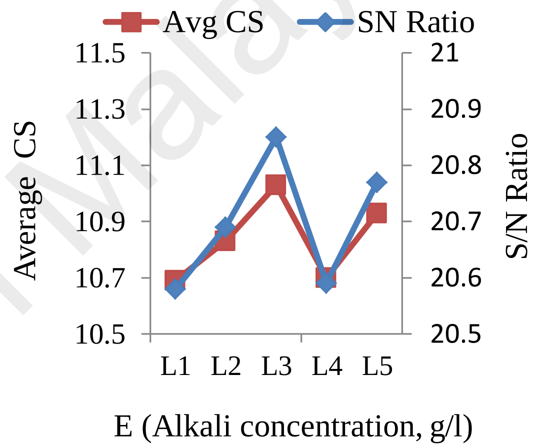
(a) Dye concentration (%) vs. avg CS (-) and S/N ratio



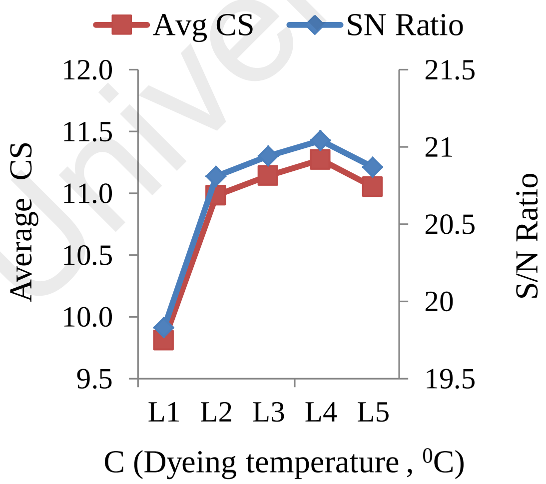
(d) Salt concentration (g/l) vs. avg CS (-) and S/N ratio



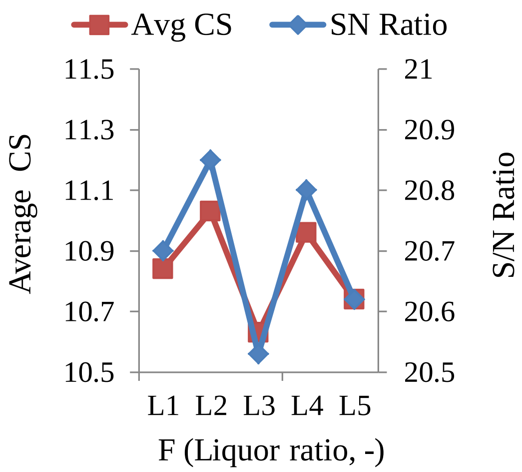
(b) Dyeing time (minutes) vs. avg CS (-) and S/N ratio



(e) Alkali concentration (g/l) vs. avg CS (-) and S/N ratio



(c) Dyeing temperature (^{0}C) vs. avg CS (-) and S/N ratio



(f) Liquor ratio (-) vs. avg CS (-) and S/N ratio

Figure 4.15: Response graph for average color strength and S/N ratio.

It is evident from Figure 4.15 (d) that color strength increases with the increases in salt concentration. This is because salt concentration suppresses negative charge formation at the fabric surface and endorses rate of dye exhaustion and fixation, which leading to higher color strength. However, salt concentration increases further than an optimum level of a certain dye concentration and alkali concentration cause dye aggregation and lower migration, which lead to decrease in dye exhaustion as well as poor color strength.

Figure 4.15(e) represents that color strength increases with the increase in alkali concentration due to develop H-bond with cellulosic-hydroxyl groups of viscose fabric. However, further increase in alkali concentration of a specific dye concentration and salt concentration made the dye and fabric more anionic which repelled each other, results in less dye uptake as well as lower color strength.

Figure 4.15(f) depicts that the effects of liquor ratio on color strength is not linear. The CS increases up to liquor ratio 1:8. However, further increase in liquor ratio of a particular dye concentration, alkali concentration and salt concentration, which lead to decrease in dye bath concentration, results in less dye uptake as well as poor color strength.

4.3.1.2 Analysis of optimum conditions

According to response Table 4.3 - 4.4 and response graph Figure 4.16, the optimal dyeing process parameters and their corresponding level values obtained are A5, B3, C4, D2, E3 and F2, which indicate dye concentration 9 %, dyeing time 60 minutes, dyeing temperature 75 ^{o}C, salt concentration 50 g/l, alkali concentration 14 g/l and bath liquor ratio 1:8 as shown in Table 4.5.

Table 4.3: S/N Ratios response Table (Larger is better).

Factors	A	B	C	D	E	F
Level 1	18.92	20.69	19.83	20.65	20.58	20.70
Level 2	20.65	20.56	20.81	**20.82**	20.69	**20.85**
Level 3	21.05	**20.78**	20.94	20.65	**20.85**	20.53
Level 4	21.40	20.74	**21.04**	20.74	20.59	20.80
Level 5	**21.48**	20.72	20.87	20.64	20.77	20.62
Delta	2.56	0.21	1.21	0.18	0.27	0.32
Rank	**1**	**5**	**2**	**6**	**4**	**3**

Table 4.4: Average color strength response Table (Larger is better).

Factors	A	B	C	D	E	F
Level 1	8.83	10.83	9.81	10.78	10.69	10.84
Level 2	10.78	10.67	10.98	**10.99**	10.83	**11.03**
Level 3	11.28	**10.94**	11.14	10.78	**11.03**	10.63
Level 4	11.75	10.89	**11.27**	10.89	10.70	10.96
Level 5	**11.86**	10.86	11.05	10.76	10.93	10.74

Table 4.5: Optimal parameters level and their corresponding values for dyeing process.

Parameters	Symbol	Level	Value	Unit
Dye concentration	A	5	9	%
Time	B	3	60	Min
Temperature	C	4	75	^{0}C
Salt concentration	D	2	50	g/l
Alkali concentration	E	3	14	g/l
Liquor ratio	F	2	1:8	(-)

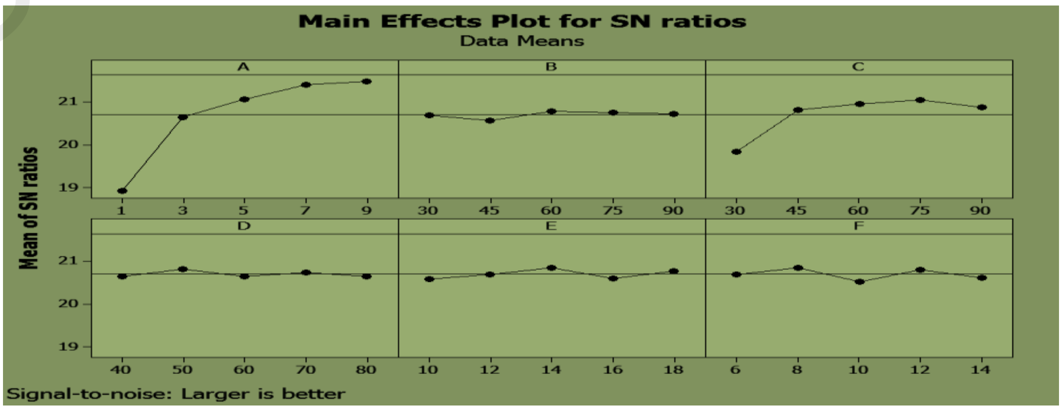


Figure 4.16: The response graph for S/N ratio.

4.3.1.3 Analysis of variance

Analysis of Variance (ANOVA) is applied to evaluate which factors significantly affect the process response. Table 4.6 illustrates an ANOVA test for S/N ratio. According to ANOVA Table 4.6, the controllable factors dye concentration (A) and dyeing temperature (C) are found to be significant (p-value ≤ 0.05) and factors B, D, E, and F insignificant (p-value>0.05) for fabric color strength at 95 % confidence level. Further, the contribution of different factors to the color strength are given away as following order: Dye concentration (74.36%)> Dyeing temperature (16.44%)> Liquor ratio (1.15%)> Salt concentration (0.91%)> Dyeing time (0.48%)> Alkali concentration (0.42%). The controllable factors A and C are significant and hence are chosen to estimate the S/N ratio for optimal parameter combination.

Table 4.6: ANOVA Table for S/N ratio.

Factor	SS	DOF	Variance	F -ratio	P- value	PC
A	65.877	4	16.4693	148.7065	<0.0001*	74.36
B	0.4212	4	0.1053	0.9508	0.4427(NS)	0.48
C	14.5662	4	3.64155	32.8808	<0.0001*	16.44
D	0.369	4	0.09225	0.8330	0.5106 (NS)	0.42
E	0.8088	4	0.2022	1.8257	0.1386 (NS)	0.91
F	1.017	4	0.25425	2.2957	0.0721 (NS)	1.15
Error	5.53728	50	0.11075			6.25
Total	88.5965	74				100

SS= Sum of Square, DOF = Degree of Freedom; *Significant at p≤0.05 and NS = Not significant at p>0.05 and PC = Percentage contribution

4.3.1.4 Confirmation of optimization study

The mean of the total SN ratios (n_m) for the 25 trials has been calculated as per below formula:

$$n_m = \frac{1}{25}\sum_{i=1}^{25} n_i \quad =20.6985(\text{dB})$$

The S/N value is predicted according to model Equation 3.15 under optimized conditions as follows:

$$\frac{S}{N} = n_m + \sum_{i=1}^{n}(n_{i-}n_{m)}$$

S/N = nm + (A5- n_m) + (B3- n_m) + (C4- n_m) + (D2- n_m) +(E3- n_m) +(F2- n_m)

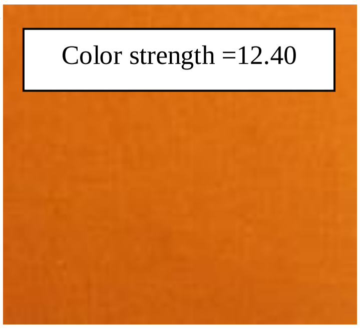
= A5+B3+C4+D2+E3+F2-5n_m

= 21.48 + 20.78 + 21.04+20.82 + 20.85 + 20.85- 5 x 20.6985

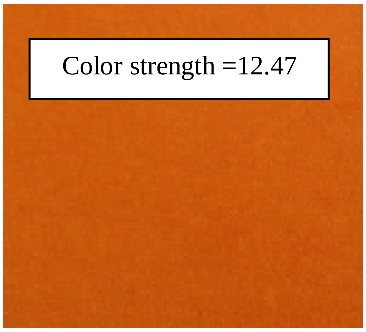
= 22.3279 (dB)

Three runs of confirmation experiments were performed under the optimal conditions. The S/N ratios of the confirmation experiments under the optimal conditions were found to be 21.9186 (dB) which was demonstrated in Table 4.7 with predicted S/N ratio.

Firstly, it is observed from Table 3.12 (Chapter 3) that the largest color strength is 12.40 (Target color strength). Further, the confirmation experimental color strength (Optimal Color strength) is found to be 12.47 under optimal conditions (Table 4.7), which is in close agreement with the target color strength (Figure 4.17). Therefore, the accuracy of the Taguchi design of experiment in optimization is confirmed (Chary and Dastidar, 2010).



(a) Photograph of target color strength



(b) Photograph of optimal color strength

Figure 17: Comparison between Target color strength and Optimal color strength.

Table 4.7: Confirmation experiment results and predicted S/N ratio.

A	B	C	D	E	F	Experimental CS			Average CS	Validation S/N	Predicted S/N
9	60	75	50	14	1: 8	12.42	12.46	12.53	12.47	21.9186	22.3279

Secondly, the 99 % confidence interval (*CI*) of the confirmation experiment was calculated using the Equation (3.16) as follows:

$$CI = \left| \left(N_{\frac{\alpha}{2}} \text{x} \frac{S}{\sqrt{m_e}} \right) \right| = \left| \left(-2.576 \text{ x} \frac{0.2547}{1.0206} \right) \right| = 0.6427$$

Where, $N_{\alpha/2}$ = -2.576, S = 0.2547 and $\sqrt{M_e}$ = N/DOF for factors = 1.0206.

The anticipated S/N ratio for the confirmation experiment could be found to be within 22.3279 ± 0.6427 with a 99 % confidence interval:

$$22.3279 - 0.6427 \leq \text{Confirmation Experiment} \leq 22.3279 + 0.6427$$

which is;

$$21.6852 \leq \text{Confirmation Experiment} \leq 22.9706$$

Where, Confirmation Experiment = 21.9186.

It is evident from the above relation that the S/N ratios for the confirmation experiments are all located within the acceptable confidence interval 21.6832 (dB) and 22.9706 (dB) at a significance level of 99 %, which confirms the reliability and reproducibility of the Taguchi design experimental results (Kuo et al., 2008).

4.3.2 Taguchi mathematical model

Regression coefficient and analysis of variance for color strength are shown in Appendix K and Appendix L, respectively. P-value for regression is 0.000 (Appendix K) which means that the model is statistically significant with more than 99 % confidence. The data of 7 samples which were not used for model development were used for the prediction, and verification of the built Taguchi mathematical model. The color strength of viscose/lyra blended knitted fabric for 7 conditions (order) have been predicted by model Equation (3.17) developed by Taguchi method. The prediction results from the developed Taguchi model were then compared with the 7 corroboration experimental results as shown in Table 4.8. The correlation between experimental and predicted fabric color strength is also graphically depicted in Figure 4.18.

It was observed from Figure 4.16 that the coefficient of determination (R^2) was found to be 0.921 (R = 0.96) between the actual and predicted fabric color strength. Therefore, it could be inferred that the developed Taguchi mathematical model can explain up to 92.1% of the total variability of fabric color strength (Majumdar and Ghosh, 2008). The mean absolute error (*MAE*) was found to be 3.48 %, which explained the good agreement between the actual and predicted color strength of viscose knitted fabric by the Taguchi mathematical model. Ashraf et al. (2014) reported lower correlation coefficient (R) of 0.806 between the color strength and yarn count. Further, Mavruz and Ogulata (2010) showed slightly lower correlation coefficient (R) of 0.91 and higher mean absolute error of 6.08 % respectively, for predicting bursting strength of knitted fabrics. The results of the R^2 and MAE % indicate that the developed Taguchi mathematical model has prediction ability and accuracy in non-linear dyeing process.

Table 4.8: Comparison between experimental and Taguchi predicted color strength (CS).

Exp No.	A	B	C	D	E	F	Experimental CS	Predicted CS	Absolute error%
1	1	60	60	40	10	8	9.15	9.55	4.41
2	3	45	45	40	10	10	10.26	9.92	3.28
3	5	60	60	50	12	8	11.44	10.96	4.17
4	5	75	60	60	16	14	11.69	10.87	7.03
5	7	60	60	70	16	6	12.11	11.7	3.39
6	9	75	60	60	16	12	12.37	12.33	0.35
7	9	60	75	50	14	8	12.47	12.68	1.72
Mean Absolute Error (*MAE*)%								3.48	
Coefficient of Determination (R^2)								0.921	

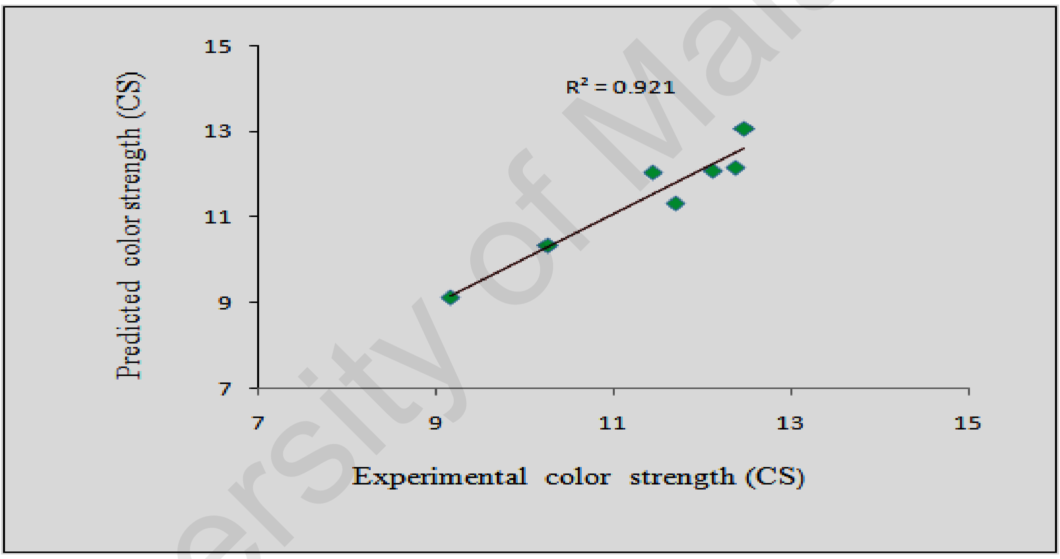


Figure 4.18: Correlation between experimental and Taguchi model predicted values of color strength.

