Development of Prediction Systems Using Artificial Neural Networks for Intelligent Spinning Machines

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Dresden, 25.01.2010 Assad Farooq

Contents

Symbols and Abbreviations

Symbol	Dimension	Designation
μ_d		Dynamic Friction
μ_s		Static Friction
PES		Polyester
CO		Cotton
PES:CO		Polyester/Cotton blend
ANN		Artificial Neural Network
δ_j		Error Signal
σ		Learning Rate
μ		Momentum-term
Δw_{ij}		Change in Weight W_{ij}
net_i		Input Function
f_i		Output Function
a_i		Activation Function
o_i		Actual Output of a Neuron
z_i		Desired Output of a Neuron
w_{ij}		Connecting weight of a Neuron
Θ		Threshold Value
J		Jacobian Matrix
LM Technique		Levenberg-Marquardt Technique
LOOCV		Leave-one-out Cross Validation

Symbol	Dimension	Designation
CV	%	Coefficient of Variance
LAP	mm	Leveling Action Point
FS	m/min	Feeding Speed
VVD	mm	Break Draft Distance
HVD	mm	Main Draft Distance
VE		Infeed Tension
VV		Break Draft
BUS		Sliver Deflection Bar Setting
VZW		Power Creel Tension
VA		Sliver Take-off Tension
e		Euler's Constant
λ		Wave Length
NN_CO1		Neural Network for LAP Prediction for Cotton 1st Passage
NN_CO2		Neural Network for LAP Prediction for Cotton 2nd Passage
NN_PES2		Neural Network for LAP Prediction for Polyester 2nd Passage
NN_PC2		Neural Network for LAP Prediction for Cotton/Polyester 2nd Passage
NEUROset		Neural Network Based Function for Leveling Action Point Prediction
NN_S_CVm		Neural Network for Sliver CVm% Prediction
NN_S_CV1m		Neural Network for Sliver CV(1m)% Prediction

Symbol	Dimension	Designation
NN_S_CV3m		Neural Network for Sliver CV(3m)% Prediction
NN_S_Cohesion		Neural Network for Sliver Cohesion Prediction
NN_Y_CVm		Neural Network for Yarn CVm% Prediction
NN_Y_CV1m		Neural Network for Yarn CV(1m)% Prediction
NN_Y_CV3m		Neural Network for Yarn CV(3m)% Prediction
NN_Y_Hairiness		Neural Network for Yarn Hairiness Prediction
NN_Y_Tenacity		Neural Network for Yarn Tenacity Prediction
NN_Y_Elongation		Neural Network for Yarn Elongation Prediction

Chapter 1

Introduction

Textile industry belongs to the oldest industrial branches and maintaining its sustained growth for improving the quality of human life. Despite of being old, spinning process is still developing and very essential for the production of most of the textile fabrics. The fact that spinning lies at the very early stage of textile processing chain, its influence on the quality of the end products is vital. Especially because of the nature of some faults that can only be seen in the thread after the subsequent processing or even after the dyeing process.

The main objective of the staple yarn spinning process is to achieve the highest possible yarn evenness with minimum imperfections, which impart uniformity in yarn strength. Consequently, these improvements positively influence the quality of subsequent processes like weaving and knitting. Better fiber control due to controlled drafting ranks ring spinning as the best yarn spinning system. As a matter of fact, ring yarn has been used as a benchmark against which the quality of yarn produced on other spinning system is judged [1].

The greater demands of quality and economy are directly associated with the development of the spinning industry. For instance, considering the fact that quality of the yarn is adversely influenced by the processing speeds, the spinning industry is always put under the extensive pressure of quality improvement at higher speeds. The Fig. 1.1 shows the Uster statistics 2007 elaborating the quality improvements that have been achieved during the last 50 years for yarn CVm% for cotton carded Ne20 and cotton combed Ne60 yarns [2].

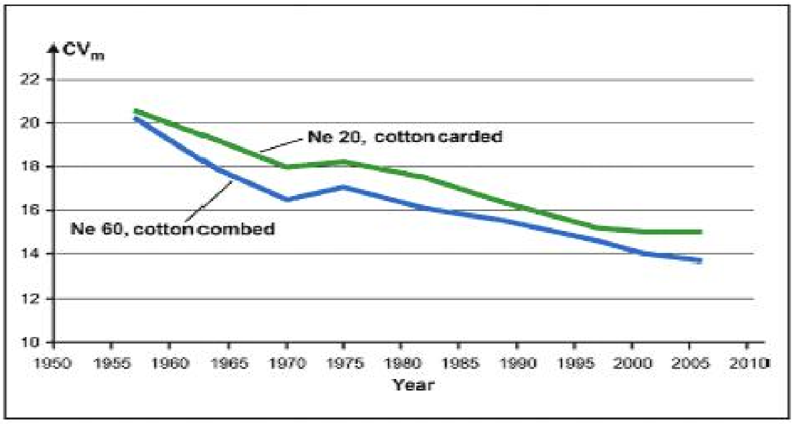

Figure 1.1: Uster Statistics 2007

The drawing process has strong influence on spun yarn quality. The significance of draw frame in the spinning process can be comprehended from the two chronological facts (i) 1972-1989 was the period of high speed draw frames, when the processing speeds was raised from 250 m/min to 800 m/min (ii) 1989-1999 was the period of development of medium and short term auto-leveling and online monitoring systems [3].

The card slivers fed to the draw frame have high unevenness value, while the combed slivers contain 'piecings' that are unbearable and must be evened out at the drawing stage to produce the improved quality yarn. At draw frame the objectives of fiber blending, fiber parallelization and sliver evenness are achieved by doubling, drafting and auto-leveling, out of which the doubling and the auto-leveling perform the quality improvement functions. An overview of the spinning process illustrates the draw frame as the last quality improvement machine [4]. This implies that the quality achieved or the defect produced at this stage will go on to influence the quality of the ultimate yarn.

The major improvement in sliver evenness is achieved by controlling the short, medium and long term variations at the draw frame. Keeping in view that doubling is never sufficient to average out all the irregularities in the incoming slivers, a lot of pressure has been put on the precise auto-leveling and draft settings. Very little reaction time associated with open loop auto leveling system increases the vitality of the auto-leveling settings, like leveling action point and leveling intensity. The criticality of these settings implies to the fact that not using an auto-leveler at draw frame is better than using a badly set one. Similarly, the importance of the precise draft setting cannot be ignored as they affect the motion of the fibers in the drafting zones. The badly set draft settings are known to produce both periodic and non-periodic irregularities due to uncontrolled fiber motion. These irregularities in the slivers can cause frequent stops in the following processes. For example the Moir-effects in woven fabrics and strips in knitted fabrics due to short-term fluctuations and cloudiness because of long-term irregularities [5, 6]. Likewise non-optimum settings at the spinning preparation machines or the unsatisfactory maintenance and cleaning at auto-leveler draw frame are associated with an increase of thick places in the slivers [7].

The determination of the interactions and relationships is inevitable for a specific advancement and optimization of a process. However, the diversity of involved parameters has made the optimization of the spinning process difficult. For instance, a wide range of material variables, i.e., the inherent fiber characteristics and the processing variables from cultivation fields to spinning mills in case of natural fibers, different chemical compositions of man made fibers, a variety of machine variables from preparation, spinning and winding machines and the climatic conditions. There are also complex interactions among the above mentioned parameters involving some or many of them. Generally speaking, the optimization of the machine settings and their interaction with fiber materials plays an imperative role in the spinning industry.

In the last century, many attempts to find out the interactions between the diverse variables had been carried out that are based mostly on mathematical and statistical models. However, in the last decade, the use of artificial neural networks has found acceptance in determining the complex interactions between various parameters. The motivation of using artificial neural networks lies in their flexibility and power of information processing as they can solve a problem *by experience and learning* the input-output patterns provided by the user [8]. The fields of applications cover medical to engineering and from agriculture to space sciences. In spinning, various attempts have been made to predict the yarn quality characteristics from raw material characteristics and to establish the relationships between different influencing parameters.

In this backdrop, the present research involves the use of artificial neural networks (ANN) as a powerful modeling technique to establish the correlations among the decisive variables of draw frame and quality of sliver and yarn. On these bases, prediction systems are developed to forecast the sliver and yarn quality. Conversely, the quick and accurate predictions of draw frame settings (draft and auto-leveling) are made in accordance with the yarn quality. Furthermore, it is highly anticipated that this prediction system might be a significant step towards the idea of an 'intelligent machine' that can be able to adjust itself according to variations in the processing materials and conditions.

Chapter 2

Significance of Draw Frame

2.1 Importance of Draw Frame in Spinning Process

The conversion of staple fibers into yarn i.e. spinning, involves many processes from bale opening to the yarn winding (Figure 2.1). Depending on the fiber characteristics of the raw material and the desired yarn characteristics, different machines and spinning methods can be employed. For example, the manufacturing of the fine yarns require the fibrous material with superior characteristics and additional machines like comber, whereas the coarse yarn can be produced using the medium to low quality fibers [3]. This implies that a compromise should be found for a cost effective end product.

In the spinning preparation, the hard pressed cotton bales are opened into small flocks. In the blow room the fiber opening executed by the nailed cylinders and scrubbing action of fibers against the grid bars cause the foreign particles, e.g. vegetable matter and metal etc, to fall under the force of gravity. Whereas the some opening and cleaning machines use the principle of centrifugal force to eliminate the foreign particles because they are heavier than fibers. A partial removal of the foreign matter is achieved at this stage. At the same time a mixing of different grades of cotton from diverse origins improves the fiber uniformity and allows an economical raw material blend. At the card machine the flocks are opened up to the single fiber state, semi-parallelized, cleaned, and finally converted into a card sliver.

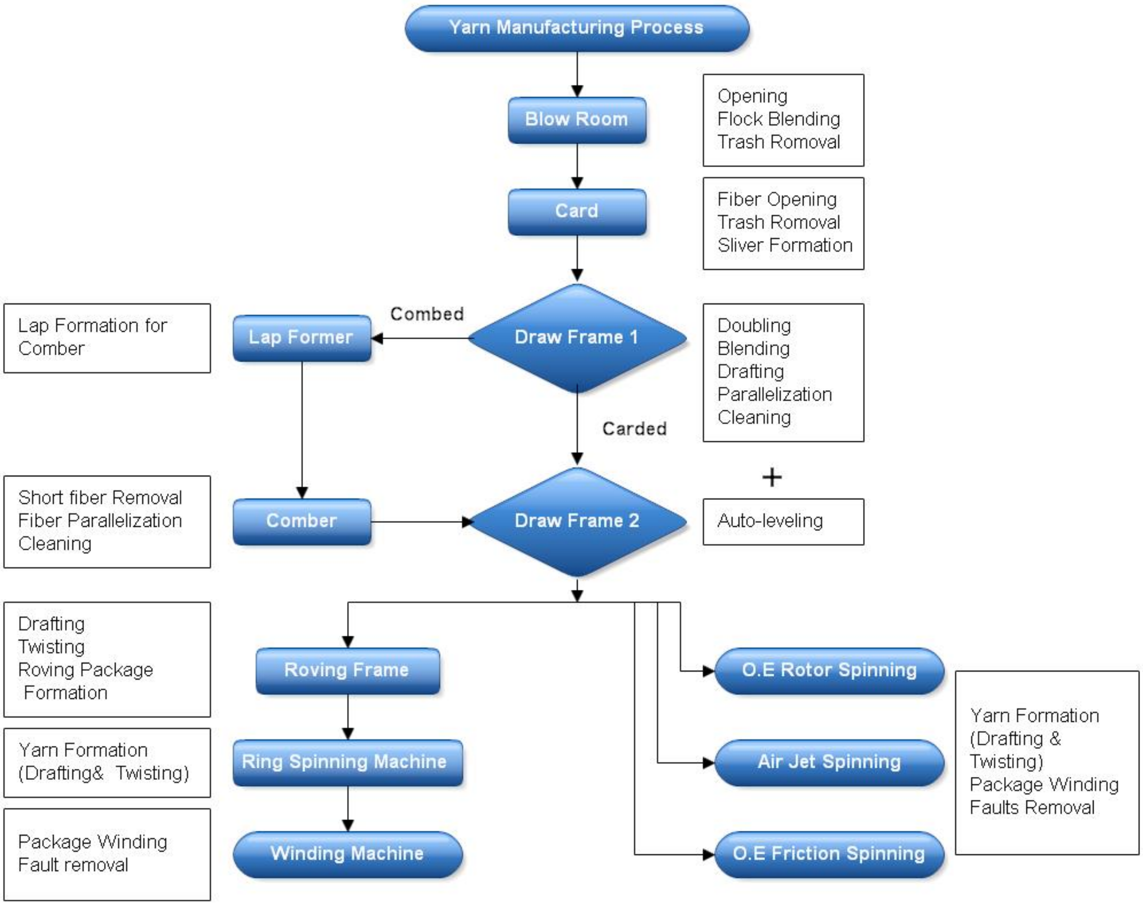

Figure 2.1: Flow Chart Diagram of the Yarn Manufacturing Process

After carding, commonly two drawing passages are used. However, the numbers of drawing passages used are largely dependent on the materials, yarn characteristics, spinning methods and requirement of end product. For instance, usually 1-2 drawing passages are required for open end spinning whereas the air-jet spinning needs 3 drawing passages. Similarly, for ring spinning the numbers of drawing passages usually vary from 2 to 3. The auto-leveling is carried out mostly for the last drawing passage. Furthermore, it is also possible to blend the different materials i.e. natural and synthetics fibers at this stage (sliver blending). Moreover, in case of polyester cotton blending, carded polyester slivers requires an additional drawing passage before blending with carded cotton slivers. The functions of the draw frame are described in detail in the later part of this chapter.

Furthermore at the draw frame stage the selection of carded or combed can be made. In case of carded yarn, the slivers after second drawing passage are fed to the roving frame and subsequently to the ring spinning machine. Whereas, for the combed yarns, slivers after first passage of drawing are fed to the lap former that produces the laps for the combing machine. Combing eliminates the short fibers, removes the impurities and parallelizes the remaining fibers. After combing one or two draw frame passages i.e. breaker and finisher draw frames are required, where the later is an auto-leveling draw frame. The ability of auto-leveler draw frame to correct the short term variations eliminates the faults due to the 'piecings' in the combed slivers and improves the resulting sliver evenness. The quality of drawing process directly influences the subsequent yarn manufacturing process. Subsequently, the combed slivers take the normal way of roving and ring spinning machines and converted into yarn.

Presently, there are various other spinning methods available such as, rotor spinning, friction spinning and air-jet spinning etc. However, the ring and open end spinning have special economic significance. The ring spinning requires the sliver to be converted into roving before processing at the ring spinning frame which does not applies to the other spinning techniques [3, 9].

Each spinning system requires different number of drawing passages for better yarn quality. For instance open-end spinning mostly requires one or two drawing passage whereas the air-jet spinning requires three drawing passage. These methods can be selected depending on the desired yarn structure and nature of the end uses.

2.2 Influence of Draw Frame on Following Textile Processes

In modern spinning process, the draw frame has an important function of the evening the slivers. However, the evenness of the slivers is essentially affected by the quality of the draft at the draw frame. There are two major causes that exert the considerable influence on sliver and yarn evenness. Firstly, the position of the draw frames in the spinning mill, which is definitively the last compensation point for correcting the faults/imperfections in the slivers. Secondly, the defect produced at draw frame itself, can exert the significant disturbances and quality related problems in the further process. Material faults (e.g. short fiber contents) and machine faults (e.g. improper draft zone settings) during the drafting cause periodic and non-periodic variations (thick or thin places) in the sliver, which create problems during the subsequent processes.

The improper draft zone settings at the draw frame are considered to be most disturbing. The approximate values from machine manufacturers are regarded as initial values for starting the optimization process. In order to obtain a better sliver uniformity and consequently good yarn properties, it is advisable to adjust the break and main draft drafting zones in accordance with the processed material. A comprehensive study conducted by 'Uster' inferred that an increase in thick places in the slivers is connected with the non-optimum settings of the spinning preparation machines and unsatisfactory maintenance and cleaning measures at auto-leveler draw frame [7]. In addition the variations caused by the poorly set auto-leveling parameters can also have worsening affect on the quality of yarn. Furthermore, process parameters, e.g., high speed can cause the improper control of the fibers inside the drafting zone, resulting in a high CVm% of sliver and then ultimate yarn.

Generally speaking, a large number of thick places and high irregularity in the slivers have negative effects on the downstream processes. The thick places can lead to process disturbances in roving frame and frequent end breakages at ring and OE-Rotor spinning machines. Moreover these thick places in the fed sliver cause air-jet spinning machine to stop. These sliver variations are also connected with the count variations in the yarn, which is in turn associated with the variation in the yarn strength. The weak patches in the yarn lead to the frequent end breakages. Such thick places and mass fluctuations of the slivers over the entire chain of the yarn production reduce of the productivity of the textile machines, which is normally connected with additional costs. Because of large yarn count variations bobbin rejection may occur at the auto cone machine.

Periodic and non-periodic irregularities in the slivers can also cause frequent stops in the following processes and produce Moir-effects in woven fabrics and strips in knitted fabrics because of short-wave fluctuations and cloudiness due to long-wave disturbances. In knitting, thick places cause even greater problems, as they limit the movement of the stitching needles. Thus miss-loops can result, which can cause holes in the knitted fabric.

Therefore, it can be inferred, from the above discussion, that the properly set draw frame setting can guarantee an optimum sliver quality which can leads to an improved quality of yarn and textile fabrics produced from it. Keeping in view the significance of the draw frame in spinning process and on following textile processes, it seems worthwhile to discuss the functions of draw frame in detail. The next section, therefore, underlines the major tasks of draw frame.

2.3 Tasks of Draw Frame

As depicted in the Figure 2.1, the draw frame is positioned at the central place in the yarn manufacturing chain. The draw frame performs the following tasks:

1. Doubling
2. Blending
3. Drafting
4. Fiber Parallelization
5. Auto-leveling
6. Cleaning

A brief overview of these tasks is presented in this section.

2.3.1 Doubling

Irregularities increase by drafting and decrease by doubling. Doubling is considered to be the simple and suitable method to even out the drawing slivers. However, this method is not very precise one. There is the possibility of feeding up to 8 slivers at the draw frame. The objective of the doubling is to achieve a sliver with better evenness. There is very small probability of coinciding thin or thick places in all fed slivers. Therefore, it is believed that these thin and thick places that tend to distribute randomly in fed slivers are compensated through doubling through averaging out effect as shown in the Figure 2.2. However, only medium to short term variations can be compensated through doubling process [10].

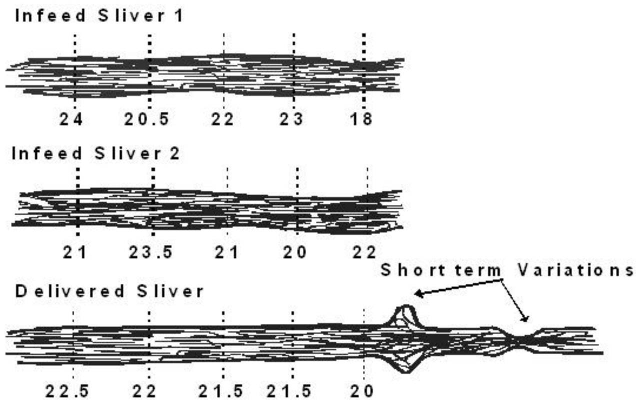

Figure 2.2: The averaging out effect due to doubling

2.3.2 Blending

Fibers can be blended using the different methods during spinning preparation, most common of them are bale blending, flock blending and sliver blending. Bale blending is done before the blow room and usually carried out in case of cotton for mixing bales of different grades to achieve an economical blend. Whereas the flock blend is usually done in blow room using the multi-mixer machine. Flock blending is the best way to achieve a very homogeneous blend. Draw frame also offers the opportunity of blending the slivers from different materials along with the additional advantages of homogeneous blend and accurate blending ratios. As the slivers fed to the draw frame have definite weight per unit length so different combinations of blend ratios can be realized. However the improved homogeneity requires at least two passages. This statement can be explained by feeding six slivers of two different materials alternatively to the draw frame. The output of the first passage will be the sliver containing the six ribbons of almost equal width. Similarly, the output of second passage will be a sliver with 36, consequently that of 3rd passage will contain 216 ribbons [9]. The draw frame is also very suitable for blending the natural fibers like cotton with man-made fibers. After carding, cotton becomes almost trash free and there is no danger of contaminating the synthetic fibers with trash [11].

2.3.3 Drafting

In literature, the drafting process is mainly described using the term "attenuation", i.e. decreasing the number of fibers in cross section, per unit length of the fiber bundle by sliding them pass each other. Logically, this also causes the reduction in the thickness of the fibrous material. So, the draft can be calculated as the

$$Draft \ = \frac{Fineness\,of\,all\,fed\,slivers}{Fineness\,of\,delivered\,sliver} \tag{2.1}$$

The drafting unit is the heart of the draw frame and quality of the sliver is mainly representative of the quality of drafting. Drafting is performed using the pairs of rollers i.e. bottom steel rollers and top rubber roller, running with successively increasing surface speeds. The top rollers are pressed on the bottom roller with an optimum pressure, while the bottom steel rollers are fluted to exert better control on the fibers passing between them. Here the draft can also be expressed as

$$Draft \ = \frac{Surface\,speed\,of\,feed\,rollers}{Surface\,speed\,of\,back\,roller} \tag{2.2}$$

3-over-3 roller drafting arrangements with pressure bar is frequently used in modern high performance draw frames. Whereas, draw frame having 4-over-3 drafting assembly, works like a 3-over-3 drafting system except the fourth roller, i.e. deflecting roller, helps to guide the sliver directly into the delivery trumpet. The drafting assembly of a 4-over-3 draw frame (RSB D-40) is shown in the Figure 2.3.

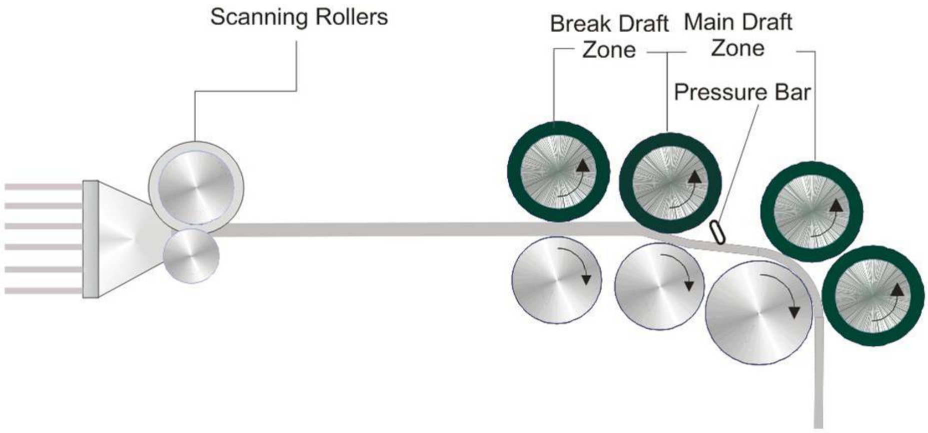

Figure 2.3: The drafting arrangement of the draw frame

During drafting the movement of the fibers is relative to each other. It is highly demanded that this movement must be kept as uniform as possible by overcoming the cohesive friction among the fibers. As drafting cannot be done ideally, i.e. achieving individual fiber control, therefore, every drafting operation is associated with irregularities. Additionally, the drafting zone settings (i.e. Back and front zone distances, break and main drafts) play a vital role for realizing a better sliver and yarn quality. Drafting process will be discussed in detail in chapter 3.

2.3.4 Parallelization

The card machine performs the function of opening and parallelizing the fibers. However, most of the fibers are not totally parallel to the sliver direction. Furthermore they also contain leading and trailing hooks. The elimination of these types of hooks cannot be carried out with single passage drawing. The trailing hooks are removed during the first passage, whereas the elimination of the leading hooks occurs during the second passage. The fibers laying at various directions in the sliver are also parallelized through drafting [11]. The degree of parallelization, however, is largely dependent on the draft zone settings. For example, using wide draft zone settings, the fibrous material cannot be controlled satisfactorily, resulting in a large amount of floating fibers and low parallelization grade, which leads to irregularities.

2.3.5 Auto-Leveling

In the yarn spinning, there are sliver weight and yarn count variations, which cannot be completely eliminated. It is vitally important that the sliver variations should be reduced through doubling and auto-leveling so that the count variations in yarn will not cause any disturbances in the end product. In principle, doubling is not enough to correct the variations in slivers. Therefore, doubling has to work in combination with the auto-leveling for better quality results.

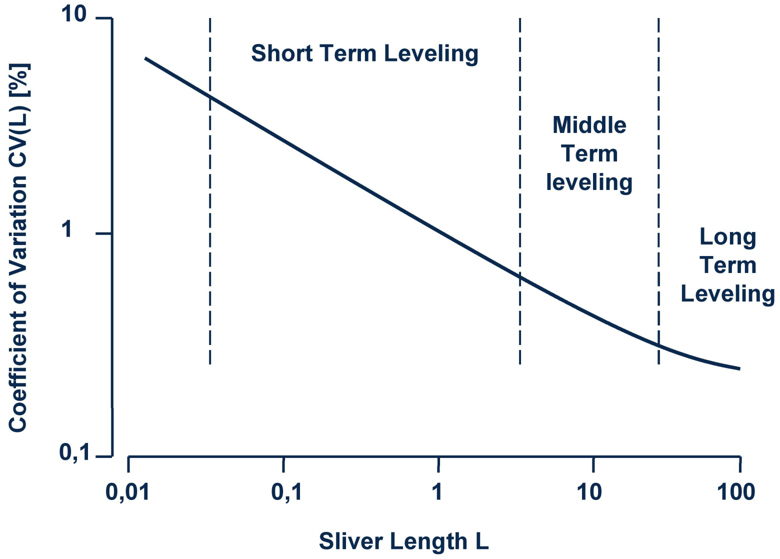

Figure 2.4: Length variation curve for slivers with length dependent leveling

The variations in slivers have different wave lengths. For example, the variations resulting from card slivers are long term, whereas periodic variations coming from combing machine are short term. The different auto-leveling systems are differentiated on the basis of wave length depended effectiveness. The Figure 2.4 shows the effective range for different auto-leveling systems. Long term variations are in the range of 25 m or longer. On the basis of this concept, long term leveler influences mass variations starting from 25 m of sliver length. The auto-leveling system to correct the medium length variations are effective starting from 2.5 m. The short term auto leveling is able to correct the faults from 3 cm to 2.5 m, as shown in Figure 2.4 [12].

The schematic diagram of the open loop and close loop auto-leveling system is being presented hereunder. Figure 2.5 depicts the main features of these two types of control system. S and A represent the locations of the sensors and actuators respectively, the dotted lines show the signal path and the solid lines illustrate the material flow.

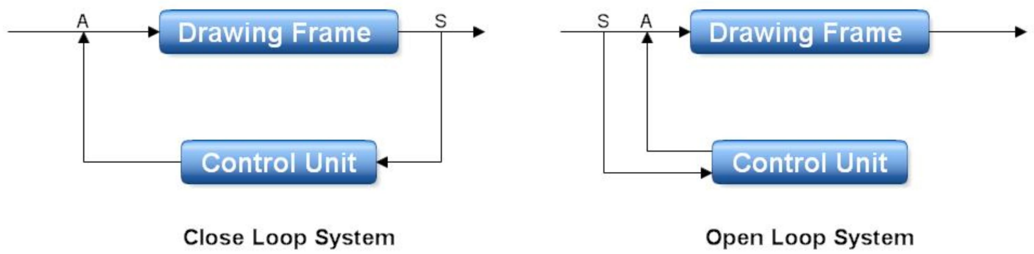

Figure 2.5: Schematic diagram of open and close loop auto-leveling systems

In the open loop control system, the total volume of all the slivers is measured at the feeding end using a scanning system. The adjustment is done by changing the draft in main drafting field. On the other hand, in the closed loop systems, the evenness of the delivered sliver is measured at delivery and adjustments are made in drafting field. The open loop systems are best suited for the short and medium term variations, while the closed loops systems perform better for the long term variations. This implies that the 'piecings' coming from the combing machines can be eliminated with the help of open loop system but closed loop system cannot correct them [10, 13].

The modern high performance draw frames are equipped with the both types of auto-leveling setup. Following paragraph describes the auto-leveling function of the Rieter draw frame RSB D-40, which was used in this research project. The Figure 2.3 depicts the scanning arrangement along with drafting rollers, whereas Figure 2.6 reveals the schematic of the auto-leveling at high performance drawing frame [14].

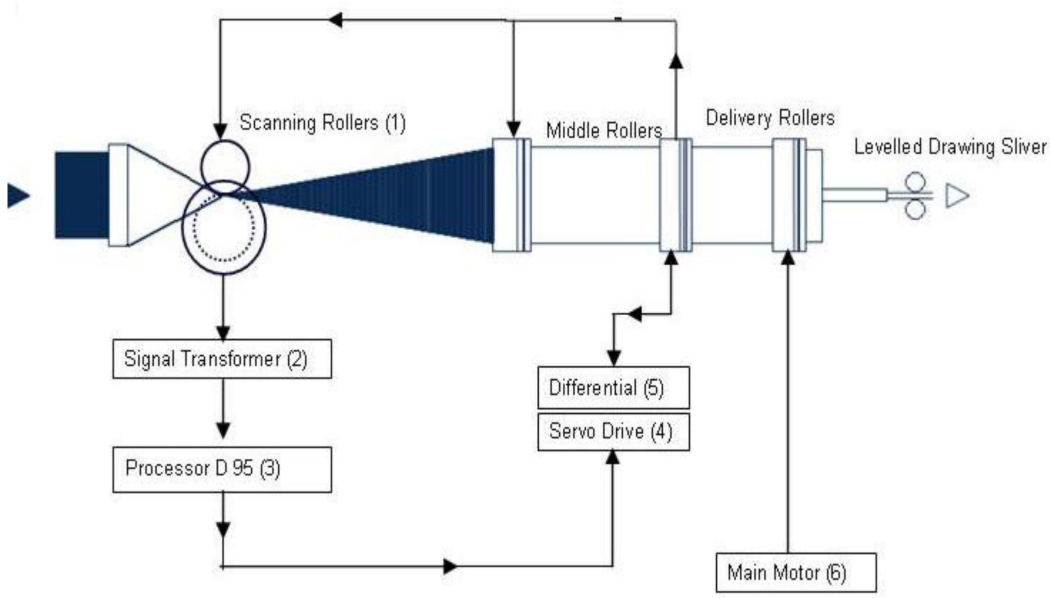

Figure 2.6: Schematic diagram of Auto-leveling system of RSB D-40

The slivers are fed through a pair of scanning rollers (1). The scanning rollers are based on mechanical scanning i.e., tongue and grove system. One roller is stationary while the other is movable. The increase or decrease in the sliver density entering through the pair of the scanning roller is measured by the displacement of the moving roller. Their movements are transformed into electrical voltage values by a signal transformer (2) and are forwarded to the processor D95 (3). The processor D95 (3) computes the proper target value for the servo drive (4) (Servo motor and Servo leveler), which is calculated using the electronic values of the infeed slivers and the delivery speed of the draw frame. The servo drive (4) determines a controlled speed for the differential (5), which drives the scanning rollers at the entry and middle cylinders. The draft change achieved in the main drafting zone causes the leveling of the volume variations in the fed slivers. The delivery rollers driven by the main motor M1 (6) run at a constant speed, so the production remains constant [14].

For better performance, all the existing sliver variations have to be regulated in the last drawing passage. The sliver mass variations have been already reduced through doubling before the auto-leveling. Therefore, the remaining irregularities are compensated by leveling device.

2.3.6 Cleaning

Apart from the main tasks, the drawing frame has an additional function of cleaning the slivers. After the carding machines, it is not possible to completely clean the fibers without damaging them. But the dust particles have the tendency to cling to the fiber surfaces through Coulomb forces. During drafting, as the fibers containing the trash particles slide past each other, the fiber-to-fiber friction releases the dust or trash particles caught between the fibers [9]. The cleaning flaps connected to the central suction system are placed over the upper rollers help to remove the contaminations like dirt, dust, broken plant particles etc [11].

This chapter has provided an overview of the function, tasks and significance of draw frame in staple yarn spinning. The next chapter digs deeper into the issues related to draw frame like drafting theories and use of Artificial Neural Networks (ANN) in textile industry, through in-depth analysis of the contemporary literature.

Chapter 3

State of the Art

3.1 Optimization of Draw Frame

As previously discussed in the Chapter 2, the draw frame exerts a significant influence on the quality of the sliver, yarn and the resultant fabrics. Doubling and auto-leveling perform quality improvement functions whereas drafting generates the irregularity in the sliver. Consequently the optimization of drafting and auto-leveling at the draw frame improves the performance of whole spinning process.

3.1.1 Drafting Process

The heart of the draw frame is its drafting zone, where the drafting of a set of slivers is accomplished. Drafting causes the fibers to parallelize and improve the condition of the fibrous assembly for further drafting processes. However, an increase in the irregularity is always associated with the drafting operation. If σ_{in} is the standard deviation of linear density of the infeed sliver and σ_{added} is the variations added due to drafting process then

$$\sigma_{out}^2 = \sigma_{in}^2 + \sigma_{added}^2 \tag{3.1}$$

In spinning industry, the irregularity is commonly measures in terms of 'Coefficient of variance (CV%)', which is given as

$$CV = 100\frac{\sigma}{\bar{x}}[\%] \tag{3.2}$$

The occurrence of mechanical faults such as roller eccentricity or worn out parts can affect the sliver irregularity dramatically [9]. However, under normal processing conditions the major factors that are known to affect the sliver irregularity and then ultimate yarn quality are classified into three major and further subgroups as shown in following Figure 3.1.

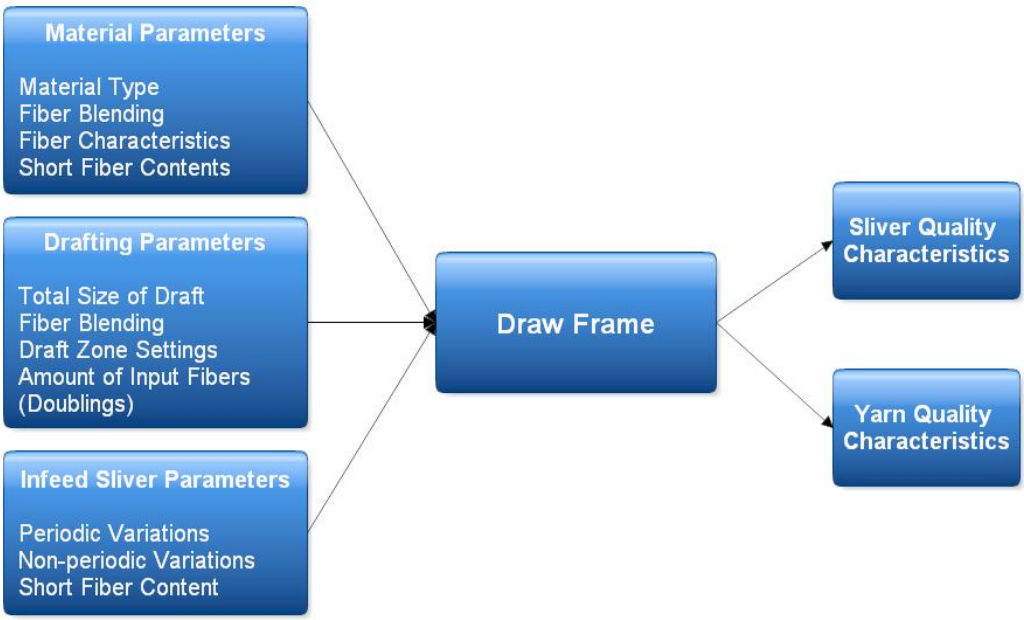

Figure 3.1: Factors effecting sliver and yarn quality

The control of fiber motion especially the control of floating fibers inside the drafting zone is the objective of irregularity reduction. In the absence of the mechanical faults, the correct setting of the drafting parameters i.e. delivery speed, distances between the rollers, top rollers pressure etc, help to do so. However the influence exerted by the infeed sliver variations is also substantial. Short-fiber content, neps, trash, and other impurities, degree of fiber parallelization, and number and extent of fiber hooks, are some of the significant factors that decide the drafting performance of infeed slivers and the resultant sliver quality [9, 15]. In order to have an in-depth look in drafting, the case of ideal drafting and its comparison with real drafting is discussed hereunder.

3.1.1.1 Ideal Drafting versus Real Drafting

The ideal drafting does not induce the additional irregularities in the drafted sliver; however the irregularities in the infeed sliver remain in the delivered sliver in the absence of doublings and auto-leveling. For ideal drafting, an infeed fibrous assembly in which all fibers are straight and parallel having same fiber length and fineness, with their leading ends equally spaced should be assumed [16]. During the ideal drafting, it is also assumed that all the fibers move at the back roller surface speed 'U' until the leading end of each fiber will be caught by the nip of the front rollers and then they are instantaneously accelerated to the front roller surface speed 'V'. Under such circumstances a complete fiber control can be achieved. The distance between any two fiber leading ends after drafting will also be equal to that of before drafting, multiplied by the draft [9]. The Figure 3.2 represents the schematic diagram of single drafting zone.

On the other hand, in real drafting this velocity change does not take place ideally. In the Figure 3.2 consider a fiber group of length 'L' moving with a velocity 'U' in the region 'AC'. As this group enters the region 'CB' it will accelerate from velocity 'U' to 'V'. This acceleration can take place anywhere in this region 'CB', because of frictional contacts of the fibers, which are already gripped by the front rollers. The region 'CB' is also known as area of floating motion. 'F' represents the floating fiber which is not gripped by either of the roller pairs. The large amount of floating fibers can cause this velocity change to occur abruptly resulting in sliver irregularities. It is generally accepted that the speed of the fibers changes from 'U' to 'V' and remains at 'V' - this is known as "two speed model". In roller drafting irregularity is the result of incomplete control of motion of single fiber or fiber groups. The irregularities are caused by the instability of the points of acceleration with respect to time and when the fibers are accelerated at the speed of the front roller discontinuously [17, 18]. The pressure bars are used in the drafting zone to achieve a better fiber control and to stabilize the process, but individual fiber control is not possible. Moreover the variations in the material properties are the basic cause of the irregularities [19].

