



HAL
open science

Modeling of textile manufacturing processes using intelligent techniques: a review

Zhenglei He, Jie Xu, Kim Phuc Tran, Sébastien Thomassey, Xianyi Zeng, Changhai Yi

► **To cite this version:**

Zhenglei He, Jie Xu, Kim Phuc Tran, Sébastien Thomassey, Xianyi Zeng, et al.. Modeling of textile manufacturing processes using intelligent techniques: a review. *International Journal of Advanced Manufacturing Technology*, 2021, 116, pp.39 - 67. 10.1007/s00170-021-07444-1 . hal-03544251

HAL Id: hal-03544251

<https://hal.science/hal-03544251>

Submitted on 8 Feb 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Modeling of Textile Manufacturing Processes Using intelligent techniques: a review

Zhenglei He¹, Jie Xu^{2,3}, Kim Phuc Tran¹, Sébastien Thomassey¹, Xianyi Zeng¹, Changhai Yi^{2,3}

¹*ENSAIT, GEMTEX – Laboratoire de Génie et Matériaux Textiles, F-59000 Lille, France*

²*School of Textile Science and Engineering, Wuhan Textile University, 430200, Wuhan, China*

³*National Local joint Engineering Laboratory for Advanced Textile Processing and Clean Production, Wuhan Textile University, 430200, Wuhan, China*

Abstract: The development of manufacturing process modeling has attracted growing attention from the textile industry as the need for quickly exploring a textile manufacturing process is increasingly costly along with the growing complexity in the process. More and more researches shift their attention from classic methods to the intelligent techniques for process modeling as the traditional ones can hardly depict the intricate relationships of numerous process factors and performances. In this study, the literature investigating the process modeling of textile manufacturing is systematically reviewed. The structure of it is in line with the procedure of textile processes from yarn to fabrics, and to garments. The analysis and discussion of the previous studies are conducted from the different applications in a different process. The factors and performance properties considered in process modeling are collected in comparison. The considerations of the previous studies in terms of inputs' relative importance, feature selection, modeling techniques, data distribution and performance estimations are analyzed and summarized. On the basis of the summaries of more than 128 related articles from the point of views of textile engineering and artificial intelligence, the limitations, challenges and future perspectives in this issue are also concluded.

Keywords: Modeling; Textile Manufacturing; Process; Intelligent; Review.

1. Introduction

Textile manufacturing is a typical traditional manufacturing industry that generally is based on small and medium enterprises with limited capacity on investing advanced engineering technologies. It relies heavily on product customization and short manufacturing cycles as distributors and consumers are increasingly looking for variety and personalization. The arising global competition press the companies in this industrial field to face the challenges of cost reduction and performance improvement, while the growing public concerns on the environment, on the other hand, impose further bounds to the textile manufacturers on the exploitation of power, water and associated resources. There is a strong need to develop novel methods in order to improve the textile manufacturing process.

Modeling techniques, first of all, can make a difference in this regard for understanding the intricate relationships between various process parameters and performance properties. However, due to the short manufacturing cycle and the wide range of product variety, textile manufacturing processes manage numerous large inputs and possible outputs variables and always feed with a complex interdependence between variables; it is highly unlikely that an exact mathematical model will ever be developed. Concerning the statistical models, because of their sensitivity to the rogue data, it is also rarely used in any branch of the textile industry (Tehran and Maleki 2011). As such kinds of classical methods essentially based on a formalization of physical laws and analysis of measured data, the mechanistic models proposed by prior researches overtly simplify the case to achieve manageable equations on the basis of a sacrifice on accuracy. These traditional methods based models can hardly even represent the vast volume of process parameter-related data, not mention to be applied in the textile manufacturing scenario. Intelligent techniques that can learn from data, by contrast, often deal with uncertainty and imprecision related to human knowledge on products and processes, can make a significant difference in this issue (X. Zeng et al. 2007).