4.4 Fuzzy Intelligent Models

4.4.1 Fuzzy model for color strength of viscose/lycra knitted fabric

Model operation, analysis of experimental results and model validation for color strength of Viscose knitted fabrics has been demonstrated as follows:

4.4.1.1 Operation of fuzzy model

The operation of the fuzzy logic model has been exposed schematically with an example in Figure 4.19. For simple expression, only one fuzzy rule (Rule 19) out of thirty six has been shown in the picture. According to the rule 19, (Table 3.18 in Section 3.5.2), if dye concentration is medium, and salt concentration medium and alkali concentration is medium, and then color strength is medium. For example, if *DC* is 3.5 %, *SC* is 25 g/l, and *AC* is 8 g/l, then all thirty six fuzzy rules are assessed concurrently to find the fuzzy output color strength (CS). After aggregation and defuzzification, the final crisp output color strength of the fuzzy set is 18.4. Using MATLAB, the fuzzy control surfaces were developed as shown in Figures 4.20 (a)-(c). The images show the mesh plots for the above example case, showing the relationships between dye concentration (DC), salt concentration (SC) and alkali concentration (AC) on the input side and color strength (CS) on the output side. The surface plots shown in Figures 4.20(a)-(c) depict the impact of DC, SC and AC on color strength.

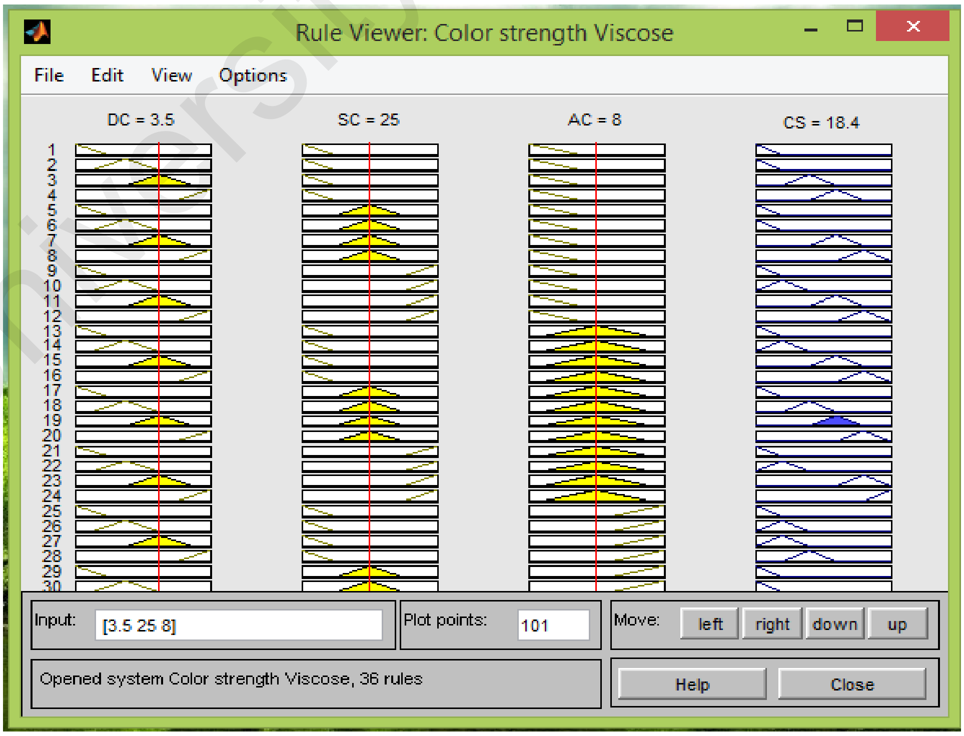
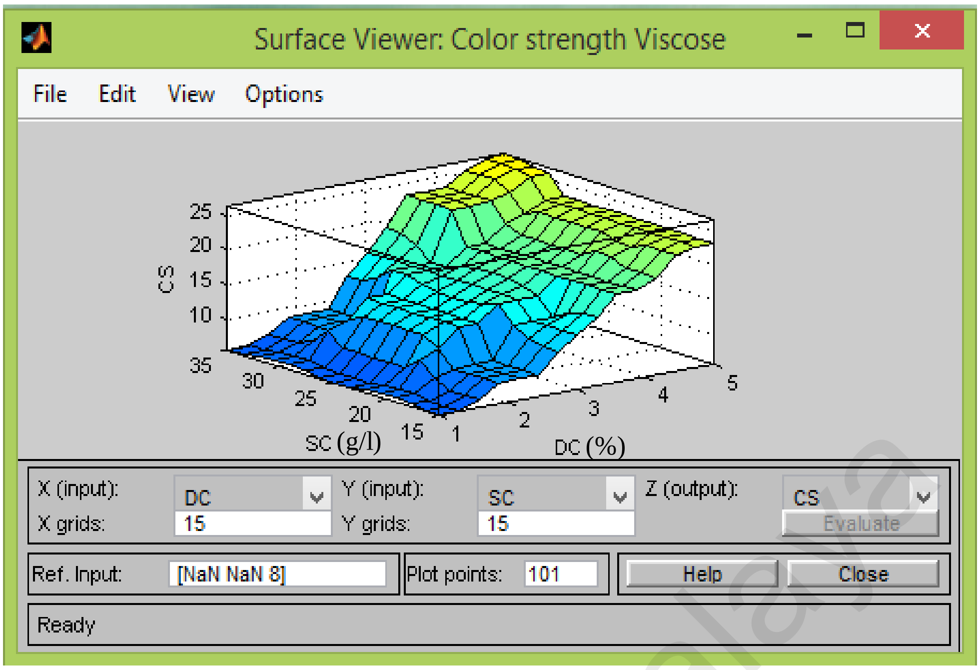
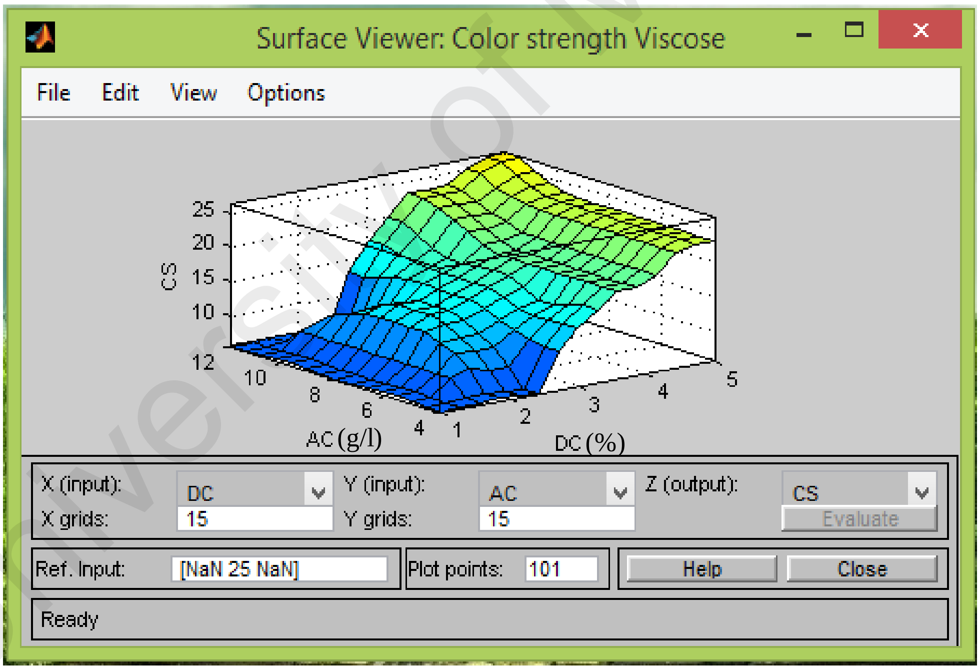


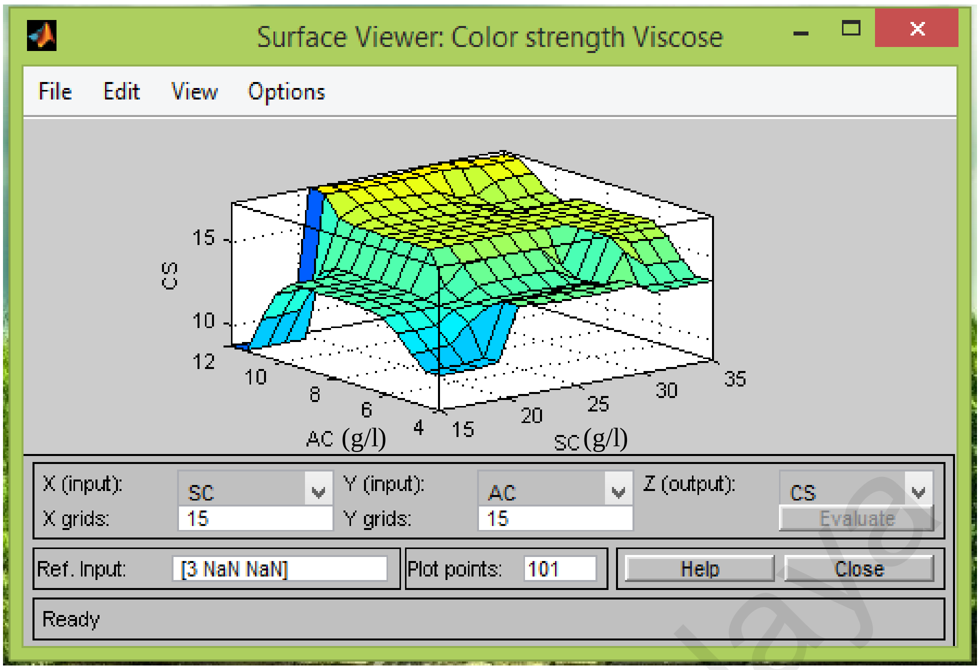
Figure 4.19: Rule viewer of the fuzzy inference system (Viscose).



(a) Effects of DC and SC on color strength (CS) at 8 g/l AC.



(b) Effects of DC and AC on color strength (CS) at 25 g/l SC.



(c) Effects of AC and SC on color strength (CS) at 3% DC.

Figure 4.20: Control surfaces of the fuzzy inference system.

4.4.1.2 Analysis of experimental results

Effects of dye concentration (*DC*), salt concentration (*SC*) and alkali concentration (*AC*) on color strength (CS) have been shown graphically in Figures 4.21-4.23. Figure 4.21 shows that color strength increases with increasing dye concentration and salt concentration and vice versa. The color strength increases slowly at first with increases in salt concentration until a certain value and then it increases quickly with further increase in salt concentration. Conversely, color strength rises significantly with increases in dye concentration. Approximately, color strength increases 10.77 % with an increase of 53 % in salt concentration while color strength increases 50.87 % with an increase of 52 % in dye concentration due to more exhaustion and absorption of dye.

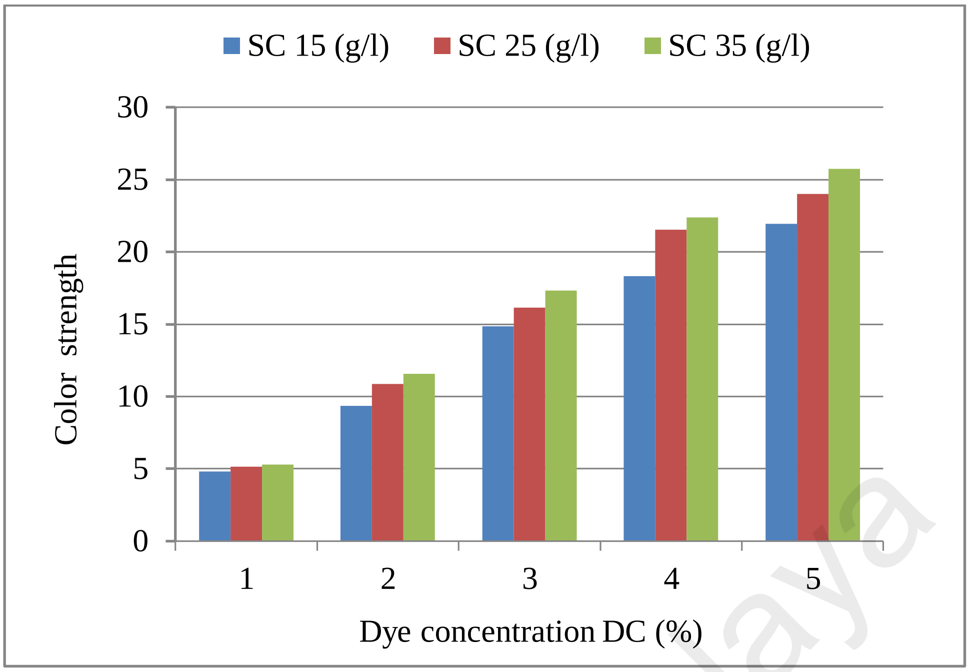


Figure 4.21: Effect of dye concentration and salt concentration on color strength at 8 g/l alkali concentration.

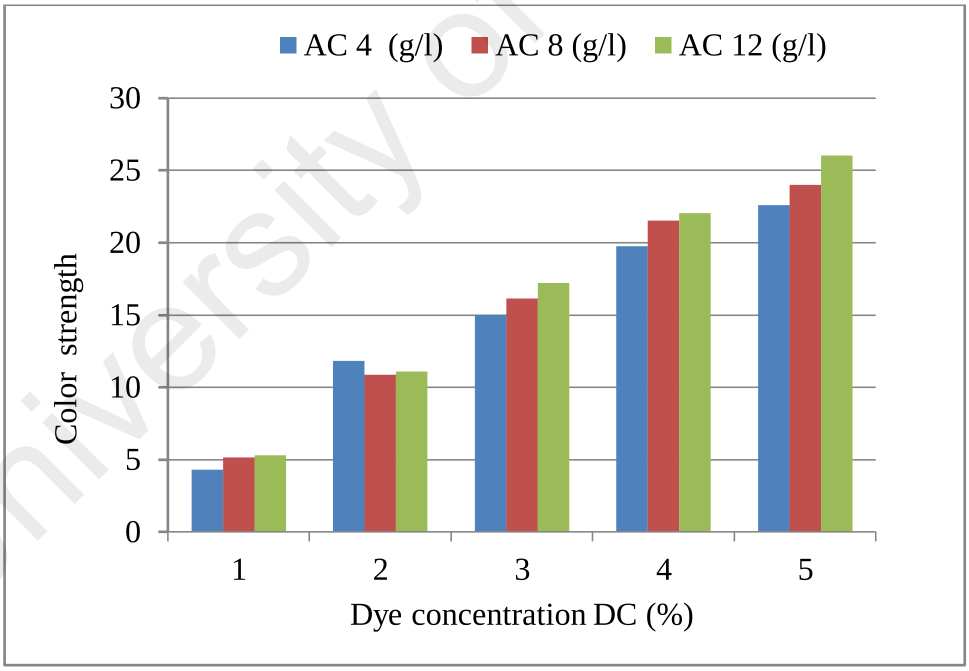


Figure 4.22: Effect of dye concentration and alkali concentration on color strength at 25g/l salt concentration.

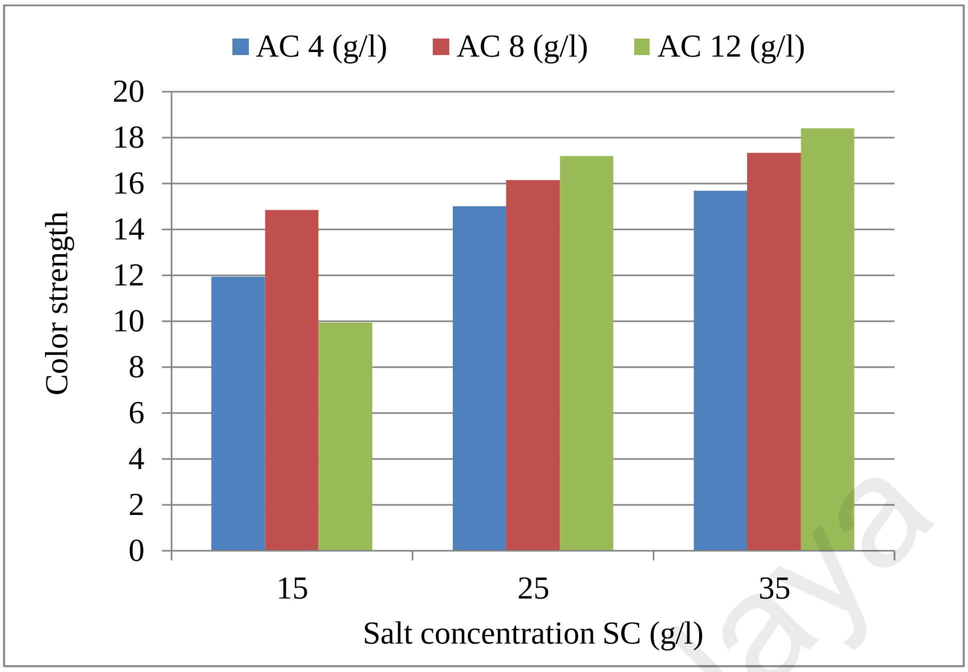


Figure 4.23: Effect of salt concentration and alkali concentration on color strength at 3 % dye concentration.