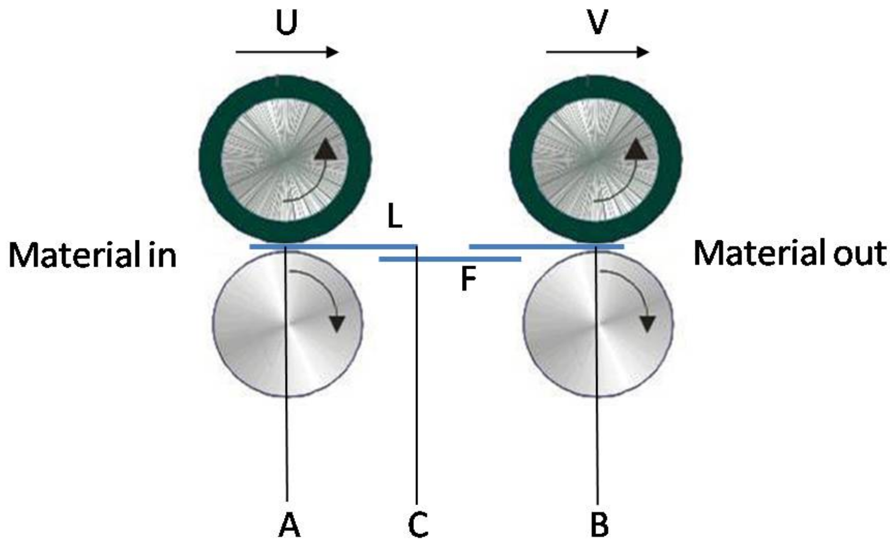

Figure 3.2: Schematic diagram of a drafting zone

As for ideal drafting an ideal fiber assembly is considered. However, in reality, the distribution of fiber lengths in a card sliver is not uniform and these fibers are neither straight nor parallel. Various studies had indicated the importance of the fiber crimp on the drafting operation [20]. For instance, Plonsker and Backer, while calculating the drafting force, observed that at lower speeds, the crimped or hooked fibers tend to exhibit erratic, springy and pulsating motions inside the drafting zone, whereas un-crimped fibers slide in relatively smooth manner. These crimped or hooked fibers also cause the entanglement or interlocking of fibers, which requires a larger force to be drafted and hence cause the irregularities.

Furthermore, the fiber length distributions commonly expressed as 'Fiber uniformity ratio', calculated on the basis of High Volume Instrument (HVI) measurements, also plays a significant role during drafting. The presence of large amounts of short fibers makes the drafting performance worse, because they will behave as the floating fibers inside the drafting zone. This situation can lead to undesirable early fiber acceleration and will cause a negative effect on the sliver evenness or may cause the drafting waves [3]. Floating fibers are subjected to two sets of forces acting at the opposite directions. From Figure 3.2 it can be postulated that the fibers that are moving slower and are in the grip of the back rollers restrain the floating fibers from accelerating while the long fibers that are in contact with the front rollers try to accelerate the floating fibers to higher velocity. As the floating fibers travel towards the front rollers the restraining force decreases while front roller influence increases. At some balance point, fibers accelerate abruptly from low to high speed, this action is associated with the law of friction, i.e. static friction is higher than dynamic friction. As the floating fibers increase their speed the neighbouring short fibers also experience the accelerating force from surroundings. However, when a fiber group accelerates un-drafted, it may cause an avalanche effect and it leaves a void behind causing a drafting wave in the drafted sliver [18, 19, 21]. Moreover, the role of optimum draft zone settings becomes imperative here. At wider draft zone settings, the short as well as long fibers will behave like floating fibers causing the irregularity to increase rapidly. On the other hand narrow draft zone settings would cause fiber breakage and fiber slippage.

The occurring drafting variations can also be explained through the conception of friction, i.e. the transfer of the roller speed to the fibers and the friction between the fibers. This can lead to the fact that the constant force does not act on all the fibers simultaneously and permanently and the mean value of the varying fiber speed changes. During the processing of the fiber materials in the drafting zone the occurring force is dependent on the many parameters like the angle of contact between fibers, parallelization state, tension, surface coatings, and environmental factors such as humidity etc. The drafting force variations occur at different place along the length of slivers and can be of different levels. Very small drafting force variations are mostly based on a jerky drafting process (stick-slip change) individually, within the existing fiber groups of the sliver. The occurrence of stick slip change is mostly dependent on the fiber type [22,23]. The experiments have shown that fiber relative movements have a considerable influence on the fiber friction. It is expressed as follows

$$\frac{\mu_d}{\mu_s} = c - ae^{bv_r} \tag{3.3}$$

Where, μ_d and μ_s are the dynamic and static friction coefficients, whereas a, b and c are the material dependent coefficients and v_r corresponds to relative velocity of fibers.

It is clear from above discussion that the ideal drafting process is not achievable. The irregularities in the drafted sliver are the result of the interaction of fiber properties and machine settings. The knowledge of the relationships between fiber properties and drafting conditions can provide answers to the questions concerning the drafting performance of different materials [24]. This enhances the need of the optimum settings on the drawing frame for its optimization.

3.1.1.2 Drafting Theories

In order to describe the drafting process comprehensively with an aim of optimizing it, many theories have been presented in last century. Some of them are being briefly presented here. The drafting operation, despite of looking very simple, is a difficult one to analyze. The major reason can be the fact that every fiber in the fibrous assembly has an individual fiber length and this fibrous assembly cannot be considered as a continuous fluid like body.

In the literature, the earlier theories cover the empirical analysis of the process. Another interesting method was the ‘geometrical method’. The method was used to find out the velocity change point. The third method was the use of mathematical relationships to find out the interactions between the input and output parameters.

The forth and most recent one is the use of computer simulations, which is a developed form of the geometrical method, but in addition also involve the use of statistical and mathematical techniques to simulate the process.

This geometrical method involves drawing the sliver on the paper using straight parallel lines representing the fibers and analyzing the process by shifting the positions of these lines. The geometrical method was considered to be suitable for analyzing the velocity-change point. Grishin’s had done the significant work in this direction [25]. As already mentioned, it cannot explain the real drafting phenomenon. Many researchers considered geometrical method to describe the steady-state motion of the fibers and cannot be applied to unsteady-state like drafting waves [18].

A large amount of mathematical work is available starting from the ideal drafting and drafting waves (previously described), the dynamic modeling of drafting process [26, 27] and frictional contacts of fibers during drafting [28, 29]. However, most of the models involve the immeasurable parameters like displacement of fiber front ends, average number of fibers, minimum and maximum lengths etc. Also, mathematical models are always based on the ideal assumptions and are applicable only when these assumptions are fulfilled. Moreover, the earlier theoretical work was based on the assumption that the fibers are capable of independent movement relative to their surrounding fibers. However, Vroomen and Monfort [30] first pointed out that the fibers tend to move in groups rather than single fibers. This is particularly true in drafting sliver.

The recent trend was the dynamical measurement of the drafting process. Cherif [3] invented the method for touch-less measurement of the fibers speeds with the help of laser Doppler anemometry. Additionally for the visualization of the movements of the fibers during drafting process super high speed video camera was used. The fact was endorsed that the fibers move in groups inside the drafting field. The measurements showed that at the low speeds a uniform fiber movement occurs whereas at high speeds a non-uniform abrupt acceleration of fibers occurs in the middle of the drafting zone. Also important is to note that this speed behaviour of the fibers is not constant over the width of the drafting zone and time. Also in a part of fibers the fiber acceleration movements are not controlled. This can be described as the stick slip movement of the fibers. Therefore, the major influence is exerted by the fiber speed behaviour and amount of the accelerated fibers in the main draft zone [3].

Indisputably, the improvements achieved in the sliver evenness are interconnected with the improvements in the spinning performance and yarn characteristics. Nevertheless, the theoretical and empirical work was significant. The insights gained by such contributions have helped to design devices and adopt the methods to improve the drafting systems. However, there is room for further improvement through the application of modern modeling techniques for enhancing the quality of the end products.

3.1.2 Auto-leveling

The optimization of the drawing frame is concerned not only with the optimization of draft settings but also connected with the optimization of the auto-leveling settings. The auto-leveling set up at a modern high speed draw frame is usually described using two important variables i.e. leveling intensity and leveling action point. Leveling intensity is a setting that decides the amount of draft change required to regulate the infeed variations. Leveling intensity is basically connected with the material to be processed because the correlation between mass and volume for different fibers is not same.

Leveling action point (LAP) is considered to be more important parameter due to its greater influence on the quality of the sliver and ultimate yarn. At the auto-leveler draw frame (RSB-D40) the thickness variations in the fed sliver are continually monitored by a mechanical device (a tongue-groove roll) and subsequently converted into electrical signals. The measured values are transmitted to an electronic memory with a parameter, the time delayed response. The time delay allows the draft between the mid-roll and the delivery roll of the draw frame to adjust exactly at that moment when the defective sliver piece, which had been measured by a pair of scanning rollers, finds itself at a point of draft. At this point, a servo motor operates depending upon the amount of variation detected in the sliver piece. The distance that separates the scanning rollers pair and the point of draft is called the zero point of regulation or the leveling action point (LAP) [31, 32]. However, during material processing the leveling action point changes from its geometric value. This implies that as the a change in frequency of the incoming variations the leveling action point also changes. Therefore, feeding speed of the fed slivers entering the draw frame greatly influences the leveling action point.

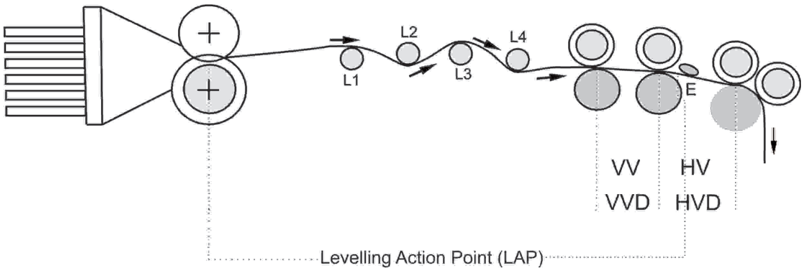

Figure 3.3: Schematic diagram of Leveling Action Point

The Uster spectrogram (Figure. 9.1) clearly depicts the faults in the sliver, in case of false selection of leveling action point. The incorrectly set leveling action point dually affects the sliver regularity i.e. leaving the defective part of the sliver un-regulated and disturbing the normal sliver. Therefore, auto-leveler must be accurately set to have a good quality sliver otherwise should be turned off to avoid unwanted irregularities in the sliver. The incorrect settings of leveling Intensity cause the variations in sliver number, while badly set leveling action point deteriorates the sliver CV%.

The complexity related to LAP is its dependence on various drawing frame settings and some of these settings are very frequently changed e.g. delivery speed and draft settings etc. Whereas, other influencing settings like feeding tension is mostly associated with the material batch changes. It is believed that LAP is dependent on the following variables [11, 14].

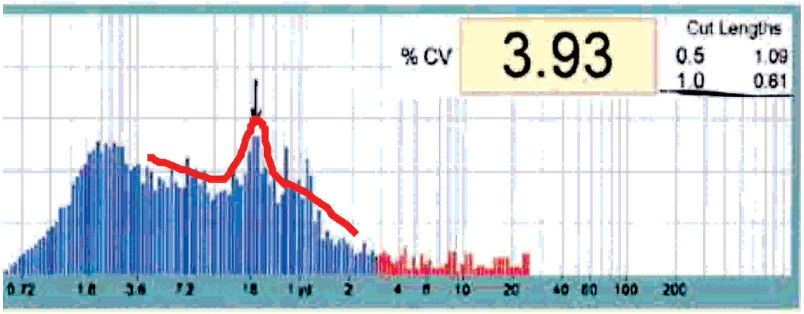

Figure 3.4: Uster Sectrogram Showing Errors due to Faulty LAP Settings

1. Material
2. Doublings
3. Draft (HV)
4. Delivery Speed (L)
5. Break Draft (VV)
6. Break draft distance (VVD)
7. Main draft distance (HVD)
8. Infeed tension (VE)
9. Sliver deflection bars
10. Infeed Variations

It is also significant to mention here another LAP influencing setting i.e. sliver deflection bars setting. This setting determines the paths of the slivers in the drafting zone. The sliver roller setting geometrically change the distance between the scanning and correction point. Obviously, this theoretical change is connected with the sliver thickness. The machine can be set at three different L2/L3 levels i.e. 1/6, 2/5 and 3/4 as shown in Figure 7.8. The frequently used setting is 2/5. Theoretically the 1/6 setting decrease the distance by 12 mm and 3/4 increase LAP by 18 mm for a sliver of 0 mm thickness. For a sliver of 3 mm thickness this increase in length is 21 mm and decrease is 11 mm.

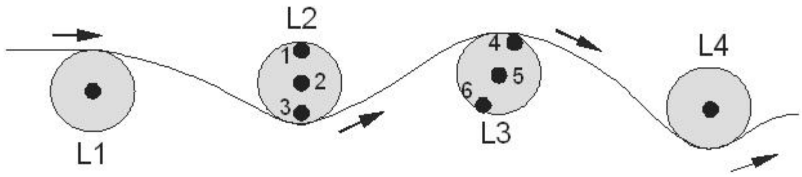

Figure 3.5: Sliver Deflection Bars Settings

In order to set the LAP value accurately, two methods, i.e., manual or automatic search function can be performed. Theoretically, it is clear that minimum CV% can only be achieved at optimum leveling action point. Therefore, finding a point having minimum CV% is the objective of both searches. The manual search includes the 7 evenness tests using the Uster tester, where CVm%, CV(1m)% and spectrograms are collectively considered. The start value can be taken from the machine panel. In the first step three Uster evenness test are carried out, i.e. with starting value, starting value +12 mm and starting value -12 mm. Then results of these tests are compared and best value is selected on the basis of CVm%, CV(1m)% and spectrograms. The second step involves 2 evenness tests, i.e. selected value from first step ±6 mm. The selection criteria for the best value are same as in first step. The third step is same like the second one, however here the 2 evenness tests are best CVm% value from second step ±3 mm were performed. The schematic diagram is given in Figure 3.6 However, the manual search is connected with the production and material losses because of the time and material required for accomplishing the manual tests [14].

The automatic search function offers a comparatively fast but accurate solution to the problem. This automatic search function at Rieter Auto-

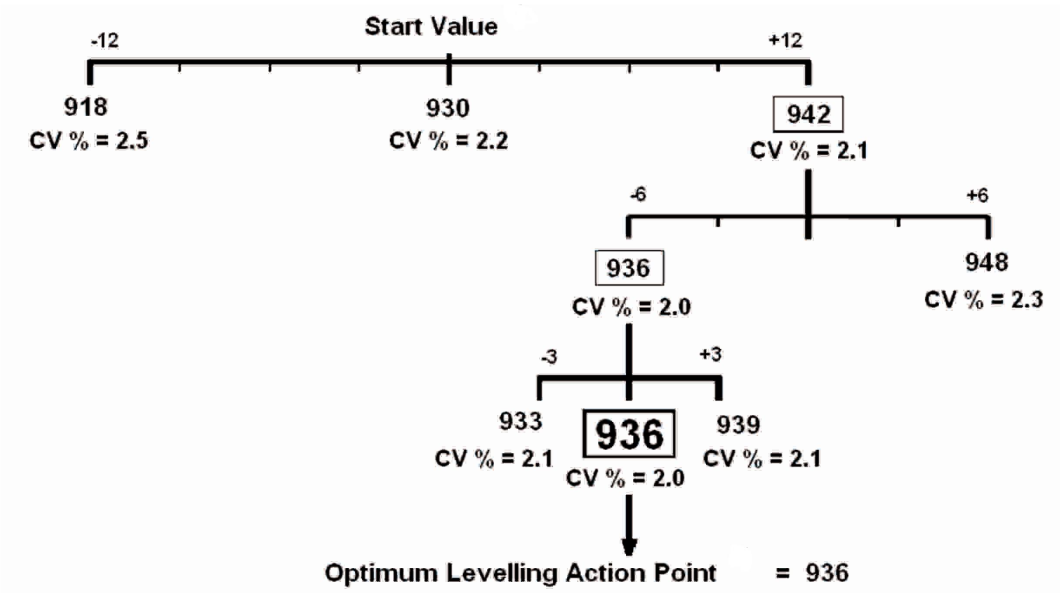

Figure 3.6: Determination of Leveling Action Point Using Manual Search

leveling Draw Frame RSB-D40 is known as "AUTOset", which is based on a minimum CVm% value seeking algorithm. During this function, the sliver is automatically scanned by adjusting the different LAPs temporarily and the resulted values are recorded. During this process, the quality parameters are constantly monitored using Rieter Quality Monitor (RQM) and an algorithm automatically calculates the optimum LAP by selecting the point with the minimum sliver CVm%. At present, a search range of 120 mm is scanned, i.e. 21 points are examined using 100 m of sliver in each case; therefore 2100 m of sliver is necessary to carry out the search function. This 2100 m sliver has to be processed again starting from the blow room. Nonetheless, this is also time-consuming method accompanied by the material and production losses, and hence directly affecting the cost parameters [14]. The Figure 3.7 depicts the user interface from RSB-D40 regarding the "AUTOset" function.The published research work for the optimization of this vitally important setting is limited and most of the written material is in the form of patents [31–33].

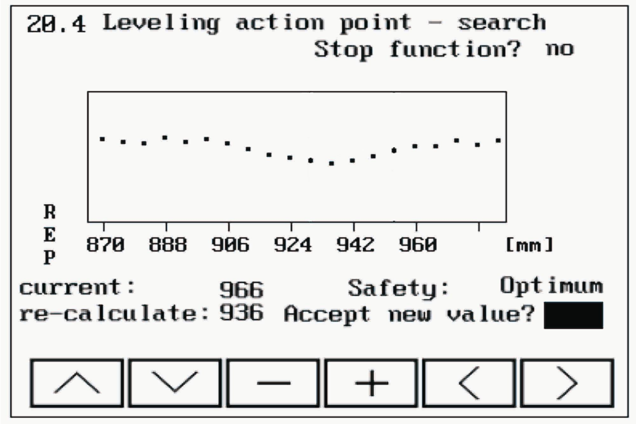

Figure 3.7: Automatic LAP search function “AUTOset” at RSB D40

It is therefore worthwhile to attempt the use of ANNs to optimize the LAP, with a hope that ANNs can develop the relationships between all influencing variables. This may help to predict a more precise LAP and the range of 120 mm may be reduced.

3.2 Ring Spun Yarns

There are different spinning technologies available for the conversion of staple fibers into yarn, like Ring spinning, Rotor spinning, Air-jet spinning and Friction Spinning etc. While comparing the spinning technologies, some important points have to be considered. Firstly, instead of various technologies present, only ring spinning, open-end yarn spinning and air jet spinning are able to gain the market share [34]. Secondly, the production of ring spinning is approximately 1/10 of rotor spinning and 1/20 of the air jet spinning. Thirdly, the inventions of ring, rotor and air jet spinning are in 1844, 1960 and late 80s respectively. However, despite of all these, almost 80% of the staple yarns are ring spun [35, 36]. The success secret of the ring spinning lies in its following advantages that are not possessed by the other technologies.

1. Wide range of materials are spun-able
2. Wide count range, i.e. large end-product flexibility
3. High quality due to the careful fiber control during spinning process
4. True twist and therefore strong and compact yarn structure
5. Suitability of the yarn structure and properties for widest range of fabric end-uses [37–39]

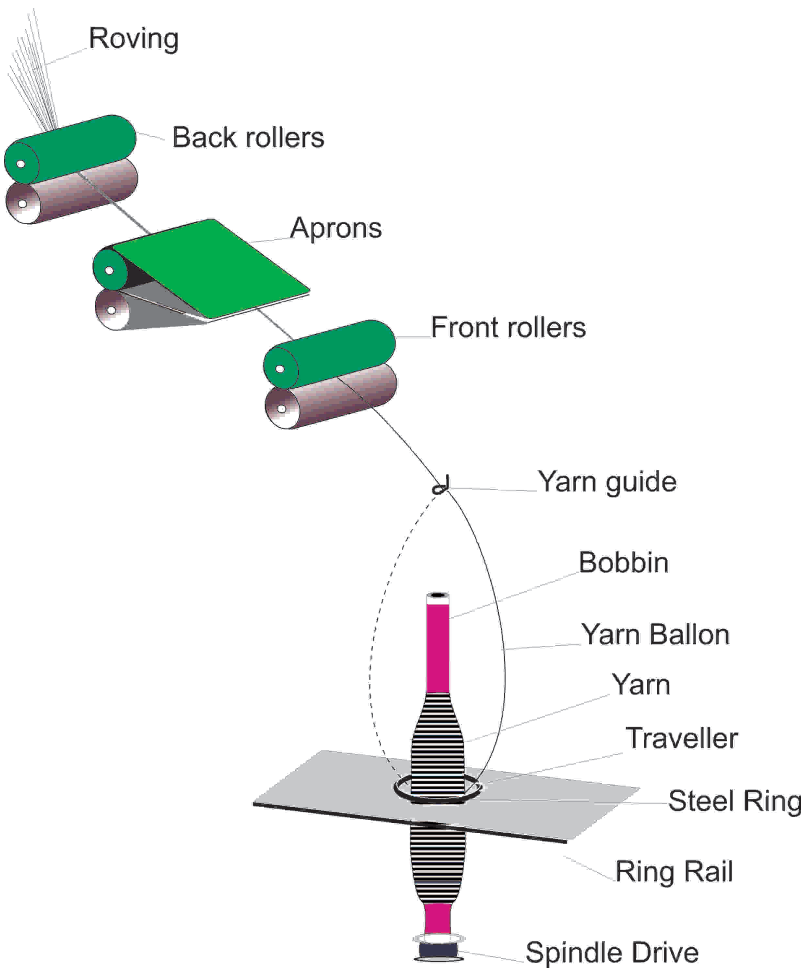

Figure 3.8: Schematic Diagram of Basic Ring Spinning Operation

All these advantages have made the ring yarn a quality benchmark against which the quality of the yarn produced by the other spinning methods is being measured [1]. The following Figure 3.8 depicts the working principle of the ring spinning machine.

On the other hand, ring spinning also has some disadvantages. Firstly, in ring spinning twist is inserted by rotating the relatively massive yarn package, which results in higher power consumption. Secondly, the yarn is produced at high tensions, so it has the tendency to break, which may cause the production losses. Thirdly, due to higher costs of production, the ring spun yarns are expensive. Last but not least, the conventional ring spun yarns are quite hairy, which may cause the pilling on the surface of the fabric and can reduce its quality. However, this disadvantage has been overcome with invention of compact ring spinning. It is a well known fact that spinning triangle is the major yarn hairiness forming zone. The compact ring spinning involves the reduction of the spinning triangle [40].

The developments in the spinning technologies are underway and machinery manufactures and spinners are being put under pressure to produce the best yarn quality at the acceptable price. Additionally, the increased level of automation and speed in the yarn manufacturing sector has expected a higher level of quality. All the same, ring spun yarns are still considered to have the ideal blend of properties. Ring spinning may lack in production speeds in comparison with the other spinning methods, nevertheless, sufficient advancements were done, like automatic doffing, link winding, use of longer ring frames and improvements in the splicing technology. These advancements pave the way for the reduction of the package size, which in turn is helpful for the use of small diameter rings and thus higher spindle speed and higher productivity may results [41].

3.3 Prediction Modeling

The optimization of a process requires exact knowledge of the process, which is on the one hand knowledge of correlations and inter-dependence between the process-determining variables and on the other hand knowledge over the actual condition of the process [3].

Yarn structure and properties are primarily influenced by fiber properties, spinning methods and most importantly process variables. Owing to the inherent non-linear relationships that exist between the process variables, material variables, and the resulting yarn properties, development of a prediction model deals with unraveling a web of interconnected complexities [42].

Until early 90s, predictive modeling has fallen into two main categories: A theoretical or Mathematical approach and an empirical or statistical approach. Both types of models have there advantages and disadvantages. For instance, the mathematical models are derived from the first principle analysis and have their basis in applied physics [43]. Therefore, they are appealing and capable of providing a better understanding of the complex relationships between the yarn properties and the influencing parameters. However, firstly these models always require simplified assumptions to make the mathematic tractable, and the validity of the model depends on the validity of the assumptions. Secondly, the mathematical models are associated with large prediction errors and therefore not reliable enough to work in practical situations due to the uncertainties connected with the real world dynamics.

On the other hand, the empirical or statistical models are easy to develop but they require the specialized knowledge of both statistical methods and designs of experiments. Extensive experimentation and test and data gathering connected with measurement errors can generate the ‘noise’ in data. Unfortunately, these models are sensitive to the ‘noise’. Also the present techniques are insufficient for precise modeling and optimizing the complex non-linear spinning process [42].

Since early 90s artificial neural networks have been employed for the determination of complex and analytically not recordable connections between parameters with success. Like their human models they learn the interrelationships in a training phase on the basis of special algorithms and provide meaningful outputs even from inaccurate input values.

Successfully applied to a wide range of problems, they offer the potential for performing complicated tasks that have previously required human intelligence. With suitable training sets, they have been taught to perform well in a wide range of applications [44]. Application areas for neural networks involve function approximation, solution of classification problems, pattern recognition (radar systems), quantum chemistry, sequence recognition (hand written recognition), system identification and control, medical application (disease diagnosis), financial application (stock markets prediction), data mining, email filtering etc.

3.3.1 Comparison of Neural Network with Other Models

In the history of neural networks applications in textiles many researchers have attempted to compare the performance of the neural networks model with the mathematical (mechanistic) and statistical models (regression equation) using the spinning based data. For instance, the comparison of neural networks with the regression equations had been done in spinning for predicting the quality of the rotor spun yarn [45] and predicting the yarn splice properties [46]. In both cases the significant nonlinearities contained in structural relationships between fibers and yarn are better understood by the neural networks and the predictions from the neural network show a higher accuracy than those of the regression analysis.

There had also been attempts to compare all three models, i.e. mathematical, statistical and ANN [47–49]. In the reported research work the relative performance of mathematical models, simple statistical models (based on regression equations), and neural networks models for prediction ring spun yarn tenacity form fiber properties and process parameters was examined [48]. It was observed that the cotton yarn tenacity prediction error for the neural network was 6.9%, as against 9.3% and 9.9% for the mechanical and statistical models, respectively. The same trend was more prominent when the three models were compared with data pertaining to ring spun polyester fiber yarns. Where, the prediction errors of 1.1%, 8% and 2.2% were observed for ANN, mathematical and statistical models respectively [50].

3.3.2 Application to Yarn Manufacturing

In the field of textile processing, neural networks (most of the back propagation type) have been used with success to predict set-marks [51], fabric defects [52], quality of knitted fabrics [53] and yarn parameters at a texturing machine in dependence of the selected machine settings [54]. Very few instances regarding the application of neural networks in yarn manufacturing have been discussed. The areas that have investigated include classification of card-web defects [55], control of sliver evenness [56] and predicting the spinability of the yarn [44].

As the current instruments cannot precisely measure the spinability of the fibers, [57] devised the neural network model for predicting the spinability of the fibers. The training data was consisted of 700 spinable and 700 un-spinable yarns for both ring and rotor yarns. The trained network was able to predict the spinablility of the test set with remarkable accuracy, with 90% of the spinable fibers and 95% of un-spinable fibers. Another study was conducted regarding the auto-levelers at drawing frame. Huang and Chang [56] have devised an artificial neural network controlled auto-leveler in which the linear density of the infeed sliver and desired linear density of delivered sliver were employed as inputs. Whereas, the ratio of front and back roller speeds was taken as output. According to their claim a trained network can improve the CV% of the delivered sliver from 3.37% (in a system without auto-levelers) to 2.73%. Use of Fuzzy self organizing controller improved the same value to 2.91%.

3.3.3 Yarn Properties Prediction

The prediction of yarn properties form fiber properties is also a scope of research for the Textile researchers over the years. They have attempted to predict the yarn properties using different fibers or fiber blends and machine input parameters by means of Neural Networks. In literature review, predicting the relationship between fiber properties and yarn strength [44], correlating the fiber blends and yarn characteristics [54], predicting the cotton yarn irregularity on the basis of 'AFIS' measurement [58], and predicting the hairiness for ring and rotor spun yarns using fiber properties [59] are few examples of the applications of ANNs.

The machine parameters along with fiber properties were also employed as Neural Networks inputs for the prediction of ring and rotor yarn properties. Sette et al [60] modelled the spinning process using fiber properties and five machine parameters as input and nine yarn properties as output. This work is the first use of genetic algorithms and neural networks in a textile process and seems to have immense potential. Also Van Nimmen et al [61] have also used genetic algorithms and neural networks for the selection of best cotton blends in terms of price and quality.

Therefore, contrasting the conventional techniques which are usually limited by strict assumptions of normality, linearity and variable independence, ANN are universal approximaters. They have the capability to learn directly from the data, i.e. training, and are able to find the relationships between input and output patterns even where the volume or variation within the data is large or the relations between variables are dynamic and nonlinear. Once trained, artificial neural networks can be evaluated very quickly, which is a benefit for optimization of a process.

Chapter 4

Objective of the Research

The description of the function of the drawing frame discussed in the chapter 2 reveals that various machine parameters can have significant influence on the sliver and yarn quality. Besides the machine parts, the machine settings, e.g. delivery speed, break draft, pressure bar, main and break draft distances can also be varied and they affect the processing and the quality one way or the other. The situation becomes more complex, when the influence exerted by the mentioned machine settings varies for different materials and materials blends at various blending ratios. The basic knowledge of the effect of these parameters already exists. Similarly work had also been done to search out the individual influences of these settings for different materials. However, not only the individual influences but also the interactions between of various influencing parameters exert significant effects on the sliver and yarn quality. The sense of combined effect of adjustable settings for different materials is lacking in the literature. Moreover, as already mentioned the main process involved in spinning i.e. the drafting process, cannot be carried out ideally, imposed constrains on the establishment of exact relations between the materials, machines and product quality.

The spinning process involves the interaction of a large number of variables like other industrial processes, but unlike other industries, the relationships among the variables and the product properties is yet to be established conclusively. The reasons are the high degree of variability in raw materials, multistage processing and lack of precise control on process variables. This situation leads to the managerial control of the spinning mill. A well experienced manager tends to develop a "feel" of the process and able to exercise some degree of control on the process. The absence of complete information about the process does not allow the researcher to establish exact relationships between the influencing parameters and the quality, but the manager with his "feel" can make intelligent guesses about the process. The possibility of human error and the lack of knowledge in a specific field are the draw backs of this control. Nevertheless, the managerial control is most commonly used in the spinning industry of the world. Logically, the "feel" of the manager is the based on the principle of "learning from examples". This implies a "learning from examples" control is best suited for the spinning industry [50].

The section 3.3.1 illustrates the better performance of the artificial neural networks in comparison with its mathematical and statistical competitors. Also interesting is the fact that ANN are theoretically based on "learning from examples", which is so far best suitable control in the spinning industry. However, it does not contain the disadvantages of managerial control like, human mistake or lack of some specific knowledge

The planned research task is divided into three phases.

The first phase involves the application of ANNs to optimize the leveling action point by reducing the material required for the adjustment and to predict the sliver quality using the drawing frames parameters (material and machine) for optimum machine functioning and better sliver quality.

The objective regarding the optimization of the leveling action point is to find out the relationships between the influencing variables and to reduce the search range, using the ANNs. Firstly the experiments will be carried out by changing the influencing parameters and the data thus acquired will be presented to the ANNs for the sliver quality and leveling action point prediction model. Figure 4.1 shows the schematic diagram of first phase.

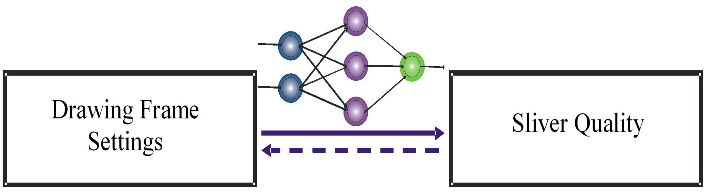

Figure 4.1: Optimization of the Sliver Quality

The second phase pertains to the usage of ANNs for the prediction of yarn quality. Various experiments will be performed by varying the different levels of the influencing parameters. The drawing frame parameters and sliver quality characteristics will be the input of ANNs, while the yarn quality characteristics will be the outputs as shown below in Figure 4.2.

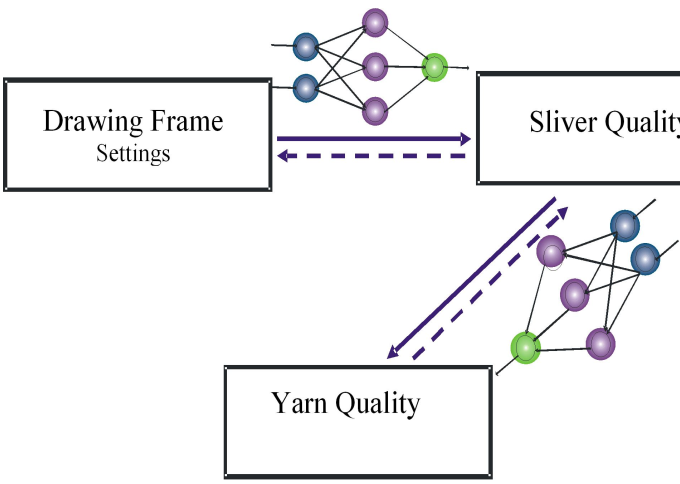

Figure 4.2: Optimization of the Yarn Quality

The third and last phase does not contain experimentation. It involves the endeavor to correlate the yarn quality characteristics with the drawing frame parameters. So that the adjustment of drawing frame settings with the help of yarn characteristics can be made possible.

Therefore, combining all three mentioned phases result in the formation of an analysis triangle. As shown in the Fig. 4.3, three arms of the analysis triangle correspond to the three different co-relation phases supported by artificial neural networks. This analysis triangle makes the basis of the present study. It is proposed that a neural network trained in such a way can function as a decision-making-tool.

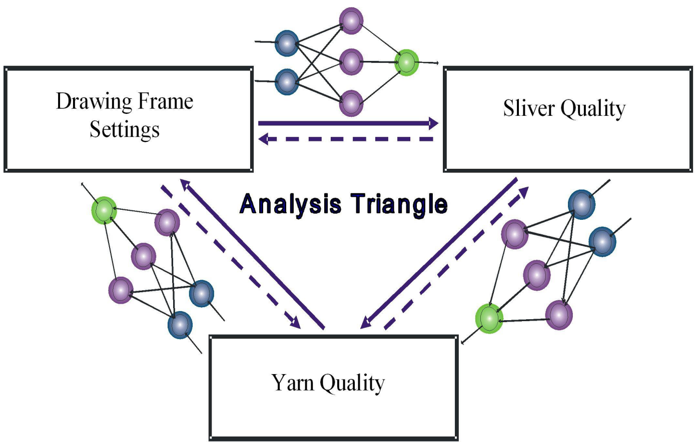

Figure 4.3: Analysis Triangle Corresponding to ANN Based Prediction System

The research work involves the development of prediction systems, which are capable of predicting the quality of sliver and ultimate yarn on the basis of the drawing frame parameters using the artificial neural networks. It is highly anticipated that these systems will result in the optimization of the spinning process. Moreover, they will also help to find out the individual as well as interaction effect of the drawing frame parameters on the yarn quality. It is highly likely that the achievement of these goals will optimize the spinning process and it will be a step forwards towards the idea of an ”intelligent machine”.

Chapter 5

Materials and Methods

On the basis of experimental structure, the present work is divided into three sections. The first section includes the experiments related to leveling action point. While the second and third sections correspond to the investigations regarding the sliver and yarn manufacturing respectively.

The goal of the research is the development of a prediction system that will be able to predict the draw frame settings along with the quality of sliver and yarn. Therefore, the experiments were planned to provide better quality input to the artificial neural networks. While planning and conducting the experiments following important points were taken into consideration.

- Artificial neural networks are not known to behave well for the extrapolations. The experiments regarding the possible maximum and minimum levels of an influencing parameter for every material were included.
- The second problem that neural network may face is the holes in data. This was avoided by selecting the proper levels of the influencing parameters. The influencing parameters exerting major influence on

the output were intensively investigated.

- Large numbers of experiments were conducted so that data set is large enough to train the neural networks properly and over-fitting should be avoided.

- In addition, it was also tried that the experimental data contain all the relevant information that have to be learned by artificial neural networks to give a better generalized performance.

5.1 Rieter Draw Frame RSB-D40

For this research project, high performance Rieter draw frame RSB-D40 was used (Figure 5.1). The basic elements of the draw frame involve the creel system for smooth feeding of the slivers to the machine by avoiding any false drafts, the scanning device for the measurement of the variations in fed slivers, the machine drives and control system to rectify these incoming variations, the drafting system for uniform and controlled drafting of the fibers and finally the coiler system with automatic can changer to deposit the sliver in the can without deteriorating its quality.

The heart of the draw frame is its drafting system. In RSB-D40, a 4-over-3 drafting system is used, where the fourth top roller performs the function of clamping the fibers and deflects them toward the web funnel. The pressure applied to fourth top roller is less than that of other three top rollers. The top rollers having different hardness can be used for various materials. The machine is capable of operation up to a delivery speed of 1100 m/min, with possibility to process fibers up to 80 mm length.

RSB-D40 is equipped with digital auto-leveling connected to high dynamic drive system. The infeed variations are measured using the mechanical

Figure 5.1: Draw Frame RSB-D40

tongue and groove system and then these variations are rectified by changing the speed of the middle drafting roller connected to the high dynamic servo drive (Principle already explained in Chapter 2). The on-line quality monitoring system Rieter Quality Monitor (RQM) is positioned between the web funnel and the coiling setup of the machine. The variations in the delivered slivers are measured with the help of RQM. The quality parameters like CV%, and length variation (values ranging from 5 cm to 5 m), sliver count and spectrogram can be displayed on the machine panel screen. The RQM also operates in connection with the auto-leveling system to carry out leveling action point (LAP) search function "AUTOset".

However, in the perspective of the auto-leveling system, there are some very important settings that should be adjusted precisely to achieve the optimal performance of machine and better quality of sliver. The adjustment of these settings is known as optimization of machine, which must be performed in case of material change.

As already discussed, this research comprises of three major portions. First one is the optimization of auto-leveling setting i.e. leveling action point. The procedure of determining the leveling action point on Rieter drawing frame RSB-D40 involves the RQM. The result of LAP search can be read directly from the machine panel. Whereas, for the manufacturing of sliver and ring spun yarn and their off-line quality testing an entire different procedure has to be followed. Furthermore, the dissimilar influencing parameters must be considered. Therefore the experiments were planned and carried out separately.

5.2 Investigations on Leveling Action Point

The materials selected and experimental procedure opted for investigations on leveling action point, are described in this section.

5.2.1 Material Selection

The material selection was based on the frequency of use in spinning industry. In the short staple spinning the mostly used materials worldwide are cotton (carded or combed), polyester, polyester/cotton blend and viscose. The second reason of this selection was the fact that draw frame settings especially that of finisher draw frame play a vital role while processing cotton or its blend with polyester. The raw materials were collected directly from industry in the form of card slivers according to the specifications given below in Table 5.1. For in depth study of leveling action point, experiments were performed on cotton carded 1st passage, cotton carded 2nd passage, polyester 2nd passage, viscose 2nd passage and polyester/cotton blend 50/50 2nd passage. Furthermore, some additional experiments like using sinusoidal sliver, polyester/cotton 67/33 and polyester/cotton 33/67 were also performed.