Since the textile manufacturing is consist of a very long chain of processes from raw material to the final product, the probable combinations of processes and parameters could be stochastic and immense when factors of the targeted performance are varied in any respects. Furthermore, the known and unknown factors cannot be interpolated and extrapolated in a reasonable way based on experimental observations or mill measurements due to the shortage of knowledge on the evaluation of the interaction and significance at weight contributing from each variable (Tehran and Maleki 2011). According to the modeling of a specific textile manufacturing process on the basis of intelligent techniques and empirical data, the performance results of proposed solutions can be properly simulated. So that the textile manufacturers can reduce the

experimental effort and physics-based process simulations in the optimization of a textile process solution. Therefore, the use of intelligent techniques is strongly related to the nature of the problem of interest.

This paper aims to briefly overview the current state of the art in applying intelligent techniques in the modeling of textile manufacturing processes. It focuses on the key textile manufacturing processes from yarn spinning to textile finishing where the intelligent techniques have been widely investigated. Meanwhile, the researches of these intelligent techniques for modeling are comparatively reviewed in terms of problem formulation and system architectures. Finally, the existing limitations and challenges, as well as future perspectives of intelligent techniques for modeling textile manufacturing process are discussed in detail to provide a base for further research.

2. Textile Manufacturing Processes

2.1 A reminder about the textile manufacturing processes

The task of textile manufacturing processes is to add value in fiber materials by means of converting the fibers into the yarns, fabrics, and finished products including garments. Among which, yarn is a semi-finished textile product for fabric-making, and yarn manufacturing was rooted in natural fibers obtained from natural plant or animal sources but dramatically expanded to the synthetic fibers nowadays. Yarn manufacturing comprises a series of processes from fiber assorting, followed by the series of continuous mechanical operations of bale opening, blending, carding, drawing, roving, and spinning (Uddin 2019). To achieve the most important properties of yarns including strength, elongation and evenness, the first half of these processes generally perform the function of blending and removing impurities of the fibers to obtain the fiber slivers, while the second half of these operations mainly play the role of mixing, straightening, orienting the fibers and drafting, twisting the slivers to strengthen and forming the yarns. The designed specification of yarns is depended upon the end-use requirement of fabric to be produced for woven or knitted end products (e.g., apparel or industrial fabrics). An introductory work published by Lawrence (Lawrence 2003) has introduced the fundamental technology of spun yarn in detail with the coverage of the rudiments of staple-yarn technology, the manufacturing process, the raw materials, and the production processes for short-staple, worsted, semi-worsted, woolen spinning, doubling, and specialty yarn, in where some of the interesting advanced topics are also discussed range from new development in fiber preparation technology, carding technology, roller drafting, ring spinning and open-end rotor spinning to air-jet spinning.

The textile fabric is at least a two-dimensional structure produced by fiber/yarn interlacing in terms of the fibrous structure of woven, nonwoven, and knitting in general. Weaving was the traditional principal source for fabric production, it joins the yarns from warp and weft directions to form the fabric with a different structure such as basic plain, twill, and satin or the fancy structures like pile, jacquard, dobby, and gauze. Because of the excellent performance in comfort, function and aesthetics, knitting also takes a considerable share in the textile market following the woven. It is implemented by inter-looping one (weft knitting) or one set of yarns (warp knitting) in fabric and garment manufacturing. For the convenience of fabric manufacturing of weaving and knitting, there are a number of pre-processes on yarns and finishing processes on fabrics involved, e.g. winding, warping, sizing, and singeing, desizing, dyeing etc. these processes facilitate the operations of weaving and knitting by strengthening and organizing yarns, and promote the quality of fabrics in terms of stability, aesthetics, comfort as well as functionalize the products (by coating or other finishing techniques), respectively. Nonwoven fabrics are increasingly consumed in recent years as found effective and economic in industrial and home applications. Nonwoven manufacturing doesn't rely on constructing yarn structures but felting and bonding by entangling fiber or filaments to form the web and consolidate the web. The most often used processes of nonwoven manufacturing are constituted of web formation by means of textile carding or wet-laid process of staple fiber and spun-laid of filaments, as well as web consolidation by needle-punching, stitch bonding, thermal bonding, chemical bonding, and hydro entanglement.