A similar phenomenon has been observed for dye concentration and alkali concentration on color strength as shown in Figure 4.22. The figure shows that color strength increases slowly with increases in alkali concentration. On the other hand, color strength increases sharply with increasing dye concentration. Approximately, color strength increases 3.8 % with an increase of 52 % in alkali concentration while color strength increases 50.87 % with an increase of 52 % in dye concentration due to more exhaustion and fixation of the dye. From Figure 4.23, it can be observed that color strength increases approximately 25 % when alkali concentration increases (50%) from 4 g/l to 8 g/l but it decreases 46% when alkali concentration increases from 8 g/l to 12 g/l at a SC of 15 g/l. The reason for a decrease in color strength within a certain alkali concentration and salt concentration (e.g. from 8 g/l to 12 g/l at salt concentration15 g/l) is probably due to the hydrolysis of dyes in higher alkali concentration and lower salt concentration. It can be further observed that color strength has an upward trend with increases in alkali concentration at salt concentration of 25 and 35 g/l.

A similar pattern has also been observed for salt concentration. Color strength has an upward trend with increases in salt concentration. Approximately, color strength increases by 6 % with an increase of 40 % in salt concentration.

From the results of this investigation, it can be evidently seen that dye concentration (*DC*) has the greatest effect on color strength (*CS*) in the dyeing process when compared to salt concentration (*SC*) and alkali concentration (*AC*).

4.4.1.3 Validation of fuzzy model for color strength of viscose/lycra knitted fabrics

The model developed in this study has been validated by experimental data of color strength (CS). The prediction accuracy of the developed fuzzy logic model was evaluated by calculating coefficient of determination (R^2) and mean absolute error (*MA*E) % from the actual and predicted fabric color strength. The predicted results from the developed fuzzy logic model were then compared with the experimental results as shown in Table 4.9. The correlation between the actual and predicted (from FL model) values of color strength under different dyeing conditions has been depicted in Figure 4.24. The relationship is significant for all the parameters. It was observed from Figure 4.24 that the coefficient of determination (R^2) was found to be 0.984 (R = 0.988) from the actual and predicted values of color strength. Therefore, it can be assumed that the developed fuzzy model can explain up to 98.4 % of the total changeability of fabric color strength. The mean absolute error (MAE) between the actual values and the predicted values of color strength was found to be 4.61 %.(< 5%). The absolute error gives the deviation between the predicted and experimental values and it is required to reach towards zero. The results of the coefficient of determination (R^2) and mean absolute error (*MAE*) % indicate that the developed fuzzy intelligent model has a very strong prediction ability and accuracy.

Table 4.9: Comparisons of actual and predicted values of color strength (CS) of viscose/lycra knitted fabrics.

SL No.	Dye concentration	Salt concentration	Alkali concentration	Actual CS	Predicted CS	AE %
1	2	15	4	8.35	8.8	5.39
2	5	15	4	18.62	18.40	1.18
3	4	25	4	19.76	18.4	6.88
4	5	35	4	23.88	23.2	2.85
5	4	25	8	21.53	23.2	7.76
6	4	35	8	22.38	23.2	3.66
7	3	25	12	17.2	18.4	6.98
8	1	35	12	5.7	5.8	1.75
9	5	35	12	27.91	26.5	5.05
	Mean absolute error (*MAE*) %				4.61	
	coefficient of determination (R^2)				0.984	

AE= Absolute Error

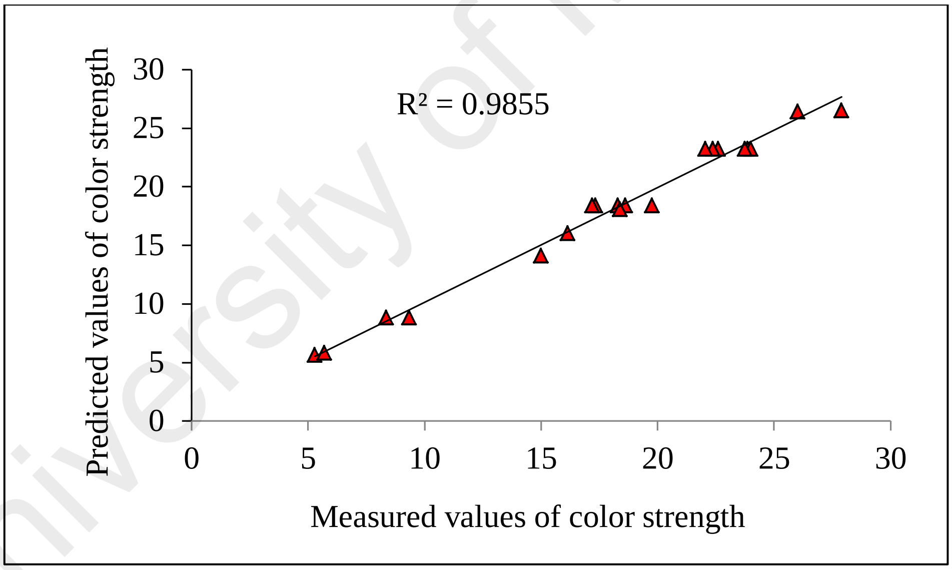


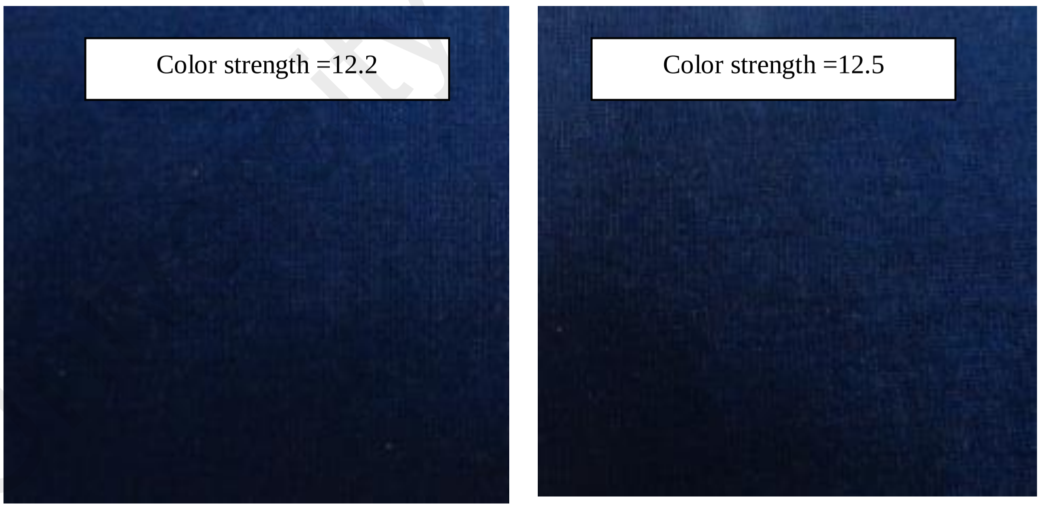
Figure 4.24: Correlation between actual and predicted values of color strength of viscose/lycra knitted fabric.

4.4.1.4 Application of the model

As per customer requirement, target color strength is 12.2. By applying developed fuzzy prediction model, color strength is predicted as 13.5 taking input variables dye concentration 3 %, salt concentration 25 g/l and alkali concentration 8 g/l.

Then, a laboratory scale experiment was conducted using the above input values and the experimental color strength is obtained 12.5. The comparison between the target color strength and the experimental color strength under predicted conditions are presented as photographic view in Figure 4.25. The percentage error between target color strength and experimental color strength is 2.5. The result indicates that the experimental color strength under the fuzzy model predicted conditions is very much closer (2.5 % error) to the target color strength.

Therefore, it can be decisively concluded that the developed fuzzy model can help in the selection of significant process parameters and their required levels to achieve a target level of product quality. On the other hand, without such a model, a dyer or producer has to conduct many trials based on assumption to attain target product quality.



(a) Target color

(b) Experimental color under predicted conditions

Figure 4.25: Photograph of target and experimental color strength.

4.4.2 Fuzzy model for color strength of cotton/lycra knitted fabric

Model Performance Investigation, analysis of experimental results and validation of fuzzy model for color strength of cotton knitted fabrics has been presented as follows:

4.4.2.1 Model performance investigation

Figure 4.26 graphically shows the operation of the developed fuzzy expert prediction model with an example. For simple demonstration, out of seventy two rules only one fuzzy rule has been depicted in the Figure. According to this rule, if dye concentration is high, dyeing time is medium and the dyeing process temperature is low then output color strength will be high. For instance, if dye concentration is 4.5 %, dyeing time is 60 minutes and process temperature is 50 ^{0}C, then all seventy two fuzzy rules are evaluated simultaneously to determine the fuzzy output color strength. Subsequent to aggregation and defuzzification, the final crisp output color strength of the fuzzy set is found to be 12.5 as shown in Figure 4.26.

Using MATLAB (version 7.10.0) the fuzzy control surfaces were developed as shown in Figures 4.27 - 4.29. It can serve as a visual depiction of how the fuzzy logic expert system operates dynamically over time. The pictures show the mesh plot for the above example cases, showing the relationship between dye concentrations (DC), dyeing time (DT) and dyeing process temperature (PT) on the input side and color strength (CS) on the output side. Figures 4.27 - 4.29 show that each of the surfaces represents in a compact way all the information in the fuzzy logic system. In addition, the images simply represent the range of possible defuzzified values for all possible inputs dye concentration, DT and PT. The surface plots shown in Figures 4.27 - 4.29 depict the impact of dye concentration, dyeing time and process temperature on the color strength.

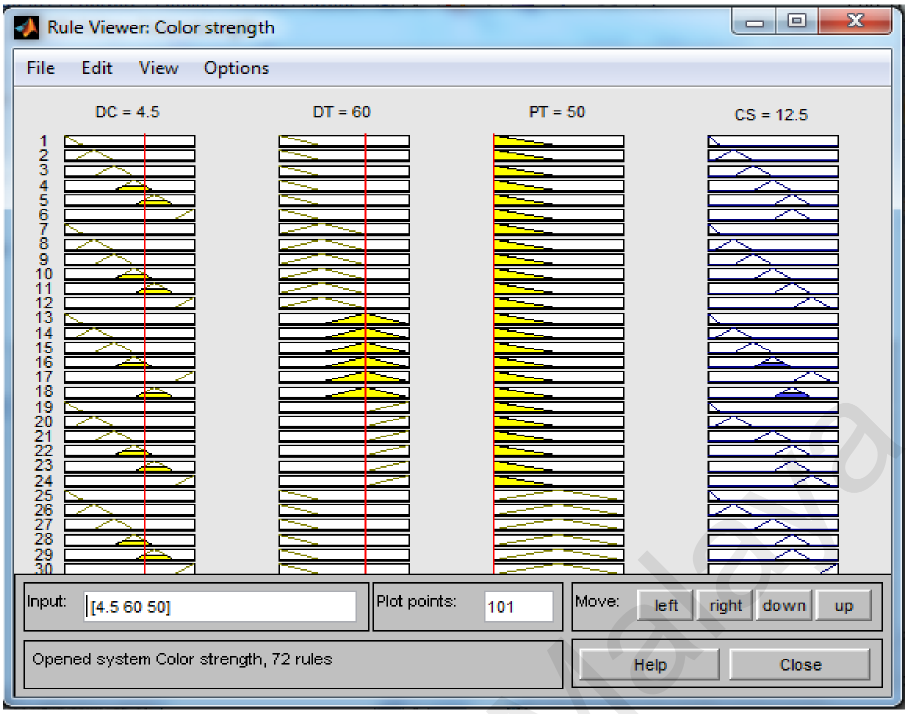


Figure 4.26: Rule viewer of the fuzzy inference system (Cotton).

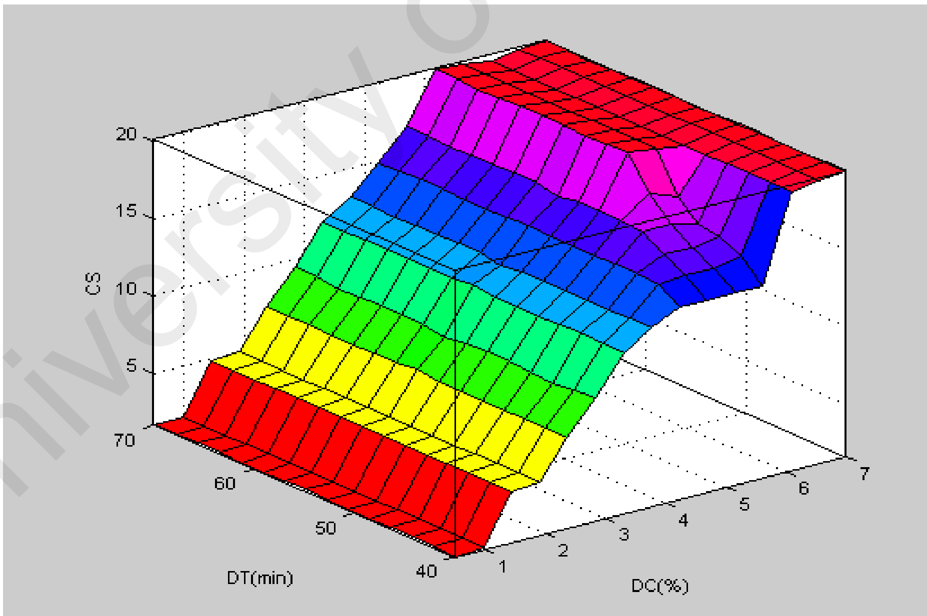


Figure 4.27: Control surfaces showing the effects of dye concentrations (DC) and dyeing time (DT) on color strength (CS) at 60 ^{0}C process temperatures (PT).

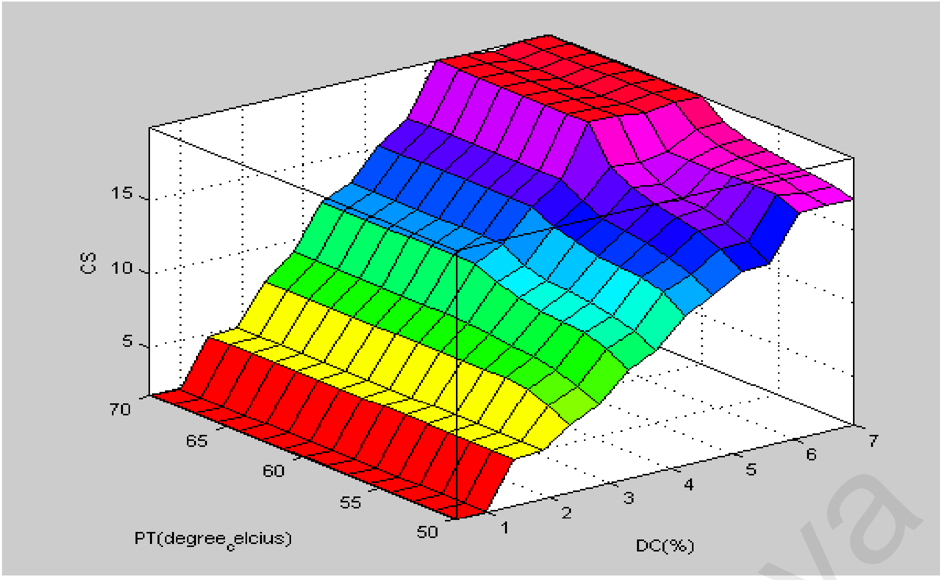


Figure 4.28: Control surfaces showing the effects of dye concentrations (*DC*) and process temperature (*PT*) on color strength (*CS*) at 60 minutes dyeing time (*DT*).

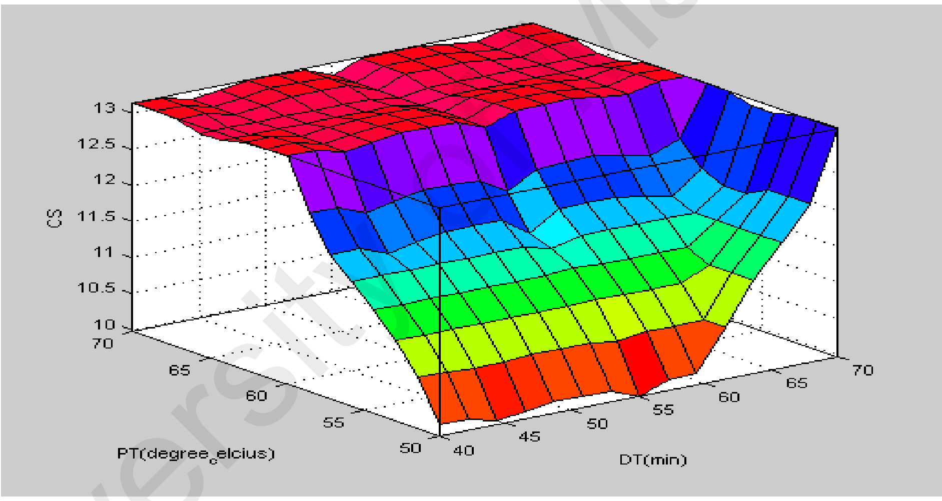


Figure 4.29: Control surfaces showing the effects of dyeing time (*DT*) and process temperature (*PT*) on color strength (*CS*) at 4.5 % dye concentration.