Materials	**Staple Length** [mm]	**Fineness** [mic]	**Sliver Number** [ktex]	**Sliver CV** [%]
Cotton Carded	28	4.1	5.55	3.5
Polyester	38	1.3	5.55	3.75
Viscose	38	1.3	5.55	3.95

Table 5.1: Specification of the card slivers taken from industry

The experimental procedure for all materials remained the same. Before conducting the experiments the materials were acclimatized in the standard temperature and relative humidity for 24 hours.

Materials	**Temperature** [°C]	**Relative Humidity** [%]
Cotton	24	46
Polyester	25	50
Viscose	25	50

Table 5.2: Standard climatic conditions

5.2.2 Machine Optimization

After conditioning, materials were prepared for the experimental phase. For Cotton 1st passage, the draw frame machine was optimized using card slivers and then auto-leveling was turned on for performing the experiments (the optimization procedure will follow). However, in case of experiments pertaining to the second drawing passage (cotton, polyester and viscose); the materials were processed for first passage using their corresponding standard optimized settings without auto-leveling. In case of polyester/cotton 50/50 blend 2nd passage, card slivers from polyester and cotton were blended in the first passage using the standard settings. The first blending passage was without auto-leveling.

For the 2nd passage, the machine was first optimized without auto-leveling. This implies that after setting the doublings and the draft according to the spin plan, the delivered sliver weight should be as close as possible to the required sliver weight. Furthermore, the spectrogram should not show any fault like chimney, which represents the accuracy of the other settings. Then the auto-leveling was turned on and the required sliver weight was entered. Then again the delivered sliver weight was determined and the actual weight was entered in the machine. Using the required and actual sliver weight the machine automatically adjusts the displacement of scanning rollers.

In the next step, the leveling intensity was determined with the help of sliver test. The sliver test involves the production of the about 100m sliver, in each case, using 6, 5 and 7 infeed slivers at similar machine settings. All three sliver produced was then weighted and A% was calculated using the following formula.

$$A\% = \frac{\left(ktex_{(n-1)} - ktex_n\right)}{ktex_n} \times 100 \tag{5.1}$$

$$A\% = \frac{\left(ktex_{(n+1)} - ktex_n\right)}{ktex_n} \times 100 \tag{5.2}$$

Where positive value of A% corresponds to over-leveling and while a negative value indicates under-leveling. The mean of these two values (without pre-sings) should be entered to the machine and it will adopt the over or under compensation. This procedure should be repeated until the A% <= ±0.5% is reached.

The compression of the scanning rollers is more when the machine is running at slow speed. So the next was the adaptation of the sliver weight at slow speed using the following formula. The X% value should not exceed from ± 0.5%

$$X\% = \frac{100 \times Sliver\ weight\ with\ slow\ speed\ [ktex]}{Sliver\ weight\ with\ normal\ speed\ [ktex]} - 100 \tag{5.3}$$

Finally the RQM was set so that it monitors the sliver weight continuously during operation. After completing the above mentioned procedures the machine became ready for carrying out the experiments.

As discussed in chapter 2, auto-leveller draw frame RSB-D40 implements an automatic search function for the optimum determination of LAP, which is based on the minimum value seeking algorithm. The sliver is automatically scanned by adjusting the different leveling action points temporarily and the resulted values are recorded using RQM. The measuring accuracy of RQM is also a point of vital importance. On the basis of previously performed experiments using carded cotton 1st passage at 300 m/min and 900 m/min, it was noticed that delivery speed has an influence on the measuring accuracy of RQM. The results of ten LAP searches conducted with same settings indicate that standard deviation and CV% is high in case of 900 m/min as compared with 300 m/min using same material. These experiments concluded that a variation of ± 6 mm in RQM measurement accuracy is possible, i.e. confidence interval of 95%. It is also imperative that the CV% of sliver measured by RQM is always less than Uster CV%, because the former does not include the variations due to coiling of sliver in cans.

Owing to the material requirement of about 2100m per test, it was not possible to carry out all the experiments for all materials. Therefore, for the first instance all the possible LAP influencing parameters were selected. The experiments were accomplished to find out the degree of influence of these parameters on LAP and to choose the highly significant parameters for the input of artificial neural network. Initially, the following parameters, given in Table 7.1, were selected based on the information provided in the instruction manual of drawing frame RSB-D40. After analyzing the results of the experiments, further experiments were conducted only for the significantly influencing variables. In addition, for the experiments pertaining to the influence of infeed variations, sliver with sinusoidal variations was also manufactured. The procedure will be explained in chapter 7.

5.3 Investigations on Sliver Quality Characteristics

In the second section of the experimental phase, the experiments regarding the sliver quality characteristics were conducted. The materials used and methods applied are presented below.

5.3.1 Material Selection

During the investigations on the sliver and yarn quality characteristics, Cotton carded, Polyester and Polyester/cotton blend 50/50 were selected. In practice, there are two commonly used methods of processing the polyester/cotton blend. The first one is direct blending to the carded cotton and polyester sliver for the 1st drawing passage and then employing the 2nd finisher passage. Whereas, the second method involves a pre-drawing passage for polyester and then blending it with carded cotton for 1st passage, followed by the finisher passage. For this research work both methods were investigated.

Influencing variables	**Materials**	**Values**
Delivery speed	Cotton 1st Passage	250; 300; 500; 700; 900; 1100 m/min
	Cotton 2nd Passage	250; 300; 500; 700; 900; 1100 m/min
	Polyester	250; 300; 500; 700; 800 m/min
	Polyester/Cotton	300; 500; 700; 900 m/min
	Viscose	250; 300 ;500; 700; 900 m/min
Infeed tension	Cotton 1st Passage	0.99; 1.00; 1.01; 1.02
	Cotton 2nd Passage	0.99; 1.00; 1.01; 1.02
	Polyester	0.98; 0.99; 1.00
	Polyester/Cotton	0.98; 0.99; 1.00; 1.01
Break draft	Cotton 1st Passage	1.15; 1.2; 1.3; 1.5
	Cotton 2nd Passage	1.1; 1.15; 1.3
	Polyester	1.15; 1.3; 1.4; 1.5; 1.7
	Polyester/Cotton	1.3; 1.4; 1.7
	Viscose	1.3; 1.5; 1.7
Break draft distance	Cotton 1st Passage	38; 41; 43; 44 mm
	Cotton 2nd Passage	40; 43; 46 mm
	Polyester	47; 49; 51; 55 mm
	Polyester/Cotton	47; 51; 55 mm
	Viscose	43; 47; 49 mm
Main draft distance	Cotton 1st Passage	36; 38; 40 mm
	Cotton 2nd Passage	35; 38; 40 mm
	Polyester	40; 42 mm
	Viscose	40; 42; 44 mm
Sliver deflection bars	Cotton 1st Passage	2/5; 1/6; 3/4
	Cotton 2nd Passage	2/5; 1/6; 3/4
	Polyester	2/5; 1/6; 3/4
	Viscose	2/5; 1/6; 3/4

Table 5.3: Experimental plan for leveling action point

Another important consideration here is the fiber characteristics of cotton. It was planned to conduct the quality experiments on medium to low quality cotton, because of two major reasons. Firstly, in real practice, the spinning industry is consistently trying to produce an economical yarn. Energy conservation is one of the major focuses of the machine manufacturers these days. However, inside the spinning mill, this objective can be achieved by reducing the waste produced and by reducing the raw material costs. Therefore, in the present research work, the cotton having high short fiber contents (SFC) i.e. 13% was used to try and model the real industrial process. The second motive behind the use of cotton having high SFC was to analyse the performance of neural networks, whether they are capable of making good prediction on low grade material or their better performance is limited to the good quality raw material. Because, the low quality material, i.e., having too many short fibers, tends to vary immensely in case of improper settings e.g. an increase in draft zone distances. An increase in draft zone distance increases the amount of floating fibers in draft zone and cause major variations in quality especially regarding the evenness characteristics of sliver and yarn. On the other hand, by comparison the materials having low short fiber contents, these settings are less critical. The quality characteristics of the cotton fibers were evaluated on HVI as well AFIS system.

The above described procedure of acclimatization at standard temperature and relative humidity was followed. The machine optimization procedure without auto-leveling and with auto-leveling was followed as explained earlier. The first drawing passage was carried out with auto-leveling switched off for all materials. The following variables given in Table 5.4were considered in order to conduct the sliver quality analysis.

Influencing variables	Materials	Values
Delivery speed	Cotton 2nd Passage	300; 500; 700; 900; 1100 m/min
	Polyester	300; 500; 700 m/min
	Polyester/Cotton with Pre-drawing	300; 500; 700 m/min
	Polyester/Cotton without Pre-drawing	300; 500; 700 m/min
Break draft	Cotton 2nd Passage	1.15; 1.3; 1.4
	Polyester	1.15; 1.3; 1.4; 1.7
	Polyester/Cotton with Pre-drawing	1.15; 1.3; 1.4; 1.7
	Polyester/Cotton without Pre-drawing	1.15; 1.3; 1.4; 1.7
Break draft	Cotton 2nd Passage	37; 40; 44 mm
distance	Polyester	47; 50; 53; 55 mm
	Polyester/Cotton with Pre-drawing	43; 46; 50 mm
	Polyester/Cotton without Pre-drawing	43; 46; 50 mm
Main draft	Cotton 2nd Passage	36; 38; 42 mm
distance	Polyester	40; 43; 47 mm
	Polyester/Cotton with Pre-drawing	39; 41; 46 mm
	Polyester/Cotton without Pre-drawing	39; 41; 46 mm
Total draft	Cotton 2nd Passage	5; 6; 7 (6 doublings); 8 (8 doublings)
	Polyester	5; 6; 7 (6 doublings); 8 (8 doublings)
	Polyester/Cotton with Pre-drawing	5; 6; 7 (6 doublings); 8 (8 doublings)
	Polyester/Cotton without Pre-drawing	5; 6; 7 (6 doublings); 8 (8 doublings)
Delivered sliver	Cotton 2nd Passage	5; 5.4 ktex
number	Polyester	4.3; 5.0; 5.9 ktex
	Polyester/Cotton with Pre-drawing	4.3; 5.0; 5.9 ktex
	Polyester/Cotton without Pre-drawing	4.3; 5.0; 5.9 ktex
Doublings	Cotton 2nd Passage	6; 8 times
	Polyester	6; 8 times
	Polyester/Cotton with Pre-drawing	6; 8 times
	Polyester/Cotton without Pre-drawing	6; 8 times

Table 5.4: Selected Variables for investigations regarding Sliver and Yarn Quality

5.4 Yarn Manufacturing

In the third section of the experimental phase, the slivers produced as the result of the above mentioned experiments were further processed to produce the ring spun yarn. In this case the slivers have to pass through roving frame and ring spinning machine to be converted into yarn. As the objective of the research is the development of a sliver and yarn quality prediction system on the basis of draw frame parameters, therefore, the main focus here was to optimize the both machines, i.e. simplex and ring frame, so that the variations caused by influencing variables at draw frame should be transported to the yarn without the induction of any additional irregularities or problems by simplex and ring frame. The following spin given in Table 5.5 plan has realized.

Material	**Sliver**	**Roving**	**Yarn**
Polyester	5 ktex	617 tex	15 tex
			20 tex
			30 tex
Polyester/Cotton (50/50)	5 ktex	617 tex	20 tex
			30tex
Cotton	5 ktex	617 tex	30 tex

Table 5.5: Spin plan for yarn manufacturing

The simplex machine Rieter F-15 and compact ring spinning machine Rieter K-44 were used for this research work. Different materials demand for dissimilar machine settings both at simplex and ring spinning machine, therefore, the investigations were carried out separately for different materials. Before actual experiments, the sliver resulted from the optimized draw frame settings were used to optimize the simplex and ring spinning machine. Roving twist, flyer speed, spacer and condensers were optimized for every material at roving frame. The break draft and main draft and draft zone distances were kept constant. Whereas at ring spinning machine, yarn twist, spacers, and ring travellers were optimized. Also here the break draft, draft zone distances and spindle speed are kept same; however main draft was changed to manufacture different yarn numbers. The important machine settings for both simplex and ring frame are presented below in Table 5.6 and 5.7.

Parameters	**Materials**		
	Polyester	**PES/CO**	**Cotton**
Spacer	Green(5.9 mm)	Black(4.4 mm)	Black(4.4 mm)
Roving Twist (T/m)	26.5	37.43	51.23
Flyer Speed (rpm)	1050	800	1100
Break Draft	1.12	1.12	1.12
Total Draft	8.105	8.105	8.105

Table 5.6: Optimized settings on roving frame for different materials

5.4.1 Testing Plan

Before testing, all the materials were acclimatized in standard atmospheric conditions i.e. Temperature 20 °C ± 2 °C and RH% 65% ± 2%. The testing plan for sliver, roving and yarn is presented in the following Table 5.8.

5.4.2 Evenness, Imperfections and Hairiness

Sliver, roving and yarn evenness was determined by passing them through the parallel plate capacitors and irregularities recorded in terms of coefficient of variation in mass of fibrous assembly (CVm%). Uster Evenness Tester (UT-3), also simultaneously measures the imperfection viz., thin, thick places and neps per thousand meters of yarn. The hairiness module of the UT-3 consists of an electronic optical sensor which converts

Parameters	Yarn Number	Materials		
		Polyester	**PES/CO**	**Cotton**
Spacer	**15 tex**	Natural(3 mm)		
	20 tex	Black(3.5 mm)	Natural(3 mm)	
	30 tex	Cream(3.75 mm)	Black(3.5 mm)	Yellow(3.25 mm)
Ring Traveler	**15 tex**	ISO Nr. 45		
	20 tex	ISO Nr. 63	ISO No. 56	
	30 tex	ISO Nr. 80	ISO No. 80	ISO No. 71
Total Draft	**15 tex**	41.00		
	20 tex	31.50	31.50	
	30 tex	20.50	20.50	20.50
Twist Multiplier		3.1	3.4	4.0
Spindle Speed(rpm)		17000	17000	17000
Break Draft		1.14	1.14	1.14

Table 5.7: Optimized settings for compact ring spinning machine for different materials

the scattered light reflection of the peripheral fibers into a corresponding electronic signal while the solid yarn body is eclipsed. Yarn hairiness is expressed in the form of hairiness value H, which is an indirect measure for the cumulative length of all fibers protruding from the yarn surface [62].

5.4.3 Sliver Cohesion

The cohesion between the fibers in a fibrous assembly or in other words the fiber to fiber friction plays an important role in determining the material behavior during the drafting operations in spinning. A proper control exerted on this fiber to fiber friction can help to eliminate the drafting

Testing Instrument	**Testing Materials**			
	Fiber	Sliver	Roving	Yarn
Uster HVI	x			
Uster AFIS Pro	x			
Uster Evenness Tester 3				
Irregularity, CV%, CV% (1m & 3m)		x	x	x
Imperfections				x
Hairiness				x
Diagram & Spectrogram		x	x	x
Rothschild Cohesion Meter				
Sliver Cohesion		x	x	
Zweigle yarn warp reel				
100 m CV%				x
Zweigle sliver warp reel				
1 m & 10 m CV%,		x	x	
Zwick 2.5				
Yarn Strength				x
Yarn Elongation				x

Table 5.8: Testing plan for fibers, slivers, roving and yarns

problems during the spinning process [63]. There are two methods for the measurement of cohesion between the fibers in a sliver or roving, i.e. static and dynamic methods.

The static method includes the clamping of one end of the sliver and applying the breaking force on the other end, like yarn strength testing. However, in dynamic method, the sliver is passed through a drafting assembly and the resistance to drafting is electronically measured [64].

Rothschild sliver cohesion meter R-2020 operates on the principle of dynamic measurement of fiber-to-fiber friction. The dynamic method is an attempt to simulate the actual drafting as it happens on draw frame. Therefore, more valid information can be recorded with this method. This information also helps to understand the drafting behavior of the fibrous material in the further drafting processes like on simplex and ring spinning machine. In view point of present research work, it is anticipated that sliver cohesion can be an important input parameter for neural networks [65].

A detailed introduction of the artificial neural networks will be presented in the next chapter. However, it is important to mention here that the neural network always required a large amount of experimental data for their successful training and better generalized performance. The requirement of the experimental data depends on the structure of neural network, which is directly associated with the complexity of the problem. Therefore, about 800 experiments were performed for training the networks and the data acquired from reliable resources were also used in addition.

Chapter 6

Artificial Neural Networks

In the scope of present research, the artificial neural networks (ANN) will be applied to the experimental data acquired from the area of staple yarn spinning. For a better understanding of the subject and their applications, a detailed introduction about the artificial neural networks is being presented here.

6.1 Introduction

The technological advancement of artificial neural networks (ANN) or simply neural networks has emerged in the last decade and immediately found lot of acceptance for solving the complex computational tasks. ANNs can be defined as structures comprised of densely interconnected adaptive simple processing elements (called artificial neurons or nodes) that are capable of performing massively parallel computations for data processing and knowledge representation [66].

As the name indicates the motivation of developing artificial neural networks came from their biological counterpart. Historically, ANNs were the most demanded computational systems that are advanced and may be intelligent to be capable of performing like human brain. The second drive may be the fact that the conventional digital computers work entirely different from human brains, so a computational system that can mimic biological neural network are valuable in the field of computation. Although ANNs were quite similarly designed like biological networks, however the main idea behind their development was not to replicate the function of biological networks but to make use of the knowledge of functionality and power of biological network for the solution of difficult problems [54]. The attractiveness of ANNs came from their following remarkable information processing characteristics.

- A neural network possesses nonlinearity, which is a significant characteristic because most of the real-world problems are non-linear and it permits better fit to the data.
- The noise tolerance of a neural network helps to offer correct prediction even in the presence of doubtful data and measurement inaccuracies.
- A neural network works in parallel and possesses the potential to be high failure tolerant. The knowledge of the networks is distributed in the form of "weights". When a part of the network stops working then the performance of the network will be reduced but total break down will not occur.
- A neural network is adaptive in nature, i.e. they can be trained for the consideration of new data.
- A neural network is capable of generalization, which means that it is able to calculate the suitable outputs for the inputs that are not present in the training data [67].

As previously described, artificial neural networks have found lots of applications in textiles. This chapter is aimed to provide a preliminary understanding of ANNs. It also includes the details of the concepts that are important for of present research work.

6.2 A Brief History of the Field

The history of artificial neural networks interrelated to the history of brain studies and brain mathematics is about 100 years old. The chronological highlights of some major breakthroughs in the field of ANNs are given as under.

1943: It is believed that it all started with a famous and revolutionary treatise of Warren McCulloch and Walter Pitts. They explained the capability of simple classes of neural networks "neurons" to compute the arithmetic and logical functions [68] [69].

1949: The book "The Organization of Behavior" by Donald Hebb was the next advance in which the classical Hebb learning rule for Synapses was explained. He argued that the neural pathways are strengthened each time they are used, a concept that afterwards became the basis of ANN learning [70].

1959: Rosenblatt wrote a book entitled "Principles of Neurodynamics", in which he presented different types of Perceptrons, a type of neural network. It was demonstrated that the perceptrons are able to learn using a learning process (Perceptron-Convergence-Theorem). Also in 1959, Bernard Widrow and Marcian Hoff developed ADALINE (Adaptive Linear Elements) and MADALINE (Multiple Adaptive Linear Elements) models [71].

1969: Marvin Minsky and Seymour Papert augmented the limits of single perceptrons and demonstrated that they were unable to solve an XOR problem [72].

1969-1985: John Hopfield presented a series of articles on 'Hopfield Networks' in 1982. In same year, Kohonen developed the 'Self-Organizing Maps'.

1986: The Back-Propagation learning algorithm for Multi-Layer Perceptrons was rediscovered which is considered to be a keystone in the history of ANNs. In order to extend the Widrow-Hoff rule to the multiple layers, David Rumelhart came up with the idea of back propagating the training error to the hidden layers [73].

1990s: The sub-field of Radial Basis Function Networks was developed. The trend of applying ANNs to the various research areas was also started.

Today: This field is progressing by leaps and bonds, from the development of new training algorithms to the advancement in the methods of overcoming the ANN's limitations. The researchers are also foreseeing the implementation of neural networks in various applications.

6.3 Biological Inspiration

The human nervous system is a controlling authority for all the biological processes and movements in the body. The human brain can be divided into two major portions, i.e. central nervous system (CNS) and the peripheral nervous system. The function of peripheral nervous system is two fold. It sends the signals from the receptors to central nervous system, which processes them. Also, it receives the signals from central nervous system and sends them to the effectors (muscles) as shown in Fig.6.1.

Figure 6.1: The Functioning of the Human Brain

The biological neuron is a structural and functional unit of a nervous system. A biological neuron consists of a cell body with a nucleus, Axon and Dendrites. At the end of the tubular Axons, that can be 1 meter long, synapses are present that serve as the connections with the other neurons. The Fig. 6.2 shows the construction of a nerve cell.

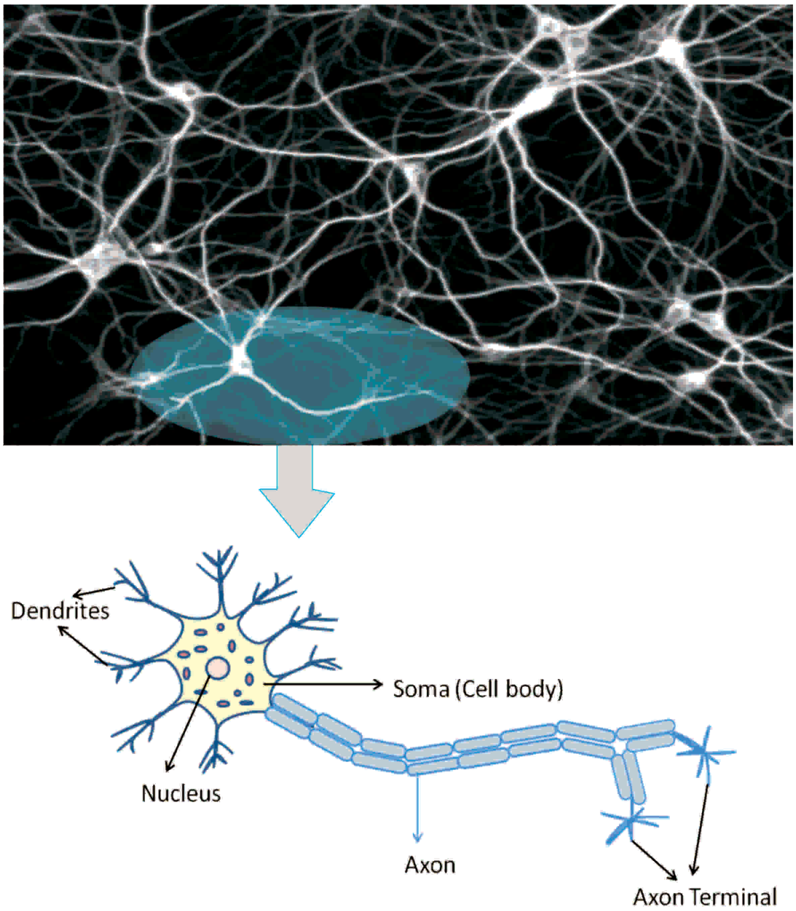

Figure 6.2: A Biological Neuron

The outgoing messages are transmitted to the other cells with the help of axons. They can originate from the CNS and extend all the way to the body's extremities, effectively providing a highway for messages to go to and from the CNS to these body extremities. Dendrites are the tree-like structure that receives the signal from surrounding neurons. They are connected with axon terminals through synapses. The neurons differ from each other depending upon the behavior and function in central nervous system e.g. behavior of axons, number of dendrites.

The human brain has a huge number of synapses. Each of the 10^{11}(one hundred billion) neurons has on average 7,000 synaptic connections to other neurons. It has been estimated that the brain of a three-year-old child has about 10^{15} synapses (1 quadrillion) [8].

As a result of extensive research in this field, some major discoveries have paved the way for the development and then further improvement of the artificial neural networks. Firstly, the "All-or-None-Law" applies to nerve cell communication as they use an on / off signal (like digital signal) so that the message can remain clear and effective from its travel from the CNS to the target cell or vice versa. Secondly, the synapses connections can be mathematically presented through weight factor wi. for each synapse. Thirdly, the neural pathways are strengthened each time they are used; this concept laid the foundation of ANN learning. Last but not least is the parallel processing of the biological neural networks. Based on this characteristic, the ANNs show powerful computation ability and high failure tolerance.

The structure of artificial neural networks was derived from the current awareness of biological neural systems [74]. The computation is performed using parallel connections of artificial neurons. An artificial neuron, a simple processing unit of an ANN, is being presented here under.

Figure 6.3 shows the diagram of an artificial neuron. Functionally, an artificial neuron accepts a set of inputs possibly form the other neurons. Usually the input channels have an associated weight, which means that the incoming information *xi* is multiplied by the corresponding weight *wi*. The summation function generates the weighted sum of all inputs. If this input exceeds the specific threshold value then it is transferred to the output, means the neuron "fire". Mathematically, the following equation shows a linear combination network having inputs and weighted connections. The network will "fire" when the weighted summation of input will exceed the thresholdΘ.

$$\sum_{i=1}^{3} x_i w_i = x_1 w_1 + x_2 w_2 + x_3 w_3 \geq \Theta \tag{6.1}$$

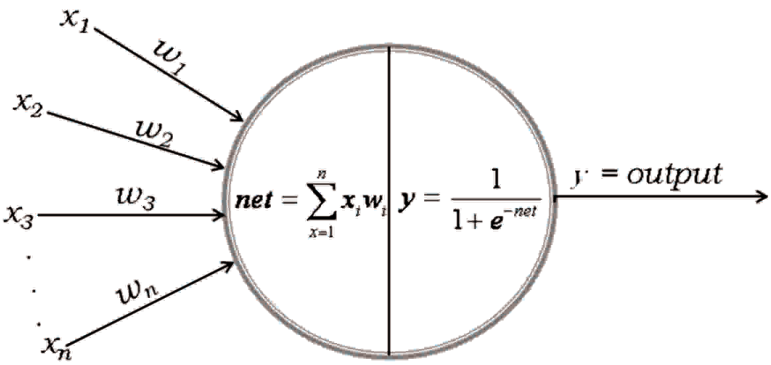

Figure 6.3: A Single Artificial Neuron

When a neuron fires then the output function is used. This function is mostly a non-linear function. The frequently used function is the sigmoid function because it is continuous and differentiable. The most common back propagation algorithm for training a network requires such characteristics. Both the biological network and ANN learn by incrementally adjusting the magnitudes of the weights or synapses strengths [75].

6.4 Exclusive OR /(XOR) Problem

In order to demonstrate the functionality and non-linearity of a simple neural network, the exclusive OR (XOR) problem will be demostrated here. The XOR function is a Boolean function with two variables. The Table 6.1 shows the inputs (x & y) and outputs (z) for a XOR problem.

The XOR function is defined as

$$Z = XOR(x, y) \tag{6.2}$$

X	**Y**	**Z**
0	0	0
1	0	1
0	1	1
1	1	0

Table 6.1: The Inputs and output for XOR problem

Because perceptrons are capable of solving only the linear problems while the XOR problem is non-linear.

The Figure

$$f(net_j) = \{ \begin{smallmatrix} +1 : net_j \geq \Theta_j \\ 0 : net_j < \Theta_j \end{smallmatrix} \tag{6.3}$$

Now considering the table, the output neuron only fires if one (but not both) of the input neurons fire. This will cause one hidden neuron, having threshold 1.5, not to fire. However the second neuron with threshold 0.5 will fire, since +1 is greater than the 0.5 threshold. The same will happen at output neuron and the desired answer, i.e. 1, will be realized.

But if both the inputs have value '1', then both hidden neurons will fire and the result is a total input of 2 - 2 = 0 to the output neuron. Since 0

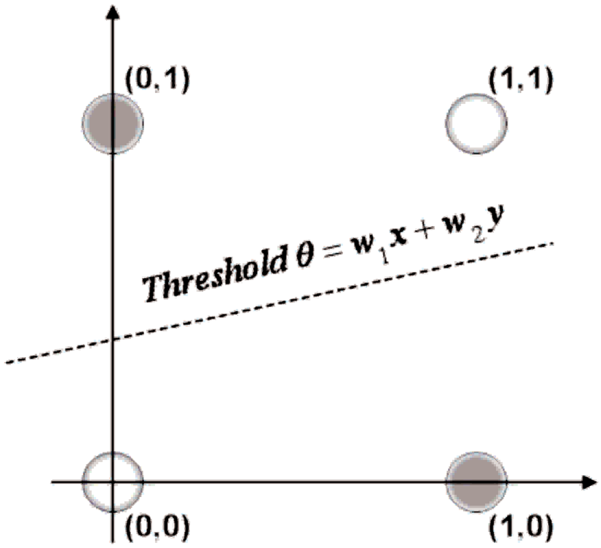

Figure 6.4: The non-linearity of XOR problem

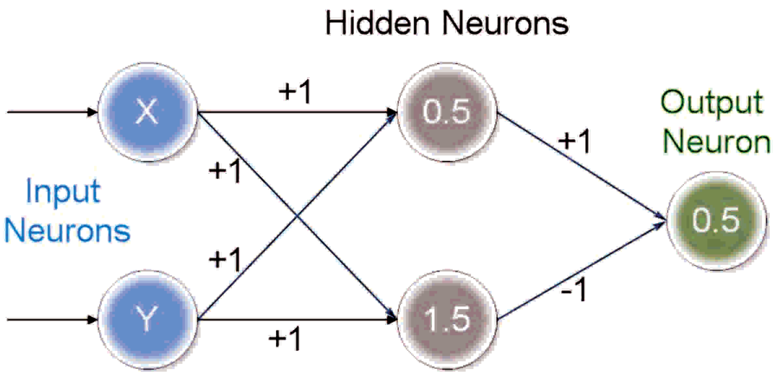

Figure 6.5: Simple neural network for XOR solution

is less than the 0.5 threshold of the output neuron, this will stop output neuron to fire. It can be inferred that the multiple layer perceptrons (MLP) can solve the non-linear separation tasks. As shown in the Figure 6.6 below.

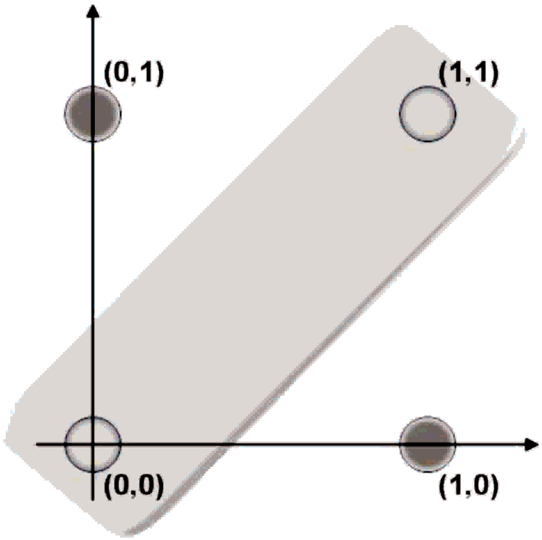

Figure 6.6: Solution of XOR problem

6.5 ANN Architecture

There are many possibilities to connect the neurons with each other in a artificial neural network. However, in the scope of present work and considering significance of different ANNs the following possibilities are being described.

6.5.1 Feedforward Network

The feedforward networks are the neural networks in which the information flows only in forward direction, i.e. from input layer to the output layer. The neurons can be nominated according to their position in the network. They are completely connected to each other in layers. The neurons that will accept the inputs are in input layer and the neurons that show calculated output are in output layer. Whereas, the neurons between the input and output layers are the hidden neurons. They may be in single or multiple layers and perform the computational tasks.

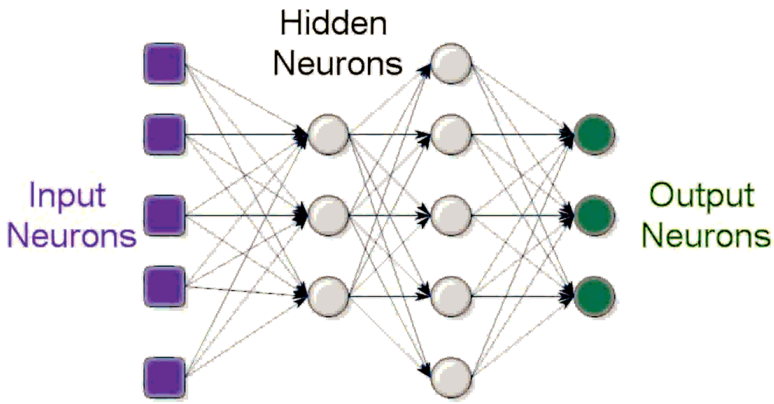

Figure 6.7: A feedforward network with two hidden layers

6.5.2 Recurrent Networks & Networks having Shortcut Connections

The recurrent networks and the feed-forward networks having shortcut connections are presented in the Figure 6.8. There are many real world problems like time dependent analysis that are very difficult to solve with feed-forward networks. So for such problems, recurrent networks or shortcut connections are employed. Hopfield networks are the popular example of recurrent networks. Both recurrent networks and the networks with shortcut connections are very powerful computational tools. However, they are also very complex and therefore, they are unstable.

6.6 Classification of ANN

Different significant features of the neural networks serve as their classification criteria. However, they are broadly classified into following types on the basis of the degree of learning supervision they need for training.

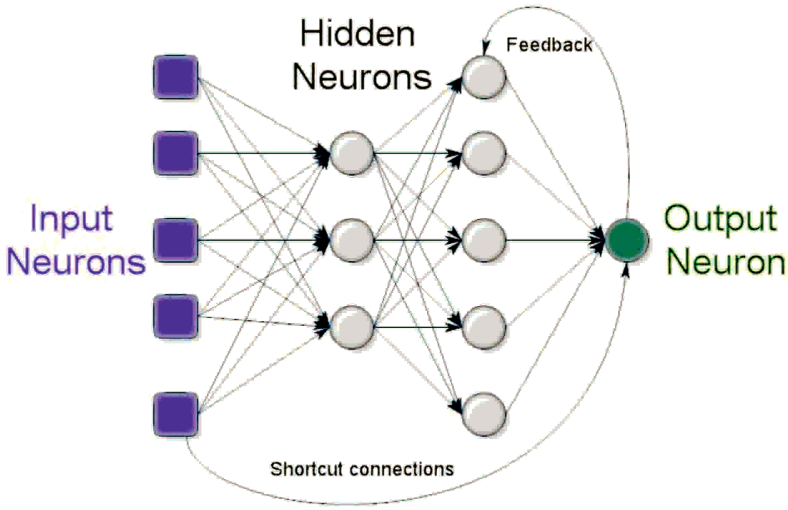

Figure 6.8: A recurrent network with shortcut connections

6.6.1 Supervised Learning

The supervised learning is an attempt to emulate the "teacher-student learning relationship". The target outputs "teacher" corresponding to the input data is provided to neural networks "student". The network tries to learn the complex relationships present in the input data in order to achieve the desired target output by adjusting the network weights. The focus of this type of training is to minimize the error between the desired and calculated outputs. In this case the most frequently used is the mean square error.

$$E = \frac{1}{2}\sum_i (z_i - o_i)^2 \tag{6.4}$$

Where *'zi'* is the target output and *'oi'* is the actual output.

Reinforcement learning is also a type of supervised learning. A schematic diagram of the supervised learning is shown below.

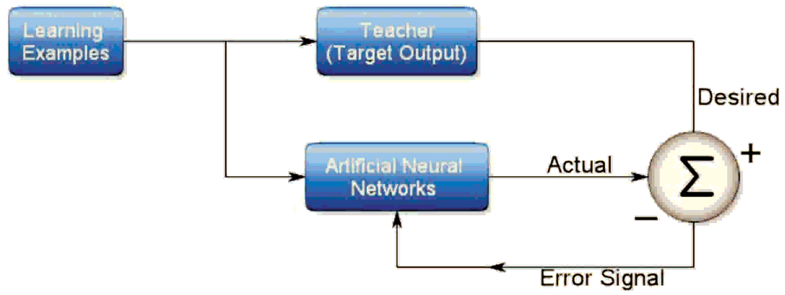

Figure 6.9: Supervised Learning of ANNs

6.6.2 Unsupervised Learning

For unsupervised training, the neural networks are not provided with the correct answers (target inputs). The ANNs attempts to learn the correlations among different sets of data by exploring it and categorize into similar classes on the basis of their similarities and dissimilarities.

6.7 Back Propagation

Back propagation or error back propagation is a learn algorithm, through which the weights of the networks are modified. There are many kinds of learning algorithms, some of them are meant for supervised training and other are for unsupervised trainings. Back propagation is best suitable algorithm for supervised multi-layer feed-forward networks. In back propagation most frequently used non-linear function is sigmoid function. i.e.

$$f(x) = \frac{1}{1+e^{-x}} \tag{6.5}$$

For simplifying, the process of back propagation can be divided into three sections.

6.7.1 Feed-forward Pass

The network training is an iterative process. In the first step, the weights are selected randomly and the input vectors are presented to the neurons of the first hidden layer. Then output signals values for each neuron in first hidden layer are determined. The output of the first layer acts as the input for the next layer. This process is repeated until the output signals for the output layer are determined. A neural network can contain one or several hidden layer depending on the complexity of the problem. The Figure 6.10 below shows a network containing two hidden layers.

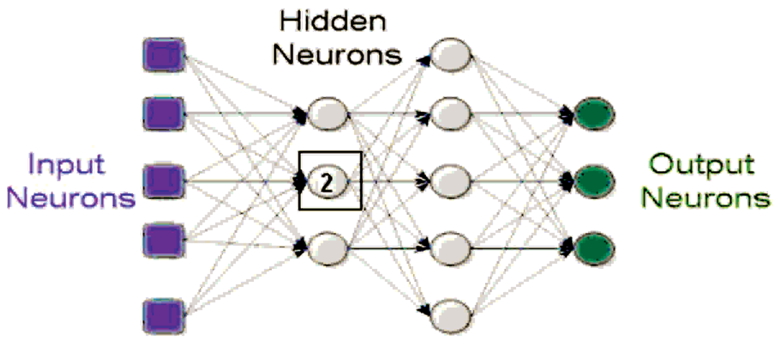

Figure 6.10: Feed-forward pass of neural network

6.7.2 Calculation of Error

The calculated output is compared with the target or desired output and the error is determined. If the error is less than a pre-determined stopping error value then the training stops, otherwise the network starts its backward pass.

6.7.3 Backward pass

In backward pass the weights are modified on the basis of a learning rule. With reference to the Figure 6.10 above, the weights are modified for the neurons starting from output layer, then for 2nd hidden layer and finally for 1st hidden layer. This implies that the error is back propagated to the hidden layers. That why the algorithm is named as Back propagation.