As one of the most vital finished textile products, garment combines the art and the technology in its manufacturing process to conform fabric to the shape of a three-dimensional body. The principal operations of it are cutting and joining of at least two pieces of fabric. Similar to the fabrics, in order to improve the performance, there is a range of finishing processes for the garment as well. Denim, as one of the most popular textile products, for example, needs further treatments like desizing, color fading (laser, enzyme washing etc.), softening after the garment-making.

2.2 Necessity for modeling

According to the rough outline of textile manufacturing processes summarized in Figure 1 (with a focus on woven textile, where the knitting and non-woven processes are not included), it is clearly known that a large number of textile processes exist in textile manufacturing range over the yarn spinning through the fabric weaving and garment finishing. These processes have numerous possibilities of combination in the real application of textile manufacturing for different production needs. For instance, the combing or the roving process of yarn spinning may be omitted in the manufacturing scenarios of certain products but it is also possible to be repeated several times with different parameters for yarns to meet the specific design requirements. Taking garment finishing as another example, some similar process effects with minor difference can be achieved by a set of

different treatments such as laser, enzyme, ozone and hydrogen peroxide etc., which means that, to a certain degree, one of these processes could be replaced by other ones in the application.

Textile manufacturing processes deals with not only the selection of processes, manufacturers or technicians need to additionally find the optimal solutions with concerns on all the factors and variables with their interaction of every single process. In particular, from the machine parameters of temperature and rolling speed to the treating variables such as time and agent concentrations, these process variables varied in the specific ranges and play the different roles in different processes. In practice, to approach the high degree of variability in materials, processes and parameters as well as the lack of precise control, the manufacturers can barely conduct trial and error and heavily rely on the expertise and experience by paying a high cost of time as well as resources(Fan and Hunter 1998).

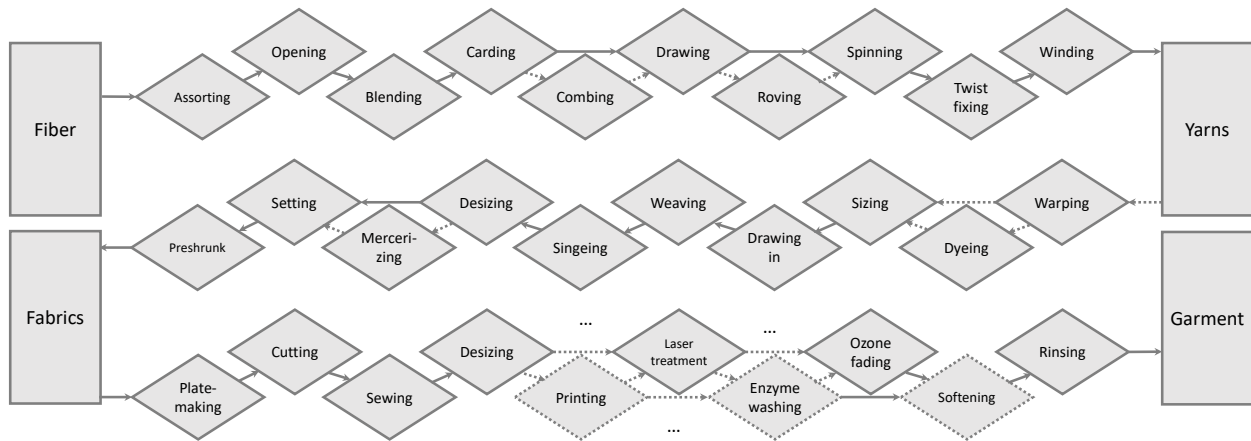


Figure 1. Principal processes of textile manufacturing from fiber to garment.