4.4.2.2 Experimental analysis

(i) **Effects of dye concentration and dyeing time on color strength**

Figure 4.30 demonstrates that color strength increases with the increasing dye concentration and dying time and vice versa. Color strength increases slowly with the increasing in dyeing time. On the contrary, color strength rises drastically with the increases in dye concentration. Approximately, color strength (CS) increases 6 % with an increase of 25 % dyeing time while color strength increases 84 % with an increase of 80 % in dye concentration. This is because the increases in dye concentration resulting in increases dye bath concentration which leading to higher dye absorption as well as increase in color strength due to more dye uptake, exhaustion and fixation of dyes.

(ii) **Effects of dye concentration and dyeing process temperature on color strength**

A similar pattern has been observed for the dye concentration (*DC*) and process temperature (*PT*) also on the color strength as shown in Figure 4.31. Figure show that the color strength increases approximately 25 % when process temperature increases (20%) from 50 ^{0}C to 60 ^{0}C but it decreases (5%) when process temperature increases from 60 ^{0}C to 70 ^{0}C at dye concentration from 2.5 % to 4.5 %. The reason for a decrease in color strength within a certain dye concentration and process temperature is probably due to the hydrolysis of dyes in higher temperature. Conversely, color strength increases rapidly with increasing dye concentration. Approximately, color strength increases 80 % with an increase of 80 % in dye concentration due to more exhaustion and fixation of dyes.

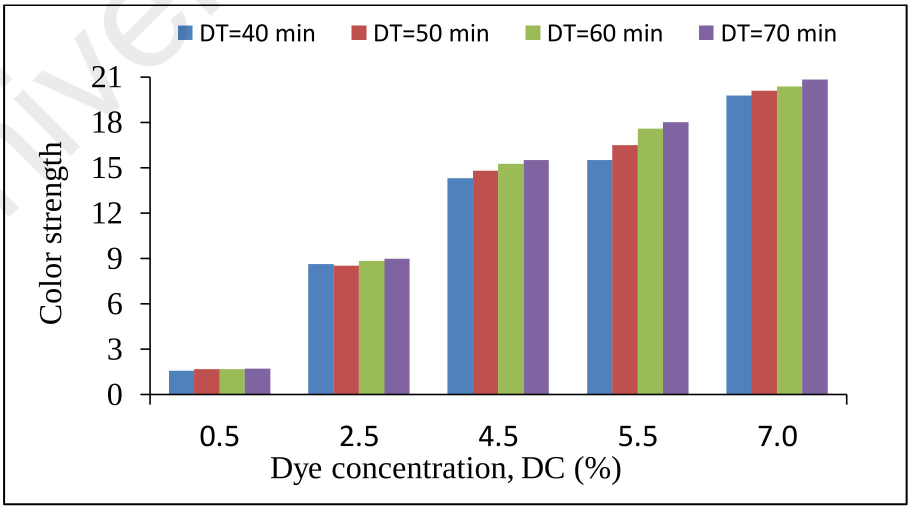


Figure 4.30: Effect of dye concentration and dyeing time on color strength at 60 ^{0}C process temperature.

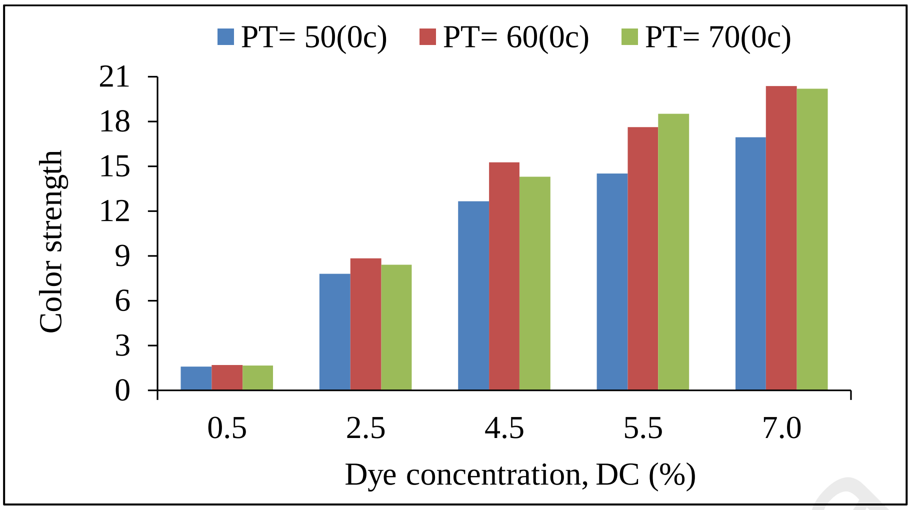


Figure 4.31: Effect of dye concentration and dyeing process temperature on color strength at 60 min dyeing time.

(iii) **Effects of dye time and dye process temperature on color strength**

From Figure 4.32, it has been observed similar phenomenon for dyeing process temperature and dyeing time on the color strength. It is observed from figure that color strength increases very slowly (approx. 3%) with increases in dyeing time from 40-70 minutes and process temperature from 50-70 ^{0}C. Decisively, it can be concluded from this research that dye concentration has the significant effects on color strength in the dyeing process rather than dyeing time and the dyeing process temperature.

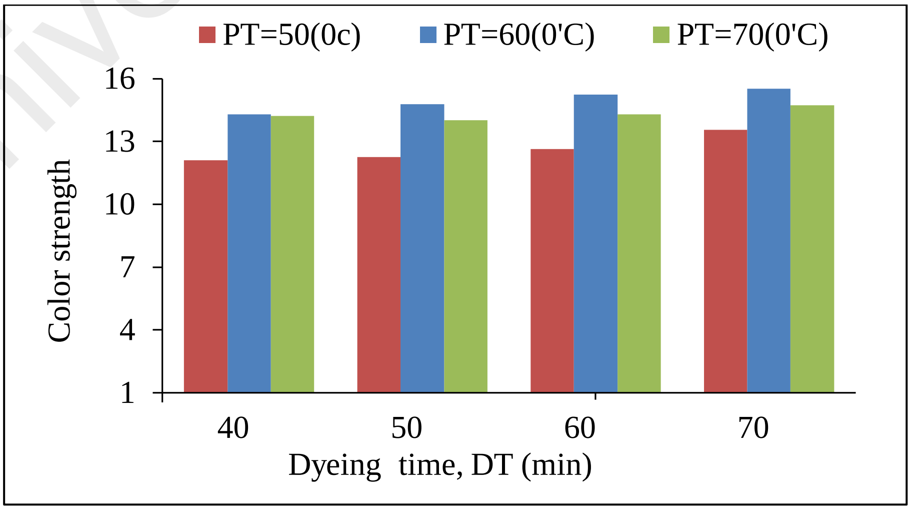


Figure 4.32: Effect of dyeing time and dyeing process temperature on color strength at 4.5 % DC.

4.4.2.3 Validation of fuzzy model for color strength of cotton/lycra knitted fabrics

The model developed in this study has been validated by experimental data of three different types of knitted fabrics such as 95 % cotton with 5 % Lycra single jersey, 100 % cotton 1x1 rib and 100 % cotton pique. Prediction was done using the fuzzy based intelligent model. The comparisons of predicted and actual values of color strength of three different types of knitted fabrics were presented in Table 4.10.

The correlations between the experimental and predicted values of color strength of different knitted fabrics under different dyeing conditions have been depicted in Figures 4.33(a), 4.33(b) and 4.33(c). The relationships were significant for all the parameters in different dyeing conditions for three types of knitted fabrics. The mean absolute errors between the predicted and actual values of color strength were found to be 2.69 %, 4.30 % and 4.02 % for single jersey (95 % cotton: 5 % lycra), 100 % cotton 1x1 rib and 100 % cotton pique knitted fabrics, respectively. The absolute errors explained the good agreement between the predicted and actual values of color strength of knitted fabric by the developed model.

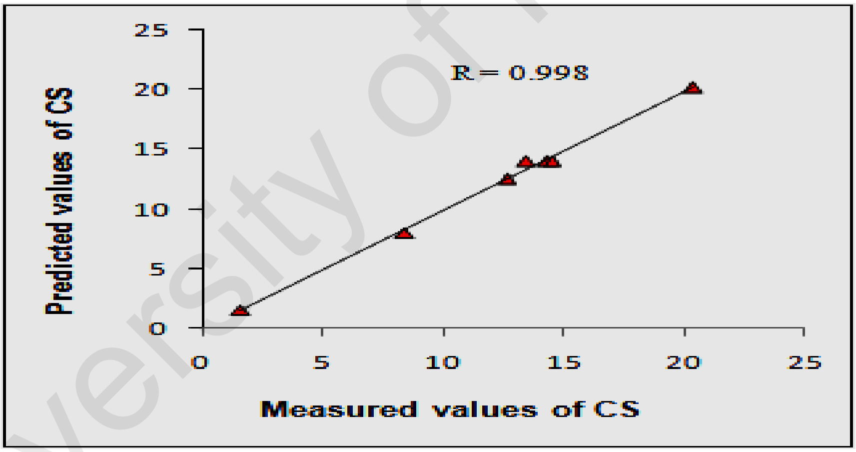
The coefficients of determination (R^2) from the predicted and actual values of color strength were found to be 0.997, 0.995 and 0.997 for single jersey,1x1 rib and pique cotton knitted fabrics respectively, which also described the excellent conformity between the predicted and actual values of color strength of knitted fabrics by the presented model.

The results of the mean absolute errors and coefficient of determination indicate that developed model exhibits excellent prediction accuracy for all three types of cotton knitted fabrics.

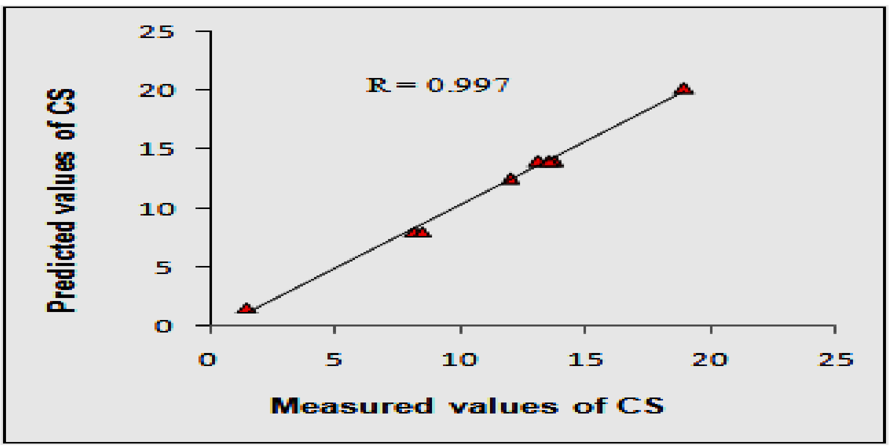
Table 4.10: Predicted and experimental values of color strength (CS) of different cotton/lycra knitted fabrics.

Exp No.	DC (%)	DT (min)	PT (^{0}C)	Pv of CS	Single jersey		1x1 rib		Pique	
					Ev of CS	AE %	Ev of CS	AE %	Ev of CS	AE %
1	0.5	60	50	1.6	1.59	0.63	1.52	5.26	1.70	5.88
2	2.5	40	70	8.0	8.37	4.42	8.16	1.96	8.45	5.33
3	2.5	70	70	8.0	8.39	4.65	8.46	5.44	8.50	5.88
4	4.5	60	50	12.5	12.64	1.11	12.00	4.17	12.70	1.57
5	4.5	40	60	14.0	14.31	2.17	13.75	1.82	14.60	4.11
6	5.5	40	50	14.0	13.50	3.70	13.10	6.87	13.70	2.19
7	5.5	60	50	14.0	14.50	3.45	13.60	2.94	14.70	4.76
8	7.0	60	70	20.1	20.38	1.37	18.98	5.90	20.60	2.43
Mean Absolute Error *(MAE)*%					**2.69**		**4.30**		**4.02**	
Coefficients of determination (R^2)					**0.997**		**0.995**		**0.997**	

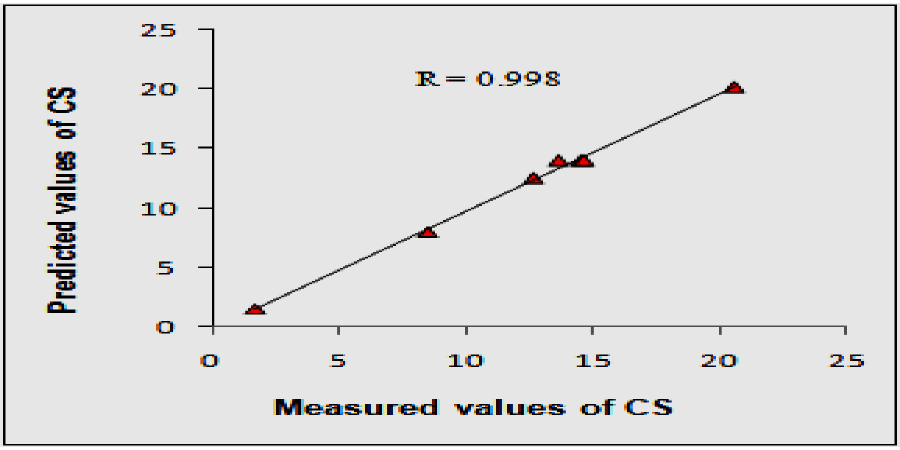
Pv = Predicted value, Ev= Experimental value, AE = Absolute Error



(a) Single jersey knitted fabric.



(b) 1x1 rib knitted fabric.



(c) Pique knitted fabric

Figure 4.33: Correlation between actual and predicted values of color strength (CS) of cotton knitted fabrics, (a) Single jersey knitted fabric, (b) 1x1 rib knitted fabric, (c) Pique knitted fabric.

4.4.3 Fuzzy model for color strength of lyocell/lycra knitted fabric

Model performance analysis, experimental analysis and validation of fuzzy model for color strength of lyocell knitted fabrics are presented as follows:

4.4.3.1 Model performance analysis

The operation of the fuzzy logic model has been shown schematically with two examples in Figure 4.34. For simple expression, only two fuzzy rules out of forty five have been shown in the picture. According to the first rule, if all the input dyeing variables are the medium level then output color strength will be level 9. Besides, according to the second rule, if dye concentration (DC) is very low and dyeing temperature (DT) and liquor ratio (LR) are high then output color strength will have level 3, which means lower value than level 9. For example, if DC is 5 %, DT is 60 ^{0}C, and LR is 8, then all forty five fuzzy rules are reviewed concomitantly to determine the fuzzy output color strength (CS). After aggregation and defuzzification, final non-fuzzy numeric color strength is obtained 13.5.

Further, as a second example, if DC is 1 %, DT is 75 ^{0}C, and LR is 12, then aggregated and defuzzified fuzzy output color strength is found 4.5.

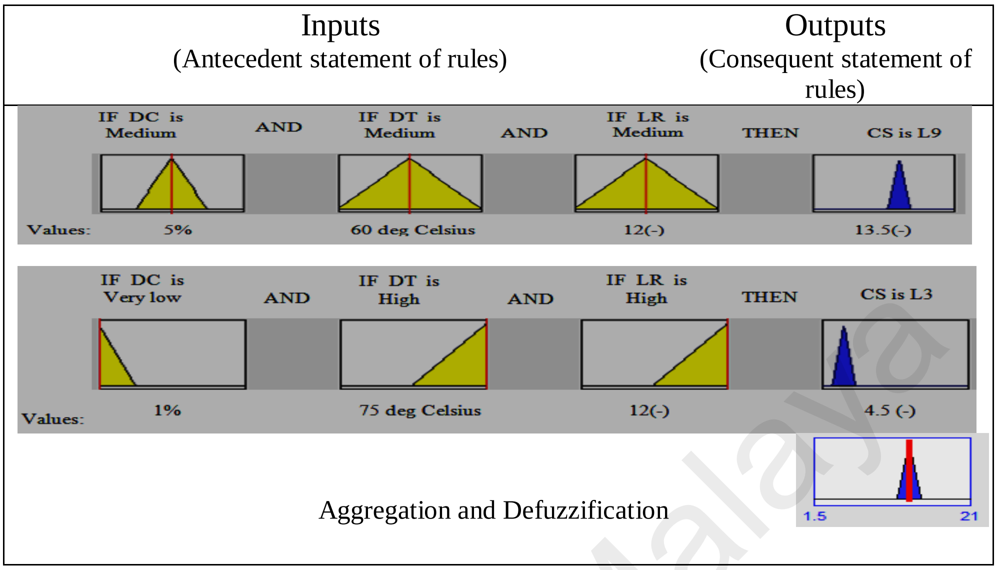
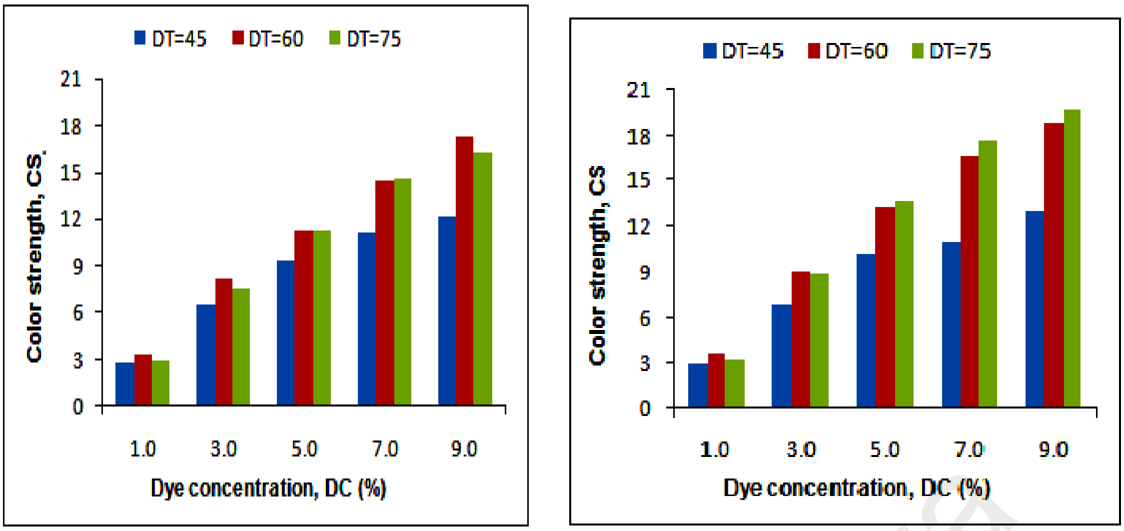


Figure 4.34: Operation of fuzzy logic model with examples (lyocell).