In the Figure 6.10, the 2nd neuron from 1st hidden layer is selected and detailed information flow inside the said neuron is given below in Figure 6.11

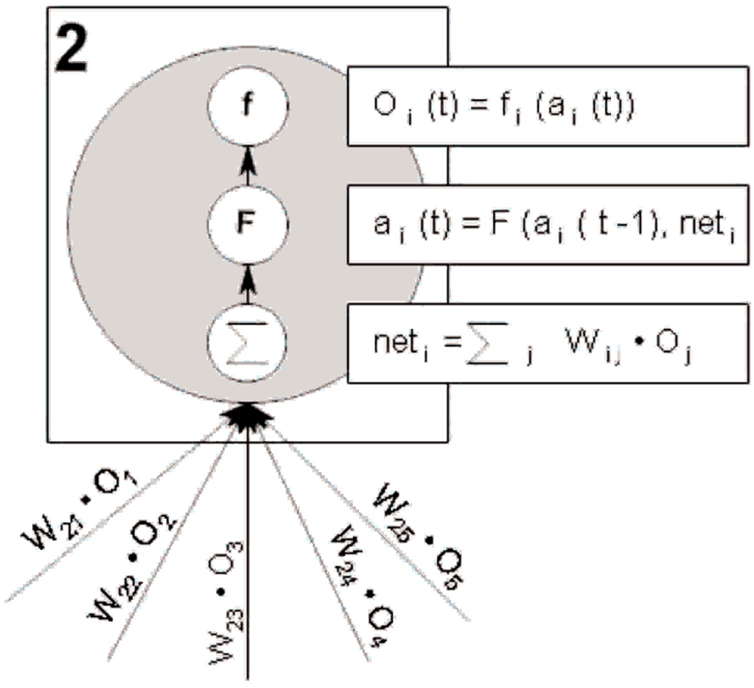

Figure 6.11: Mathematical Operations inside a neuron during back propagation

This neuron takes its input from all neurons of the previous layer, multiplied with a variable weight factor W. The total input is then added and converted to output through an activation function. This output is then given to the neurons in the next layer.

The frequently used functions are

$$net_i \;=\; \sum_j w_{ij} \;\cdot\; o_j \quad (InputFunction) \tag{6.6}$$

$$a_i \;=\; net_i \quad (ActivationFunction) \tag{6.7}$$

$$o_i \;= a_i \quad (OutputFunction) \tag{6.8}$$

For a Neuron *'i'* the back propagation rule, i.e. on the basis of which the modification of its weights takes place, is given as

$$\Delta w_{ij} \;=\; \sigma \;\cdot \delta_j \;\cdot\; o_j \tag{6.9}$$

Also

$$\Delta w_{ij} \;=\; w_{ij}\,(t+1) \;-\; w_{ij}(t) \tag{6.10}$$

Where, $\Delta w_{ij}$is the change in the weightw_{ij}, δ_j is the error single, σ represents constant learning rate and o_j is the output.

The advantage of the back propagation algorithm lies in its flexibility to be used for diversity of problems, which has given back propagation neural network the reputation of "Universal Approximaters". However, in addition with some other disadvantages, back propagation algorithm is considered to be slow. In order to overcome this problem "momentum" term is frequently added in the back propagation algorithm. Using the momentum term the learning rule will be

$$w_{ij}(t+1) \;=\; w_{ij}(t) + \sigma \;\cdot \delta_j \;\cdot\; o_j \;+\; \mu \cdot \Delta w_{ij}(t) \tag{6.11}$$

Where, μ is the momentum-term.

The above section has described an overview of the back propagation. The detailed information about the back propagation algorithm can be found in [76, 76–78]

6.8 Training a Neural Network

6.8.1 Input Selection

The accurate input selection for neural networks requires exact knowledge of the process, which is the understanding of interconnections of input variables as well as the overall awareness of the process to be modeled. As a matter of fact that ANN are good at ignoring irrelevant inputs nevertheless a large number of irrelevant inputs cause the network to behave badly. Also irrelevant inputs may not require an increase in the number of hidden neurons but they will increase the number of weights of the network, which will in turn increase the requirement of training data. Also, a proper input selection will allow the network to generalize well avoiding the over-fitting. Therefore, at the start of the network training the selection of relevant input i.e. the inputs that have concrete associations with the outputs, should be selected [79, 80].

6.8.2 Pre-processing of Data

Normalizing the input and target variables tend to make the training process better behaved by improving the numerical condition of the problem. The significance of normalizing the data increases when the inputs of the neural networks contain the input variables having large magnitudes along with the variables with small magnitudes. In this case, the network will perceive that the input variables having large magnitude have a greater influence on the output, so it will assign larger weights to them, which will reduce the importance of other input variables. Data normalization converts all the input variables in a same range so that each variable has an equal chance to exert its influence on the output [81]. Also back propagation uses the steepest descent method and is sensitive to data scaling. However, on the other hand the normalization imposes a restriction that the ANN model will perform poorly on the out of range test data (extrapolation) [82].

Usually, the training data is normalized between maximum and minimum values of [0 & 1] or [1& -1] respectively. Another possibility is to normalize the data between the mean and the standard deviation of variables.

The input variables can be normalized between 0 and 1 using the following equation.

$$P_n = \frac{(P - P\min)}{(P\max - P\min)} \tag{6.12}$$

Where Pn is the normalized value of input value P whereas, Pmin and Pmax are the minimum and maximum values of the variable P.

6.8.3 Network Initialization

The neural network initialization is the assigning of initial values for the weights, thresholds and activation functions to all network connections [67]. As the back propagation is the optimization of the network error in correspondence of its weights, in view of some scientists the initialization of weights has a great impact on the network speed, its convergence and generalization [83]. However other studies imply that initialization has an insignificant effect on both the convergence and final network architecture [84]. Usually all the variable weight factors are initialized using random values. This randomization helps the non symmetrical assigning of the weights. Because the learning rule cannot eliminate the symmetrical network weights so a large part of the network will have same weight vectors that will reduce the capacity of the network.

The second important part of the network initialization is the assigning of activation function to the hidden units. As already mentioned the role of activation or transfer function is to transform sum of all the incoming signals and determine the firing intensity of neuron. The activation function induces the non-linearity in the neural network and make them a powerful non-linear problem solver. However, the basic requirement for an activation function to be used in back propagation is that it should be continuous and differentiable. Considering this sigmoid function is the most commonly used activation function followed by 'tanh' (hyperbolic tangent)

6.8.4 Problems During Training

6.8.4.1 Error Surface

The back propagation is based on a gradient descent method and its objective is to find an absolute or global minimum of the error surface. Neural network error surfaces are exceedingly complex and contain local minima, flat spots and plateaus, saddles points and long narrow ravines [85]. In back propagation same like other gradient descend methods the problem of getting stuck in a local minima is very common [86]. However, it is not possible to find the global minimum analytically. If this local minimum is close to the global one than the performance of the trained network will be better. On the other hand if the local minimum is far away from the global minimum, the network will show poor results and will not be able to converge properly. Furthermore the complexity of the error surface is associated with that of neural network. This implies that the possibility of getting stuck in the local minima increases with the increase in the networks weights and number of neurons

6.8.4.2 Underfitting and Overfitting

The goal of neural network training is to produce a network which produces small errors on the training set, and which also responds properly to novel inputs. When a network performs as well on novel inputs as on training set inputs, the network is said to be well generalized. The generalization capacity of the network is largely governed by the network architecture (number of hidden neurons) and plays a vital role during the training. A network which is not complex enough to learn all the information in the data is said to be under-fitted. On the other hand the network that is too complex to fit the "noise" in the data, leads to overfitting. "Noise" means variation in the target values that is unpredictable from the inputs of a specific network. All standard neural network architectures such as the fully connected multi-layer perceptrons are prone to over-fitting. Moreover, it is very difficult to acquire the noise free data from the spinning industry due to dependence of end products on the inherent material variations and environmental conditions etc [87, 88].

6.8.5 Optimization of Network Parameters

6.8.5.1 Network Structure

The capacity of the neural network depends on network structure, i.e., the number of hidden layers and the number on hidden neurons in these layers. The greater is the number of hidden neurons, the greater will the connected weight vectors and so will be its ability to learn complex patterns. The network weights can be easily calculated. For instance, a neural network having 5 input neurons, 6 hidden neurons in 1st layer, 5 neurons in 2nd layer and 1 output neurons corresponds to a 5-6-5-1 network. The network weights will be ($5 \times 6 + 6 \times 5 + 5 \times 1 = 65$). On the other hand, using too many hidden neurons can make the network complex. So instead of learning the trends and relationships between the inputs and the outputs, it will start learning the data points [89]. The major drawback of this situation is that the network will not generalize well. This implies that it will perform very well on the training data but very poorly on the unseen data i.e. test data. The reason that the back propagation networks are prone to over-fitting, the selection of network structure in accordance with the complexity of the problem is very important. There are also other methods to avoid the over-fitting. These methods will be described later.

6.8.5.2 Learning Rate

The learning speed of a neural network is strongly dependent on the learning rate as it determines the amount of weight change during successive iterations. A high learning rate designates the high new information learning speed of the network. Whereas a low learning rate causes the weights to change slowly and so is the speed of learning of the new information [8].

Considering the disadvantages of the high learning rate, a network that "learns" the new information quickly also "forgets" the already learned information at the same pace. Moreover, as the training is accelerated because of large steps on the error slope, it decreases the stability of the process and increases the risk of overshooting the global minimum.

On the other hand, a small learning rate helps a slow but steady search of the global minimum. Also small learning rate is suitable for superior "remembering capacity" of the neural network. The recommended value of the learning rate is from 0.0 to 1.0 [90].

A constant learning rate during the whole training process is optional, an adaptive learning rate, i.e. a variable learning rate for different training phases, is believed to be more efficient. Normally, a high learning rate away from minimum and a small learning rate near the minimum are suggested, however it is difficult to predict the distance from the minimum [67].

6.8.5.3 Momentum

The motive of the inclusion of momentum term in back propagation is to improve the search instability and to avoid the local minimum during the learning process. Basically, the momentum factor determines the direction and amount of weight change. It adds a fraction of weight change of previous cycle to weight change of current training cycle. This results a weight change in the same direction after coming across a local minimum. Momentum allows the network to ignore small features in the error surface and allows the gradient to leave flat plateau swiftly. However, the danger of overshooting the global minimum remains. The weight update using the momentum term is given already in equation.

It is clear from the equation that there exists a close association between momentum and the learning rate. Momentum can be kept constant during the training process or it can be adaptive. The value of momentum factor lies between 0.0 and 0.9 with 0.5 to 0.9 being most commonly used. The selection of a suitable momentum factor depends on the nature and complexity of the problem and mostly it is determined by the trial and error method.

6.8.6 Levenberg-Marquardt Technique

Back propagation was a breakthrough in neural network research, however it tends to be slow and have a poor convergence rate. Back propagation is based on the gradient decent method, and the biases and networks weights move in the opposite direction to the error gradient. Therefore, as the error gets smaller, the steps down the gradient also decrease until the error minimum is reached [91]. A lot of researches have been carried out to speed up the back propagation algorithm. As previously explained, most common is the use of momentum term, variable learning rate [92]. However, Levenberg-Marquardt (LM) technique is widely accepted and most efficient and performs better by using an approximation of Newton's method. Although it requires more memory, it is much fast than back propagation. For instance, if back propagation needs 454 epoch to converge, then LM technique requires only 4 epochs. In LM technique the following update rule is used.

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \tag{6.13}$$

Where 'J' is the Jacobian matrix of derivatives of each error to each weight, 'μ' is the scalar and 'e' is the error vector and 'I' is the identity unit matrix. If the scalar μ is very large, this technique approximates the gradient descent, but if it is small, the expression becomes the Gauss-Newton method. Because this method is faster but tends to be less accurate when near an error minimum, the scalar μ, is adjusted like the adaptive learning rate. As long as the error gets smaller, μ is bigger, but if the error increases, μ is smaller. In scope of this research work only small information is being given about the LM technique, a more detailed description of the technique can be found in literature [92, 93].

6.8.7 Generalization

6.8.7.1 Early Stopping

Early stopping is the most commonly used technique to tackle the over-fitting problem. This involves the division of training data into three sets, i.e. Training set, Validation set and Test set. The validation error normally descends during the start of training, as well as the training set error. However, when the over-fitting starts, the error on the validation set typically increases. When the validation error increases for a specified number of iterations, the training is stopped and the weights and biases are returned to the minimum of the validation error. However, this method has the draw back that a large part of the data (validation set) can never be the part of the training [94].

6.8.7.2 Regularization

The other solution of the over-fitting is regularization, which is the method of improving the generalization by constraining the size of the network weights. Mackay [95] discussed a practical Bayesian framework for back-propagation networks, which consistently produces networks with good generalization.

The initial objective of the training process is to minimize the sum of square errors:

$$E_D = \sum_{i=1}^{n}(t_i - a_i)^2 \tag{6.14}$$

Where, t_i are the targets and a_i are the neural network responses to the respective targets. Typically, training aims to reduce the sum of squared errors F = ED. However, regularization adds an additional term; the objective function, which is given by

$$F \ = \ \beta E_D \ + \ \alpha E_W \tag{6.15}$$

In Equation 6.15, E_W is the sum of squares of the network weights, and αandβ are objective function parameters. The relative size of the objective function parameters dictates the emphasis for training. If $\alpha << \beta$, then the training algorithm will drive the errors smaller. If $\alpha >> \beta$, training will emphasize weight size reduction at the expense of network errors, thus producing a smoother network response [96].

The Bayesian School of statistics is based on a different view of what it means to learn from data, in which probability is used to represent the uncertainty about the relationship being learned. Before seeing any data, the prior opinions about the true relationship might be expressed in a probability distribution over the network weights. This probability distribution will define the relationship. After the program conceives the data, the revised opinions are captured by a posterior distribution over network weights. Network weights that seemed plausible before, but which do not match the data very well, will now be seen as being much less likely, while the probability for values of the weights that do fit the data well will have increased [97], [98], [99].

In the Bayesian framework the weights of the network are considered random variables. After the data is taken the posterior probability function for the weights can be updated according to the Bayes' rule:

$$P(w|D, \alpha, \beta, M) \ = \ \frac{P(D|w, \beta, M)P(w|\alpha, M)}{P(D|\alpha, \beta, M)} \tag{6.16}$$

In Equation 6.16, D represents the data set, M is the particular neural network model used, and w is the vector of network weights. $P(w|\alpha, M)$ is the prior probability, which represents the knowledge about the weights before any data is collected. $P(D|w, \beta, M)$ is the likelihood function, which is the probability of data occurring, given the weights w. $P(D|\alpha, \beta, M)$ is a normalization factor, which guarantees that the total probability is 1 [96].

In this study, MATLAB Neural Networks Toolbox function "trainbr" was employed, which is an incorporation of the Levenberg–Marqaurdt algorithm and the Bayesian regularization theorem (or Bayesian learning) into back propagation to train the neural network to reduce the computational overhead of approximation of Hessian matrix and to produce good generalization capabilities. This algorithm provides a measure of the network parameters (weights and biases) being effectively used by the network. The effective number of parameters should remain the same, irrespective to the total number of parameters in the network. This eliminates the guesswork required in determining the optimum network size.

6.9 Testing A Trained Network

The traditional and most commonly used method for testing a trained network is "split-sample" "hold-out" method. In this method, the data is divided into two data sets, i.e. Training data and Test data. Only the training data set is used to determine the weights of neural network while the test data set remains unseen to network and is used to analyze the predictive performance of the network as shown in figure below.

However, the training and test performance of neural network is heavily dependent on selection method for training and data sets. Also it is influenced by the data points that which data points are in training set and

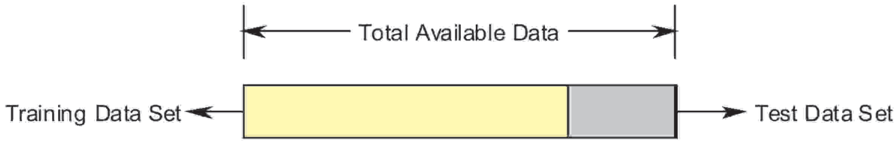

Figure 6.12: hold-out method for testing the neural network performance

which are in test set. Furthermore, all the data can never be the part of test set on which its performance will be proved.

In order to overcome this problem k-fold cross validation technique is used [100]. In this method, the data is divided into k subsets. For each training, one of the k subsets is used for the test set and the remaining k-1 subsets for training the network. In the Figure 6.13, the k-fold cross validation technique is elaborated with k=4.

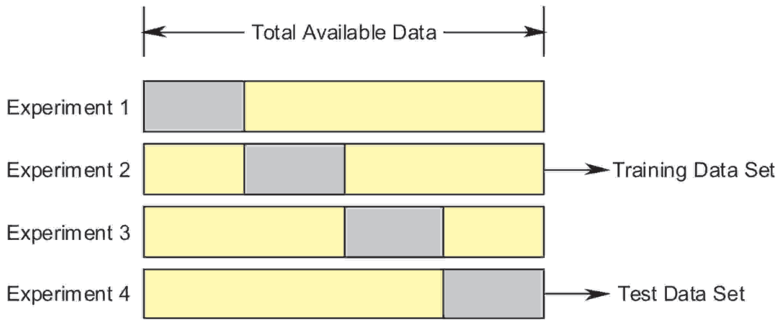

Figure 6.13: Cross Validation technique for testing neural network performance

The advantage of this technique is that it is independent of the selection or division of the data sets. However, the training cycle should rerun for k times. Most commonly used cross validation are 10% cross validation and 20% cross validation, where one subset consists of 10% and 20% of total data respectively. The average error E of all k trials can be calculated using the following.

$$E = \frac{1}{k}\sum_{i=1}^{k} E_i \tag{6.17}$$

Leave-one-out cross validation (LOOCV) is K-fold cross validation taken to its logical extreme. If there are 'N' number of data points available then for LOOCV, k=N, i.e., K equal to the number of data points. LOOCV takes much time in comparison with 10% and 20% cross validations, however is a very good method to evaluate the trained models [101].

6.10 Applications

Neural networks offer the better solution of the problem in comparison with other modelling techniques. They can recognize and classify the complex, vague and noise patterns. A conventional algorithm that can analyse such data is very hard to establish. Neural network can therefore be employed for the problems with many example but not explicit description. Some of such problems are:

- Classification With the help of neural networks it is possible to classify the different inputs in to various classes.
- Prediction This is most frequently used application of the neural networks in which the inputs are used to predict the outputs. The trained neural networks possess the ability to learn the relationships between the inputs and output and are able to make an accurate prediction for unseen inputs. Many examples regarding the prediction, especially in field of textiles are already described in chapter 3.
- Pattern Recognition For the pattern recognition, a specific pattern should be generated by providing an input pattern. This property of

neural network can be used for performing the tasks such as recognizing the hand writings (OCR), face and hand gesture recognition [102].

- Function Approximation

  The function approximation is the learning of a function that approximately generates the same output as produced by a process to be modeled. A large number of such and other applications are found in financial management and in industry (e.g. in data processing and machine construction etc.) and also in the medical field. With the help of neural networks the complex tasks can be solve with relatively high accuracy and short time. However the success of the neural networks depends on the structure of the networks and the quality of the data used to train them.

6.11 Conclusion

Comprehending all the above mentioned details, i.e., structures, training, network parameters, evaluation techniques and application areas, the artificial neural networks can be used in field of textiles. As the matter of fact that neural networks are really good in understanding the complex relationships and able to perform very good in the presence of large number of input variables, make them the potential modeling technique for the yarn manufacturing process. It is highly anticipated that the power and flexibility of the neural networks can generate good quality results in the area of staple yarn spinning and the complex relationships between the machines, processing material and end product can be understood.

6.12 Software Description

In order to train the artificial neural networks for the present research work, a Graphic User Interface (GUI) shown in Figure 6.14 is programmed using Matlab software and Artificial Neural Network Toolbox at Institute of Textile Machinery and High Performance Material Technology, TU Dresden. The program is capable to acquiring the data from MS EXCEL, training the networks and making the predictions on the basis of trained networks. The detailed description is given as under.

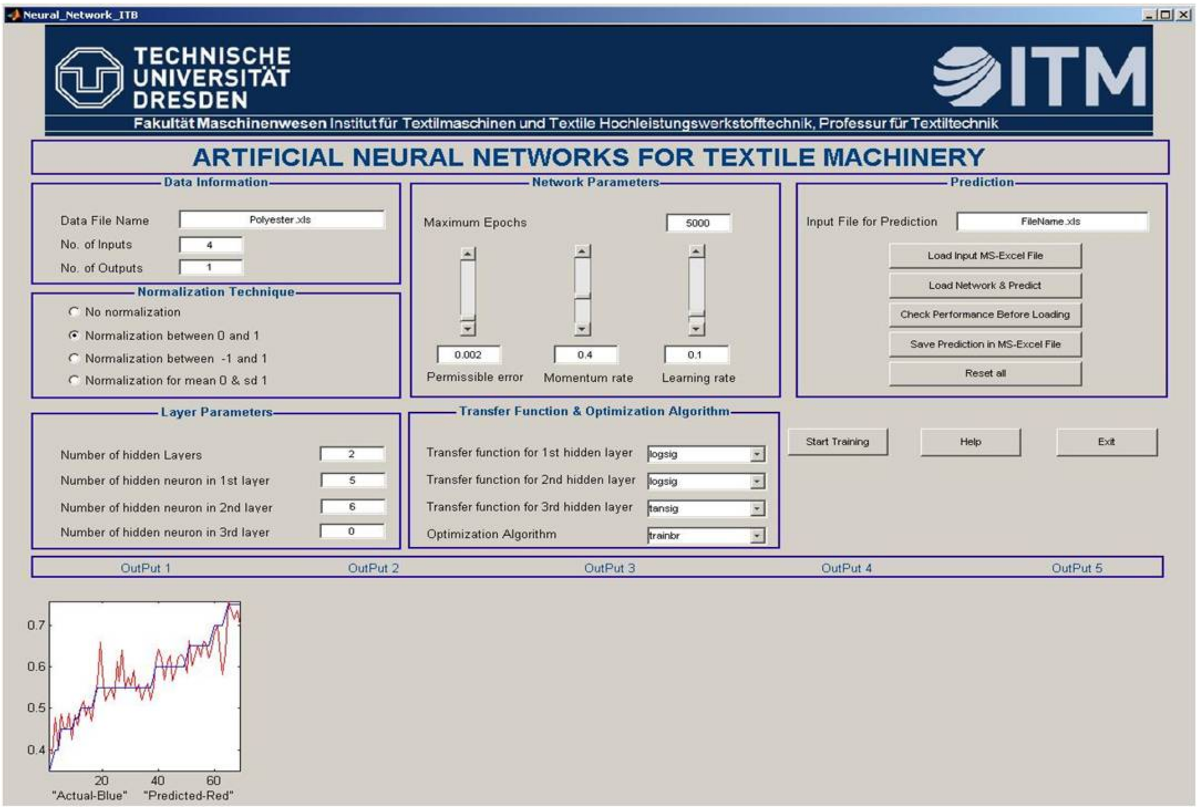

Figure 6.14: Graphic User Interface of Artificial Neural Network for Textiles

The graphic user interface (GUI) for training the artificial neural networks is divided into different sections. This GUI is designed to receive the data from MS EXCEL files. The section "data information" shown below in Figure 6.15, takes the data from the entered MS EXCEL file, however the

MS EXCEL file should be located in same directory. Entering the number of inputs and output will assign them automatically. For instance, as given below, the program will assign first three columns of MS EXCEL table as input and fourth as output.

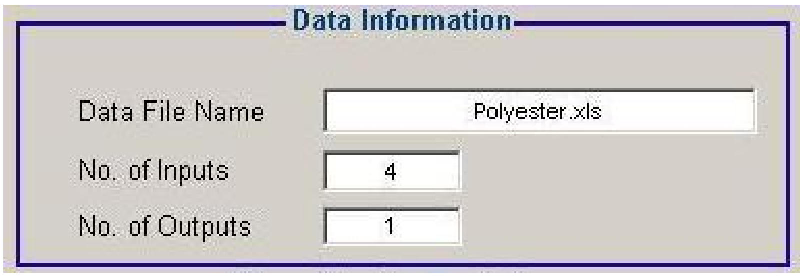

Figure 6.15: Data acquiring section

The second section regarding the normalization techniques allow the opportunity of pre-process the data using three frequently applied normalization methods, i.e., between 1 & 0, between -1 &+1 and between mean and standard deviation. Optionally, the data can be normalized in MS EXCEL and then entered to GUI, using the option 'No normalization'.

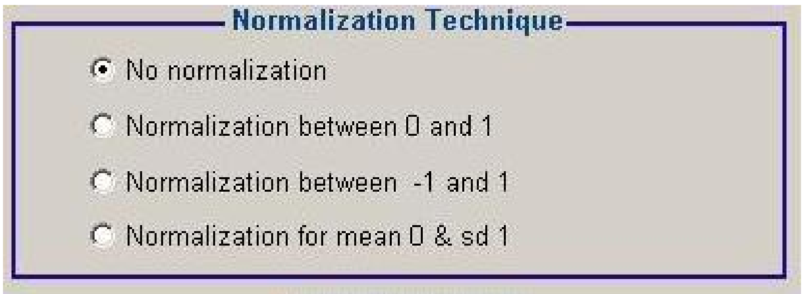

Figure 6.16: Selection of Normalization Technique

The next important section takes the input for the network structure. The number hidden layers can vary from 1 to 3. Also number of neurons in each hidden layer can be entered. As shown below in Figure 6.17, in case of using 2 hidden layer, the number of hidden neurons in 3rd layer should be entered as 0.

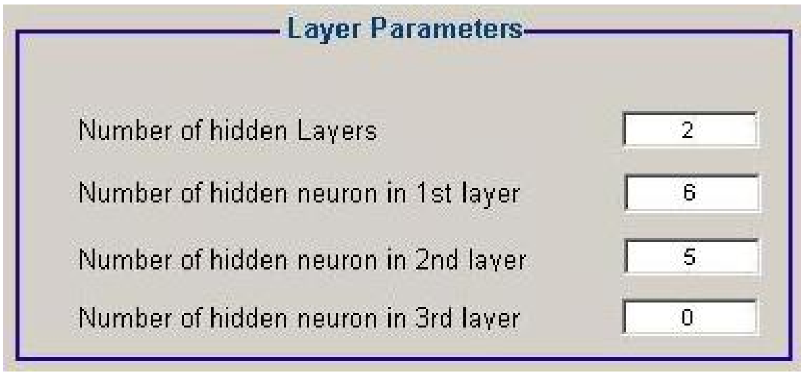

Figure 6.17: Choosing the Network Structure

The next section pertains to the setting of vital network parameters for training, i.e. Maximum Epochs, Permissible error, Momentum rate and Learning rate (Figure 6.18). The values of these parameters can be set here. The details of setting them can be found in earlier part of this chapter.

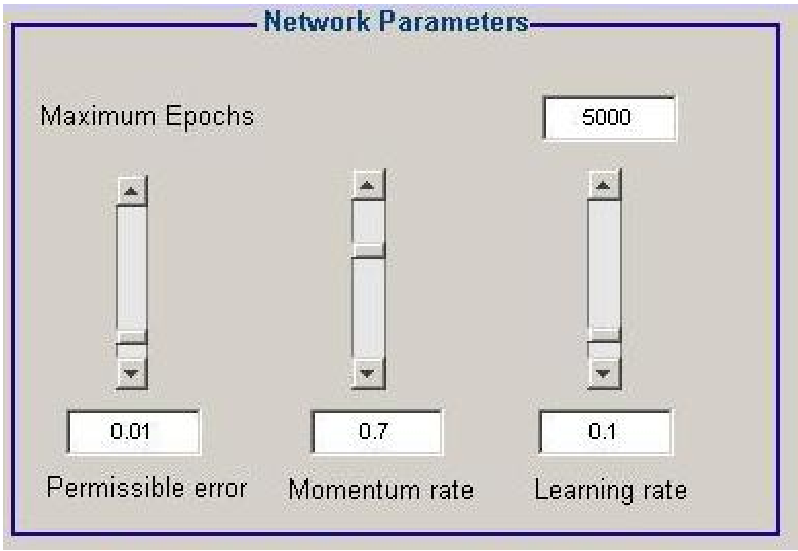

Figure 6.18: Adjusting the network training parameters

The options regarding the transfer functions or activation functions and optimization Algorithm can be adjusted in next section. The transfer functions can be set on for hidden layers, as the transfer function for the output layer remains linear. Matlab Neural Network tool box offers a diversity of learning algorithm for the training of neural networks. All of them are included in the software and can be used as required (Figure 6.19).

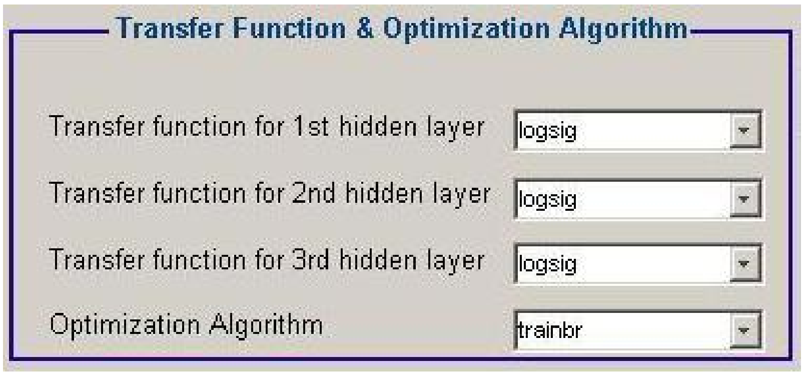

Figure 6.19: Selecting the activation functions and optimization algorithm

Referring the Figure 6.14, the button ‘Start Training’ will start the training process. The error performance during training can be seen by an automatically generated graph. After finishing the training performance can be seen on lower half of GUI under ’output’. Also at completion, the network can be saved as a *.mat file.

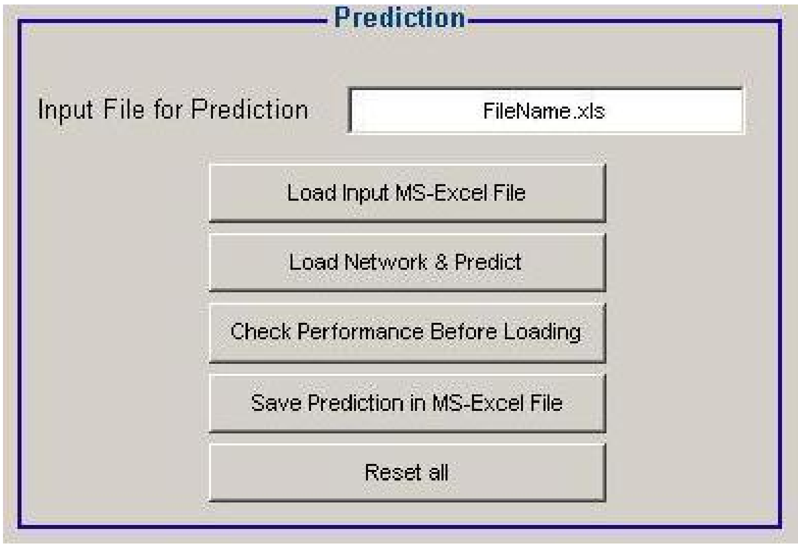

Figure 6.20: Prediction on unseen data

After saving the network the prediction on the test data or unseen data, stored in a MS EXCEL file, can be performed by the following section of GUI.

Chapter 7

Leveling Action Point

This chapter encircles the comprehensive analysis of the leveling action point (LAP) as affected by various machine influencing parameters with respect to different processing materials. It therefore includes; the experimental results of leveling action point at different machine settings, a comparative analysis of different processing materials, the selection of relevant influencing parameters for artificial neural networks (ANN), training of ANNs and finally the testing the quality of the prediction. Furthermore, the multiple regression analysis is also preformed on the experimental data.

7.1 LAP Influencing Parameters

Every material demands different machine settings to produce an optimal sliver quality. For instance, the combed cotton cannot be processed with the same speed like carded cotton because of fiber piecings which lead to less sliver cohesion. Similarly, polyester needs less infeed tension in comparison with cotton and can only be processed up to 700 m/min. Moreover, different materials need different draft zone distances depending mostly on their fiber length distributions. Therefore, results pertaining to the influence of various draw frame parameters corresponding to variety of processing materials are being presented. For a comprehensive analysis, following two approaches were considered.

- Studying the influence of individual parameters by optimizing the draw frame for each material and then changing the levels of influencing parameters.

- Try to find out the existing interactions between these parameters. For instance, investigations on infeed tension at low, medium and high feeding speeds.

7.1.1 Feeding Speed

The experiments have proved the feeding speed as a major LAP influencing parameter. However the drawing machine RSB D40 offers no possibility to set the feeding speed. So, the feeding speed is considered as a relation of delivery speed, draft and number of doublings according to equations.

$$Feeding\,Speed = \frac{Delivery\ speed\ (L)}{Draft\ (V)} \tag{7.1}$$

or

$$Feeding\,Speed = \frac{Delivered\ Count\ X\ Delivery\ speed}{Doublings\ X\ Feed\ Count} \tag{7.2}$$

The following figure 7.1 depicts the effect of variable delivery speeds on the LAP regarding different materials. During experiments only delivery speeds were changed whereas the other machine settings were kept at the optimized level. As a matter of fact that delivery speed is indirectly proportional to the LAP, a linear downward trend is visible for all the materials. However, this downward trend is not truly linear especially in case of cotton.

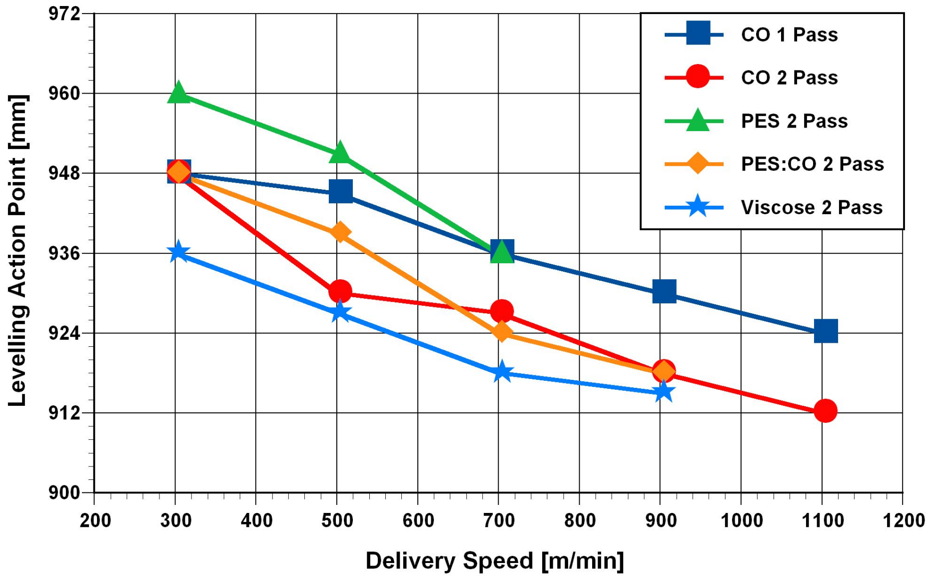

Figure 7.1: LAP Curves as Affected by Variable Delivery Speeds

The figure 7.1 also clears the LAP positioning of the materials at optimum settings. The polyester needs less infeed tension for processing in comparison with other materials, which clears the high LAP value for polyester. However the low LAP values for the Viscose may be due to the smooth surface of viscose fibers.

Moreover, the same downward trend was exhibited by changing the feeding speed when the fed sliver weight, delivered sliver weight and doublings were kept constant. Referring to equation 7.2, an increase in the number of doublings will decrease the feeding speed and this will result in a higher LAP value and vice versa. However, in order to find out the individual influence of doublings and draft, the experiments shown in the table 7.1 were performed using carded cotton for 2nd passage. The feeding speed was kept constant at variable levels of draft and doublings.

Expt. Nr.	Feeding Count [ktex]	Doublings [-]	Delivery Count [ktex]	Delivery Speed [m/min]	Feeding Speed [m/min]	Draft [-]	LAP [mm]
1	5.45	4	4.70	300	64.68	4.64	948
2	5.45	6	4.70	450	64.68	6.96	942
3	5.45	8	4.70	600	64.68	9.28	948
4	5.45	4	4.70	550	118.58	4.64	930
5	5.45	8	4.70	1100	118.58	9.28	930

Table 7.1: Investigations on Draft and Doublings at Constant Feeding Speeds

Experiments from 1 to 3 (in the table 7.1) refer to the feeding speed of 64.68 m/min while experiments 4 and 5 were carried out at 118.58 m/min. The LAP results indicate no change in case of feeding speed of 118.58 m/min, where the doublings were increased from 4 to 8 and the total draft from 4.64 to 9.28. Whereas in case of feeding speed 64.68 m/min, the experiment 2 shows a decrease of 1 LAP point i.e. 6 mm, which can be attributed to the measurement accuracy of the Rieter Quality Monitor RQM. In brief, varying the total draft or the number of doublings has no or negligible influence on LAP, provided the feeding speed is kept constant.

The selection of the feeding speed as a major LAP influencing parameter demands further in depth study. figure 7.2 elaborates the experimental results using Cotton for 2nd drawing passage conducted at various possible settings. These experiments provide a detailed insight about the effect of feeding speed at different processing machine settings shown in figure 7.2. The quasi-linear downward trend with increasing feeding speed is quite eminent. Also the comparison of the settings 1, 3 and 4 reveals the effect of infeed tension in interaction with the feeding speed. This implies the high tension results in the short LAP.