The relationship between textile manufacturing process factors is extremely nonlinear and hardly-understood, the effects of these factors on corresponding product properties are unclear (J. Eppers 1995). Human knowledge illustrates its limitation in this situation. Hence, a systematic study of modeling the textile manufacturing process is desperately needed. But different from previous works using classical models relied on physical laws or simplified assumptions, intelligent techniques that can learn from data would be more effective and applicable in this issue.

3. Modeling of textile manufacturing processes

3.1 Modeling systems

The model is a simplistic representation of the real phenomenon. It is often used to simulate the performance of a process or a product with various manufacturing solutions, thus the trial and error involved in process design and solution optimization can be obviated to a certain extent. Due to the extremely nonlinear relationship between the factors and performances of the textile manufacturing process, the process modeling is used to be conducted with intelligent techniques which comprise artificial neural network (ANN), Fuzzy logic, support vector machine (SVM), gene expression programming (GEP), and random forest etc.

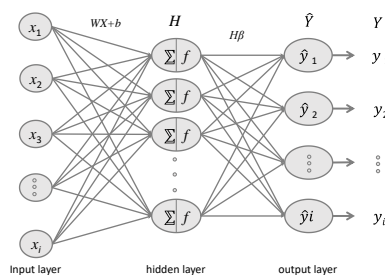


Figure 2. An example of the artificial neural networks architecture.

The ANN is a widely investigated artificial intelligence approach in the textile sector(Sette and Van Langenhove 2003). It is based on the inspiration of the human brain that interconnects numerous neurons in different hidden layers to process the complex information of a specific input–output relation(Patterson 1998). ANN consists of at least one hidden layers apart from

the input layer and output layer (the structure of ANN with a single-hidden layer, as an example, as illustrated in Figure 2.), where the nodes in the former endow weights to connect the nodes in the latter, and the adjustment of these weights performs the key function in the ANN training process for accurately modeling the relationship between inputs and outputs as well as sliding down the error surface. The determination of the number of hidden nodes generally bounds to the complexity of the modeled problem and the predictive performance with regard to approximation ability and generalization ability at the same time. Besides the weights endowed in these hidden nodes, the sum-up of inputs multiplying the weights is passed through to an activation function (such as ReLU and Sigmoid) in the hidden neuron, which converts the output to a fixed range of values. Such transmission is continued and repeated between the layers to adjust the weights and bias by learning from training data so that the trained ANN model can predict the value of output finally. Initially, the weights in hidden nodes are randomly given, and the error is consequently very high, a cost function depending on the error would be introduced to train the nets in terms of optimizing the weights using certain algorithms (e.g. back-propagation (Rumelhart, Hinton, and Williams 1985)).

Fuzzy logic was developed by Prof. Lotfi A. Zadeh in 1965 as an extension of crisp logic (Zadeh 1965). It is built on the structures of qualitative description in approximation rather than exactness. The variables are 1 and 0 or true and false in binary logic, as an example of crisp logic, while the boundaries are not that clear in Fuzzy logic as there are interference Fuzzy sets contain intermediate states with partial membership ranging from 0 to 1 to define uncertainty. For instance, when the temperature higher than 40°C indicates “hot”, as input and output variable, there would be intermediate states named in linguistic terms like “quiet hot”, “warm”, and “cool” and so on in a Fuzzy inference system by dividing the universe of discourse into a number of sub-regions, rather than only “not hot” is considered for any temperature $\leq 40^\circ\text{C}$ in classic logic. In general, the Fuzzy inference process formulating the mapping from a given input to an output using Fuzzy logic in terms of four steps, namely fuzzification, interference, rule base, and defuzzification. The interpretation of these operations is approachable in (McNeill and Thro 2014). Fuzzy techniques are usually applied in order to solve control problem by formulating linguistic rules, but the use of it for process modeling is also very popular in the textile manufacturing industry as the data and relations among variables might not be crisp in this domain due to the involvements of human subjectivity and a large number of qualitative descriptions (Veit 2012).