4.4.3.2 Experimental analysis

(i) Effects of dye concentration and dyeing temperature on color strength

Figures 4.35(a) and 4.35(b) demonstrate that color strength increases with the increasing in dye concentration and dyeing temperature and vice versa. Color strength increases slowly with the increasing in dyeing temperature. On the contrary, color strength rises significantly with the increases in dye concentration. Approximately, color strength (CS) increases 5 % with an increase of 25 % dyeing temperature while color strength increases 78 % with an increase of 75 % in dye concentration. A possible explanation for this may be the increases in dye concentration results in increases dye bath concentration which leading to higher dye uptake as well as increase in color strength. It is observed that the effect of dye concentration and dyeing temperature on color strength is more prominent for 1x1 rib fabrics than single jersey.

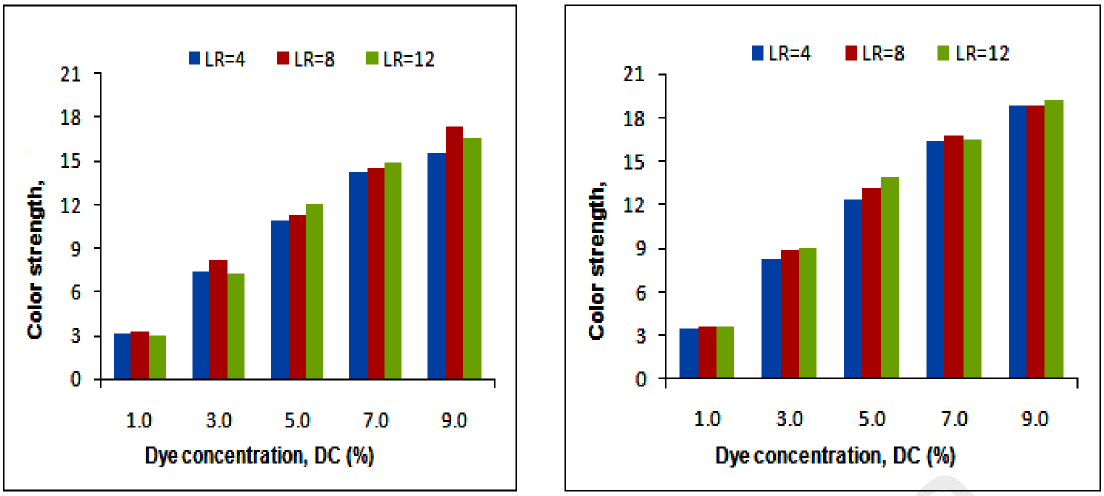


(a) Single jersey (b) 1x1 Rib

Figure 4.35: Effect of dye concentration (*DC*) and dye temperature (*DT*) on color strength of lyocell knitted fabrics at liquor ratio 8.

(ii) Effects of dye concentration and liquor ratio on color strength

Figures 4.36(a) and 4.36(b) show that color strength (CS) increases with increasing in dye concentration (DC). However, the effect of liquor ratio on color strength is not linear. Color strength decreases with increasing in liquor ratio up to dye concentration increases from 1-3 %. But color strength increases with increasing in liquor ratio further than dye concentration 3% and continue it up to 7 % dye concentration. However, further increase in liquor ratio of a particular dye concentration, which lead to decrease in dye bath concentration, results in less dye uptake as well as poor color strength. A similar trend has been found that the impact of dye concentration and liquor ratio on color strength is more intensive for 1x1 rib fabrics than single jersey.



(a) Single jersey (b) 1x1 Rib

Figure 4.36: Effect of dye concentration (DC) and liquor ratio on color strength of lyocell knitted fabrics at dye temperature (DT) 60 ^{0}C.

4.4.3.3 Validation of fuzzy model for color strength of lyocell/lycra knitted fabrics

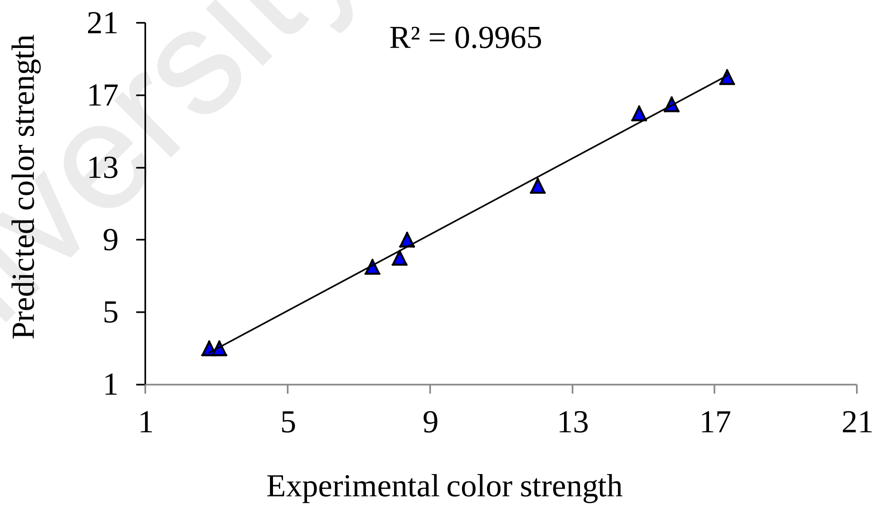
The model developed in this study has been validated by experimental data of two different structures of knitted fabrics such as 95 % lyocell with 5 % lycra single jersey and 100 % lyocell 1x1 rib. Prediction was performed using the fuzzy based intelligent model. The comparisons of predicted and experimental values of color strength of two dissimilar structures of knitted fabrics were presented in Table 4.11.

Table 4.11: Predicted and experimental values of color strength (CS) of different lyocell/lycra knitted fabrics.

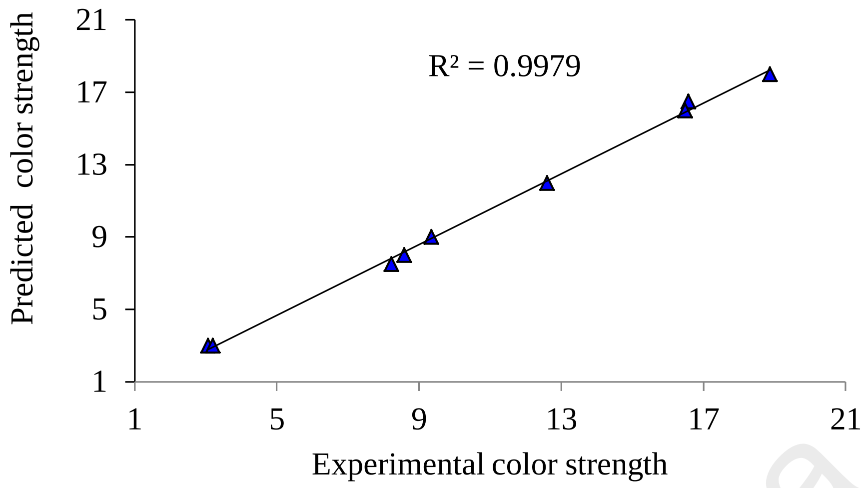
Exp No.	Dye concentration (%)	Dyeing temp. (^{0}C)	Material Liquor rario	Predicted CS	Single jersey		1x1 rib	
					Actual CS	AE %	Actual CS	AE %
1	7	45	4	9.0	8.36	7.66	9.36	3.85
2	3	60	4	7.5	7.38	1.63	8.24	8.98
3	7	75	4	16.5	15.80	4.50	16.58	0.48
4	1	45	8	3.0	2.79	7.53	3.07	2.28
5	3	60	8	8.0	8.15	1.84	8.60	6.98
6	7	60	8	18.0	17.4	3.69	18.88	4.66
7	1	45	12	3.0	3.07	2.28	3.21	6.54
8	7	45	12	12.0	12.00	0.25	12.61	4.84
9	7	60	12	16.0	14.90	7.53	16.50	3.03
10	9	75	12	19.5	18.30	6.32	21.25	8.24
Mean Absolute Error (*MAE*) %					4.32		4.99	
Coefficient of determination (R^2)					0.996		0.997	

AE = Absolute Eror

The correlations between the experimental and predicted values of color strength of different knitted fabrics under various dyeing conditions have been depicted in Figures 4.37(a) and 4.37(b). The mean absolute errors between the predicted and actual values of color strength were found to be 4.32 % and 4.99 % for single jersey and 1x1 rib fabrics respectively. The absolute errors explained the good agreement between the predicted and experimental values of color strength of knitted fabric by the developed model. The correlation coefficients (R) from the predicted and experimental values of color strength were found to be 0.998 (R^2 = 0.996) and 0.998 (R^2= 0.997) for single jersey and 1x1 rib respectively, which also described the excellent conformity between the predicted and experimental values of color strength of knitted fabrics by the presented model. The results of the mean absolute error and correlation coefficient show that developed fuzzy model performs well for two different structures of lyocell knitted fabrics.



(a) Single jersey knitted fabrics



(b) 1x1 rib knitted fabrics

Figure 4.37: Correlation between experimental and predicted values of color strength of lyocell knitted fabric, (a) Single jersey knitted fabrics, (b) 1x1 rib knitted fabrics.

4.4.4 Comparison of fuzzy models performance for viscose/lycra, cotton/lycra and lyocell/lycra knitted fabrics

The fuzzy models have been developed for the prediction of color strength of three cellulosic textile materials such as viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics. The developed fuzzy models have been validated by experimental data of color strength for above cellulosic textile materials.

The comparison of prediction performance of fuzzy models in terms of coefficient of determination (R^2) and Mean Absolute Error (%) for aforesaid three cellulosic textile materials are presented in Table 4.12.

Table 4.12: Comparison of fuzzy models performance for viscose/lycra, cotton/lycra and lyocell/lycra blended knitted fabrics.

Statistical prediction error	Viscose fabric	Cotton fabric	Lyocell fabric
Coefficient of determination (R^2)	0.984	0.998	0.996
Mean Absolute Error (*MAE*) %	4.61	2.69	4.32

4.4.5 Fuzzy model for bursting strength of viscose/lycra knitted fabrics

Model performance and experimental results have been analyzed followed by model validation and are presented as follows.

4.4.5.1 Model performance analysis

The schematic operation of the fuzzy intelligent prediction model has been depicted with an example in Figure 4.38. For simple expression, only one fuzzy rule out of twenty four has been shown in the picture. As per this rule, if knitting stitch length (*SL*) is low (L), yarn count (*YC*) is low (L) and yarn tenacity (*YT*) is medium (M) then output fabric bursting strength (*BS*) will be Level 5 (L5). For example, if input *SL* is 2.8 mm, *YC* is 30 Ne and *YT* is 15.5 g/tex, then all twenty four fuzzy rules are evaluated concurrently to determine the fuzzy output bursting strength. After aggregation and defuzzification, the final crisp output bursting strength of the fuzzy set is 330 kPa.

Using MATLAB Fuzzy Toolbox, the fuzzy control surfaces were developed as shown in Figures 4.39 - 4.40. These can serve as a visual depiction of how the fuzzy logic expert system operates dynamically over time. The images show the relationship between knitting stitch length (*SL)*, yarn count (*YC*) and yarn tenacity (*YT*) on the input side and bursting strength (*BS*) on the output side. The surface plots shown in Figures 4.39 - 4.40 depict the impact of stitch length, yarn count and yarn tenacity on bursting strength.

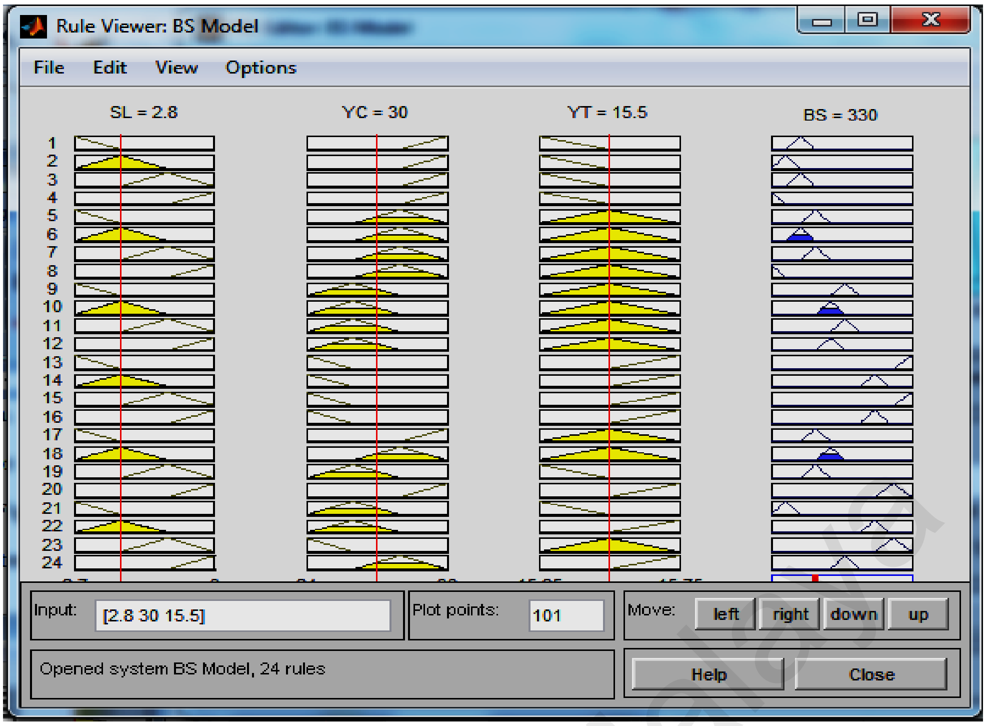


Figure 4.38: Graphical operation of the fuzzy prediction model (BS).

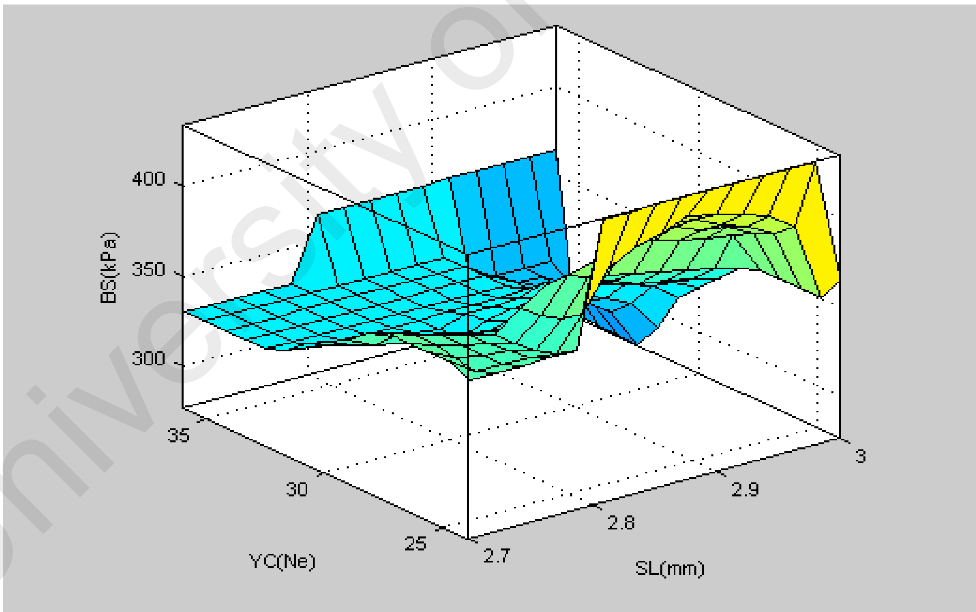


Figure 4.39: Surface plot showing the impact of stitch length and yarn count on bursting strength.