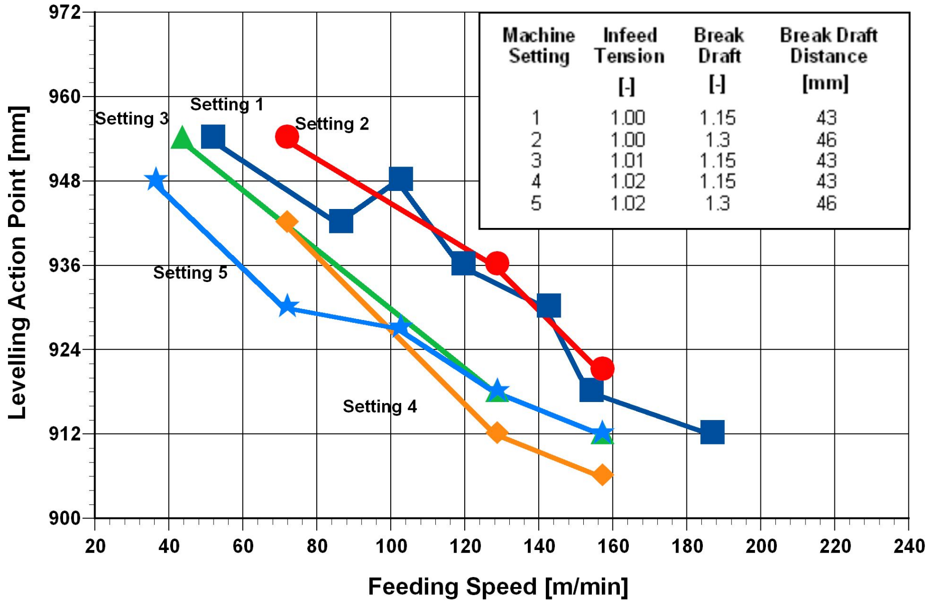

Figure 7.2: LAP Curves as Affected by Variable Feeding Speeds for Cotton 2nd Passage

Similar experiments were also performed on cotton carded 1st passage and polyester 2nd passage. However, due to large amount of experimental data it is not possible to present all of them. Therefore, an overview is being given here.

A descending tendency was observed from the experiments conducted on the cotton carded 1st passage. However, the curves are wavier in comparison with the 2nd passage. This can be attributed to the non-parallel state of fibers inside the card sliver. In contrast, the curves acquired from the experiments on polyester 2nd passage and polyester cotton blend exhibited better linearity. Also as polyester can only be processed up to a delivery speed of 700 m/min, because of the thermoplastic nature of polyester. The polyester fibers tend to melts due to high temperatures produced when processed at higher speeds. Therefore for polyester fibers the effects of the high dynamics couldn't be explored.

Concluding the above analysis regarding the influence of feeding speed on the LAP, it can be argued that feeding speed is an important parameters for all the materials tested. Its inverse proportionality with LAP is not ideally linear and additionally it also varies for different materials.

7.1.2 Infeed Tension

The infeed tension (VE) is the collective tension in all the slivers before entering into the drafting zone. VE is a mechanical setting on the draw frame RSB-D40 and should not be considered in Newton. In order to avoid false drafts, the sliver should slightly sag at the beginning, between all the guiding points. After this, there should be a stepwise increase in the tension. Moreover, it should be noted that every material requires its own ideal infeed tension for optimal results. This implies that the infeed tension is strongly material dependent [11]. For example, an optimum infeed tension setting for the polyester is 0.99 whereas that of combed cotton is 1.02, which obviously refers to the cohesion between the fibers inside the fiber strand.

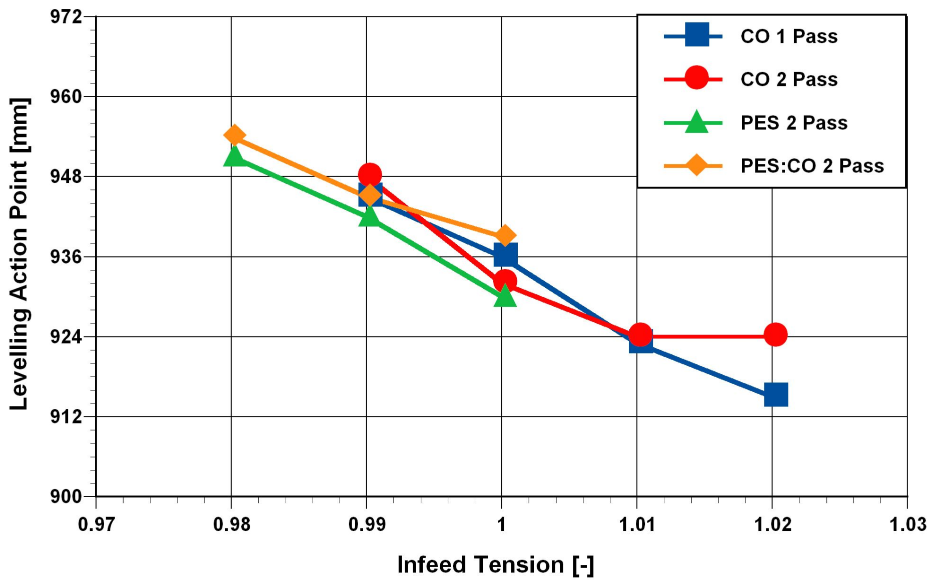

Figure 7.3: LAP Curves as Affected by Variable Infeed Tension Settings

The results indicated that the infeed tension strongly influences the LAP. An indirect proportionality exists between infeed tension and LAP. This implies an increase in infeed tension is known to be resulted in shorter LAP values. The graph 7.3 presents the LAP of the different materials at their optimum settings.

Cotton carded for 1st and 2nd passages showed the same trends at same levels and parallel to each other. However, they deviated from each other at level 1.02. Polyester and PES/CO blend showed a steady decrease for LAP while increasing the infeed tension. The amount of change in LAP is also noticeable, i.e. at least 6 mm, by one level increase in infeed tension, excluding the last point in case of Cotton carded 2nd passage. However, an overall average decrease in LAP is approximately 9 mm per one level increase in infeed tension, which speaks out the significance of the infeed tension with reference to the LAP.

The following figure 7.4 indicates the behaviour of variable infeed tension in dependence of feeding speed, break draft and break draft distance corresponding to polyester 2nd passage. The influence of the feeding speed is apparent at the high feeding speeds i.e. machine settings 3, 4 and 5 showed the shorter LAP in comparison with the machine settings 1 and 2. Also all the lines remain almost parallel to each other for the change of 0.98 to 0.99 infeed tensions, i.e. low to normal infeed tensions.

However, in case of settings 3 and 4, i.e. at higher speed an alteration in infeed tension from 0.99 to 1.00 bring about a higher than normal change. This implies that despite of the individual influence of infeed tension and machine dynamics, also the interaction of both also exerts the significant influence. Furthermore, higher break drafts and break draft zone settings also exert their influence that can be revealed by comparing the machine settings 2 and 5. Almost similar results were exhibited by the other materials i.e., cotton carded 1st and 2nd passage and polyester/cotton (50/50) blend.

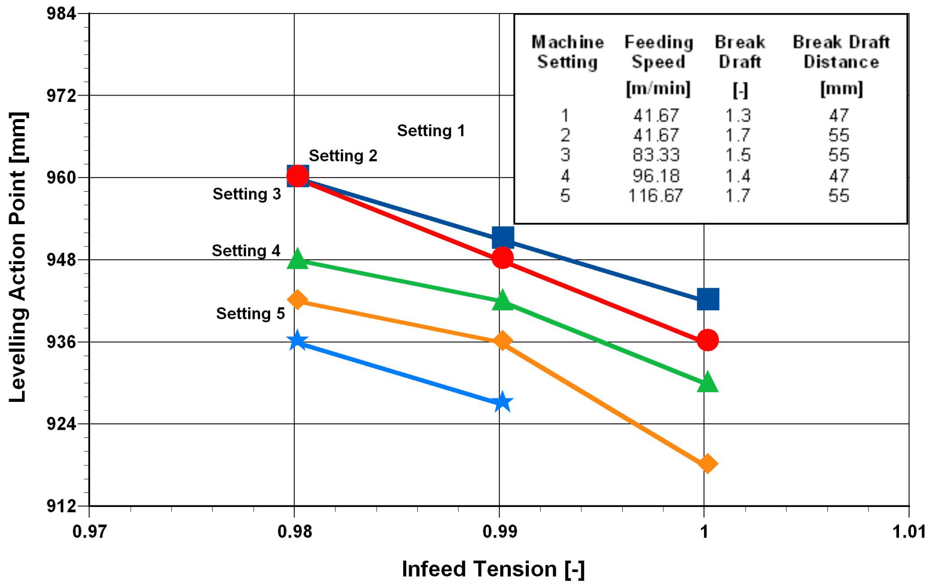

Figure 7.4: LAP Curves as Affected by Variable Infeed Tensions for Polyester 2nd Passage

7.1.3 Break Draft

As in case of feeding speed and infeed tension, the LAP exhibits an indirect proportionality with break draft. However, the expected trend was not revealed by the experiments. The results are being presented in the graphical form hereunder.

Generally speaking, the influence of the break draft on LAP is relatively weak and also not well-defined. While looking at the figure 7.5 the minimum tendency in the downward direction can be seen which is opposite in case of cotton 2nd passage. For Polyester the LAP value is longer for first by increase the break draft while a further increase resulted in short LAP value. The indefinite trends in LAP value exhibited due to varying different levels of break draft can be associated with the measurement accuracy of the RQM.

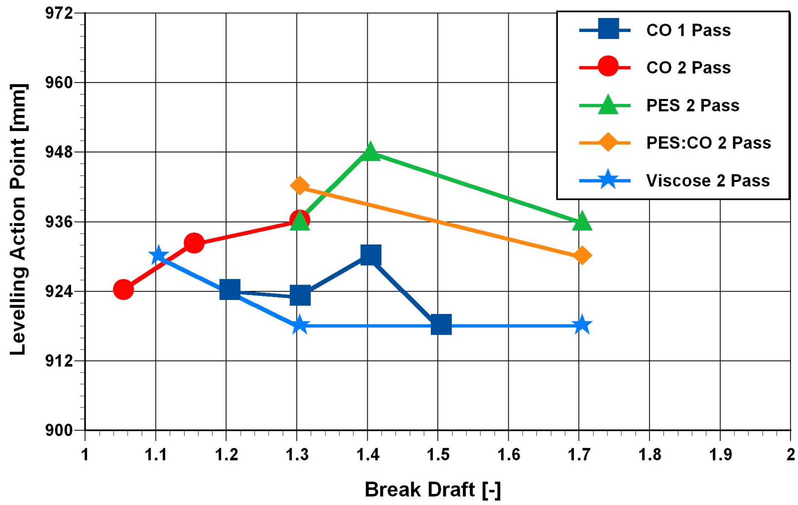

Figure 7.5: LAP Curves as Affected by Variable Break Drafts

The results achieved by the efforts to find out the interactions between the break draft and other machine settings are also vague. This implies that no clear trend is visible. Nevertheless, break draft is an influencing variable but its influence is relatively weak in comparison with feeding speed and infeed tension.

7.1.4 Break Draft Distance

In the next stage, the break draft distance was investigated as another possible LAP influence parameter. According to the instructional manual of the machine RSB-D40, it is believed that an increase in the break draft distance will decrease the LAP. The break draft distance showed a relatively low influence which is less than expected. The results pertaining to the variable break draft distance for different materials at their respective optimum settings are presented in figure 7.6. As in case of break draft, the trend for break draft distance is not truly downward. It varies differently and no clear statement can be given here.

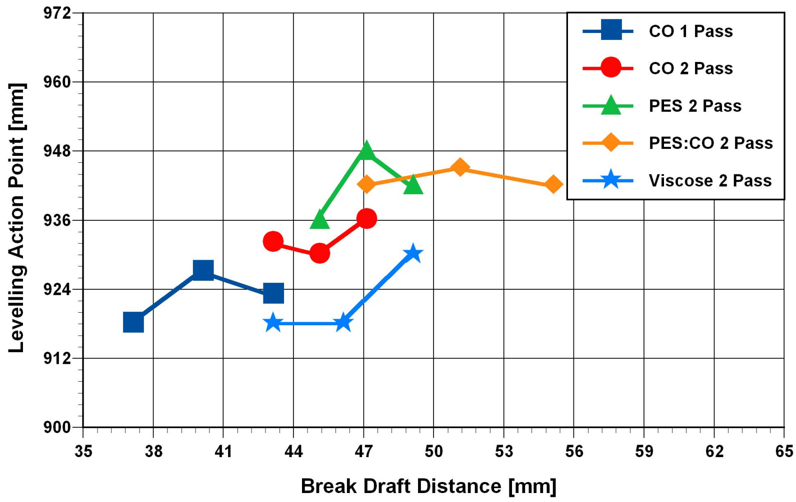

Figure 7.6: LAP Curves as Affected by Variable Break Draft Distances

This behaviour of LAP change with respect to variable break draft distance is not limited to the optimized settings. The experiments conducted at different settings and various materials also showed the similar results. However importantly, an increase of 3 mm in break draft distance brings about a LAP change of at least 3 mm in either upwards or downwards direction.

7.1.5 Main Draft Distance

The main draft distance is investigated as another possible influence parameter. According to the instruction manual of the machine RSB-D40, a wider main draft distance results in a short LAP value. This statement could not be proved by the experiments. The results regarding the variable main draft distance have been presented in the graph. There is no significant increase or decrease in LAP at various levels of main draft distance. This small or negligible change can be attributed to the measurement accuracy of RQM.

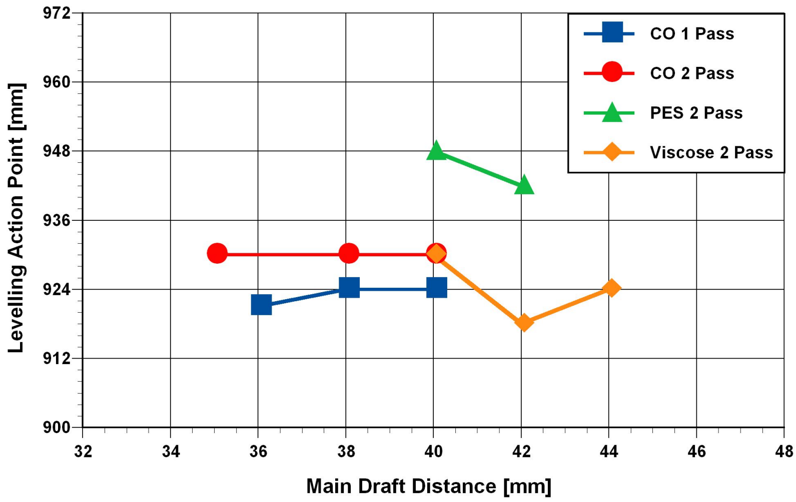

Figure 7.7: LAP Curves as Affected by Variable Main Draft Distances

This phenomenon of LAP having not effected with the change in main draft distance can also be explained theoretically. The fibers in the main drafting zone are divided into two groups. The first group of the fibers are those which are in the grip of the middle rollers or have a frictional contact with these fibers. The second group are the 'accelerated fibers' which are under the influence of the front rollers running at higher speed. These fibers are either in the grip of the front rollers or have frictional contact with the fibers griped by them. As mentioned earlier, the leveling action point is the distance from scanning roller to this point 'E'. The imaginary point 'E' lies in the main drafting zone where the first group of fibers ends or simply speaking it is between the both fiber groups. Therefore, the experimental results can be justified on the basis of two fiber groups theory.

7.1.6 Sliver Deflection Bars

It is already described in chapter 3, the sliver deflection bar settings "Bandumlenkstbe" (BUS) increase or decrease the LAP distance geometrically.

The machine can be set at three different L2/L3 levels i.e. 1/6, 2/5 and 3/4 as shown in figure 7.8. The frequently used setting is 2/5. Changing this machine setting brings about a variation in LAP distance which is dependent on the thickness of the fed slivers. The following table 7.2explains the change in the sliver length from L1 to L4 in dependence with sliver thickness. The following measurements were made using CAD software. Geometrically, the 1/6 setting decrease the distance by 12 mm and 3/4 increase LAP by 18 mm for a sliver of 0 mm thickness. For a sliver of 3 mm thickness this increase in length is 21 mm and decrease is 11 mm.

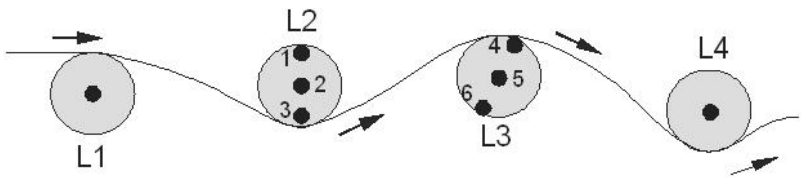

Figure 7.8: Sliver Deflection Bar Settings

The investigations were performed to find out whether this change of path affects the LAP geometrically or not. The experiments on different materials were carried out at the optimize settings by changing the three possible settings of sliver deflection bars. The results are presented in the following figure 7.9.

The figure 7.9 depicts the LAP change in the correct direction when the length is increased or decreased. Also in case of Cotton 1st Passage, Cotton 2nd Passage and Polyester the change in LAP is almost equals to the geometrical change, i.e. a change of -12 mm and +24 mm at 1/6 and 3/4 respectively with respect to the medium distance setting of 2/5. But a significant difference between the geometric change of LAP and the measured LAP value was observed in case of Viscose. Here a value of -27 mm and +30 mm was determined.

	L2	L3	Sliver Thickness [mm]	Sliver Length [mm]
Maximum Distance	3	4	0	322.6
	3	4	1	325.9
	3	4	2	329.4
	3	4	3	333
Medium Distance	2	5	0	304.2
	2	5	1	306.7
	2	5	2	309.3
	2	5	3	312.1
Minimum Distance	1	6	0	292.9
	1	6	1	294.6
	1	6	2	296.4
	1	6	3	298.3

Table 7.2: Geometrical Change in Length due to Sliver Thickness

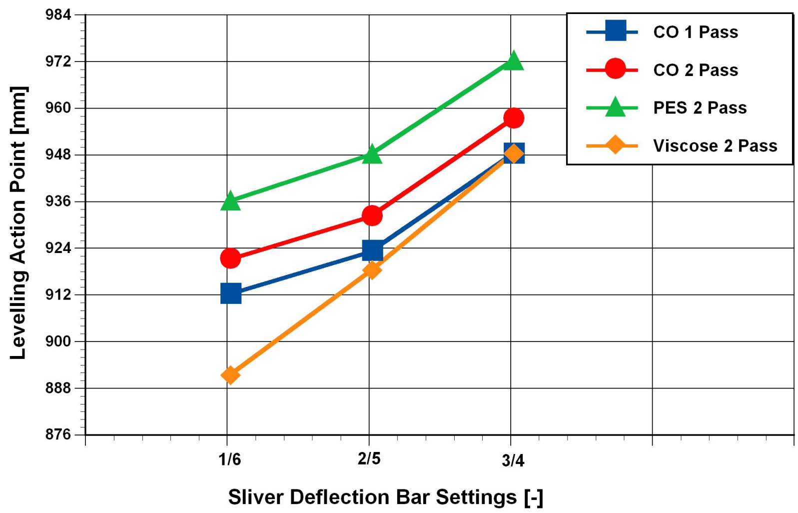

Figure 7.9: LAP Curves as Affected by Different Sliver Deflection Bar Settings

The thickness of the slivers plays an important role in the non-uniform change in the LAP. Moreover another reason is the variations in the friction. By increasing or decreasing the BUS the angle of contact between the slivers passing on the BUS changes, which in turn can change the friction and results in different LAP. This occurs especially in case viscose because of the smooth surface of the fibers.

Considering the Coulomb's friction between the sliver and the circular deflection bars, the magnitude of the applied force 'F2' can be described using the Euler-Eytelwein formula

$$F_2 = F_1 \cdot e^{\mu \cdot \alpha} \tag{7.3}$$

Where,

F_1 = Reaction force
e = Euler′s Constant
μ = Friction Constant
α = Wrap around angle

7.1.7 Infeed Variations

Variations in the fed slivers are considered to be the important LAP influencing variable. However, it is difficult to measure their influence on LAP because in practice these variations enter the machine randomly.

In order to investigate this influence, sinusoidal irregularities were artificially produced in the sliver in the first cotton passage. These irregularities were induced by running the machine in inching mode and giving the sinusoidal signals at the scanning rollers. Two different slivers having wave length of 0.25m and 0.5m and amplitude 30% were produced as shown in table 7.3. The figure 7.10 shows the Uster diagram of the produced sliver having sinusoidal variations.

Delivery Speed (Inching mode)	**Draft** [-]	**Feeding Speed** [m/min]	**Wave Length** [m]	**Amplitude** [%]	**Frequency** [Hz]
100	6	17	0.50	±30%	3.33
100	6	17	0.25	±30%	6.67

Table 7.3: Manufacturing of Sinusoidal Sliver

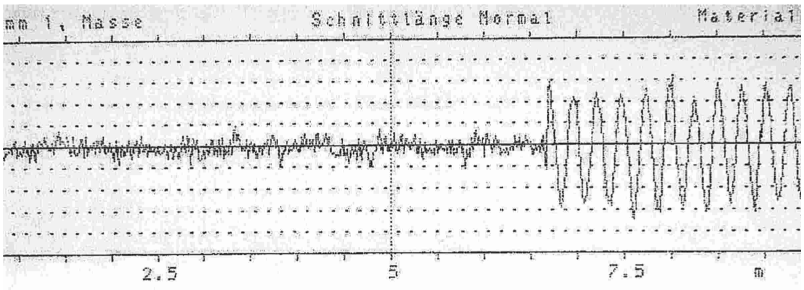

Figure 7.10: Uster diagram of sinusoidal sliver

Then these artificially produced defective slivers were then fed to the draw frame along with normal slivers in the second drawing passage. The six sliver doublings, i.e. (5 normal + 1 defective) were used. This implies that the variation of 30% is reduced to 5% due to the averaging out effect of the doublings. The experimental plan given in Table 7.4 below was used to perform the LAP searches at different frequencies of infeed variations. The frequency can be expressed as

$$f = \frac{\nu}{\lambda} \tag{7.4}$$

Where

f=frequency

$\nu = speed$

$\lambda = wavelength$

Experiment 1 and 4 are performed using the normal 6 slivers so that the other experiments should be compared with reference to them.

Expt. No.	Delivery Speed [m/min]	Feeding Speed [m/min]	Wave length [m]	Frequ-ency [Hz]	Infeed Tension [-]	Break Draft [-]	Break Draft Distance [mm]
1	500	83	Normal	0	1.01	1.15	43
2	500	83	0.5	2.78	1.01	1.15	43
3	500	83	0.25	5.56	1.01	1.15	43
4	900	150	Normal	0	1.01	1.15	43
5	900	150	0.5	5	1.01	1.15	43
6	900	150	0.25	10	1.01	1.15	43

Table 7.4: Experimental Plan for Investigating the Infeed Variations

According to the theory, the open loop systems are able to correct the infeed variation up to a certain frequency and wave length depending on the efficiency of the auto-leveling systems. For instance, a high frequency of the infeed variation will decrease the reaction time of the servo motor, which will cause it to perform abnormally. The Uster results after the drawing passage confirm that the induced faults are corrected by auto-leveling system.

The results pertaining to LAP reveal that a frequency of 2.78 Hz has no effect on the LAP. However, for frequency 5.56 and 5 Hz i.e. for the experiment 3 and 5, a change of 6 mm is observed, while this change increases to 9 mm for 10Hz. Concluding the investigations, it can be deduced that there is a definite influence of the infeed variations on the LAP, however this influence is lower than expected. Moreover higher dynamics of the machine can also increase this influence.

7.2 Comparison Among Materials

The earlier part of this chapter elaborates the role of various influencing parameters on the leveling action point (LAP). It also explores the dissimilar behaviour of various materials under varying processing conditions and machine settings. Therefore, 'materials' should also be considered as an influencing factor along with other machine parameters.

As already mentioned that different materials require their own specific processing settings, impose constrain on the comparison of materials corresponding to LAP using similar machine settings. Especially, the comparison of natural and synthetic fibers cannot be made on this basis. However, there is possibility to compare different synthetic materials having same fiber lengths and fiber finenesses. Therefore, the polyester and viscose fibers having same fiber length were processed using the similar machine settings and then compared on the basis of LAP results.

7.2.1 Comparison Between Polyester and Viscose

Comparing the polyester with viscose for second drawing passage, it was observed that LAP value for polyester is longer than viscose. The cause can be attributed to the less infeed tension (VE) while processing polyester. Moreover, for all other tension settings i.e., creel tension (VZ), power creel tension (VZW) and take-off tension (VA), polyester needs a less tension. Also the standard processing delivery speed for polyester is 600 m/min whereas that of viscose is 800 m/min.

On the contrary, the LAP searches carried out on polyester 38 mm and Viscose 38 mm using the same LAP influencing settings for the second drawing passage show another side of picture. The following figure 7.11 indicates the difference in LAP values at nine settings given in table 7.5. The difference of one search point i.e. (3 - 6 mm) is obvious for six settings along with same values for two settings. Experiment no. 8 being the exception where a difference of two search point i.e. 12 mm is evident.

Expt. No.	Feeding Speed [m/min]	Sliver Deflection Bars [-]	Infeed Tension [-]	Break Draft [-]	Break Draft Distance [mm]
1	41.67	2/5	0.98	1.3	47
2	50.00	2/5	1.00	1.5	51
3	83.33	2/5	0.98	1.5	51
4	83.33	2/5	0.99	1.5	50
5	83.33	2/5	1.00	1.3	47
6	116.67	2/5	0.98	1.5	51
7	116.67	2/5	0.99	1.3	47
8	116.67	2/5	1.00	1.7	47
9	133.33	2/5	1.00	1.7	55

Table 7.5: Experimental Plan for Comparing Polyester and Viscose

The mean absolute difference of 4.33 mm and the correlation coefficient $r = 0.94$ was calculated between the two materials. It can be deduced that characteristic nature of material requiring different processing settings at the draw frame has a major influence on LAP.

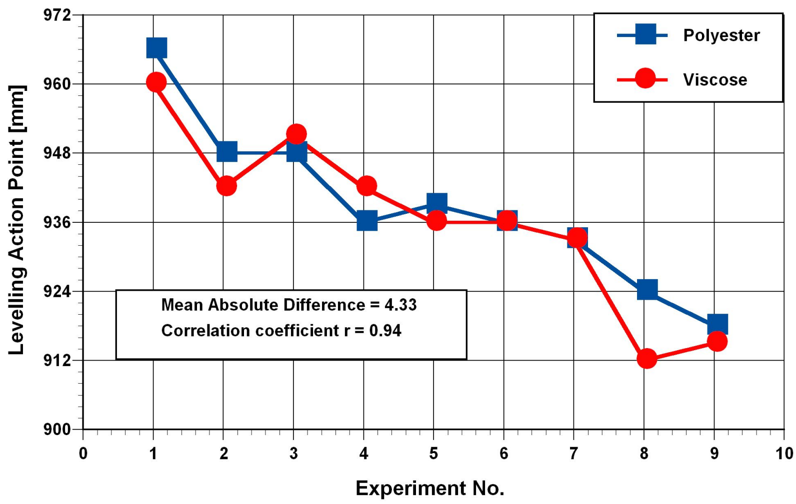

Figure 7.11: Comparison of LAP Results for Polyester and Viscose at Same Processing Settings

7.2.2 Polyester/Cotton Blends

Because of the diversity of the applications, the fibrous materials are blended at the draw frame. The most frequently processed blend in the textile industry is blending of polyester with cotton. However, these blends are not necessarily 50/50. They can be blended in all possible blend ratios like 80/20, 75/25, 65/35 etc. and their reverse combinations. Therefore, a LAP comparison of polyester, polyester/cotton blend (50/50), polyester/cotton blend (67/33) and polyester/cotton blend (33/67) processed at similar machine settings is being presented hereunder.

The LAP searches for various polyester/cotton blends (PES/CO 50/50, PES/CO 67/33 and PES/CO 33/67) were also carried out using same LAP influencing settings. The following graph compares the polyester with its cotton blends corresponding to LAP.

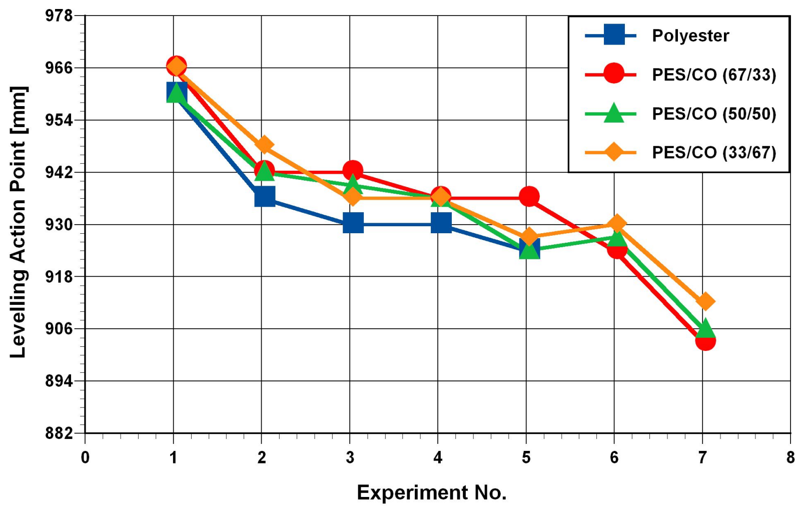

Figure 7.12: Comparison of LAP Results for Different Polyester/Cotton Blends at Same Processing Settings

Expt. No.	Feeding Speed [m/min]	Sliver Deflection Bars [-]	Infeed Tension [-]	Break Draft [-]	Break Draft Distance [mm]
1	50.00	2/5	0.98	1.3	47
2	50.00	2/5	1.00	1.7	55
3	83.33	2/5	1.00	1.4	50
4	116.67	2/5	0.99	1.4	51
5	116.67	2/5	1.00	1.4	51
6	150.00	2/5	0.99	1.4	51
7	150.00	2/5	1.01	1.7	55

Table 7.6: Experimental Plan for Comparing Different Polyester/Cotton Blend Ratios

The experimental investigations performed for leveling action points on different polyester/cotton blend ratios compared at same settings showed almost same LAP results. The maximum variations observed during these experiments between the said materials are 12 mm that occurs twice. The lower LAP values for polyester as compared to polyester/cotton blends are also obvious from the graph. The last two experiments (Experiment no. 6 and 7) were performed at a delivery speed of 900 m/min; therefore experiments for pure polyester were not conducted.

7.3 Multiple Linear Regression Analysis

The regression analysis also provides the opportunity to compare the different materials. As previously concluded, the effects of the major LAP influencing factors like feeding speed and infeed tension, are quasi linear so it seems worthwhile to carry out a linear multiple regression analysis. Four factors namely, feeding speed (FS), infeed tension (VE), break draft (VV) and break draft distance (VVD) are considered for a multiple linear regression analysis. The following equations for leveling action point (LAP) corresponding to different materials are resulted from the analysis.

Cotton Carded 1st Passage

$$LAP = 2154 - \{(0.2968 \times FS) - (1142 \times VE) - (26.28 \times VV) - (0.122 \times VVD)\} \tag{7.5}$$

Cotton Carded 2nd Passage

$$LAP = 1700 - \{(0.369 \times FS) - (670 \times VE) - (23.6 \times VV) - (0.533 \times VVD)\} \tag{7.6}$$

Polyester 2nd Passage

$$LAP = 1837 - \{(0.2523 \times FS) - (875 \times VE) - (22.8 \times VV) + (0.449 \times VVD)\} \tag{7.7}$$

Polyester Cotton (50:50) 2nd Passage

$$LAP = 1758.4 - \{(0.2771 \times FS) - (755 \times VE) - (27.4 \times VV) - (0.072 \times VVD)\} \tag{7.8}$$

VISCOSE 2nd Passage

$$LAP = 1342 - \{(0.322 \times FS) - (432 \times VE) - (14.9 \times VV) + (1.49 \times VVD)\} \tag{7.9}$$

The other advantage of the multiple linear regression analysis is that the materials can be compared at same settings. For instance, the following graphs constructed on the basis of the above mentioned equations reveal some important information.

The both graphs show that using same machine settings viscose and polyester exhibit shorter LAP values, in comparison with cotton/polyester blend and pure cotton. This can be attributed to the surface smoothness of the both fibers. Also lines from polyester and viscose lie side by side confirm the previously explained comparative work on the basis of experiments at same settings. The slope of the line of each material corresponds to the change in LAP value with respect to the one level change in influencing parameter. Using the MLR analysis equations this change was calculated and is presented in following Table 7.7.

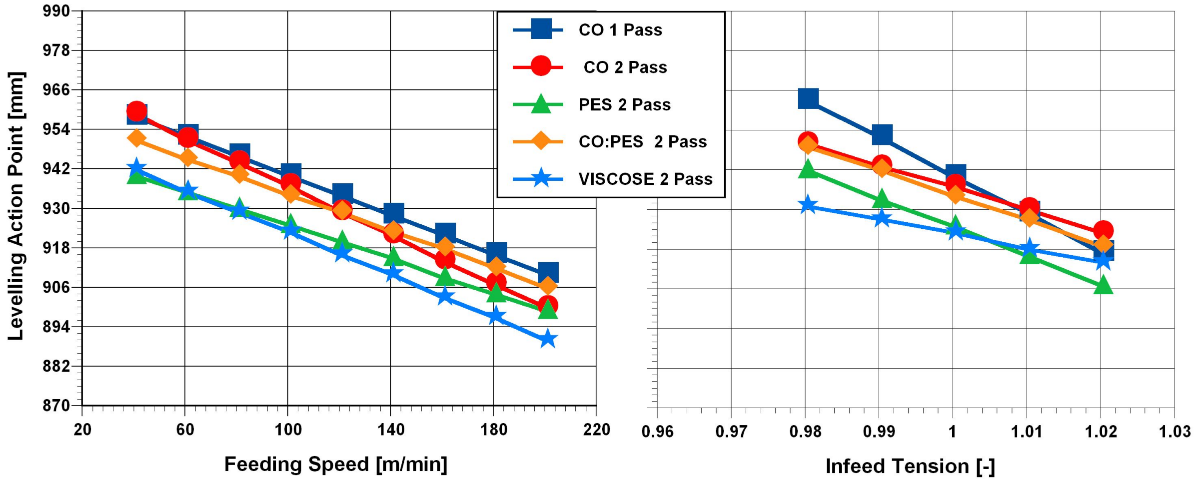

Figure 7.13: Multiple Linear Regression Analysis for Feeding Speed and Infeed Tension

Variable	**Change**	**Cotton 1st Pass**	**Cotton 2nd Pass**	**Polyester 2nd Pass**	**CO:PES 2nd Pass**	**Viscose 2nd Pass**
Feeding Speed	**17 [m/min]**	5.0	6.3	4.3	4.7	5.5
Infeed Tension	**0.01**	11.4	6.7	8.8	7.6	4.3
Break Draft	**0.1**	2.6	2.4	2.3	2.7	1.5

Table 7.7: Multiple Linear Regression Analysis

It is clear from the Table 7.7 that an increase of 17 m/min will result in approximately 5-6 mm decrease in Leveling action point. Here 17 m/min change in feeding speed is selected because it corresponds to the 100 m/min change in delivery speed, provided the weight of fed slivers and delivered sliver remain constant (this implies that in case of 6 times doublings the draft should be 6 times). The significance of this result corresponds to the frequently occurring situation in the spinning industry where the speed of finisher draw frame is changed (usually 100 m/min) depending on the requirements of ring spinning machines. Similarly an increasing the infeed tension to one level (0.01), for instance from 1.00 to 1.01 will also cause LAP to decrease to approximately 6 mm. However cotton 1st passage being the exception where this change is about 12 mm. Similarly, changing break draft value to 0.1 results in a 3 mm shorter LAP value. This also confirms the previously mentioned experimental analysis.

7.4 Training and Test Performance of Neural Networks

7.4.1 Selection of Relevant Input Parameters

In artificial neural network modeling, the importance of selecting input relevant parameters cannot be ignored. In viewpoint of artificial neural network training, it is recommended to decrease the number of input parameters, if possible. As more input neurons make the ANN structure more complex i.e. increasing the number of network weights. Hence, data requirement for a better generalized network will increase. On the other hand, simple network structure can generalize better and are able to perform better on the unseen data. A decrease in input spaces helps to avoid the curse of dimensionality, which in turn assists to improve the generalization capability of the networks. This objective of reducing the input parameters can be achieved by following two techniques.

- On the basis of the experimental results, ignoring the input parameters having negligible or no influence on the output.

- Using the combined parameters, i.e. representing the combined effect of individual variables, instead of using the individual parameters.

Therefore, on the basis of results and analysis described in previous sections of this chapter, following inferences are deduced to select the relevant parameters for neural networks training.

- Selecting the feeding speed as collective parameters instead of considering delivery speed, doublings and draft as individual input parameters.

- Removing the main draft distance as an input parameter

- Eliminating infeed variations as an input parameter

- Considering sliver deflection bars settings as geometrical change in LAP distance. This implies that instead of using this setting as an input parameter for neural networks, the networks will be trained using the experiments conducted on most frequently used setting, i.e., 2/5. In case of other two settings, i.e. 1/6 and 3/4, the subtraction of 12 mm (1/6) or addition of 18 mm (3/4) can be made respectively.

The following figure 7.14 shows the schematic view of the neural network structure for the prediction of leveling action point.

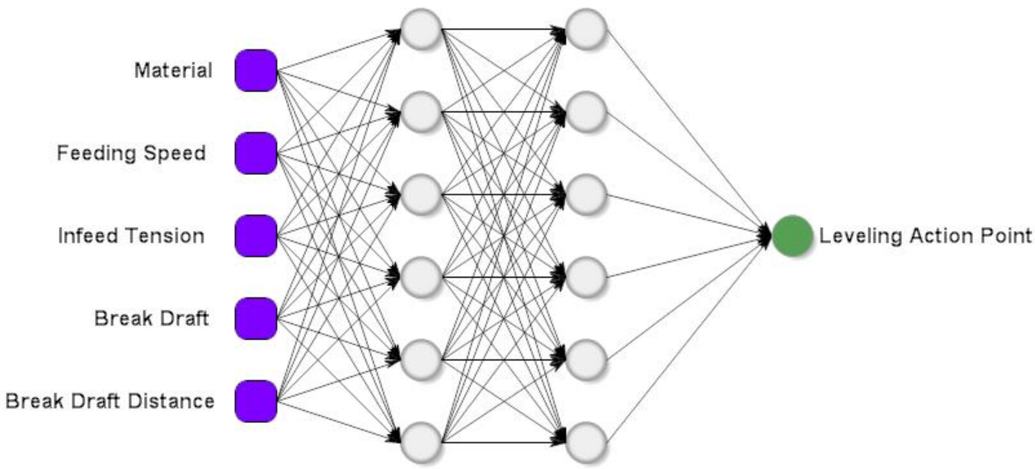

Figure 7.14: Schematic diagram of ANN Structure for LAP

7.4.2 Analysis Using Artificial Neural Networks

The artificial neural network analysis is conducted on the basis of materials namely, Cotton 1st passage, Cotton 2nd passage, Polyester 2nd passage, Polyester/Cotton blend 50/50 2nd passage. Here, Cotton 1st and 2nd passage are considered individually due to their different performance in the experimental analysis which is mainly attributed to the degree of fiber parallelization.