Aside from the ANN and Fuzzy logic, applications of the hybrid models combining the fuzzification technique of Fuzzy logic with the learning capability of ANN are also widely accessible in the textile industry. Fuzzification maps an input value to Fuzzy sets in a certain universe of discourse, thus increasing the separability of classes in the feature space and facilitating the training data fitting in the Neuro-Fuzzy model to be more accurate. Neural network techniques help the Fuzzy modeling procedure learn the information from the data and compute the membership function parameters that best allow the associated Fuzzy inference system (FIS) to track the given input–output data. Taking Adaptive-Neuro-based Fuzzy Inference System (ANFIS) as an example, it is a hybrid algorithm that transforms the Fuzzy inference system into a functional equivalent adaptive network (Jang, 1993). ANFIS applies the back-propagation-type gradient descent to obtain the appropriate Fuzzy rules and associated parameters, meanwhile uses the least square method to specify the output of each rule (Beşdok, 2004; Jang & Sun, 1993; Zanganeh, Mousavi, & Shahidi, 2009). It is able to work under uncertain noisy and simulate complex nonlinear mappings which right fits the advantages of both ANN and Fuzzy logic.

Support vector machine (SVM) is a popular machine learning tool for classification and regression based on statistic learning theory, it is first identified by Vladimir Vapnik and his colleagues in 1992 (Vapnik 2013). Support Vector Regression (SVR) is the most common application form of SVM. A typical feature of it is that instead of minimizing the observed training error, SVR minimizes the generalized error bound so as to achieve generalized performance. And it only relies on a subset of the training data due to the cost function for building the model neglects any training data that is close (within a threshold ϵ) to the model prediction (Basak, Pal, and Patranabis 2007; SMOLA 2004). Compared with neural networks, SVR assures more generalization on the foundation of structural risk minimization, and generally performs better with less training samples.

Gene expression programming (GEP) is a development of genetic algorithm (GA) and genetic programming (GP) proposed by Ferreira (Cândida Ferreira 2001). Most of the genetic operators used in GA can also be implemented in GEP with minor changes in terms of five components: the function set, terminal set, fitness function, control parameters and stop condition. Unlike the parse-tree in canonical GP, the individuals in GEP are encoded as linear strings of fixed length, and then are expressed as nonlinear entities (expression tree) of different sizes and shapes when evaluating their fitness. More detail regarding the mechanism of GEP can be found in (Cândida Ferreira 2006).

Random Forest is an ensemble-learning algorithm depending on the bagging method composed of a weighted combination of multiple independently-constructed regression trees to classify or predict certain variables (Breiman 2001). It constructs each tree using a different bootstrap sample of the data (successive trees do not rely on earlier trees), and different from regression tree splitting each node using the best split among all variables, random forest uses the best among a subset of predictors randomly chosen at that node (Andri Liaw and Wiener 2002). Therefore, a simple unweighted average over the collection of grown trees would be taken for prediction in the end. In general, combining multiple regression trees increases predictive

performance. It accurately predicts by taking advantage of the interaction of variables and the evaluation of the significance of each variable (Andy Liaw and Wiener 2002).

3.2 Modeling yarn manufacturing process

The key properties of yarn generally are achieved from spinning methods which form a continuous fibrous structure with required stable linear density and strength, so that there are over half of the process modeling of yarn manufacturing reported previously concentrated on the spinning processes ranging from ring-, rotor-spinning and air-jet spinning to melt spinning, blended spinning and core spinning. While in addition to the spinning process, yarn manufacturing needs to be merged fibers to sliver and roving via a series of processes like carding, combing and roving beforehand, and after the spinning of yarn, on the other hand, certain treatments may be needed to produce specific or customized effects (such as splicing), where the applications of intelligent modeling in these areas are also blooming.