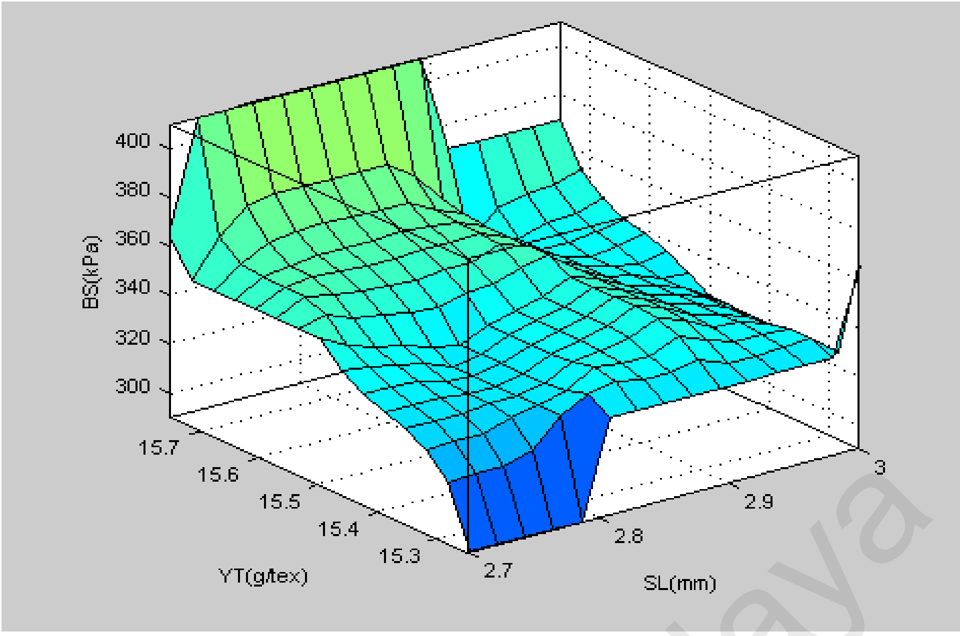


Figure 4.40: Surface plot showing the impact of stitch length and yarn tenacity on bursting strength.

4.4.5.2 Analysis of experimental results

Effects of stitch length, yarn count and yarn tenacity on bursting strength have been depicted in Figure 4.41 - 4.42. It is obvious from Figure 4.41 that decrease in knitting stitch length from 3.0 mm to 2.7 mm only slightly increases the fabric bursting strength. Approximately, bursting strength increases 15-20 % with a decreasing of 10 % in stitch length. The reason for an increase in bursting strength with decreasing in stitch length is probably due to increasing number of loops per unit area which bears the multidirectional forces. On the other hand, the effect of decreasing the stitch length is not linear, as a consequence, while the stitch length decreases further than an optimal level, produced fabric turn into more stiffer and less extensible, hence resulting in fabric holes as well as poor bursting strength. A similar phenomenon has been observed for yarn count on bursting strength as shown in Figure 4.42. It shows that fabric bursting strength increase a little with the decreasing of yarn count and vice versa. Nearly, the bursting strength increases 30 - 40 % with a decreasing of 30 % in yarn count due to the increasing of yarn linear density which would result in increasing in bursting strength.

Since, effect of yarn count on bursting strength is not linear, as a result, produced fabric turn into more stiffer and less extensible, while the yarn count decreases with a lower stitch length more than an optimal point, hence ensuing in poor bursting strength. In contrast, the effect of yarn tenacity on the bursting strength is much more reflective as compared to stitch length as shown in Figure 4.42.

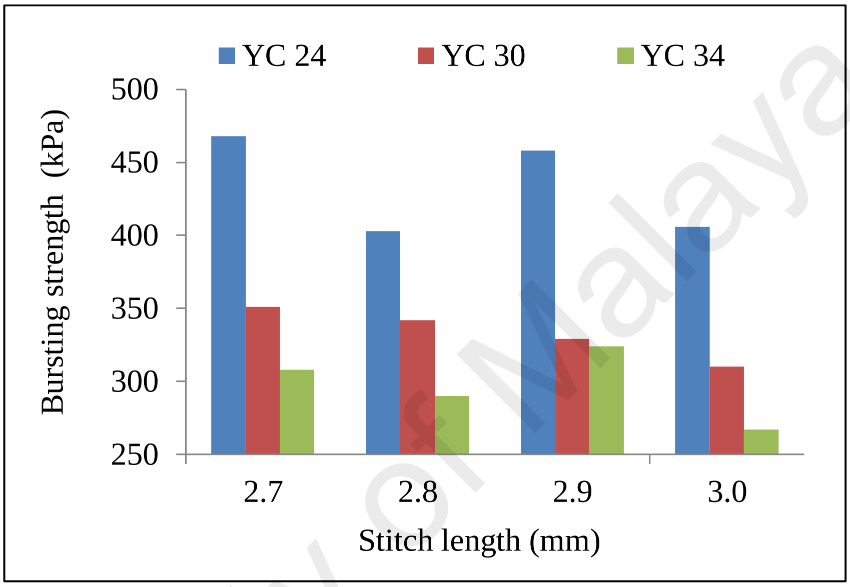


Figure 4.41: Effect of stitch length and yarn count on bursting strength.

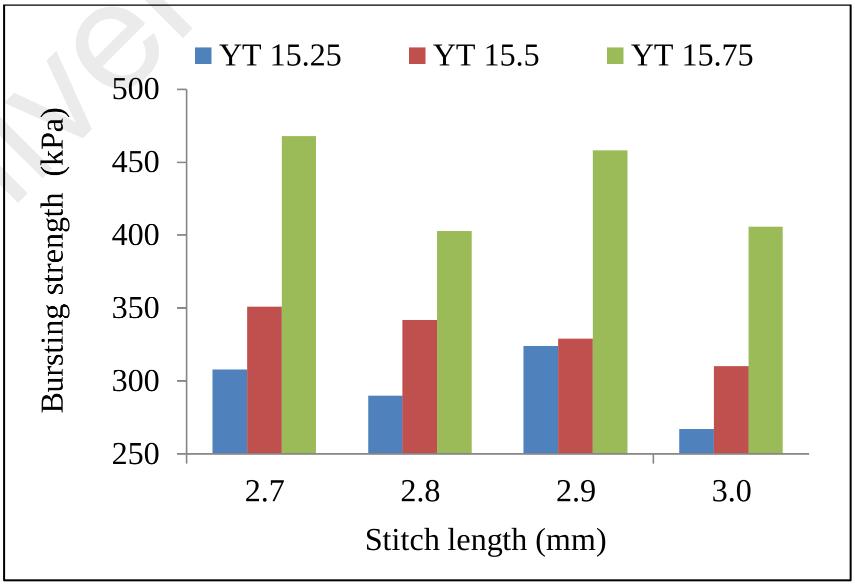


Figure 4.42: Effect of stitch length and yarn tenacity on bursting strength.

The Figure 4.42 shows that fabric bursting strength increases drastically with the increasing of yarn tenacity and vice versa. Approximately, the bursting strength increases 40 - 50 % with an increasing of 3 % in yarn tenacity. Basically, yarn is the main material for fabrics and yarn tenacity indicates the yarn strength, thus yarn tenacity increases means fabric strength increases. However, it was found from Figure 4.42 that knitting stitch length and yarn tenacity has strong interaction on fabric bursting strength. The extensibility of the fabric decreases whilst the yarn tenacity is increased further at lower stitch length levels and as a result the bursting strength obtains a descending tendency. From this investigation, it is evidently observed that yarn tenacity has the greatest and main effect on bursting strength when compared to knitting stitch length and yarn count. Therefore, it is very important to maintain optimum level of knitting parameter in the knitting process in order to achieve required bursting strength with good quality fabrics.

4.4.5.3 Validation of fuzzy model for bursting strength of viscose/lycra knitted fabric

The developed prediction model has been validated by experimental data. Prediction was done using the fuzzy logic rule viewer. The results from the developed fuzzy logic (FL) model were then compared with the 12 validation experimental results as shown in Table 4.13. The correlations between predicted values and experimental values of fabric bursting strength are also depicted in Figure 4.43. The correlation coefficient *(R)* between the experimental bursting strength and that predicted by the Fuzzy logic model was found to be 0.980 (R^2 = 0.961). Therefore, it can be assumed that the developed fuzzy logic model can explain up to 96.1% of the total variability of fabric bursting strength.

The mean absolute error (*MAE*) between the actual values and the predicted values of bursting strength was found to be 2.6 %.(< 5%). The absolute error gives the deviation between the predicted and experimental values and it is required to reach towards zero. The results of the correlation coefficient (*R*) and mean absolute error (*MAE*) % indicate that the developed fuzzy intelligent model has a very strong prediction ability and accuracy.

Table 4.13: Comparison of predicted and experimental values of fabric bursting strength.

ExpNo.	Stitch length (mm)	Yarn count (Ne)	Yarn tenacity (g/tex)	Predicted Bursting strength	Experimental bursting strength	Absolute error%
1	2.7	34	15.25	310	308	0.65
2	2.8	34	15.25	290	290	0.00
3	2.9	34	15.25	310	324	4.32
4	3.0	34	15.25	278	267	4.12
5	2.7	30	15.50	350	351	0.28
6	2.8	30	15.50	330	342	3.51
7	2.9	30	15.50	350	329	6.38
8	3.0	30	15.50	324	310	4.52
9	2.7	24	15.75	452	468	3.42
10	2.8	24	15.75	410	403	1.74
11	2.9	24	15.75	452	458	1.31
12	3.0	24	15.75	410	406	0.99
	Mean absolute error (*MAE*)%				**2.60**	
	Coefficient of determination (R^2)				**0.961**	

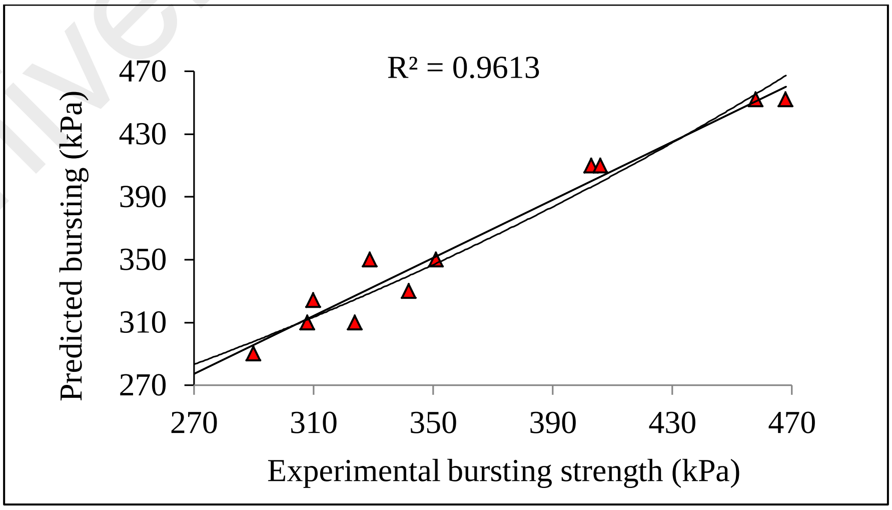


Figure 4.43: Correlation between experimental and fuzzy model predicted values of bursting strength.

4.5 ANN Prediction Model

In this section, ANN model performance investigation, model validation and comparison with Fuzzy model have been presented as bellows.

4.5.1 ANN model performance investigation

ANN prediction model for color strength is developed using MATLAB (version 7.10.0) ANN toolbox. Dye concentration (%), salt concentration (g/l) and alkali concentration (g/l) are used in input layer while color strength is used separately as output layer. The learning algorithm called the back-propagation was applied for the single hidden layer. The learning method levenberg-marquardt (LM) is used with 6 neurons in hidden layer for each network. Inputs and outputs have been coded in the range of (0.1– 0.9) as neural network able to works efficiently within this range. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function is used in hidden layer while purelinear (purelin) transfer function is used in output layer. For each network MATLAB ANN toolbox default setting is used for other training parameters. The experimental results of color strength for ANN prediction model test and validation are shows in Table 4.14. These experimental results are coded to use as test and validation value during training ANN are shown in the Table 4.15.

Table 4.14: Experimental values for testing and validation ANN.

Trial No.	Input values			Target values
	DC	*SC*	*AC*	*CS*
	(%)	(g/l)	(g/l)	
1	2	15	4	8.35
2	5	15	4	18.62
3	4	25	4	19.76
4	5	35	4	23.88
5	4	25	8	21.53
6	4	35	8	22.38
7	3	25	12	17.20
8	1	35	12	5.70
9	5	35	12	27.91

Table 4.15: Coded value for testing and validation ANN.

Trial No.	Coding Inputs values			Coding target values
	X_{DC}	X_{SC}	X_{AC}	X_{CS}
1	0.300	0.100	0.100	0.195
2	0.900	0.100	0.100	0.565
3	0.700	0.500	0.100	0.606
4	0.900	0.900	0.100	0.755
5	0.700	0.500	0.500	0.670
6	0.700	0.900	0.500	0.701
7	0.500	0.500	0.900	0.514
8	0.100	0.900	0.900	0.100
9	0.900	0.900	0.900	0.900

Subsequent to successful training of neural network, the ANN prediction model for color strength of viscose/lycra knitted fabric has been developed as a function of dye concentration, salt concentration and alkali concentration and presented in equation (4.1).

$$CS = \frac{1}{1+e^{-(1.4046F_1+1.5616F_2-1.6564F_3-0.054146F_4-0.28785F_5+0.77399F_6-0.87087)}} \qquad (4.1)$$

where F_i (i = 1, 2,……6) is the weighted sum of the input that can be calculated according to Equation (4.2) (Moezzi et al.2015):

$$F_i = \frac{1}{1+e^{-E_i}} \qquad (4.2)$$

and E_i can be calculated according to Equation (4.3) (Hosain et al., 2012b).

$$E_i = C_1DC + C_2SC + C_3AC + C_4 \qquad (4.3)$$

In Equation 4.3, C_1, C_2, C_3 are the Weights values and C_4 is the bias value of input variables. Weights and bias value of input to hidden layer and hidden to output layer is obtained from MATLAB neural network toolbox are shown in Table 4.16.

Table 4.16: Weight and biases between input layer and hidden layer for color strength.

	$E_i = C_1DC + C_2SC + C_3AC + C_4$			
i	*C1*	*C2*	*C3*	*C4*
1	2.713	3.1275	2.9573	-5.0879
2	2.3216	-4.217	-1.6475	-3.0528
3	2.2162	-2.0334	4.1038	-1.0176
4	-0.83205	-3.5037	-3.5943	-1.0176
5	1.8137	-4.6997	-0.71458	3.0528
6	-3.5132	3.4559	-1.2655	-5.0879

4.5.2 ANN model validation and comparison with Fuzzy model

The ANN prediction model has been validated by the same experimental result used to validate the fuzzy model. The correlations between the actual color strength and that predicted by the ANN model are depicted in Figure 4.44. The Coefficient of determination (R^2), Root Mean Squire (*RMS*) and Mean absolute errors (*MAE*) between the predicted and experimental values of color strength of knitted fabric are found to be 0.992, 0.726 and 3.28 %, respectively which explained the good agreement by the developed ANN model. Ability of prediction and comparison of performance of the Fuzzy and ANN models are presented both numerically in Table 4.17 and graphically in Figure 4.45. It was found from Figure 4.45 that the prediction results of Fuzzy and ANN models for all color strength parameters are parallel with experimental results. Further, it was observed from Table 4.17 that all the results of coefficient of determination (R^2), root mean squire (RMS) and mean absolute error (MAE) % are very closer with each other's which indicate the ability and accuracy of Fuzzy and ANN models to predict color strength of viscose knitted fabrics. It was concluded that both models have ability and accuracy to predict the fabric color strength effectively in non-linear domain. However, ANN prediction model shows slightly higher prediction accuracy than that of Fuzzy model.

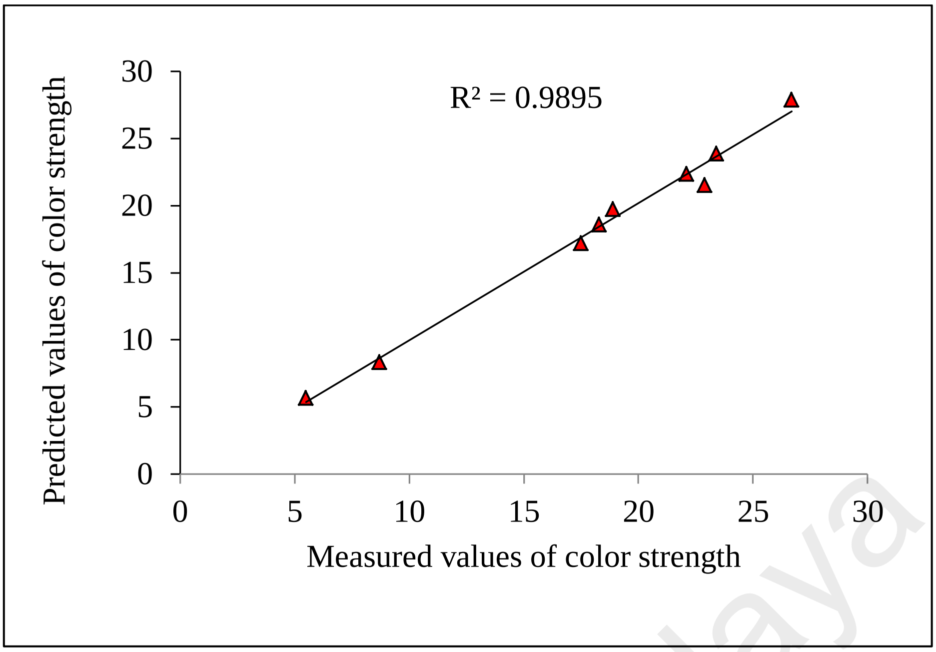


Figure 4.44: Correlation between measured and ANN model predicted color strength.