Approximately 500 experiments were conducted and used for training the networks. The training was carried out using the different normalization techniques, like normalization between -1 and +1, between mean value and standard deviation, however the normalization between 0 and 1 was proved to generate better results. Therefore, the experimental data is preprocessed between 0 and 1. The training matrix for the prediction of leveling action point is shown in Figure 7.15. The neural networks NN_CO1, NN_CO2, NN_PES2 and NN_PC2 corresponds to Cotton 1st passage, Cotton 2nd passage, Polyester 2nd passage, Polyester/Cotton blend 50/50 2nd passage, respectively.

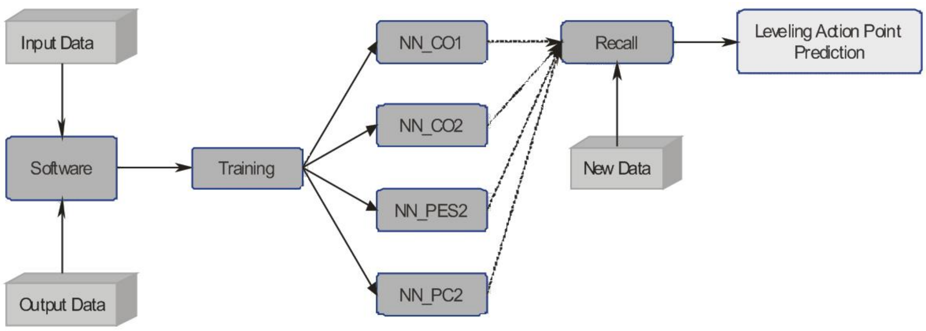

Figure 7.15: Training Matrix for Leveling Action Point

7.4.2.1 Cotton 1st Passage

The data pertaining to cotton 1st passage is subjected to the neural network training using the training parameters shown in Table 7.8. As previously explained, the Matlab training algorithm "trainbr" is employed for training. According to the traditional training and testing method (hold-out method), the data was divided into two data sets, i.e. training and test set, which are selected randomly. After training the data is post-processed to get the original values from the normalized data. The prediction accuracy of the trained network is depicted in the following graph. Mean absolute error on the test set is 5.95 mm, which corresponds to the 4.94% regarding the 120 mm range of LAP. However, in this part of the analysis it is planned to use the mean absolute error instead of mean absolute error percentage because the former clearly shows the error as the difference between the experimental and predicted LAP values in mm.

Network Parameters	**Network Parameters**
Number of Neurons in Input Layer	**4**
Number of Neurons in First Hidden Layer	**6**
Number of Neurons in Second Hidden Layer	**7**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.07**
Momentum	**0.7**
Number of Epochs	**5000**
Stopping Error	**0.002**

Table 7.8: Network Parameters for NN_CO1

Presently cross-validation is the technique being used instead of hold-out method. As mentioned in Chapter 6, this technique offers a possibility to test the trained network using all the data step by step. The Cross validation analysis, i.e. 20%, 10% and Leave-one-out cross validations, is conducted on the data and the mean absolute error, 5.37 mm, 5.50 mm and 5.35 mm is reported respectively. The following diagram elaborates the results of Leave-one-out cross validation (LOOCV). The histogram shows the difference between the experimental and predicted values. The difference remains within 12 mm. However, one value can be seen at -17 mm. This experiment was conducted at highest possible settings for cotton 1st passage, i.e. delivery speed = 1100 m/min, infeed tension = 1.02, Break draft 1.5 and Break draft distance 43 mm. So the major difference between the experimental and predicted value is due to the extrapolation, and the neural networks have showed their shortcoming here. Nevertheless, the LOOCV results have revealed that the LAP within a range of 12 mm can be predicted using the artificial neural networks.

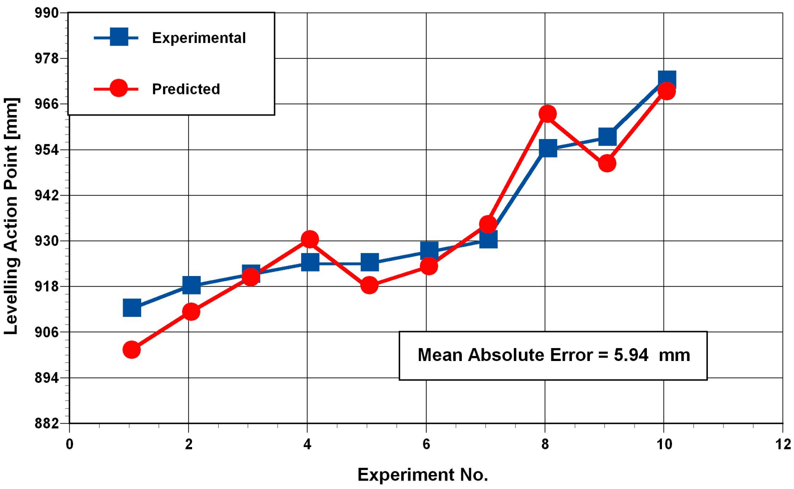

Figure 7.16: Test Set Performance of NN_CO1

7.4.2.2 Cotton 2nd Passage

The data regarding the cotton 2nd passage is subjected to neural network training firstly using the training and test sets as described above. The number of hidden layers and the number of nodes per hidden layer in the neural network architecture are determined using different combinations of network parameters. These parameters are given in following table 7.9.

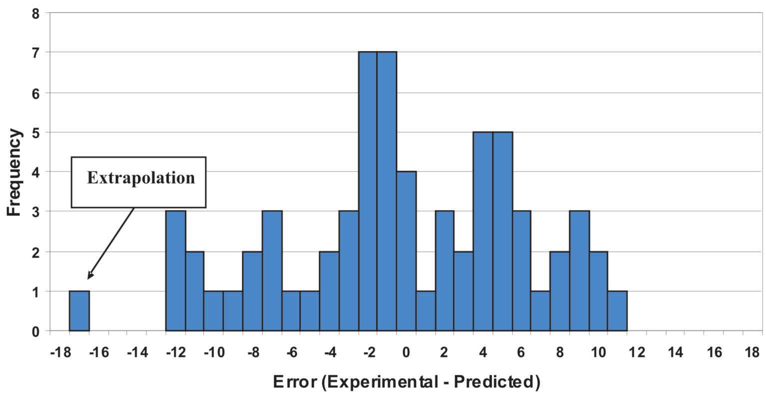

Figure 7.17: Histogram of Leave-one-out Cross validation for Cotton 1st Passage

Network Parameters	Network Parameters
Number of Neurons in Input Layer	**4**
Number of Neurons in First Hidden Layer	**5**
Number of Neurons in Second Hidden Layer	**6**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.1**
Momentum	**0.7**
Number of Epochs	**5000**
Stopping Error	**0.01**

Table 7.9: Network Parameters for NN_CO2

The following graph depicts the test set performance of the NN_CO2 on ten randomly selected data sets. The reported mean absolute error is 3.21 mm, which is considerably better than that of NN_CO1. .

The values of mean absolute error as the results of 20% cross validation, 10% cross validation and Leave-one-out cross validation are determined as 4.94 mm, 5.07 mm and 4.27 mm respectively. The mean absolute error values calculated from the cross validation is comparatively higher than that of the test data set. This leads to the conclusion that cross validation results are more valid, instead of using randomly selected test data set, where the neural network performance can be accidentally better or

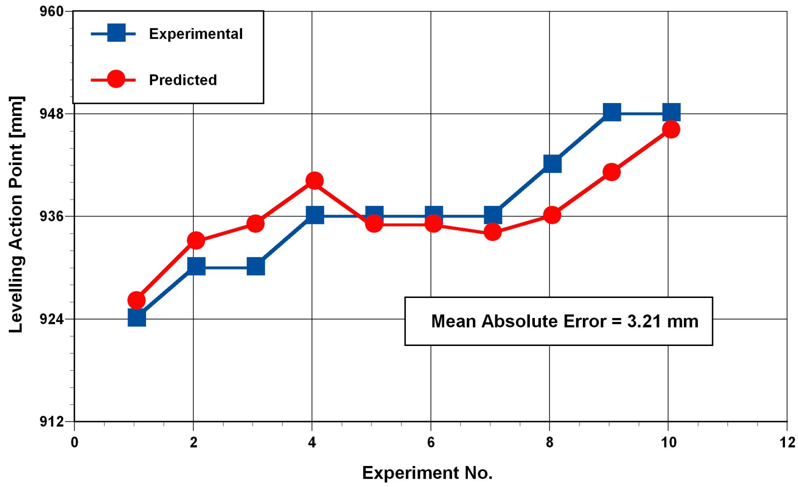

Figure 7.18: Test Set Performance of NN_CO2

worse. It is also clear for the following histogram presenting the results of NN_CO2, that all the error values remain with in the range of 12 mm.

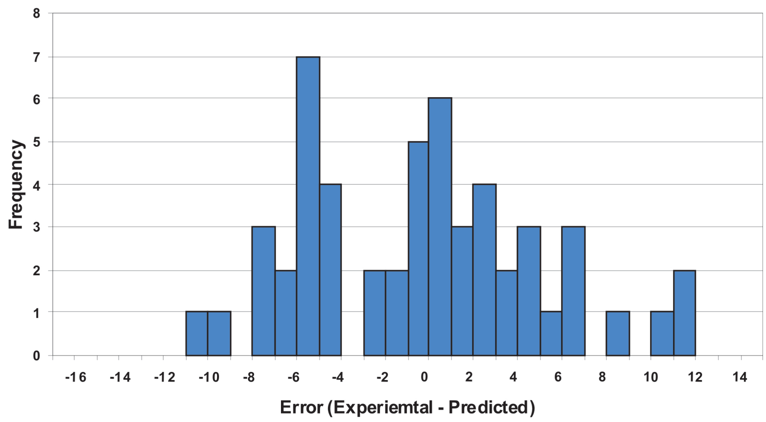

Figure 7.19: Histogram of Leave-one-out Cross validation for Cotton 2nd Passage

7.4.2.3 Polyester 2nd Passage

NN_PES2 was training using data obtained from the experiments conducted on the polyester for the second passage. The four inputs neurons, namely feeding speed, infeed tension, break draft and break draft distance and one output neuron for leveling action point are selected. The numbers

Network Parameters	Network Parameters
Number of Neurons in Input Layer	**4**
Number of Neurons in First Hidden Layer	**5**
Number of Neurons in Second Hidden Layer	**5**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.01**
Momentum	**0.6**
Number of Epochs	**5000**
Stopping Error	**0.01**

Table 7.10: Network Parameters for NN_PES2

of neurons in 1st and 2nd hidden layers are determined using trial and error. Five hidden neurons in both layers showed better performance. The other network parameters are given in the following table 7.10.

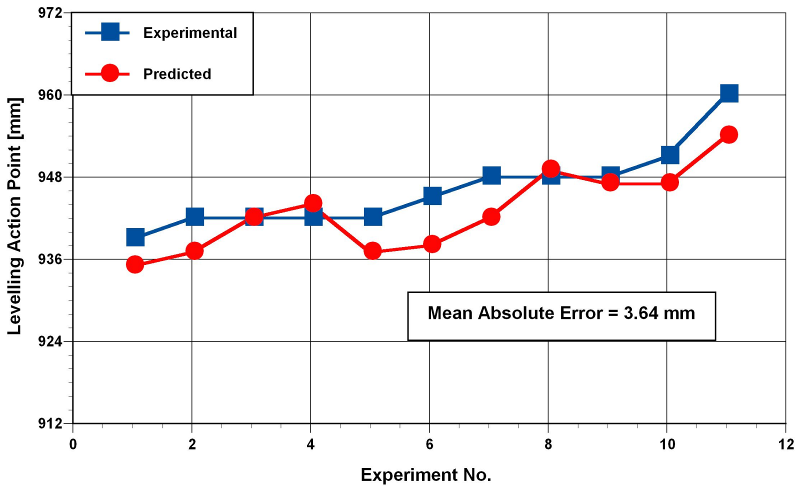

Figure 7.20: Test Set Performance of NN_PES2

The performance of the NN_PES2 on the test data, i.e. unseen data is shown in figure 7.20 . The mean absolute error calculated is 3.64 mm, which shows a highly significant resemblance between the experimental and predicted values. The mean absolute error as the results of 20% cross validation is calculated as 3.71 mm whereas that of 10% cross validation is 3.70 mm. The histogram describing the results of Leave-one-out cross validation is shown below. The mean absolute error of 3.55 mm is reported for LOOCV. The same trend of having the difference between the experimental and predicted values with in 12 mm is also visible here. Also, approximately 82% of the values are limited to 6 mm area.

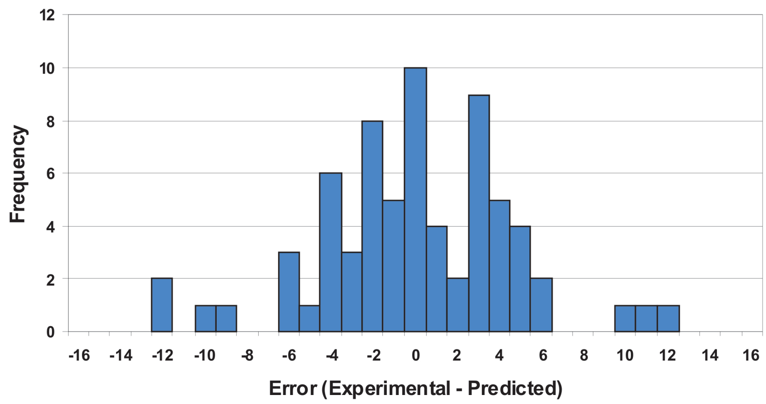

Figure 7.21: Histogram of Leave-one-out Cross validation for Polyester 2nd Passage

7.4.2.4 Polyester/Cotton 50/50 2nd Passage

Lastly, the data pertaining to polyester/cotton blend 50/50 for 2nd passage is sub-jected to the neural network software to training the network NN_PC2. The net-work architecture and training variables concerning to NN_PC2 are presented in the following Table 7.11.

After training, the network was tested on the unseen data, i.e. test set. The following graph represents the results between the experimental and predicted data. The mean absolute error for NN_PC2 is determined as 2.87 mm. It is also visible for the graph which shows a very good overlapping of both curves. The mean absolute errors for cross validation analysis regarding NN_PC2 are mentioned as, 3.17 mm for 20% cross validation, 3.19 mm for 10% cross validation and 3.25 mm for leave-one-out cross validation. Here the range within which the error values lie is 11 mm.

Network Parameters	Network Parameters
Number of Neurons in Input Layer	4
Number of Neurons in First Hidden Layer	5
Number of Neurons in Second Hidden Layer	5
Number of Neurons in Output Layer	1
Learning Rate	0.07
Momentum	0.6
Number of Epochs	5000
Stopping Error	0.01

Table 7.11: Network Parameters for NN_PC2

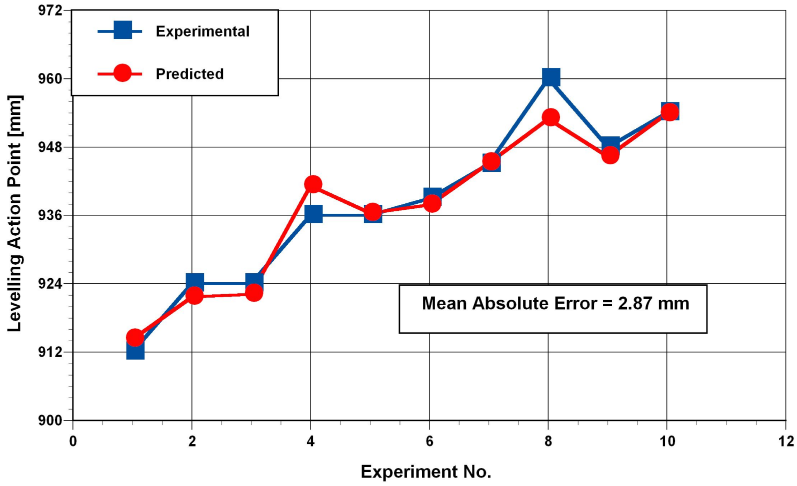

Figure 7.22: Test Set Performance of NN_PC2

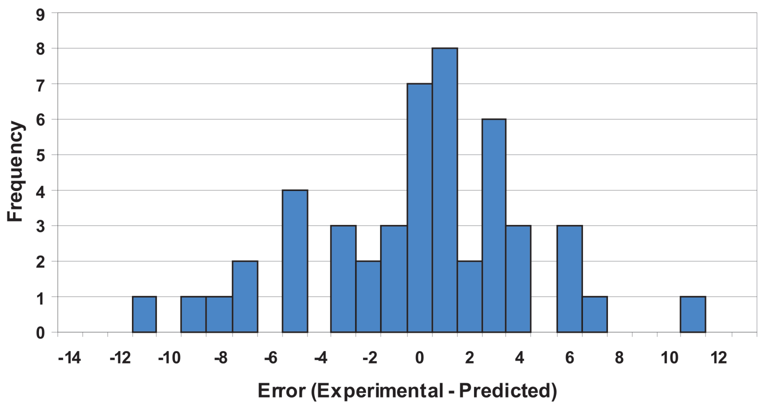

Figure 7.23: Histogram of Leave-one-out Cross validation for PES/CO 2nd Passage

7.4.3 Performance of the Trained Networks Using Industrial Data

The cross validation performance of the trained networks speaks out for the validity of the neural network prediction. The mean absolute error remains less than 6 mm for all four materials and individual error for all the experiments is within the range of 12 mm.

However, the possibility that various kinds of cotton grown in different parts of the world might have significant influence on the LAP was also kept in view and investigated. Rieter Ingolstadt, after the installation of its machine RSB-D40 gathers the machine performance data from all over the world. This data was used as a test data to measure the performance of the trained networks.

7.4.3.1 Cotton Carded

The first instance is for the cotton 1st and 2nd passage. The data were tested using the corresponding neural networks NN_CO1 and NN_CO2. The results are presented in the following graph. The mean absolute error calculated is 5.84 mm, which implies that trained networks also hold good for industrial data.

7.4.3.2 Cotton Combed

The second part of the data acquired from the industry was regarding the combed cotton. The data pertaining to combed cotton was tested using NN_CO2. The graph presenting the prediction results is shown below. A mean absolute error of 5.93 mm was calculated in this case. However, there are 2 cases where the individual prediction is more than 12 mm.

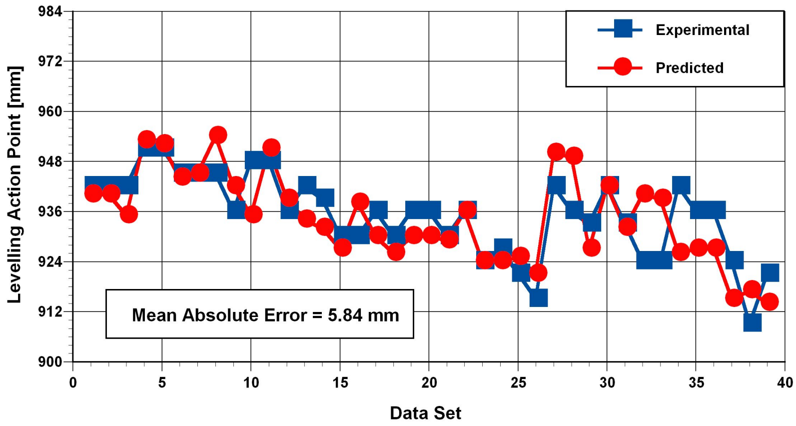

Figure 7.24: Test Set Performance of NN_CO1 NN_CO2 on Industrial Data

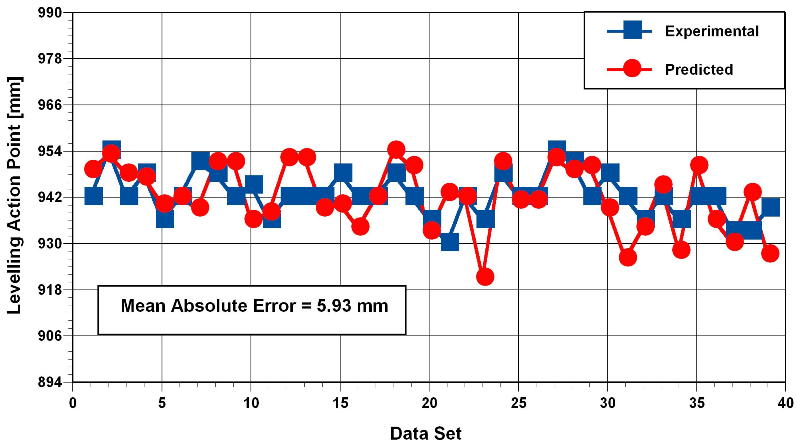

Figure 7.25: Test Set Performance of NN_CO2 on Industrial Data for Combed Cotton

7.5 Conclusion, Practical Applications and Future Pathways

The analysis of results given in this chapter has revealed many interesting facts about the Leveling Action Point. In the light of the experimental results, multiple linear regression analysis, neural networks training and their testing with cross validation and on industrial data, following key inference are deduced.

- The significant LAP influencing parameters are (1) Materials (2) Feeding Speed (3) Infeed Tension (4) Break Draft (5) Break Draft Distance

- Sliver Deflection Bar setting also changes the LAP, but geometrically. Therefore, it is possible to add or subtract the change from the prediction due to sliver deflection bars

- Polyester and Viscose tends to have similar LAP values at same machine settings

- Similarly, the different blend ratios of polyester/cotton have LAP values comparable with that of polyester/cotton blend 50/50

- A 100m/min increase in delivery speed will result in 6mm shorter LAP value, i.e. one point of auto search function. Whereas one level increase in infeed tension will at least decrease LAP up to 6mm

- The neural networks are fully capable for accurate prediction of the LAP for various frequently used industrial materials using the different machine set-tings as input parameters

- The mean absolute error remains within 5% for all the materials. Moreover, the individual predictions are with in 12mm limits, which refer to 2 points each in both plus and minus directions

On the basis of achieved results following practical applications are being proposed.

7.5.1 Leveling Action Point Prediction Function "NEUROset"

The procedure of Automatic Search Function "AUTOset" has been explained in chapter 3. For automatic searching of leveling action point the "AUTOset" function has to determine the CV% of 21 points, i.e. from 870 mm to 990 mm range, with 6 mm distance between the two points. Approximately, 100m sliver is required to measure the CV% for one point. This implies that a complete search requires about 2100m sliver.

In the framework of the present research work a search function "NEUROset" is being proposed. "NEUROset" based on the trained neural networks (NN_CO1, NN_CO2, NN_PES2 NN_PC2) will be able to limit the search to 5 points. The function "NEUROset" can work in combination with "AUTOset" for the recommendations of the search starting point. For instance, if the predicted LAP value from "NEUROset" is 942 mm, then 930 mm will be the starting point for "AUTOset" as described in the following Figure 7.26. This search will be limited to 5 points. Moreover, in case the starting or the ending search point (e.g. 930 mm starting and 954 ending in figure) has lowest CV% value, then it is reco mmended to perform two more points should be scanned in the direction of said point. This will add to the surety of the search.

The Graphic User Interface (GUI), offering the possibility to calculate the leveling action point is shown in Figure 7.27. This LAP prediction program is also written in C Language.

The second significant and potential application of the LAP prediction using ANN is associated with the manual LAP search (Figure 3.6). The manual search begins with a recommended start value and the success of the manual search is entirely dependent on this start value. The selection of this value is associated with the technical know how of the personals

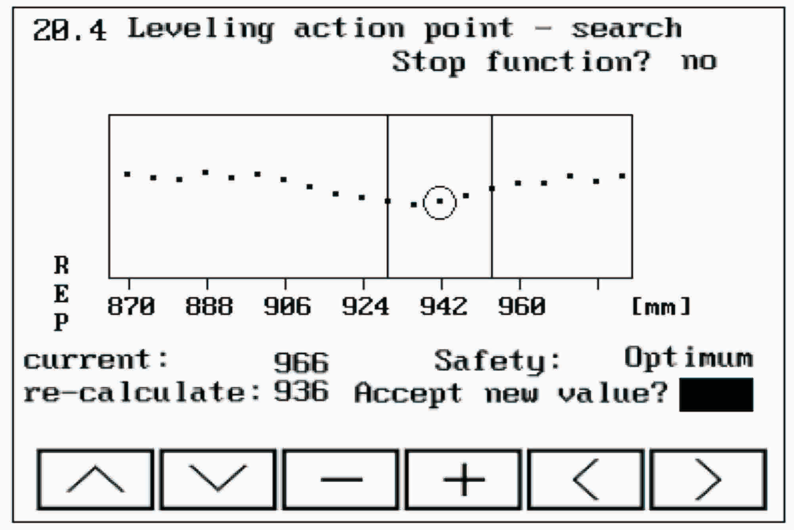

Figure 7.26: Proposed Search Range using NEUROset

working in the spinning mill. Therefore, the human error or the errors due to untrained or less experienced staff can occur. According to the theory of neural networks, they are trained on the basis of experiences or practical problem and have the capability to substitute the lack of experience possessed by the textile workers. Similarly, in the present case, the use of neural networks is anticipated for the recommendation of the starting value. Thus, avoiding the undesirable errors due to less experienced working personals. The following Figure 7.27 shows the GUI, for predicting the LAP value.

The intelligently predicted setting will shorten the search range, which will cause waste reduction of the spinning mill. Furthermore, time required to set the LAP will be reduced helping the increased productivity. This will also offer a major benefit to the spinning mills where speed and material changes are very frequent and a large variety of yarns are manufactured. In addition, the precise predictions can also improve the quality of sliver and ultimate yarn.

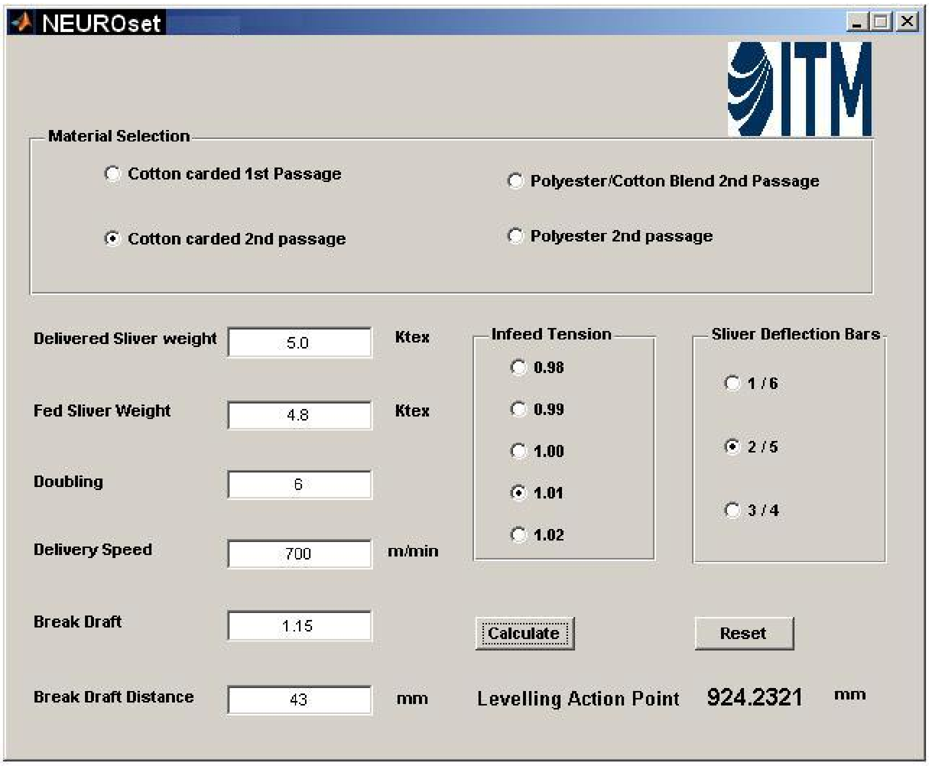

Figure 7.27: Graphic User Interface for LAP Start Value for Manual Search

Consequently, for the future prospective of machine development, this can be a big step forward towards the development of an intelligent machine, which will be able to adopt its settings due to change in machine dynamics, mechanical settings and even in case of material change at the machine. Most importantly it requires less material to perform these functions.

Chapter 8

Analysis of Sliver Characteristics

The draw frame settings cause the vital sliver and yarn characteristics to change both positively and negatively. The present chapter explores the possibility of connecting the draw frame settings and sliver quality parameters through the use of artificial neural networks. In first section, the results of physical testing pertaining to the sliver quality characteristics as affected by various materials and drawing frame variables are presented. The second section includes the artificial neural networks based analysis. It is observed that trained neural networks are able to recognize the complex interactions between the said variables and prediction system involving these variable can be constructed.

In order to carry out the experimental phase, the machine was optimized for each material separately and effects of different influencing parameters were determined by varying various levels of settings. It is also important to consider that all of the experiments are meant for ring spinning, therefore the results presented below pertain to the second drawing passage with auto-leveling. For conducting the experiments with auto-leveling, the three settings namely, leveling intensity, adaptation to slow speed and leveling action point (LAP) are of high significance. The machine was optimized for leveling intensity and for slow speed only in case of change of material. However, Leveling action point was optimized before conducting the experiments that involve the LAP influencing parameters according to the results presented in chapter 7. In order to use the material economically, the manual searches were conducted for adjusting the LAP. The trained artificial neural networks, as explained in last chapter, were used to recommend the start value for the manual search for more than 150 experiments. Then the standard procedure was adopted for the manual LAP search. Based upon the CV% results and spectrograms generated by Uster evenness tester, the results of chapter 7 were reinforced that the LAP value lies within 12 mm range of the value recommended by artificial neural networks.

The following important draw frame variables were selected to find out their influence on the sliver quality.

8.1 Sliver Quality Influencing Parameters

It is also important to mention here that a large amount of experiment were carried out in order to observe the influence of draw frame parameters on the sliver quality. For each experiment, Uster evenness testing and sliver cohesion force testing were performed. Due to the large amount of experimental data, it is not sensible to include all the results in this dissertation. Therefore the complete results are not presented here. For instance, mostly the different CV% values (CVm%, CV(1m)%, CV(3m)%) have shown similar trend, so only one of them is discussed instead of all three.

8.1.1 Effect of Delivery Speed

The effect of delivery speed on the sliver unevenness corresponding to cotton, polyester and cotton/polyester (50/50) blend is presented in the following Figure 8.1. The experiments were performed for the second drawing passage with the auto-leveling turned-on. This implies that infeed materials have relatively good fiber parallelization, while the short and medium term variations are compensated by the auto-leveling during the second passage.

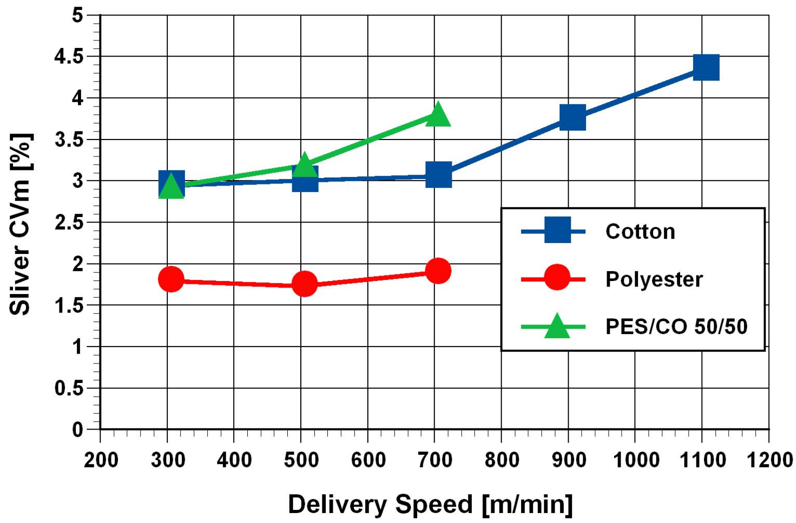

Figure 8.1: Sliver CVm [%] as Influenced by Delivery Speed

The polyester sliver has the better evenness in comparison with cotton and polyester/cotton blend which can be attributed to the longer fiber length and better fiber length distributions for polyester. Also, only in case of polyester/cotton blend there is remarkable deterioration of sliver evenness at 700 m/min, otherwise the variation in delivery speed at lower levels, up to 700 m/min, does not influence the sliver evenness seriously. However, for cotton at 900 m/min and 1100 m/min a change in delivery speed caused the CVm% value to increase steeply, which can be due to the uncontrolled movements of the accelerated fibers (the second fiber group according to two fiber groups theory) at high speeds. Furthermore, a high percentage of short fibers in cotton adversely affects the sliver evenness.

The following Figure 8.2 regarding the middle term variations in the sliver evenness, i.e., CV(1m)% and CV(3m)%, indicates almost the same trends as in case of CVm%. However, the unevenness of polyester sliver shows a regular upwards trend with the increase in delivery speed.

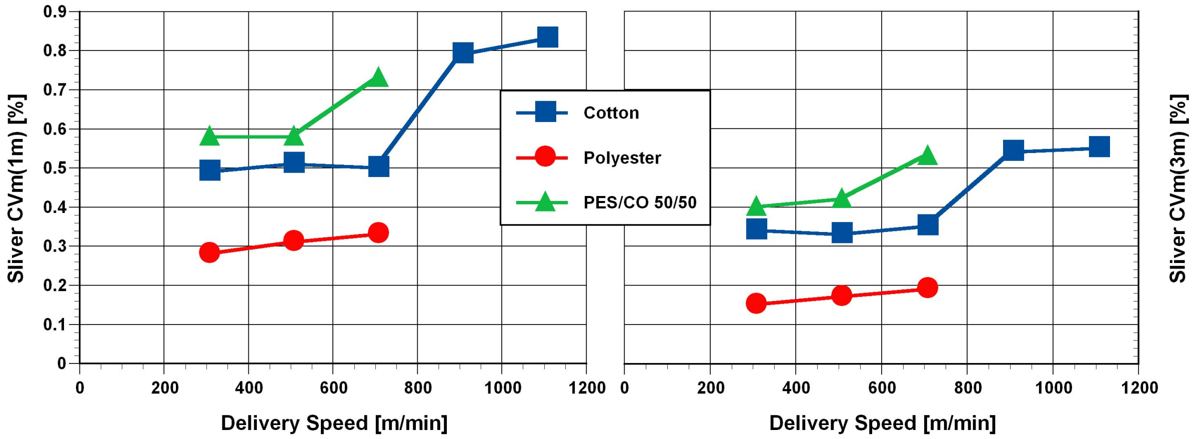

Figure 8.2: Sliver CV(1m)[%] CV(3m)[%] as Influenced by Delivery Speed

The laboratory results corresponding to the sliver cohesion as affected by the variations in the delivery speeds is given below in Figure 8.3. For all three materials the delivery speed of the sliver is directly proportional to the sliver cohesion. This implies that an increase in delivery speed tends to increase the sliver cohesion. All three materials have their different levels of fiber cohesion, cotton sliver having the lowest followed by polyester/cotton blend and then polyester. The lower sliver cohesion values of cotton slivers are attributed to the shorter fiber lengths and high short fiber contents.

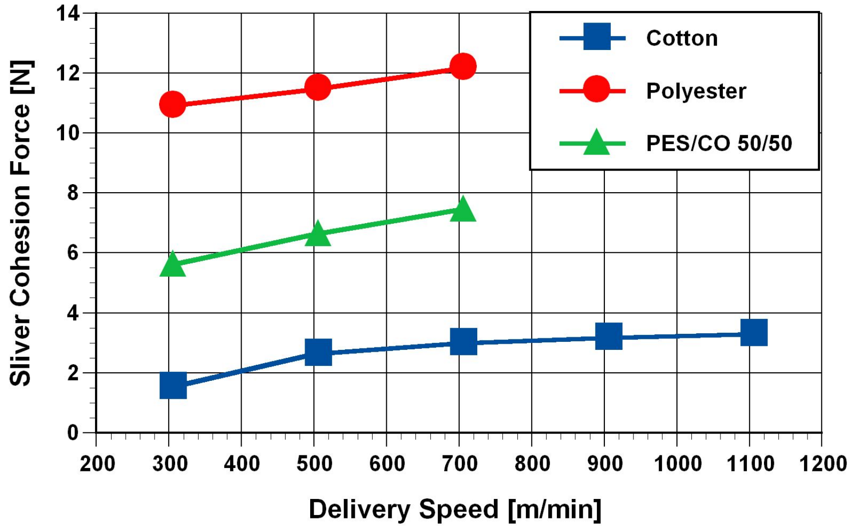

Figure 8.3: Sliver Cohesion [N] as Influenced by Delivery Speed

8.1.2 Effect of Break Draft

The influence of the break draft change on the sliver evenness shows a strong material dependence, i.e., mean fiber length and the fiber length distributions. The Figure 8.4 depicts that in case of polyester the CVm% decreases by increasing the break draft up to 1.3 and then further increase in break draft causes the CVm% to increase. This implies that a normal optimal trend is shown by polyester. However, in case of cotton and polyester/cotton blend the maximum evenness is achieved at the minimum break draft level. Also, it is also important to consider here that experiments were performed at standard settings for each material. Therefore, the results pertaining polyester and polyester/cotton blend (50/50) were performed at delivery speed of 500 m/min whereas that of cotton is 700 m/min.

The whole phenomenon is associated with the static fiber to fiber friction. An increase in the break draft allows the fibers to slide over each other, thus reducing the static friction between the fibers. As a result, the fibers especially the floating fibers tend to show uncontrolled movements in the main drafting zone, which are in turn associated with the draft disturbances and unevenness of the delivered sliver.

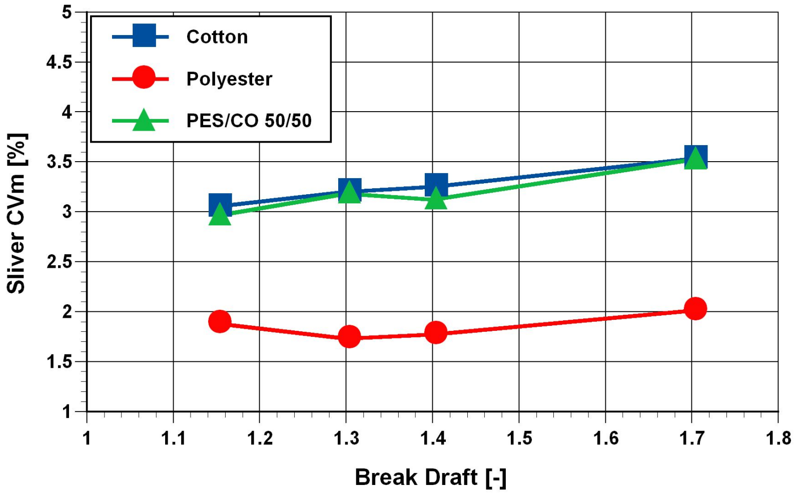

Figure 8.4: Sliver CVm [%] as Influenced by Break Draft

8.1.3 Effect of Break Draft Distance

The experiments concerning to the variations in break draft distance have revealed an overall modest effect on the sliver evenness. Polyester/cotton blend has shown a more influence of break draft distance in comparison with polyester and cotton slivers, where the increase in clamping point distance in the break draft zone increases the CVm% slightly, as shown in Figure 8.5. This small effect of the break draft distance may be due to the controlled motion of the fibers in the break draft zone is because of less difference between the speeds of the back and middle roller, i.e., low break draft. Therefore, there is no possibility of having an early acceleration of fibers. Also fiber-to-fiber friction is higher in break draft zone in comparison with the main draft zone. Similarly here, the delivery speed for cotton experiments was set to 700 m/min whereas that of polyester and polyester/cotton blend (50/50) are 500 m/min.