Table 4.17: Comparisons of prediction performance for Fuzzy and ANN Model

SL No	DC (%)	SC (g/l)	AC (g/l)	Actual CS	Fuzzy Model		ANN Model	
					Predicted CS	AE %	Predicted CS	AE %
1	2	15	4	8.35	8.80	5.39	8.70	4.19
2	5	15	4	18.62	18.40	1.18	18.30	1.720
3	4	25	4	19.76	18.40	6.88	18.90	4.350
4	5	35	4	23.88	23.20	2.85	23.40	2.010
5	4	25	8	21.53	23.20	7.76	22.90	6.360
6	4	35	8	22.38	23.20	3.66	22.10	1.250
7	3	25	12	17.2	18.40	6.98	17.50	1.740
8	1	35	12	5.7	5.80	1.75	5.50	3.51
9	5	35	12	27.91	26.50	5.05	26.70	4.34
Coefficient of determination (R^2)					0.984		0.992	
Root mean Squire (*RMS*)					1.025		0.726	
Mean absolute error (*MAE*) %					4.61		3.28	

AE = Absolute Error; CS = color strength

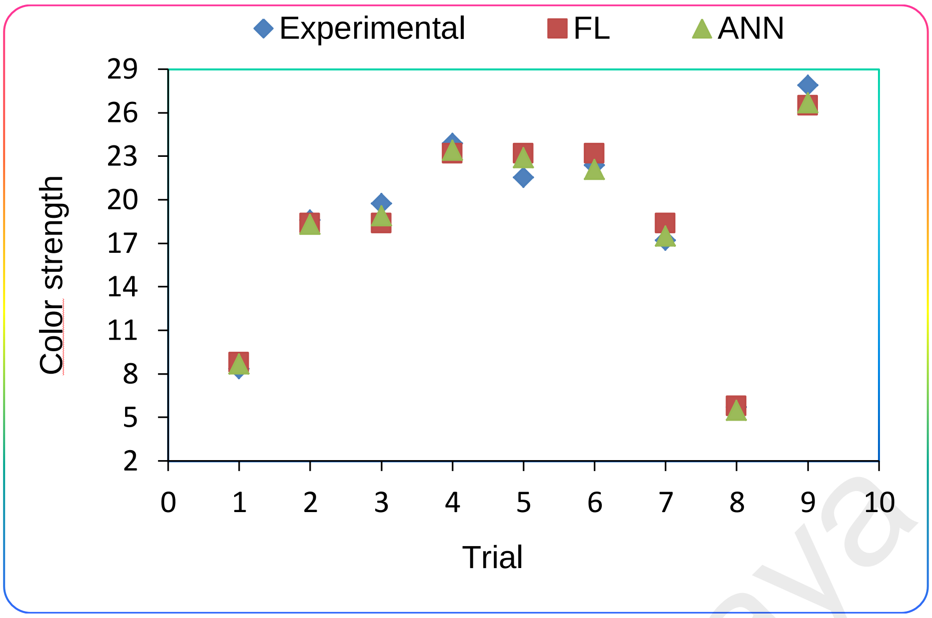


Figure 4.45: Comparison of Fuzzy and ANN predicted results with experimental result for color strength.

4.5.3 Comparison of Taguchi, Fuzzy and ANN Models

In this study, Taguchi mathematical model, Fuzzy intelligent model and ANN intelligent model have been developed for the prediction of color strength of viscose/lycra blended knitted fabrics. In fact Taguchi mathematical model and ANN intelligent models have been developed only for viscose/lycra blended knitted fabrics in order to compare the Fuzzy intelligent model performance as well as find the best model for the prediction of color strength. It was found that Fuzzy and ANN intelligent model showed better prediction accuracy than the Taguchi mathematical model. However, ANN model exhibits slightly higher prediction than the Fuzzy intelligent model. The Comparison of Taguchi mathematical model, Fuzzy intelligent model and ANN intelligent model are shown in Table 4.18.

Table 4.18: Comparisons of prediction performance for Taguchi, Fuzzy and ANN Model in terms of coefficient of Determination (R^2).

Prediction Error	Taguchi Mathematical Model	Fuzzy Intelligent Model	ANN Intelligent Model
Coefficient of determination (R^2)	0.92	0.98	0.99

4.6 Resin Finishing Model

4.6.1 Model performance analysis

The resin finishing model developed by the fuzzy technique has been depicted graphically with examples in Figure 4.46. Out of nine fuzzy inference rules, only one rule has been demonstrated in the image. For example, if resin concentration (RC) is 75 g/l, softener concentration (SC) is 15 g/l, and curing time (CT) is 135 sec, then all nine fuzzy rules are evaluated simultaneously to determine the fuzzy output length-way shrinkage, width-way shrinkage and bursting strength. Following aggregation and defuzzification, the final crisp output length-way shrinkage, width-way shrinkage and bursting strength of the fuzzy set are found 1.8 %, 1.93 %, and 318 kPa, respectively as shown in Figure 4.46.

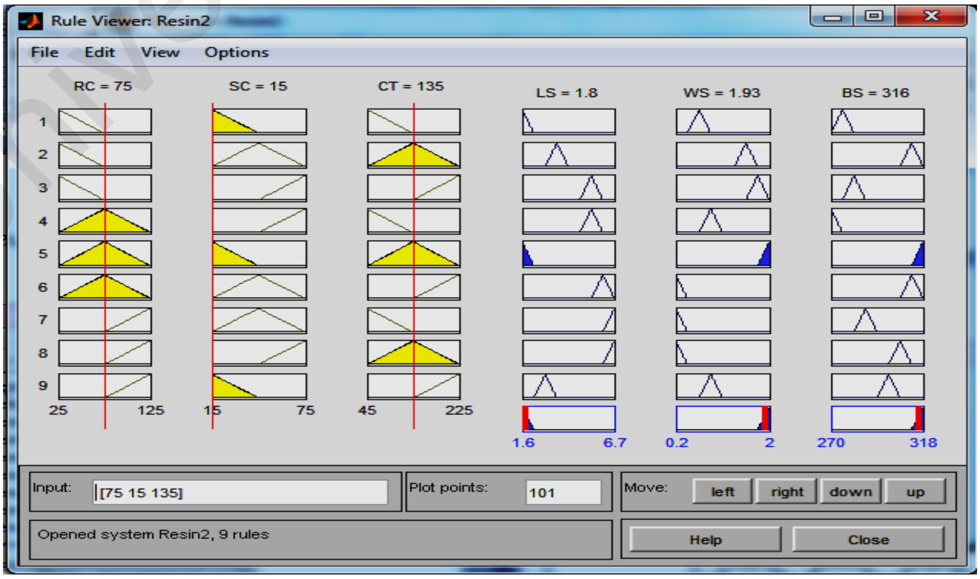
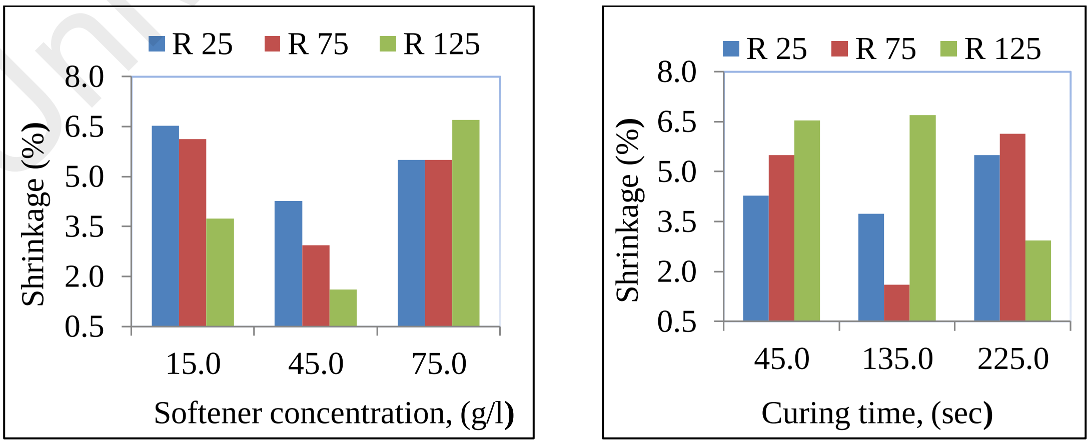


Figure 4.46: Graphical operation of resin finishing model.

4.6.2 Experimental analysis

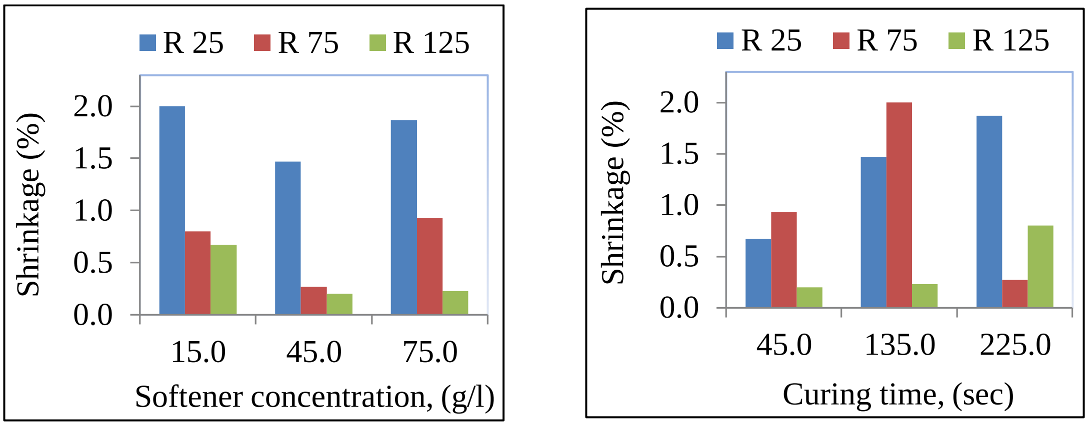
(i) Effect of resin concentration, softener concentration and curing time on the fabric shrinkage

The effect of resin concentration, softener concentration and curing time on the fabric shrinkage is graphically depicted in Figure 4.47 and 4.48. It is clear from the Figures that an increase in resin concentration results in decrease in fabric shrinkage. This may be attributed to decrease in free hydroxyl groups in the viscose cellulose due to cross linking with the resin. It can also be observed from Figures 4.47 and 4.48 that the effect of increasing resin concentration is not linear. With an initial increase in resin concentration, the shrinkage decreases readily but then rather steadily after further increase in the concentration. This is because with an initial cross linking, the availability of free hydroxyl groups decreases for further cross linking. Further, it is found that effect of softener concentration on fabric length and width-way shrinkage is not linear. The maximum shrinkage control is found to be in 125 g/l resin concentration and 45 g/l softener concentration. Furthermore, at lower resin concentration, the effect of increasing time is considerably significant in reducing the fabric shrinkage due to effective resin cross linking. However, a higher resin concentration a bit compensates the time shortage and even for less curing time shrinkage is effectively reduced.



(a) (b)

Figure 4.47: Effects of resin, softener and curing time on length–way fabrics shrinkage.



(a) (b)

Figure 4.48: Effects of resin, softener and curing time on width–way fabrics shrinkage.

(ii) Effect of resin concentration, softener concentration and curing time on the fabric bursting strength

The effect of resin concentration, softener concentration and curing time on the fabric bursting strength is graphically depicted in Figure 4.49 and 4.50. It is clear from the figures 4.49 that an increase in resin concentration results in decrease in fabric bursting strength. This may be attributed to several factors including increase in fiber embitterment, decrease in yarn elongation and slippage properties, fabric stiffening or some cellulosic degradation during acidic resin finishing conditions. It can be noticed from Figure 4.50 that the effect of increasing curing time is more prominent at lower resin concentration. However, at higher resin concentration there is much bursting strength loss even at shorter curing time. The addition of softener results in improvement in the fabric bursting strength. This may be attributed to decrease in fiber and yarn brittleness and stiffening, and increase in yarn slippage properties due to softener application. The effectiveness of increasing softener concentration for improvement in the fabric bursting strength is better at lower resin concentration but poor at higher resin concentration.

This may be due to the fact that any loss of fabric bursting strength due to stiffening and brittleness induced by the resin may be compensated or recovered by the softener but any loss that would have occurred due to cellulose degradation could not be recovered by the application of softeners.

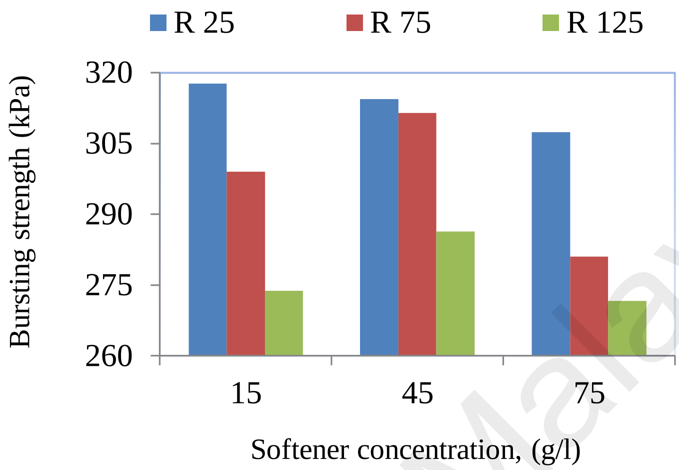


Figure 4.49: Effect of resin and softener on bursting strength.

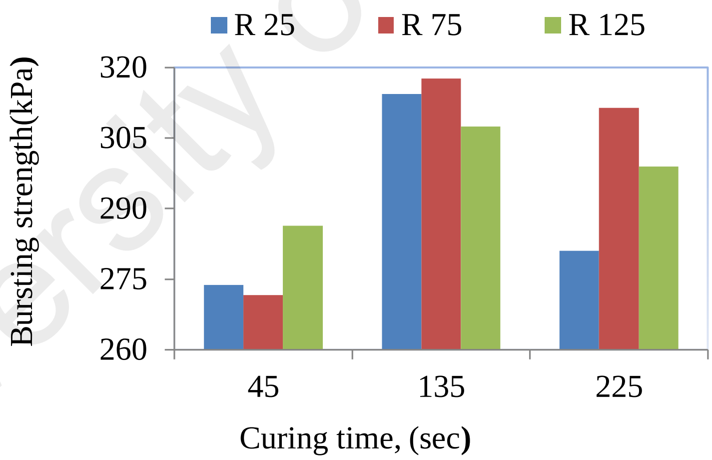


Figure 4.50: Effect of resin and curing time on bursting strength.

4.6.3 Validation of resin finishing model

The resin finishing model has been validated by experimental data. The comparisons of predicted and experimental values of shrinkage and bursting strength of viscose plain knitted fabrics were illustrated in Table 4.19. Further, the correlations between the experimental and predicted values of shrinkage and bursting have been depicted in Figures 4.51 - 4.53.

The mean absolute errors between the predicted and actual values of length way shrinkage (LS), width way shrinkage (WS), and bursting strength (BS) were found to be 3.74 %, 6.17 % and 0.45 %, respectively. In addition, the correlation coefficients (R) from the predicted and experimental values of LS, WS, and BS were found to be 0.998 (R^2 = 0.996), 0.992 (R^2 = 0.991) and 0.998 (R^2 = 0.996), respectively. The results prove that resin finishing model executes excellent for shrinkage control.

Table 4.19: Comparisons of predicted and experimental shrinkage and bursting strength.