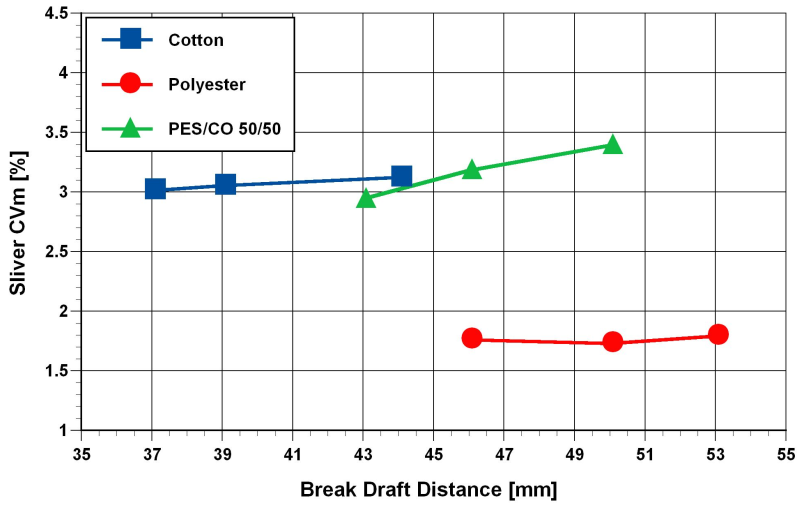

Figure 8.5: Sliver CVm [%] as Influenced by Break Draft Distance

8.1.4 Effect of Main Draft Distance

The laboratory testing results pertaining to the experimental variations in the main draft distance are presented in the following Figure 8.6. The Figure depicts that the change in main draft distance has affected the CVm% of the sliver, however, this influence is material dependent. In case of polyester sliver the minimum CVm% is achieved at middle setting, whereas for other two materials, i.e., for cotton and polyester/cotton blend, the minimum value is realized at the minimum distance between the middle and front roller. This affect can be justified by the presence of the larger amount of short fibers in the infeed slivers, in case of cotton and polyester/cotton blend. These short fibers will act as the floating fibers in the main drafting zone especially in case of wider main draft zone settings. Therefore, the wider settings increase the amount of floating fibers which in turn cause draft disturbance resulting in a higher CVm% value. Similar trends have been exhibited for medium term variations, i.e., CV(1m)% and CV(3m)%. Furthermore, for determining the effect of main draft distance on sliver cohesion, no clear trend is visible.

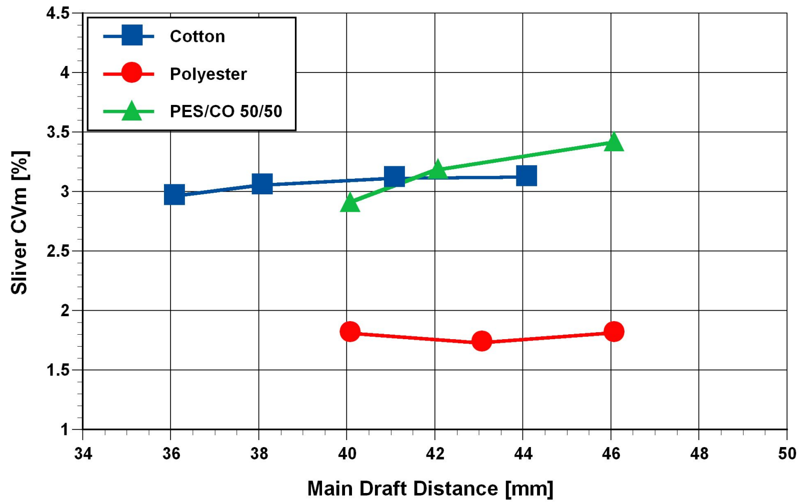

Figure 8.6: Sliver CVm [%] as Influenced by Main Draft Distance

8.1.5 Effect of Doublings

Before discussing the results about the effect of doublings on the sliver characteristics, it is important to mention that these experiments were conducted for 6 and 8 doublings. As delivered sliver weight was kept constant, i.e., 5 ktex, hence the draft was increased along with doublings. This implies that 6 times draft was used for the 6 sliver doublings and 8 time draft for 8 sliver doublings. The Figure 8.7 represents the influence of doublings on the sliver evenness. It is clear that for all three materials, 8 doublings with 8 times draft have high CVm%.

In roller drafting, it is well known fact that irregularities increase with drafting and decrease with doubling. However, the worsening effects of drafting can be more than the average out effect of doubling and a higher CV% is achieved.

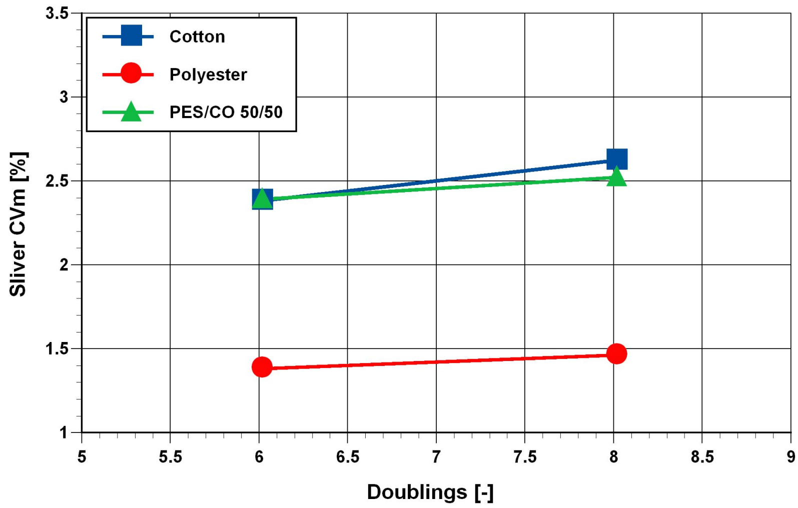

Figure 8.7: Sliver CVm [%] as Influenced by Sliver Doublings

8.1.6 Interaction effects among influencing variables

In the previous section the individual influences of the machine parameters on the quality of the sliver were revealed. It is clear that various machine parameters exert different influences with respect to materials being processed. Nevertheless, it is not easy to understand all the complex individual influences between the machine parameters and the materials. In addition, not only the individual influences but also the interactions between of various influencing parameters exert significant effects on the sliver quality. The numerous interactions between the influencing parameters along with their individual influences tend to exert a combined effect on the quality of the manufactured product. In order to explain the interactions between the influencing variables, consider the following Figure 8.8, which indicates the effect of break draft on the sliver quality at different delivery speeds for polyester/cotton blend.

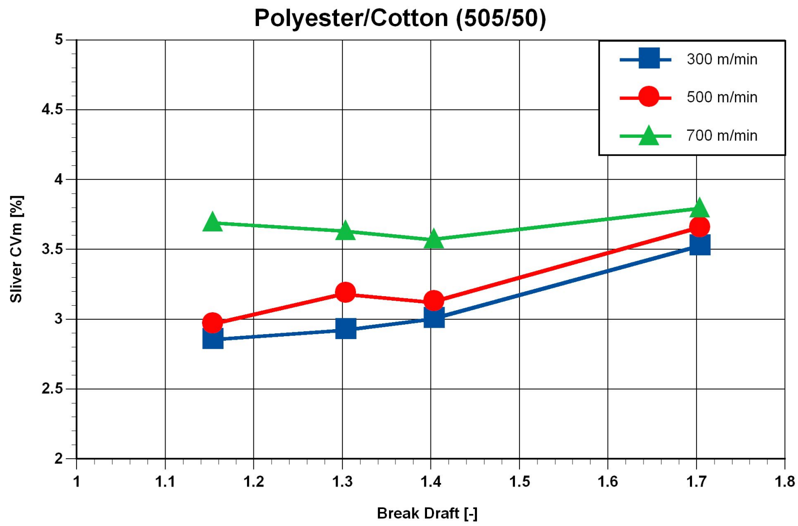

Figure 8.8: Sliver CVm [%] as Influenced by Break Draft and Delivery Speeds

The Figure 8.8, depicts the results of sliver CVm% for polyester/cotton blend as affected by the different break draft at three delivery speeds. It can be seen that all three lines are different to each other, which indicates the dissimilar behaviour of the drafted fibers at various levels of machine dynamics.

As mentioned earlier in chapter 3, the drafting process cannot be performed ideally. Also the draft disturbances tend to increase at high speeds and in the presence of more short fibers, which explains the different trend showed by polyester/cotton blend at 700 m/min delivery speed. Also, the individual effect of delivery speed is clear, which implies that delivery speed of 300 m/min has shown better CVm% followed by 500 m/min and then 700 m/min.

There are numerous interactions present between draw frame parameters and sliver quality and hundreds of experiments are needed to cover all of them. In addition to this, the non-ideal behaviour of the fibers inside the drafting zones has made the mathematical and statistical modeling of drafting process very complex.

Therefore, the situation demands for the use of artificial neural networks, in order to describe all the individual and interaction effects from the information present in the data. The trained neural networks are anticipated to intelligently predict the quality of the sliver on the basis of which the draw frame can be set “intelligently”. The analysis conducted on the basis of artificial neural networks in being presented in the next section.

8.2 Training and Test Performances of Neural Networks

8.2.1 Selection of Relevant Input Parameters

As already explained in chapter 7, the selection of input parameters plays a vital role for successful training and better testing performance of the neural networks. However, at the draw frame a large number of quality influencing parameters are involved. As previously described, they exert their individual influences as well as the combined influences involving the two or more of them together. Hence, it is not possible to eliminate any of them for reducing the number of inputs for neural networks. Therefore, all the possible quality influencing parameters were taken into consideration. This implies, the influencing parameters discussed earlier in this chapter, i.e. materials, delivery speed, break draft, main draft, break draft distance, main draft distance, doublings as well as two additional parameters, i.e. infeed sliver weight and delivered sliver weight. Here, it is important to consider the delivered sliver weight as an input parameter, because evenness values of sliver is strongly dependent on the number of fibers present in the cross-section of the sliver. A thick sliver should have a better evenness value and vice versa. The experiments were carried out to cover the most frequently industrially used range of delivered sliver weight from

4 ktex to 5.5 ktex. The following Figure 8.9 shows the schematic view of the neural network structure for the prediction of sliver CVm%.

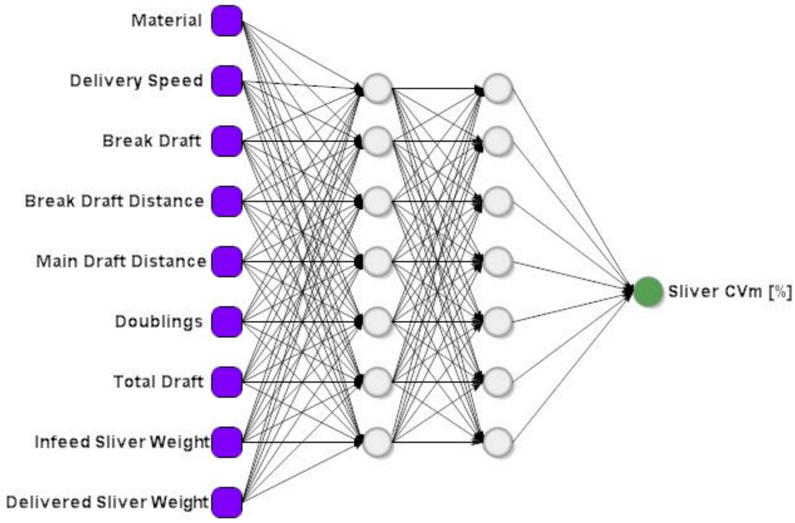

Figure 8.9: Schematic diagram of ANN Structure for Sliver CVm [%]

8.2.2 Analysis Using Artificial Neural Networks

In order to analyse the sliver quality characteristics using the artificial neural networks the analysis was conducted on the basis of sliver quality parameters. The large number of input parameters for sliver quality prediction tends to increase the networks weights and hence more experiments are needed to train a good generalized network. Therefore, it is not ideal to train different networks for every material.

Before starting the training the data was normalized between 0 and 1. For sliver quality prediction four neural networks, i.e. for sliver CVm%, sliver CV(1m)%, sliver CV(3m)% and sliver cohesion, were trained. The training matrix for the prediction of sliver quality is shown in Figure 8.10. The neural networks NN_S_CVm, NN_S_CV1m, NN_S_CV3m NN_S_Cohesion corresponds to sliver CVm%, sliver CV(1m)%, sliver CV(3m)% and sliver cohesion, respectively.

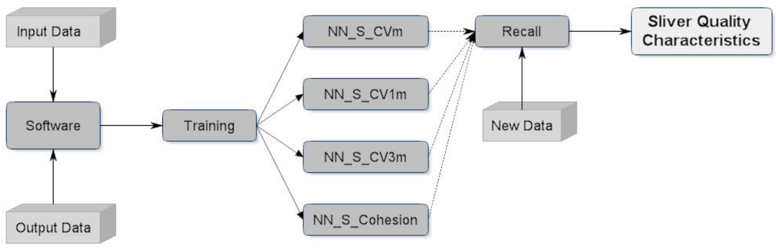

Figure 8.10: Training Matrix for Sliver Quality Prediction

8.2.2.1 Sliver CVm%

The experimental data concerning to the CVm% was subjected to the neural network training and the network "NN_S_CVm" was trained. The nine input neurons as mentioned in Figure 8.9 were selected. The numbers of neurons in 1st and 2nd hidden layers are determined using trial and error. A network having 15 hidden neurons, i.e. eight hidden neurons in first layer and seven in second hidden layer showed better performance. The other network parameters are given in the following Table 8.1.

Network Parameters	**Values**
Number of Neurons in Input Layer	**9**
Number of Neurons in First Hidden Layer	**8**
Number of Neurons in Second Hidden Layer	**7**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.02**
Momentum	**0.5**
Number of Epochs	**2000**
Stopping Error	**0.001**

Table 8.1: Network Parameters for NN_S_CVm

The test performance (hold out method) of the NN_S_CVm on the test data, i.e. unseen data is shown in Figure 8.11.

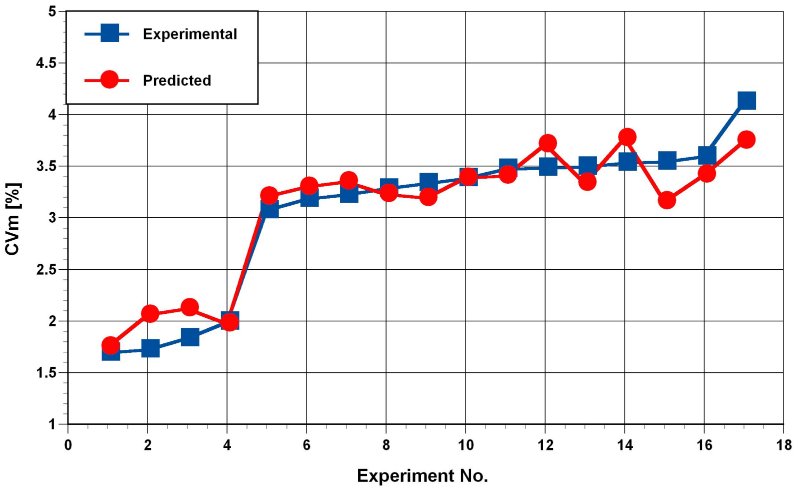

Figure 8.11: Test Set Performance of NN_S_CVm

The mean absolute error calculated is 0.165 in terms of CVm% value, which corresponds to a mean absolute error of 6.68%, as the CVm% values are normalized between 1.5 and 4. The results clearly show a highly significant resemblance between the experimental and predicted values. The mean absolute error in terms of CVm% values as resulted from 10% cross validation is calculated as 0.175% whereas that of 20% cross validation is 0.182.

8.2.2.2 CV(1m)%

The data pertaining to CV(1m)% is fed to the neural network software for training the network NN_S_CV1m. The best structure of neural network and training parameters concerning to NN_S_CV1m achieved after several attempts of training and testing are given in the Table 8.2.

After training, the network was tested using the hold-out method to check the generalization capability of the trained network. It is revealed that a mean absolute error in term of CV(1m)% value is 0.090, which indicates that there exists a strong correlation between the experimental and pre-

Network Parameters	Values
Number of Neurons in Input Layer	9
Number of Neurons in First Hidden Layer	7
Number of Neurons in Second Hidden Layer	7
Number of Neurons in Output Layer	1
Learning Rate	0.05
Momentum	0.6
Number of Epochs	2000
Stopping Error	0.001

Table 8.2: Network Parameters for NN_S_CV1m

dicted values. The following Figure 8.12 represents a very good overlapping of both curves.

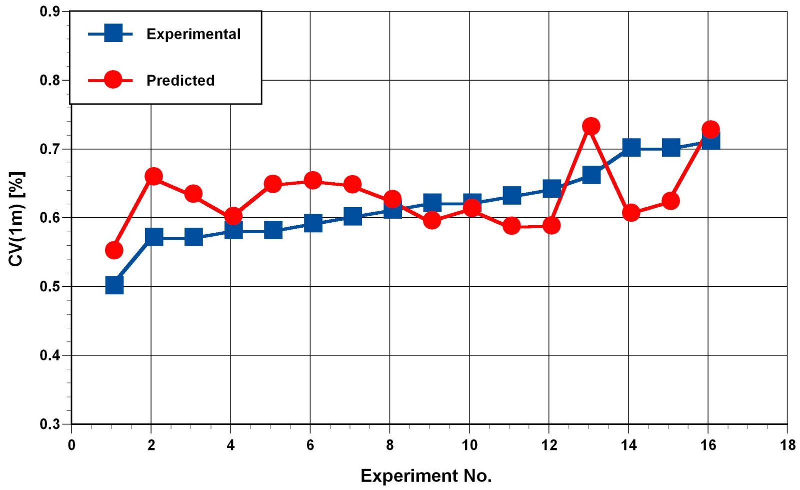

Figure 8.12: Test Set Performance of NN_S_CV1m

The mean absolute errors for cross validation analysis in terms of CV(1m)% values regarding NN_S_CV1m are mentioned as, 0.094% for 10% cross validation and 0.102% for 20% cross validation.

8.2.2.3 Sliver CV(3m)%

The data pertaining to CV(3m)% is subjected to the neural network training using the training parameters written in Table 8.3. As already described, the Matlab training algorithm ”trainbr” is used for training. The prediction accuracy of the trained network is depicted in the following Figure 8.13. Mean absolute error on the test set as given in term of CV(3m)% values is 0.0894%. The Cross validation analysis, i.e. 10%, 20% cross validations, is conducted on the data and the mean absolute error in terms of CV (3m)% values is 0.296% and 0.099% is reported respectively. The little difference between the experimental and predicted values indicates the goodness of fit for the neural networks.

Network Parameters	**Values**
Number of Neurons in Input Layer	**9**
Number of Neurons in First Hidden Layer	**6**
Number of Neurons in Second Hidden Layer	**7**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.07**
Momentum	**0.7**
Number of Epochs	**2000**
Stopping Error	**0.001**

Table 8.3: Network Parameters for NN_S_CV3m

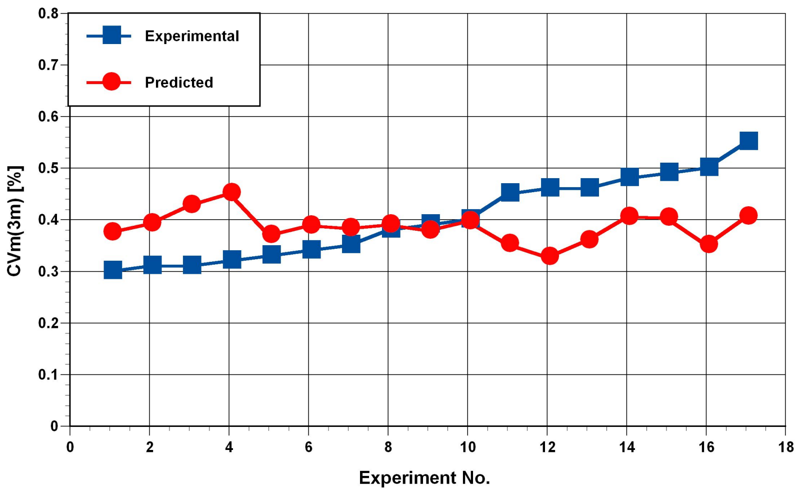

Figure 8.13: Test Set Performance of NN_S_CV3m

8.2.2.4 Sliver Cohesion

The data regarding the sliver cohesion is subjected to neural network training using the randomly selected training and test sets. The number of hidden layers and the number of nodes per hidden layer in the neural network architecture are determined using trial and error. These parameters as described in following Table 8.4 were selected.

Network Parameters	**Values**
Number of Neurons in Input Layer	**9**
Number of Neurons in First Hidden Layer	**5**
Number of Neurons in Second Hidden Layer	**6**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.09**
Momentum	**0.7**
Number of Epochs	**2000**
Stopping Error	**0.001**

Table 8.4: Network Parameters for NN_S_Cohesion

The following Figure 8.14, depicts the test set performance of the NN_S_Cohesion on randomly selected data sets. The reported mean absolute error is 0.251 [N].

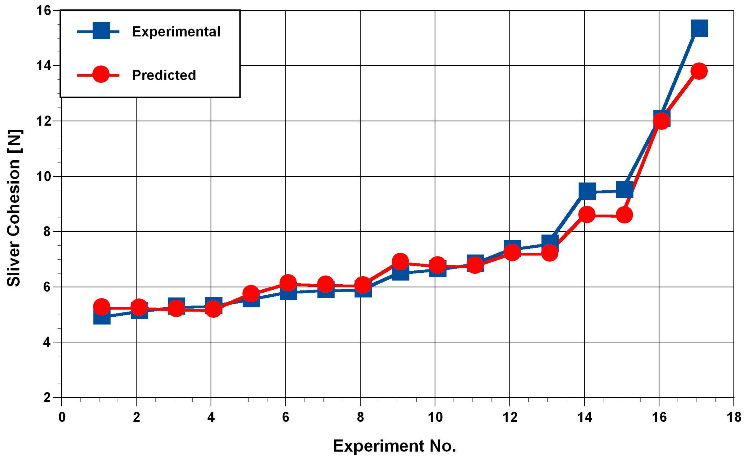

Figure 8.14: Test Set Performance of NN_S_Cohesion

The values of mean absolute error as the results of 10% cross validation and 20% cross validation are determined as 0.5623 [N] and 0.296 [N] respectively.

8.3 Conclusion

As revealed from the above mentioned analysis, the neural networks are fully capable of predicting the quality of the sliver on the basis of the various machine parameters for different materials. The low mean absolute error values for test sets and also for cross-validation point to the excellent quality of the prediction. It can also be deduced that not only it is possible to predict the quality of the sliver, but also the draw frame parameters, especially the draft zones settings can be adjusted on the basis of the predicted sliver quality. These results presented here along with the results of previous chapter, i.e., about leveling action point, corresponds to the achievement of goal of the present research.

Concluding, it can be stated that use of artificial neural networks on the draw frame was successful. The neural networks are able to understand the underlying relationships between the draw frame parameters and sliver quality characteristics. The draw frame parameters, especially the draft zones settings as well as the auto-leveling setting, i.e., leveling action point can be predicted and the trained networks are capable of producing a quality output for the unseen data given to them.

Chapter 9

Analysis of Yarn Quality

The last part of present research corresponds to the yarn manufacturing using the slivers produced at various settings of quality influencing draw frame parameters. As previously mentioned the roving frame F-15 and compact ring spinning machine K-44 were optimized separately for each material. The efforts were also made to use the optimized settings that should remain constant for all experiments belonging to each material. The objective of this practice was to minimize any influence exerted by the simplex and ring machines. So the experimental change done at draw frame should be transmitted to the yarn without any disturbances or additional irregularities due to simplex and ring spinning machines. In order to achieve this objective the Uster spectrograms of the slivers, rovings and yarns were continuously monitored. The Figure 9.1 indicates the spectrogram of roving produced using the sliver having variations due to abnormal main draft distance. The variations from 70 cm to 1 m correspond to the sliver 9-12 cm variations in sliver which are multiplied by 8.1 times draft at roving frame.

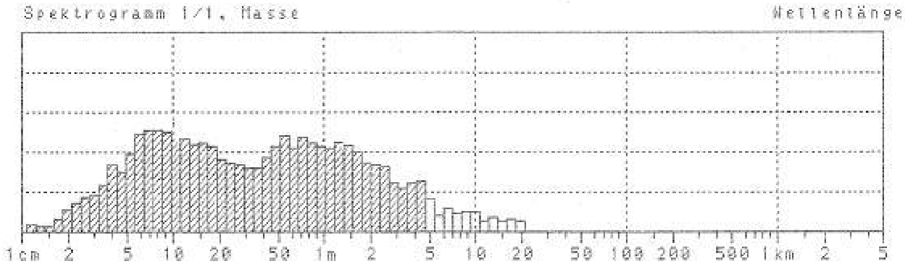

Figure 9.1: Spectrogram of Roving Produced from the Experimental Sliver

The advantage of this methodology was to avoid the use of noisy data for artificial neural networks. The noisy data can be defined as the output data having the influences that are not present in inputs. Therefore, it is highly anticipated that the true relationships between the draw frame parameters and yarn quality can be established.

Due to numerous interactions involved and large amount of experiments conducted, it is not possible to include here all the analysis concerning to the laboratory testing. Therefore, a brief analysis of the influences of draw frame parameters on the yarn quality on the basis of physical testing is presented here.

9.1 Yarn Quality Influencing Parameters

Before describing the influences of the draw frame parameters on the yarn quality characteristics, it is important to notice that a large number of yarn spinning experiments were carried out using all three materials, i.e., polyester, cotton and polyester/cotton blend (50/50). All each yarn produced, Uster evenness testing (CVm%, CV(1m)%, CV(3m)% and yarn hairiness) and tensile testing (yarn tenacity and yarn elongation) were performed. All the results can not be presented here in order to retain the volume of dissertation within limits. Therefore some of the results are being presented hereunder. Broadly speaking, the yarn evenness values, i.e., CVm%, CV(1m)% and CV(3m)% have shown similar tendancies. Therefore, all the graphs are not included. As explained in the chapter 5 "materials and methods", three different yarns, i.e. 15 tex, 20 tex and 30 tex were manufactured. However, it was not possible to manufacture 20 tex using cotton, because of high percentage of short fibers present in it. Therefore, the results presented under corresponds to 30 tex yarn, so that the connection between the different materials can be described.

9.1.1 Influence of Delivery Speed

The influence of the delivery speed at draw frame on the yarn evenness has revealed that drafting process in strongly material dependent. At the slow speeds the CVm% values remain almost constant. However, afterwards a further increase in the delivery speed causes the deterioration of the yarn evenness. It is important to mention here that the influence of the delivery speed on yarn CVm% showed almost the same trend as in case of sliver CVm%. The overall coefficient of variations for polyester are much better than cotton and polyester/cotton blend, which is due to better fiber length distributions. The high CVm% for PES/CO blend can be seen at 700 m/min. In contrast to the cotton the yarns from the polyester slivers depict a controlled worsening of the quality. This happen due to the abrupt change in the speed of the draft fibers, which is more pronounced at high machine dynamics and in the presence of higher amount floating fibers.

Effect of delivery speed of on tenacity and elongation of ring spun yarns is also material dependent. Polyester yarn having more fiber strength and manufactured from an even sliver, have produced a strong yarn of tenacity 38 cN/tex. Furthermore, an increase in the delivery speed at draw frame causes the tenacity of polyester ring spun yarn to reduce. For cotton the tenacity almost remains constant upto 700 m/min and then decrease for 900 m/min and 1100 m/min. Similarly for polyester/cotton blend, the tenacity for 300 m/min and 500 m/min remains almost constant, but a considerable desend is shown for 700 m/min speed.

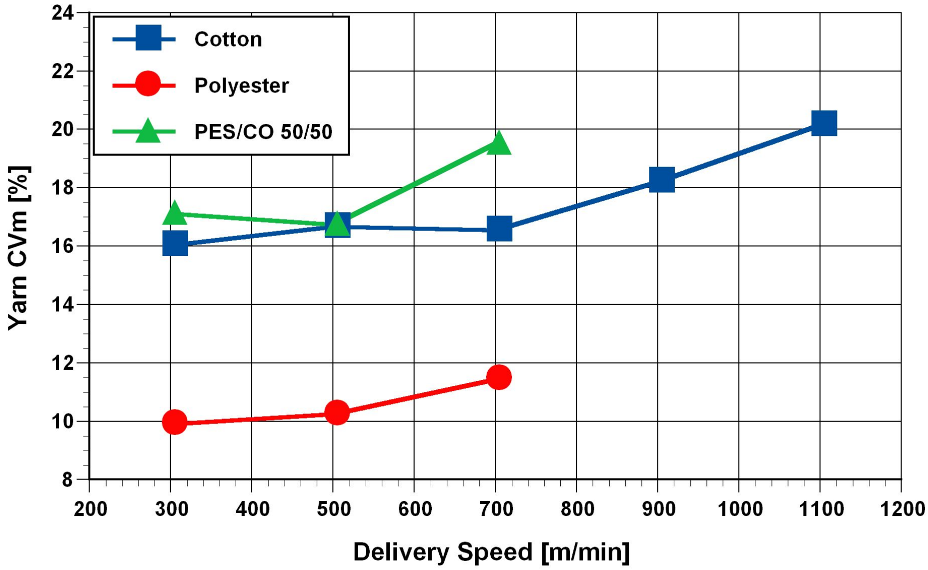

Figure 9.2: Yarn CVm [%] as Influenced by Delivery Speed

9.1.2 Influence of Break Draft

The break draft change at draw frame exerts a highly significant influence on the yarn quality. Considering the middle term variations, i.e. CV (1m)% and CV (3m)%, it is revealed that the best yarn quality can be achieved only at optimum break draft settings. The results of middle term variations for ring yarn show the resemblance with results achieve from the slivers.

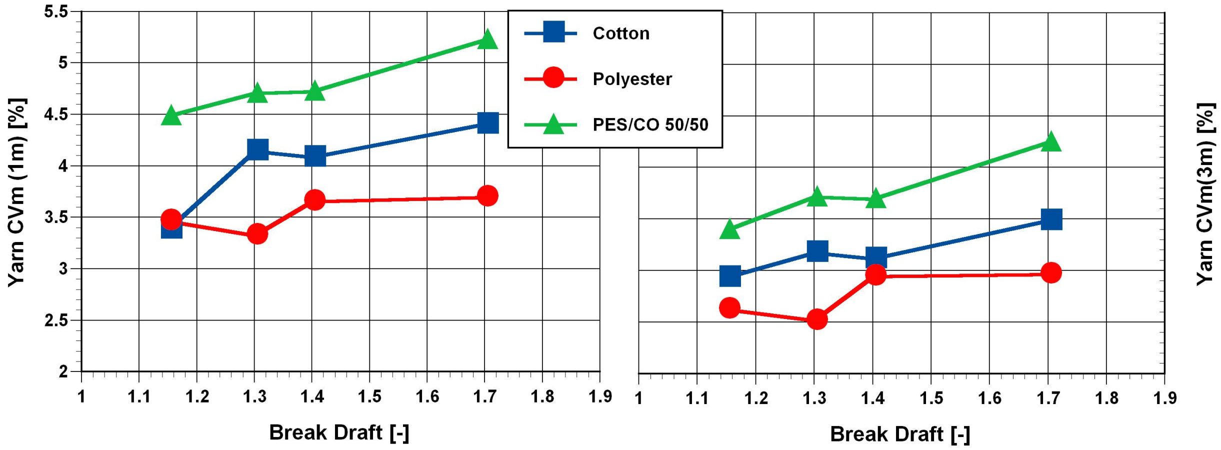

Figure 9.3: Yarn CV (1m) [%] and CV (3m) [%] as Influenced by Break Draft

As explained by the Figure 9.3, the polyester ring yarn shows a more even yarn at break draft 1.3. On the other hand, for cotton and polyester/cotton blend the lower middle term variations are achieved at minimum break draft, i.e. 1.15, which is due to the presence of high short fiber contents. Approximately the same trend is exhibited by the strength parameters of the ring spun yarns, which endorsed the fact that even yarn has more strength in comparison with the uneven yarns.

9.1.3 Influence of Break Draft Distance

The influence of the break draft distance is exhibited in the Figure 9.4. The influence exerted by break draft distance is less as compared with that of delivery speed and the break draft. However a clear trend is visible. This implies that an even yarn is achieved at the optimum break draft distance setting. This optimum is achieved at middle distance setting in case of polyester and polyester/cotton blend. On the other hand the best CVm% is resulted from the narrowest setting for cotton, i.e. 37 mm, which is due to the higher percentage of short fiber present in cotton. These short fibers tend to behave as the floating fibers in case of wider break draft zone or main draft zone settings. The short term variations in yarn evenness, i.e., CV (1m)% and CV(3m)% also show the same trend as CVm% due to variations in the break draft. The influence of break draft distance variations on the strength parameters of the ring spun yarn is relatively modest.

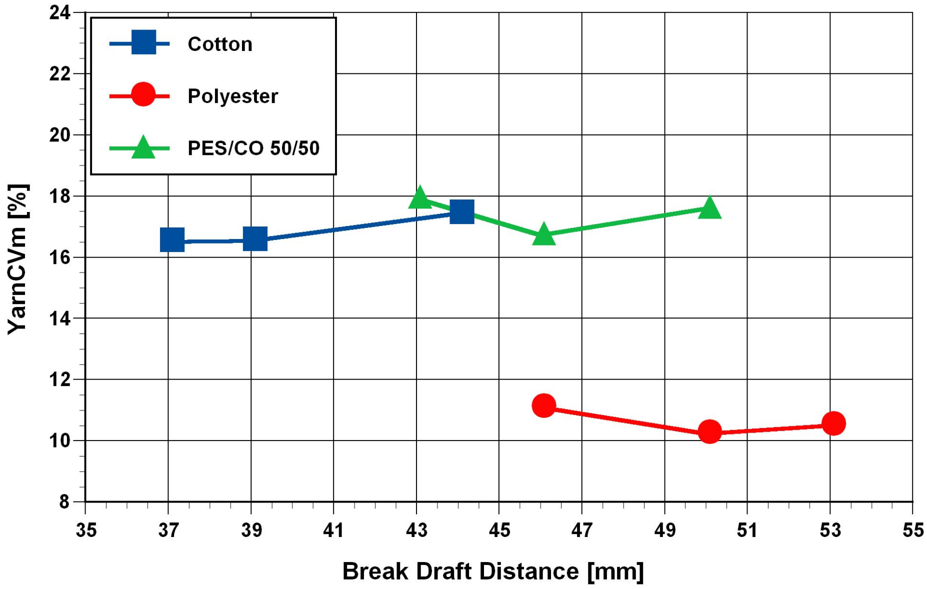

Figure 9.4: Yarn CV m [%] as Influenced by Break Draft Distance

9.1.4 Influence of Main Draft Distance

The effect of main draft distance on the quality of the ring spun yarn for CV (1m)% is presented in the figure 9.5. It is noticed that influence of main draft distance on the quality of the ring yarn is more obvious, in comparison with the effect of break draft distance. This is because of higher speeds and draft ratio between middle and front rollers in contrast with the back and middle rollers, which causes the uncontrolled motion of the fibers in the drafting zone. The wider main draft settings tend to increase the amount of floating fibers, which cause draft disturbance, especially when fibers are moving at higher speeds. On the other hand narrow settings tend cause the draft disturbances, because the resistance to drafting and acceleration of the fibers is increased. The same results are shown in the following Figure 9.5.

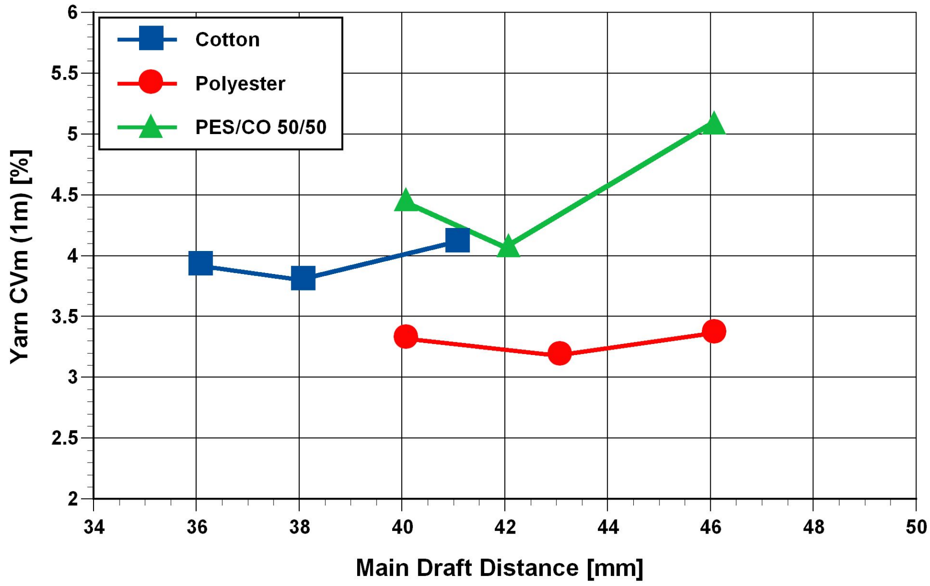

Figure 9.5: Yarn CV (1m) [%] as Influenced by Main Draft Distance

Moreover, as in case of break draft distance the influence of main draft distance on the strength parameters of the yarn is relatively small in comparison with that of delivery speed.

9.1.5 Miscellaneous Influences

In the previous section, it is explained the yarn quality is inter-linked with the drawing parameters. However, in addition to the factors mentioned there are other individual and combined influences that affect the quality of yarn and then that of final textile product.

For example, the experiments related to doublings and draft i.e., using 8 doublings and 8 times draft, have inferior yarn quality as compared with the experiments using 6 doublings and 6 times draft. An increase in total draft tends to increase the irregularities in the sliver and yarn, but it also increases the parallelization of the fibers which has a positive effect on the yarn quality. However, in the presence of high short fiber contents and / or wider main draft zone settings, the yarn evenness decreases steeply with an increase in total draft at draw frame. For instance, in case of polyester/cotton blend (50/50), the CVm% for 6 times draft is 16.72% while the measured CVm% for 8 times draft is 19.98%. In contrast, in case of polyester there is marginal increase in CVm%, i.e. 10.23% and 10.45% for 6 times and 8 times draft respectively.