Ex No .	Resin	Softener	Curing time	Length-way shrinkage			Width-way shrinkage			Bursting strength		
	g/l	g/l	sec	Ev	Pv	AE (%)	Ev	Pv	AE (%)	Ev	Pv	AE (%)
1	25	15	45	-4.27	4.15	2.81	0.67	0.65	2.99	273.80	276	0.80
2	25	45	135	-3.73	3.51	5.9	1.47	1.55	5.44	314.40	312	0.76
3	25	75	225	-5.50	5.42	1.45	1.87	1.78	4.81	281.00	282	0.36
4	75	75	45	-5.50	5.42	1.45	0.93	0.88	5.91	271.60	272	0.15
5	75	15	135	-1.60	1.8	12.5	2.00	1.93	3.50	317.70	316	0.54
6	75	45	225	-6.13	6.06	1.14	0.27	0.27	0.37	311.40	312	0.19
7	125	75	135	-6.70	6.5	2.99	0.23	0.27	16.96	307.40	306	0.46
8	125	15	225	-2.93	2.88	1.71	0.80	0.88	9.37	299.00	300	0.33
Mean Absolute Error (%)				**3.74**			**6.17**			**0.45**		

Ev = Experimental value; Pv = Predicted value; AE = Absolute Error

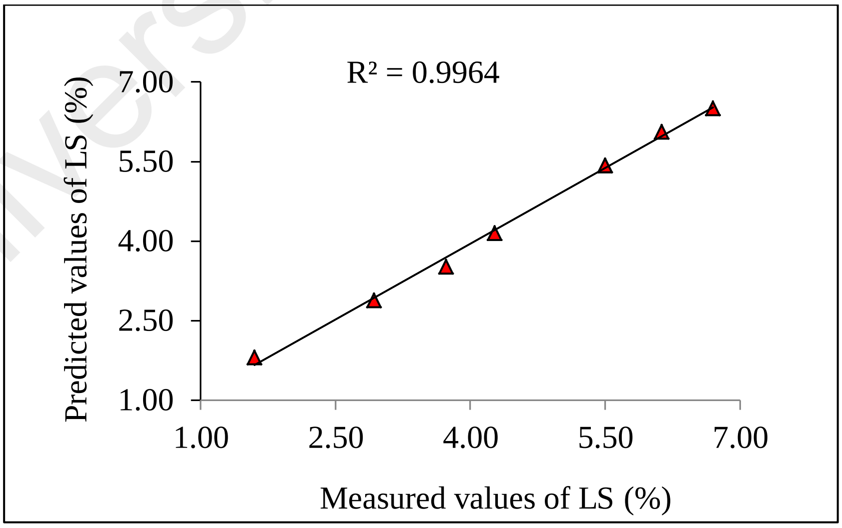


Figure 4.51: Correlation between experimental and predicted values of length-way fabrics shrinkage.

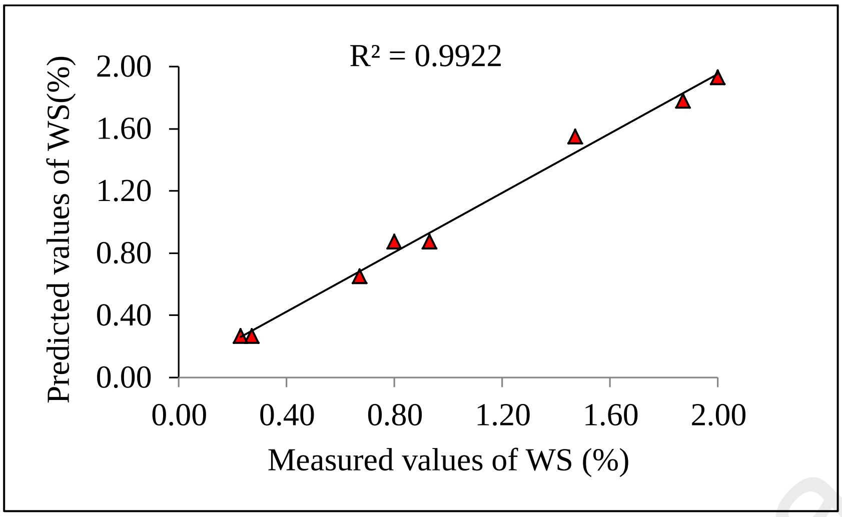


Figure 4.52: Correlation between experimental and predicted values of width–way fabrics shrinkage.

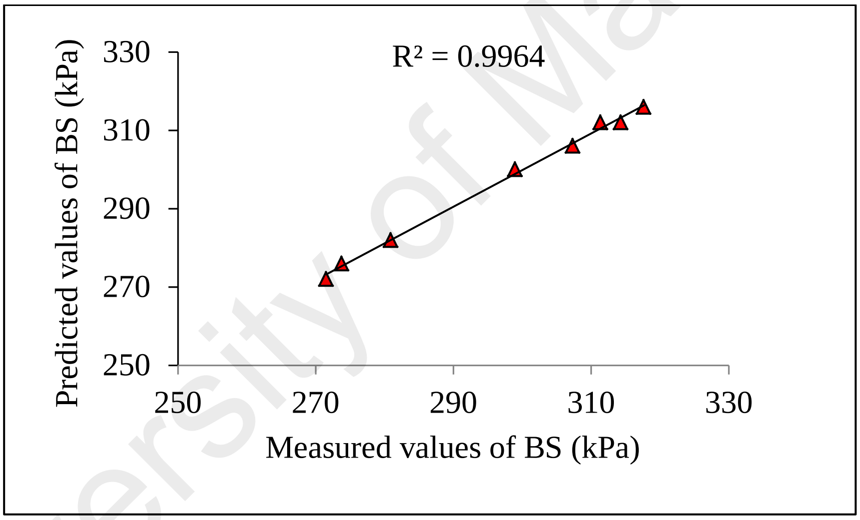


Figure 4.53: Correlation between experimental and predicted values of fabrics bursting strength.

4.7 Comparison with Previous Related Study

In this section, the present study is compared with the related previous study which is published in recognized international journals. Color strength, bursting and prediction performance of developed prediction models are compared with recent studies and presented in separate rows as shown in Table 4.20.

According to results of this study and comparison with other related study it can say that both fuzzy logic and artificial neural networks have prediction ability for quality characteristics of textile materials. However, ANN model exhibits better prediction performance than fuzzy model. This result is consistent with previous related study published in different international journals and conferences.

Table 4.20: Prediction performance comparison of fuzzy model with other study on dyeing and textile in terms of coefficient of determination (R^2).

		Materials and Methods		Prediction parameters	
		Materials	Methods	Color strength	Bursting strength
Present study		Viscose fabrics	Fuzzy logic	0.984	0.990
			ANN	0.992	-
			Taguchi	0.921	
		Cotton fabrics	Fuzzy logic	0.998	-
		Lyocell fabrics	Fuzzy logic	0.998	-
Previous study	Ashraf et al., 2014	Cotton fabrics	Statistical method	0.80	-
	Fazeli et al., 2012	Cotton fabrics	Full factorial experimental design	0.983	-
	Zavareh et al., 2010	Cotton fabrics	Central composite design	0.984	-
	Jamshaid et al., 2013	Cotton fabrics	Regression	-	0.991
			ANFIS	-	0.996
	Mavruz and Ogulata, 2010	Cotton fabrics	Taguchi	-	0.83

CHAPTER 5

CONCLUSIONS AND RECOMMENDATION

5.1 Conclusion

Optimization of the dyeing process and modeling of quality characteristic of viscose/lycra blended knitted fabrics is an important area of research for textile and dyeing industries in order to meet the customers' demands. The main objective of this study was to optimize the dyeing process parameters and develop prediction model for color strength of viscose/lycra, cotton/lycra, and lyocell/lycra and bursting strength of viscose/lycra blended knitted fabrics. All the objectives set up for this research investigation have been achieved successfully that can be concluded as follows:

- From the preliminary experimental study, it has been found that color strength increases rapidly for viscose /lycra knitted fabrics while increases slightly for cotton /lycra knitted fabrics with the increases of dye concentration, dyeing time, temperature and salt concentration. However, the effects of dyeing time and temperature on color strength were found not to be linear for both fabrics and the maximum color strength was found to be at 60 ^{o}C for 75 minutes. Dye concentration is the most significant factors and alkali concentration less significant factors for color strength. Conversely, color strength decreases sharply for viscose /lycra knitted fabrics while decreases slightly for cotton /lycra knitted fabrics with the increases in liquor ratio as well as fabric GSM and maximum color strength was found to be at 1:8 liquor ratio. Furthermore, alkali bleaching has more influence on color strength for cotton fabric than that of viscose fabrics. The Multi-functional dyes because of high substantivity show highest color strength as compared to Vinyl sulphone dyes for both fabrics.

Moreover, bursting strength increases with the increases in fabric GSM but decreases with the increases in blend fiber ratio for cotton/lycra knitted fabrics and viscose/lycra knitted fabrics. However, the effect is more significant for cotton/lycra than that of viscose/lycra fabrics. Enzymatic effect on cotton fabric was much more profound than that of viscose. It was found that fastness of the dyed fabrics depends much more on the type of reactive dye classes and dyeing methods rather than washing parameters and type of fibers. It was concluded that viscose fabrics color strength is approximately 60 % stronger than cotton and bursting strength is 100 % weaker than cotton in the same input conditions.

- From the Taguchi design of optimization, the optimal parameters in the dyeing process have been identified as dye concentration 9 %, Time 60 minutes, temperature 75 ^{o}C, salt concentration 50 g/l, alkali concentration 14 g/l and liquor ratio 1:8. From ANOVA, it was found that dye concentration and dyeing temperature are significant factors (p-value $\leq$ 0.05) than other conditions in the dyeing process. Further, the coefficient of determination (R^2) and mean absolute error between the actual color strength and that predicted by the Taguchi mathematical model were found to be 0.921 and 3.48 %, which explain the good agreement. Furthermore, from analysis of normal probability plots of the residuals that plots are generally fall on a straight line, meaning that mathematical model is suitable in better predicting. It was found from abovementioned results that Taguchi method is efficient on the optimization and prediction in complex dyeing with less than 5 % mean absolute error.

- The developed fuzzy prediction models for color strength of Viscose/lycra, Cotton/lycra and Lyocell/lycra blended knitted fabrics confer an excellent perceptive about the interaction between dyeing process variables and their effects on the fabric color strength. In addition, fuzzy prediction models for bursting strength of Viscose/lycra blended knitted fabrics give an outstanding perceptive about the interaction between knitting process variables and their effects on the fabric bursting strength.

  It has been found that dye concentration has the greatest and main effects on the fabric color strength as well as yarn tenacity has the greatest and main effects on the fabric bursting strength than others variables in the dyeing and knitting process respectively. The developed fuzzy models performances have been validated experimentally in terms of color strength and bursting strength. It was found that the prediction accuracy of the developed models were logically excellent as:

  a) The correlation coefficient (R) and mean absolute error were found to be 0.992 and 4.61 % (<5%), respectively, which show good agreement between the actual and predicted values of color strength of viscose/lycra blended knitted fabric by the presented model.

  b) The mean absolute errors between the predicted and experimental values of color strength were found to be 2.69 %, 4.30 % and 4.02 % for single jersey, 1x1 rib and pique cotton knitted fabrics respectively. The correlation coefficients (R) from the predicted and actual values of color strength were found to be 0.998, 0.997 and 0.998 for single jersey, 1x1 rib and pique cotton knitted fabrics respectively. The results showed good prediction performance for three different structured cotton knitted fabrics such as single jersey, 1x1 rib and pique by the developed model.

c) The mean absolute errors between the predicted and actual values of color strength were found to be 4.32 % and 4.99 % for single jersey and 1x1 rib lyocell fabrics, respectively. The correlation coefficients (*R*) from the predicted and experimental values of color strength of lyocell fabrics were found to be 0.998 and 0.998 for single jersey and 1x1 rib respectively. The results exhibit excellent prediction accuracy for two different knitted constructions like single jersey and 1x1 ribs of lyocell fabrics by the proposed model. It was found that fuzzy intelligent models exhibit excellent prediction performance for three different cellulosic textile materials such as Viscose/lycra, Cotton/lycra and Lyocell/lycra blended knitted fabrics on diverse knitting construction with coefficient of determination more than 0.984 and mean absolute error less than 5 %.

d) The correlation coefficient (*R*) and mean absolute error were found to be 0.990 and 2.88 % (<5%), respectively for fabric bursting strength, which explained the close agreement between the two by the developed model.

- The coefficient of determination (R^2) and mean absolute error (*MAE*) were found to be 0.992 and 3.28 %, respectively, between the actual fabric color strength and that predicted by ANN prediction model. On the other hand, the coefficient of determination (R^2) and mean absolute error (*MAE*) were found to be 0.984 and 4.61 %, respectively, between the actual fabric color strength and that predicted by fuzzy logic model. It was found that both the models have ability and accuracy to predict the fabric color strength effectively in non-linear domain. However, ANN model exhibits slightly better prediction accuracy than that of fuzzy intelligent model.

It is confirmed that the shrinkage of fabrics was reduced by increasing resin concentration and curing time with severe loss in fabric strength. However, optimal shrinkage control with minimum loss in fabrics loss can be achieved by applying softener. The mean absolute errors between the predicted and actual values of length way shrinkage (*LS*), width way shrinkage (*WS*), and bursting strength (*BS*) were found to be 3.74 %, 6.17 % and 0.45 %, respectively.

In addition, the coefficients of determination (R^2) from the predicted and experimental values of *LS, WS*, and *BS* were found to be 0.996 (R = 0.998), 0.991 (R = 0.992) and 0.996 (R = 0.998), respectively. It was found that fuzzy resin finishing model can play a vital role for maximum shrinkage control with minimum possible loss in fabrics bursting strength.

Finally, it is decisively concluded that fuzzy intelligent models developed in this study can be applied as decision making support tools for the production engineer in textile and dyeing industries which can help in the selection of significant process parameters and their required levels to achieve a targeted level of product quality. On the other hand, without such a model, a production engineer has to conduct many trials based on assumption to achieve target product quality.

5.2 Recommendations for future study

The Fuzzy and ANN intelligent models developed in this study can contribute to reduce process time and production cost as well as to improve productivity in the textile and dyeing industries as efficient tools. However, following recommendations are made in order to further stabilize the developed intelligent models for textile and dyeing industries.

- In the present study, only single color has been used for developing color strength model. Future work can be done using multi-color combination for the development of color strength model to get more accurate results.
- Fuzzy logic model can be developed further with increasing number of input variables based on expert knowledge and some preliminary test data.
- In the present study, intelligent models have been developed for color strength and bursting strength of knitted fabrics by using Fuzzy and ANN method. Although, ANN model can approximate any kind of functional relationship from input-output data. However, ANN model needs large amount of experimental data and it does not reveal the core logic based on which decision can be taken. Conversely, fuzzy logic model present the linguistic rules which interpret the relationship between inputs and outputs. But developing fuzzy rules is difficult and it often requires the tacit knowledge of the domain expert. Hence, future work can be done for developing a hybrid model using ANN and Fuzzy logic technique in order to achieve the benefits of both soft computing techniques.

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List of Publications and Papers Presented

Journal Papers

1. **Ismail Hossain,** Altab Hossain and Imtiaz Ahmed Choudhury, (2015). Color Strength Modeling of Viscose/Lycra Blended Fabrics Using a Fuzzy Logic Approach. *Journal of Engineered Fibers and Fabrics, 10*(1): 158-168.

2. **Ismail Hossain,** Altab Hossain and Imtiaz Ahmed Choudhury, (2015). Dyeing Process Parameters Optimization and Color Strength Prediction for Viscose/Lycra Blended Knitted Fabrics using Taguchi Method. *The Journal of the Textile Institute,* 1-11, DOI:10.1080/00405000.2015.1018669.

3. **Ismail Hossain,** Altab Hossain and Imtiaz Ahmed Choudhury, (2014). Fuzzy Knowledge Based Expert System for Prediction of Color Strength of Cotton Knitted Fabrics. *Journal of Engineered Fibers and Fabrics,* (Ms ID: JEFF-D-14-00002R1, r**evised manuscript has been submitted with minor correction).**

4. **Ismail Hossain,** Imtiaz Ahmed Choudhury, Azuddin Bin Mamat and Altab Hossain (2015). Application of Fuzzy Logic and Taguchi Design of Experiment in Predicting Bursting Strength of Viscose Plain Knitted Fabrics. *International Journal of Clothing Science and Technology*, (**under review**).

5. **Ismail Hossain,** Imtiaz Ahmed Choudhury, Azuddin Bin Mamat and Altab Hossain (2015). Predicting the Color Properties of Viscose Knitted Fabrics Using Soft Computing Approaches. *The Journal of the Textile Institute*, (**under review**).

6. **Ismail Hossain,** Imtiaz Ahmed Choudhury, Azuddin Bin Mamat**,** Abdus Shahid, and Ayub Nabi Khan (2015). Predicting the Mechanical Properties of Viscose/Lycra Knitted Fabrics Using Fuzzy Technique. *Advances in Fuzzy Systems*, **(under review**).

Conference Papers:

(i) **Ismail Hossain**, Altab Hossain, I. A. Choudhury, A. Bakar and A. Shahid, (2013). Color Strength Modeling of Knitted Fabrics Using Fuzzy Logic Approach. *International Conference on Mechanical, Industrial and Materials Engineering (ICMIME 2013), 1-3 November 2013, RUET, Rajshahi, Bangladesh*, pp.870-875**.**

(ii) **Ismail Hossain,** Altab Hossain I. A. Choudhury, Abu Bakar and Hasib Uddin, (2014). Prediction of Fabric Properties of Viscose Blended Knitted Fabrics by Fuzzy logic Methodology, *International Conference on Mechanical and Civil and Architectural Engineering 2014, (ICMCAE 2014), 19-20 February 2014, Kuala Lumpur, Malaysia*, pp.100-106.

(iii) **Ismail Hossain,** Altab Hossain, I. A. Choudhury, A. Bakar and A. Shahid, (2014).Color fastness Modeling of viscose dyed Fabrics Using Fuzzy Expert System,*10th International Conference on Mechanical Engineering (ICME 2013), 20-22 June 2014, BUET, Dhaka, Bangladesh*.(Paper ID: 365).