Similarly, main draft distance not only exerts its individual effect on the quality of the yarn, but also the influence of main draft distance combined with that of delivery speed produce the diverse results.

Moreover, it is also inferred that short term and medium term variations in the sliver have a strong correlation with that of yarn. These results point to the fact that quality improvement achieved or defect produced at finisher draw frame will directly affect the yarn quality. However, it is conditional to the properly optimized roving and ring spinning machines, so that they may not add further irregularities to the yarn. Furthermore, it was noticed that sliver cohesion is a very important measurement parameter and it significantly correlates with the strength parameters of the yarn.

Finally, it can be deduced that there is an interconnected web of influences between the draw frame and yarn quality. Therefore, the artificial neural networks are being applied reveal these interactions.

9.2 Analysis of Yarn Quality Using Artificial Neural Networks

9.2.1 Selection of Relevant Input Parameters

The selection of input parameters plays a significant role for the successful training of artificial neural networks. The same input parameters that were used for the sliver quality analysis (materials, delivery speed, break draft, break draft distance, main draft distance, doubling and total draft) were also considered for the analysis of the yarn quality. However, infeed sliver weight and delivered sliver weight were excluded, because for the analyzing the yarn quality on the basis of draw frame parameters, all draft settings at roving and ring spinning machines were constant.

The second point of the consideration here was the yarn number. As it is already mentioned the cotton used for the present research contains a high percentage of short fibers. So, it was not possible to manufacture the 20 tex yarn from it, hence, 30 tex yarns were produced. Whereas using the other two materials both 20 tex and 30 tex yarns were manufactured. Therefore, yarn number was selected as an additional input parameter, to make the training of neural network using all the data possible. Furthermore, it is anticipated that network will be able to predict the yarn quality characteristics for all yarns between the yarn number range of 20 tex and 30 tex.

Therefore, the eight quality influencing parameters were taken into consideration as presented in the following schematic diagram 9.6.

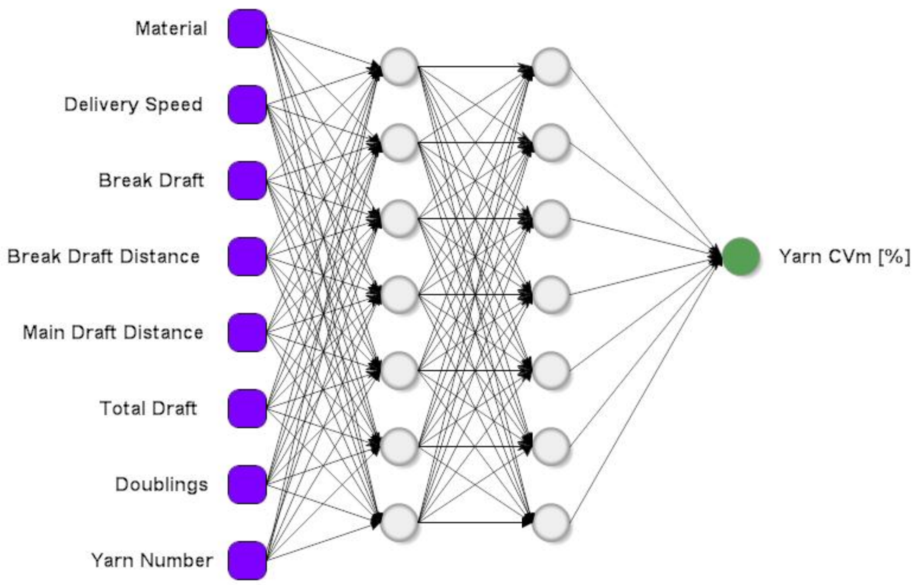

Figure 9.6: Schematic diagram of ANN Structure for Yarn CVm [%]

9.2.2 Analysis Using Artificial Neural Networks

The neural network analysis concerning to the yarn quality was performed on the basis of yarn quality parameters. As discussed before the eight input parameters are taken into account. The same procedure of normalization was adopted, i.e. data was normalized between 0 1. For predicting the yarn quality characteristics six neural networks, i.e. for yarn CVm%, yarn CV(1m)%, yarn CV(3m)% and yarn hairiness, yarn tenacity and yarn elongation were trained.. The neural networks NN_Y_CVm, NN_Y_CV1m, NN_Y_CV3m, NN_Y_Hairiness, NN_Y_Tenacity and NN_Y_Elongation, corresponds to yarn CVm%, yarn CV(1m)%, yarn CV(3m)%, yarn hairiness, yarn tenacity and yarn elongation at break respectively. The training matrix for the prediction of yarn quality is shown in Figure 9.7.

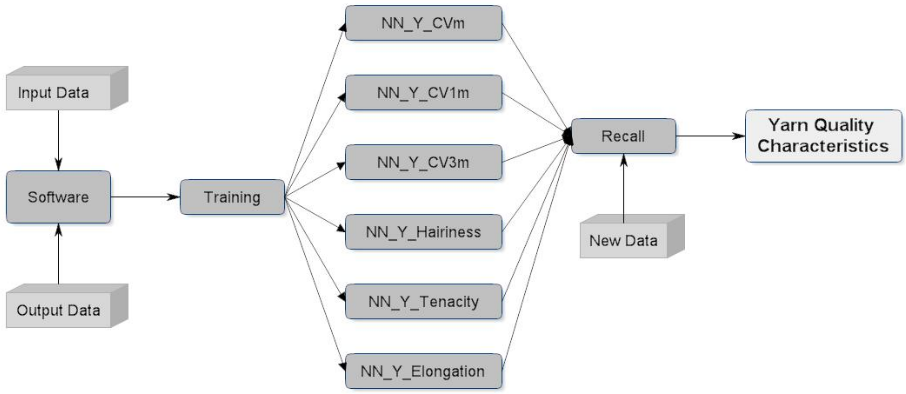

Figure 9.7: Training Matrix for Yarn Quality Prediction

9.2.2.1 Yarn CVm%

The prediction performance of yarn evenness, i.e. CVm% is presented in the Figure 9.8, while the network training parameters are given in the Table 9.1. The Figure 9.8 depicts a very close correlation between the experimental and predicted values. The mean absolute error for NN_Y_CVm for the hold-out method is calculated as 1.820% as expressed in terms of CVm%. Whereas the mean absolute error results for 10% cross validation and 20% cross validation are 1.6% and 2.393%. A high error in case of 20% cross validation may be due to the less number of experiments available for the training.

Network Parameters	**Values**
Number of Neurons in Input Layer	**8**
Number of Neurons in First Hidden Layer	**7**
Number of Neurons in Second Hidden Layer	**6**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.04**
Momentum	**0.5**
Number of Epochs	**2000**
Stopping Error	**0.01**

Table 9.1: Network Parameters for NN_Y_CVm

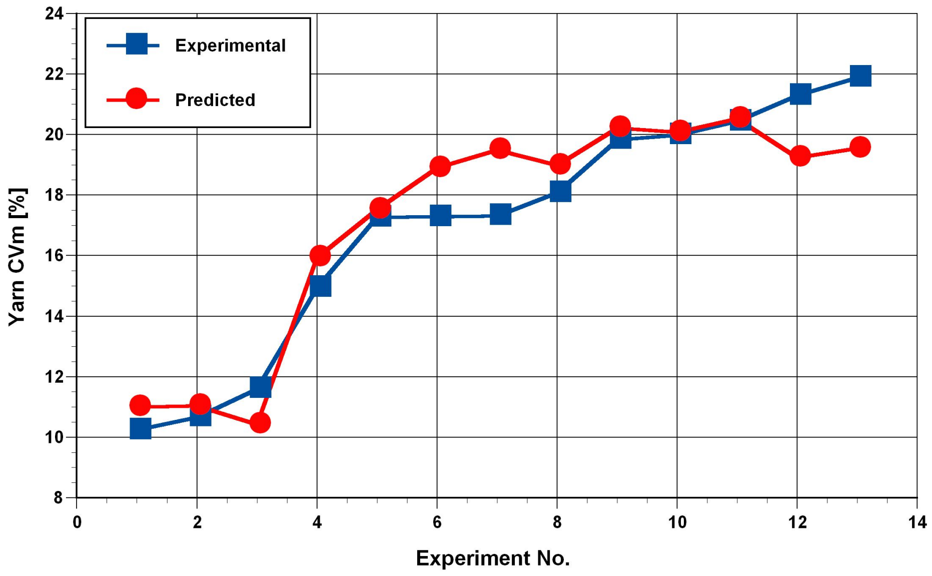

Figure 9.8: Test Set Performance of NN_Y_CVm

9.2.2.2 Yarn CV (1m)%

The data pertaining to medium term variations, i.e. CV (1m)% was subjected to neural network training. The following network parameters given in Table 9.2 are achieved by trying the various combinations of hidden neurons learning rate and momentum. The network structures having minimum error were then tested using the cross validations. At the end the network having the minimum generalization error was selected.

Network Parameters	**Values**
Number of Neurons in Input Layer	**8**
Number of Neurons in First Hidden Layer	**5**
Number of Neurons in Second Hidden Layer	**6**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.09**
Momentum	**0.7**
Number of Epochs	**2000**
Stopping Error	**0.001**

Table 9.2: Network Parameters for NN_Y_CV1m

The test performance of the trained network in represented in Figure 9.9. The mean absolute error as expressed in terms of yarn CV (1m)% is 0.1856%, whereas mean absolute error recorded in case of 10% cross validation is 0.1822%.

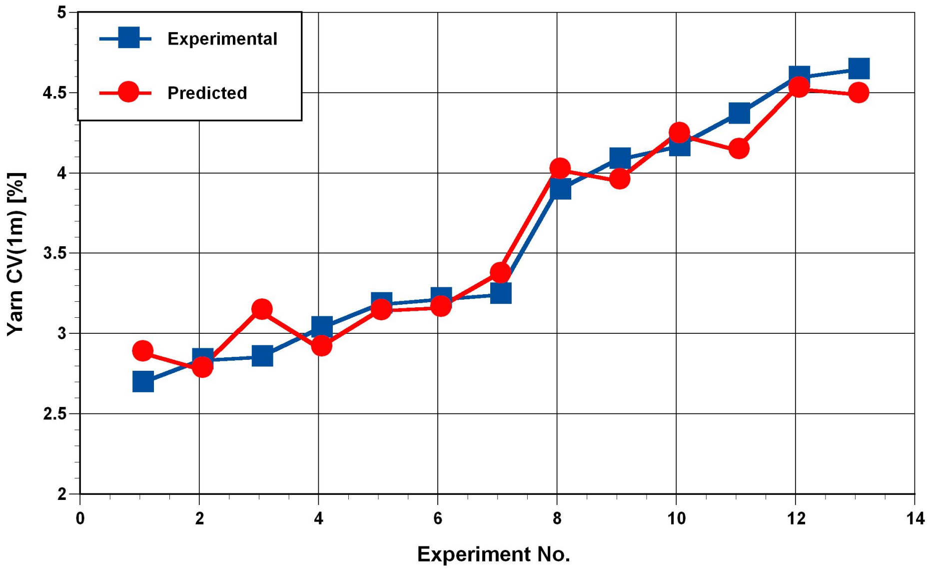

Figure 9.9: Test Set Performance of NN_Y_CV1m

As usual, the 20% cross validation was also performed and a mean absolute error of 0.3132 was reported, which is on the higher side because for each training phase about 20% data was not available for training.

9.2.2.3 Yarn CV (3m)%

The data regarding the yarn CV (3m)% is subjected to neural network training firstly using the randomly selected training and test sets. The number of hidden layers and the number of nodes per hidden layer in the neural network architecture are determined using trial and error. These parameters as described in following Table 9.3 were selected. The neural network NN_Y_CV3m trained on the basis of data concerning yarn CV (3m)% showed a very good test performance.

Network Parameters	Values
Number of Neurons in Input Layer	**8**
Number of Neurons in First Hidden Layer	**5**
Number of Neurons in Second Hidden Layer	**6**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.1**
Momentum	**0.7**
Number of Epochs	**1000**
Stopping Error	**0.001**

Table 9.3: Network Parameters for NN_Y_CV3m

The following Figure 9.10, depicts the test set performance of the NN_Y_CV3m on randomly selected data sets. The reported mean absolute error is 0.0935% in term of CV (3m)%. The values of mean absolute error as the results of 20% cross validation, 10% cross validation and Leave-one-out cross validation are determined as 0.0994%, 0.1965% respectively.

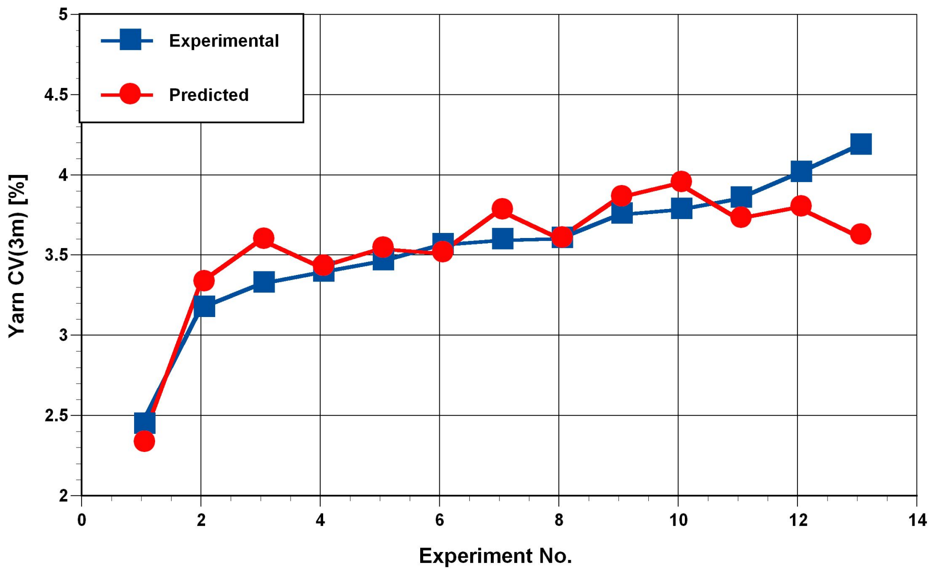

Figure 9.10: Test Set Performance of NN_Y_CV3m

9.2.2.4 Yarn Hairiness

NN_Y_Hairiness corresponds to the trained neural network for the prediction of yarn hairiness on the basis of draw frame parameters. It is well known fact that yarn hairiness is mainly dependent on fiber length distributions of the processed materials. Also for these experiments the compact ring spinning machine K 44 was used, that is why the hairiness value are lower than that of conventional ring spinning machine. However, the underlying association of the draw frame parameters and the yarn hairiness is completely understood by the neural networks as shown in Figure 9.11. Therefore a mean absolute error of 0.2321 in terms of hairiness value was observed. Similarly the 10% cross validation mean absolute error was reported as 0.213 and that of 20% cross validation is 0.4216.

Network Parameters	**Values**
Number of Neurons in Input Layer	**8**
Number of Neurons in First Hidden Layer	**5**
Number of Neurons in Second Hidden Layer	**6**
Number of Neurons in Output Layer	**1**
Learning Rate	**0.1**
Momentum	**0.7**
Number of Epochs	**1000**
Stopping Error	**0.001**

Table 9.4: Network Parameters for NN_Y_Hairiness

The network parameters are given in the table, and the Figure 9.11 indicates the difference between the experimental and predicted values and confirms a good fit of the neural networks in case of yarn hairiness.

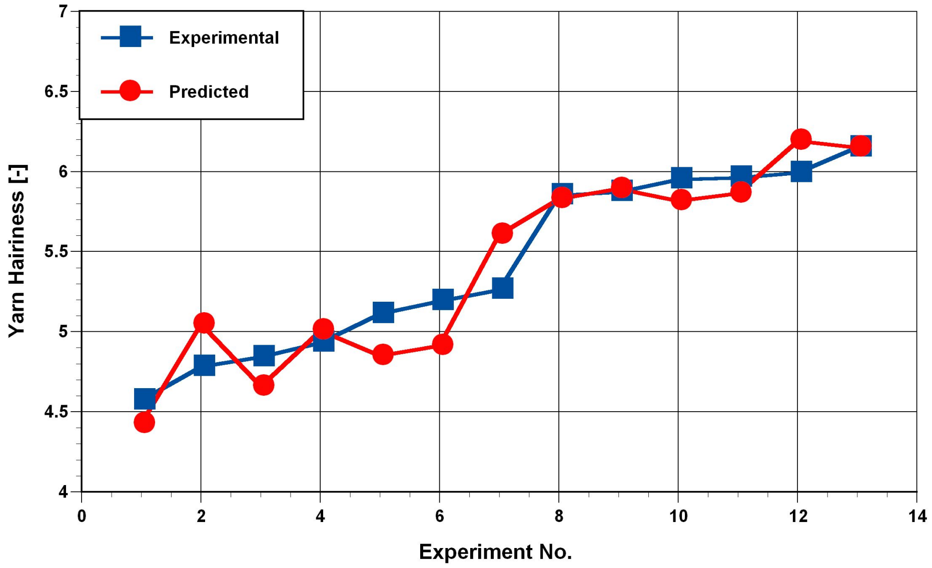

Figure 9.11: Test Set Performance of NN_Y_Hairiness

9.2.2.5 Yarn Tenacity

NN_Y_Tenacity corresponds to a 7-5-6-1 network structure as shown in the following Table 9.5. NN_Y_Tenacity represents the neural network that is trained to understand the complex relationships between the draw frame parameters and the yarn tenacity while the yarn twist for each material remains constant. The following Figure 9.12 shows a very good overlapping of the experimental and predicted values and a mean absolute error of 1.103 [cN/tex] is reported. The Figure 9.12 also represents the test performance of the NN_Y_Tenacity at three different levels. The lowest yarn tenacity pertain to the cotton, while the middle and high values are for polyester/cotton blend (50/50) and polyester respectively. In all three cases a very good association between the experimental and predicted values have been achieved. The mean absolute errors for 10% and 20% cross validations are 1.213 [cN/tex] and 2.289 [cN/tex] respectively.

Network Parameters	Values
Number of Neurons in Input Layer	8
Number of Neurons in First Hidden Layer	5
Number of Neurons in Second Hidden Layer	6
Number of Neurons in Output Layer	1
Learning Rate	0.09
Momentum	0.7
Number of Epochs	1000
Stopping Error	0.001

Table 9.5: Network Parameters for NN_Y_Tenacity

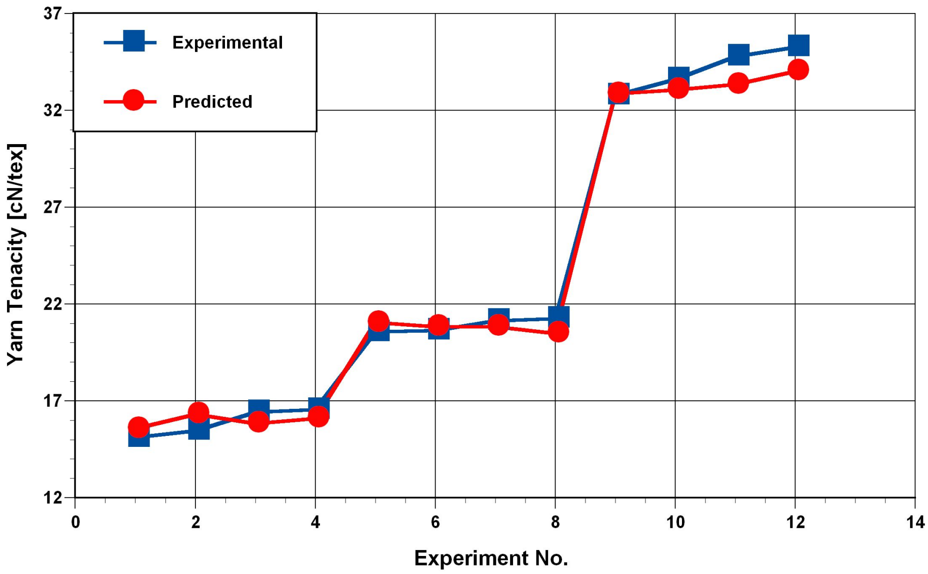

Figure 9.12: Test Set Performance of NN_Y_Tenacity

9.2.2.6 Yarn Elongation

The yarn elongation at break is another important strength parameter for the yarn quality. NN_Y_Elongation was trained to correlate the draw frame parameters and the yarn elongation. It was observed that neural network can be trained on the basis of draw frame settings to predict the yarn elongation.

Network Parameters	Values
Number of Neurons in Input Layer	8
Number of Neurons in First Hidden Layer	8
Number of Neurons in Second Hidden Layer	5
Number of Neurons in Output Layer	1
Learning Rate	0.02
Momentum	0.5
Number of Epochs	1000
Stopping Error	0.003

Table 9.6: Network Parameters for NN_Y_Elongation

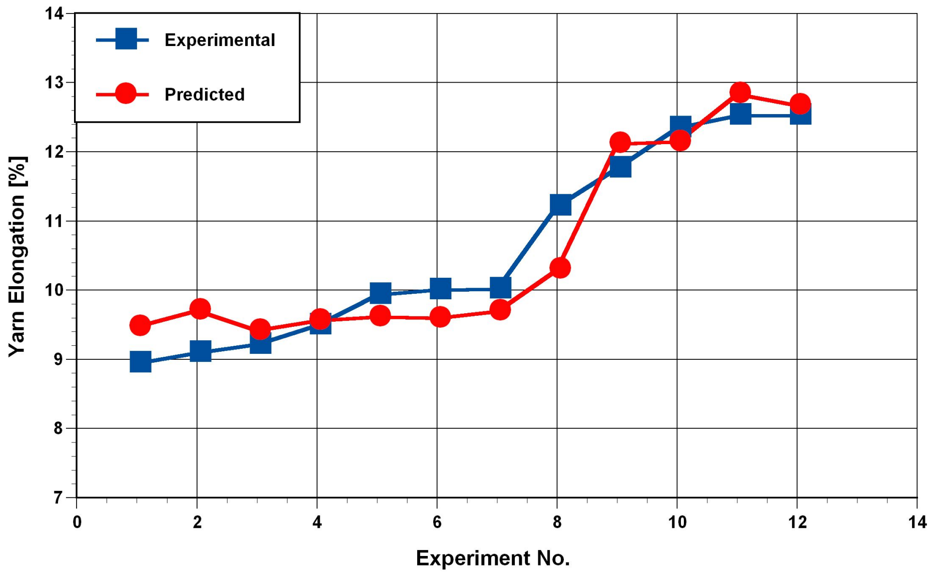

Figure 9.13: Test Set Performance of NN_Y_Elongation

A 8-8-5-1 neural network reported a mean absolute error of 0.2736% as expressed in term of yarn elongation. The results are being presented in the following Figure 9.13. The mean absolute errors in terms of elongation are 0.3155% and 0.3236% as reported for 10% and 20% cross validations respectively.

9.3 Conclusion

The variations in the draw frame parameters influence the yarn quality characteristics, i.e. the evenness, hairiness and strength characteristics of yarn. However, these effects are strongly material dependent. In this part of research natural fiber (cotton), man-made fiber (polyester) and their blend (polyester/cotton 50/50) were taken into consideration. All three materials behave different under the effect of the changes made at draw frame. The above mentioned results also revealed the significance of draw frame, from where the quality of the yarn can be precisely controlled.

These influencing draw frame parameters affect the yarn quality characteristics individually, as well as collectively involving a combined effect of two or more than two parameters. For instance, an increase in delivery speed at draw frame significantly deteriorates the yarn-CV-values. Same is the case with a non-optimized break draft settings, which largely increase the yarn-CV-values. Similarly a faulty main draft distance great influences the yarn quality, however, the intensity of this effect increases at high machine dynamics. Therefore, main draft distance along with delivery speed also exerts their combined influence.

Moreover, it is also observed that yarn quality is strongly connected with the sliver quality. The influences of draw frame variables on the sliver quality are largely similar to their effects on yarn quality. Therefore, it can be said that the quality of finisher draw frame sliver is a reflection of yarn quality.

The use of artificial neural networks for understanding the underlying relationships between the draw frame parameters and yarn quality as well as its predicting on the basis of draw frame parameters is successful. The trained networks are able to predict the yarn quality characteristics and mean absolute errors of less than 5% are calculated between the experimental and predicted values. This implies that a confidence level of 95% has been achieved.

Chapter 10

Concept Development of Intelligent Spinning Machines

10.1 Applications of Research

The successful results and its analysis on the basis of artificial neural networks (ANN) not only confirm the ability of neural networks to learn the complex relationship associated with the spinning process but also their potential to make a correct prediction of sliver and yarn quality. This will in turn enable the user to predict the optimum settings based on the sliver and yarn quality. The intelligent shortening of leveling action point (LAP) search range, the prediction of sliver and yarn quality and possibility to set the draw frame on the basis quality parameters lead towards the achievement of the research objectives. This implies the goals of the present research which corresponds to the development of a prediction system are successfully met.

The implication of the presented prediction system based on the analysis triangle has achieved these fruitful results.

- The leveling action point search can be reduced to one fourth, which essentially decreases the material requirements for settings, thus reducing the amount of waste produced in the spinning mill.
- The precision and intelligent setting of leveling action point can strongly enhance the sliver and ultimate yarn quality.
- In case of marginal change in LAP influencing variables a manual search can be performed using a precise 'start value' recommended by neural networks.
- The optimization of draw frame, which is vital for producing a quality yarn, can be done on basis of sliver and yarn quality characteristics.
- The prediction system based on artificial neural networks can be very helpful to greatly reduce the range of trial error method for optimizing the draw frame within sensible limits.
- The need of extremely experienced and skillful managers in the spinning industry can be reduced and the better quality results can be achieved with less experienced managers. Additionally the human errors can be avoided.
- The precise adjustment of draw frame settings on the basis of sliver and yarn quality characteristics can greatly help to achieve the quality related objectives in spinning industry.
- The intelligence of artificial neural networks can be therefore induced in the draw frame, to make it capable of making intelligent decisions in cases of change of material or infeed sliver variations etc.

10.2 Concept for Intelligent Spinning Machines

The development of computer-aided manufacturing systems has led to the evolution of computer integrated manufacturing. Now, the manufacturing systems are trying to achieve more and more flexibility in product design, process planning, scheduling, process control, and quality assurance. Therefore, it is anticipated that next phase will be the development of intelligent manufacturing system. This can be accomplished through intelligent system that can adapt to changes in their environment (like variations in infeed materials etc).

The quality of yarn is largely depended on the quality of raw material from which it is being manufactured. The fiber characteristics as well as the blending of variety of fibers play a vital role not only towards the quality of end product but it also influences the manufacturing costs. Some studies have been carried out to predict the yarn quality with the help of fiber characteristics using artificial neural networks. Thus, predicting the appropriate blend as well as fiber characteristics for required yarn.

However, the spinning process consists of a set of inter-related operations performed by different machines and consequently various intermediate products (like card sliver, drawing sliver, roving etc.) are produced. Therefore, the fibers - machines interactions become very important. Setting of machine intelligently in accordance with the material being processed is the key to optimization of spinning process. In present research three different prediction tasks (leveling action point, sliver characteristics and yarn characteristics) were successfully performed using the drawing frame parameters as input to artificial neural networks as shown in Figure 10.1. This implies that the neural networks are capable of understanding the fibers - machine interactions. Also through the use of trained artificial neural networks the draw frame can be intelligently set on the basis of sliver as well as yarn quality characteristics. In conclusion, the ability of artificial neural network for the using in spinning process is proved.

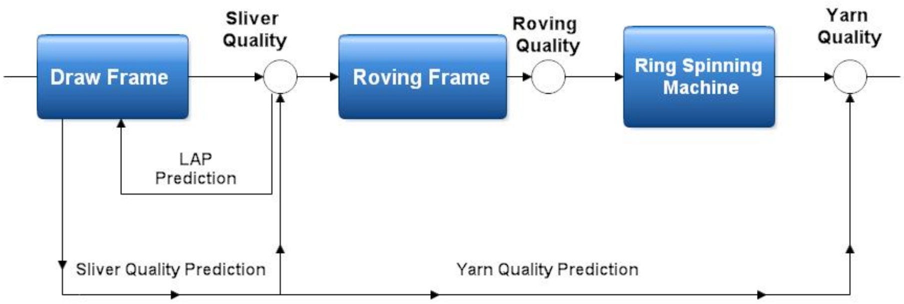

Figure 10.1: Objective Achieved by Present Research

On the basis of presented results, the concept for intelligent spinning machines is proposed here for further studies in present area of research. The said system based on artificial neural networks corresponds to the intelligent environment that should have the following characteristics.

1. The intelligent system should be customer driven, i.e., the yarn quality as well as the other requirements like scheduled delivery date provided by the customer should be emphasized in the system.
2. The optimum machine settings and process parameters can be predicted with respect to infeed material and quality produced.
3. The properties of raw materials / infeed materials can be determined on the basis of end product.
4. The quality of each intermediate product should be assured.

The Figure 10.2 represents the schematic diagram of the intelligent system. It shows the spinning process from card sliver to yarn involving three machines, i.e. draw frame, roving frame and ring spinning machine. Three individual trained neural networks (ANN for draw frame, ANN for roving frame and ANN for ring spinning machine) are connected to individual machines. These three networks should be capable to predicting the quality characteristics of product produced at each machine on the basis of infeed material characteristics and machine settings.

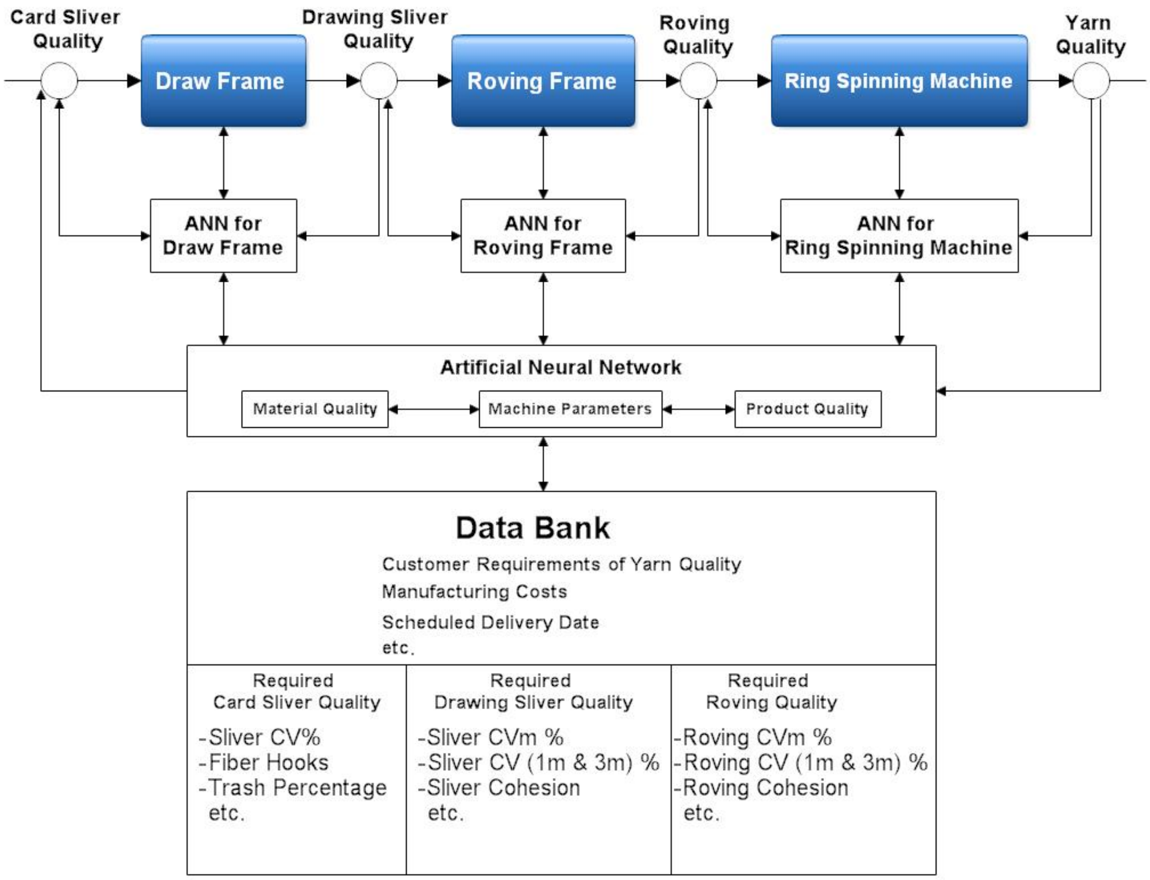

Figure 10.2: Concept for Intelligent Spinning Machines

Conversely, by entering the different levels of machine parameters along with infeed material characteristics to these trained neural networks and calculating their responses on the produced quality, the machines can be set optimally on the basis of required quality. Also, these trained neural networks should provide the additional advantage of predicting the optimum machine settings without trial and error, thus saving the time and material.

In the next step, these three ANNs will be connected to another trained neural network which in turn should be connected to a data bank. The data bank should include the information about the quality requirements for yarn, provided by the customer, along with scheduled delivery data and manufacturing costs. Moreover, the required card sliver, drawing sliver and roving qualities should also be entered in the data bank. Furthermore, the information from individual machine networks should be shared. All these components will comprise an intelligent system which can be capable of providing the many benefits. The following two scenarios are considered here.

Forwards (Card sliver to Yarn)

It is anticipated that the proposed intelligent system should be capable of predicting the yarn quality on the basis of card sliver characteristics and machine settings. Thus, the quality requirements provided by the customer can be compared with the predicted quality. This comparison can provide the opportunity to decide whether it is possible produce the yarn with customer specified characteristics or not. Thus, the potential of raw material and the machinery can be truly judged.

Backwards (Yarn to Card Sliver)

In backward direction, the intelligent system can offer many advantages. The determination of optimum settings for required quality is one of them. Suppose that customer requires cotton yarn having CVm equals to 13 %. Using the neural network based intelligent system, it can be predicted that for given raw material such yarn can be produced only with a drawing sliver of CVm less than 3 %, which is not possible at higher draw frame speeds like 1000 m/min. Therefore, the speed of draw frame should be reduced to achieve the required quality. At this stage, the information regarding the scheduled date of delivery and manufacturing costs already provided to the intelligent system can calculate that economical viability of production. Also, the accepted delivery date with the scheduled delivery time can be considered. Furthermore, the quality of each intermediate product can be assessed. Therefore the quality of whole spinning chain will be assured.

On the basis of results achieved by present research, the concept of the intelligent system for spinning machines has been proposed. It is anticipated that with the use of artificial intelligence the spinning machines can help them to get involved in the decision making process for the optimization of spinning process.

Chapter 11

Summary and Outlook

In the scope of present research work, draw frame RSB-D40 was selected as the central spinning machine where quality of the yarn and the ultimate textile product can be controlled. The work was divided into three phases, pertaining to leveling action point (LAP), sliver quality and yarn quality. Mainly the work was focused on polyester, cotton and polyester/cotton blend (50/50), while viscose was also used for the phase regarding leveling action point.

The LAP searches were carried out automatically at the RSB-D40 using Rieter Quality Monitor (RQM). On the other hand the quality characteristics of the sliver and yarn were determined by physical testing in the laboratory. For all three phases the analysis on the basis of laboratory results as well as the analysis based on artificial neural network was performed. In order to train the neural networks, the software using Matlab was developed.

In the first phase regarding LAP, it is inferred that materials, feeding speed, infeed tension, break draft and break draft distance are significant LAP influencing parameters. Sliver deflection bar setting also geometrically changes the LAP. Moreover, the different blend ratios of polyester/cotton have LAP values comparable with that of polyester/cotton blend 50/50. Also it was revealed that 100 m/min increase in delivery speed will result in 6 mm shorter LAP value. The analysis conducted on the basis of artificial neural network has shown that mean absolute error remains within 5 % for all the investigated materials (cotton carded 1st passage, cotton carded 2nd passage, polyester, viscose and different blending ratios of polyester/cotton blend). Moreover, the individual predictions are with in 12 mm limits, which refer to 2 points each in both plus and minus directions. On the basis of achieved results a neural network based function "NEUROset" has been proposed, which requires only 5 search points. Furthermore, the "start value" for manual LAP search can also be proposed using the neural networks.

The laboratory results concerning to sliver quality in second phase of the work have shown individual as well as the combined effects of the draw frame parameters. Delivery speeds, break draft, break and main draft distances, doublings, total draft have significant influence on the sliver quality. However, these influences are strongly dependent on the type of material and fiber length distributions. With the help of neural networks the individual and multiple interactions between the draw frame variables and the sliver quality can be determined and the prediction of sliver quality can be made. The low mean absolute error values achieved for test sets and also for cross-validations correspond to the excellent quality of the prediction. It is not only possible to predict the quality of the sliver, but also the draw frame parameters, especially the draft zones settings can be adjusted on the basis of the predicted quality.

In the third phase the yarn quality was assessed on the basis of draw frame parameters. The slivers manufactured in second phase were processed to convert them into yarn. The yarn of 20 tex and 30 tex were manufactured, in order to cover the industrially most frequently used range of yarn numbers. It was revealed from the laboratory results that the draw frame parameters that have affected the sliver quality also showed their effects in the yarn characteristics. Similar to the sliver quality analysis, the individual and combined effects of the draw frame parameters can be seen. In addition, it was observed that yarn quality is strongly connected with the sliver quality. Therefore, quality of finisher draw frame sliver is a reflection of yarn quality. The use of artificial neural networks for understanding the underlying relationships between the draw frame parameters and yarn quality as well as its predicting on the basis of draw frame parameters is successful. The trained networks are able to predict the yarn quality characteristics and mean absolute errors of less than 5 % are calculated between the experimental and predicted values.

This research work is can be applied directly to the spinning industry for precise settings, waste reduction and time required to optimize the machines. The intelligent machine can effectively compensate the conventional trial and error method used in the spinning industry for achieving the optimized machine settings. Additionally, the future intelligent spinning machines equipped with artificial intelligence will be able to take part in the decision making process in spinning industry and capable to adopt themselves accordingly for material change or infeed variations.

The concept of intelligent spinning machines has been proposed, which should be the next step towards the further development of the spinning machinery after the inclusion of sensor systems and full scale automation to avoid the negative influence of worker on the quality of the product. The involvement of machine in the decision making process in spinning industry can bring out the fruitful results and disadvantages like less experienced staff and human errors can be avoided. Also "learning from experiences" ability of artificial neural networks can be fully utilized in the spinning industry.

In broader prospective, the significant results achieved during this research work pave the way for the utilization of the artificial neural networks for the other textile processes, like manufacturing processes following spinning, e.g. knitting and weaving, or new textile fields like electro-spinning.

List of Figures

List of Tables

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