In order to understand the mechanism of the yarn manufacturing process, the essential factors of it in terms of the fiber properties and the process parameters that have been considered in previous works for modeling spinning and other yarn manufacturing processes are listed with the targeted process performance features in Table 1, Table 2 and Table 3 respectively. Regarding the number marks of properties in these three tables, which will be used in Table 4 to refer to the input and output respectively of the sorted different yarn manufacturing process models introduced in overviewed works, coupled with details of a reference, modeling techniques, data sets used and testing accuracy. Note that certain information of these works is merged into cells when it is found identical and published by the same researchers from different works of literatures. The number list given in Table 4 refers to the process or methods of 1) Ring spinning, 2) Rotor spinning, 3) Air-jet spinning, 4) Blending spinning, 5) Core spinning, 6) Worsted spinning, 7) Vortex spinning, 8) Melt spinning, 9) Splicing, 10) Texturing, 11) Drawing

3.2.1 Processes or methods

The modeling of the yarn manufacturing process was mainly drawn in spinning processes such as ring spinning, rotor spinning and air-jet spinning, where the earliest employments of intelligent modeling techniques in textile manufacturing sector were reported (Pynckels et al. 1995; L. Cheng and Adams 1995; Ramesh, Rajamanickam, and Jayaraman 1995). Ring spinning is the most common and traditional spinning technique. The use of it for spinning cotton yarn has lasted for hundreds of years without significant changes. Ring frame ensures the very fine quality of yarns with a high speed of production, and facilitates the stable performance of the following process to achieve high quality textile products. Rotor spinning provides a lower cost option with higher productivity to yarn manufacturers. Full automation is realized in the rotor spinning process from speed frame to winding, with the increasing importance of productivity in the textile industry, it is becoming more prominent than the conventional ring spinning in many textile manufacturing sectors (Grosberg and Iype 1999). Air-jet spinning is essentially a pneumatic-spinning method, which consists in passing a drafted strand of fibers through one or two fluid nozzles located between the front roller of a drafting system and a take-up device. The use of swirling airflow in the stage of inserting a twist into the yarns achieves air-jet spinning the fastest industrial production of staple fiber yarns.

The blending of fibers is one of the most important functions in the yarn spinning process. It involves not only the concern of mixing different batches of cotton in case of unevenness and uniformity problems, but also the consideration of taking advantages of each contributed desirable properties to the final product from different materials. Color is one of the benefits and one of the most significant characteristics of textiles can be achieved from this procedure. Thevenet et al. (Thevenet, Dupont, and Jolly-Desodt 2003) proposed an interesting model to predict the color obtained from fibers blended spinning process using feedforward neural networks. As a special type of blended yarn, core-spun yarn is also widely used in textile products. It is a yarn with a certain structure comprised of two component fibers that one of it performs the function of core whereas the other plays the role of a sheath or covering. The most common applied core-spun yarn is cotton/spandex stretch yarn. It enables textile comfort with fashion leisure style as well as ultimate fit. Almetwally et al. (Almetwally, Idrees, and Hebeish 2014) and Doran and Sahin (Doran and Sahin 2019) compared ANN with multilinear regression model and SVM model for modeling elastane core yarn spinning process respectively.

Worsted spinning parallels fibers that have been combed to remove shorter bits to a yarn with a short draw to keep the fibers in their parallel alignment. Worsted yarns have more twists inserted, which makes them firmer and stronger. Mozafary and Payvandy (Mozafary and Payvandy 2014) constructed an ANN model to approximate this complicated manufacturing process from a draw and doubling of wool/polyester fibers to twisting of yarns with an investigation of 70 parameters. Vortex spinning can be viewed as a refinement of jet spinning, or a natural development in fascinated yarn technology. Pei and Yu (Pei and Yu 2011) released a model adopted to predict the vortex yarn tenacity from some vortex spinning process and nozzle parameters such as nozzle pressure, jet orifice angle, twisting surface angle, and the distance between the nozzle inlet and the hollow spindle. Melt spinning is the most economically useful method for producing artificial fibers in the industry, Kuo et al. (Kuo, Hsiao, and Wu 2004a, 2004b) applied Fuzzy logic and ANN respectively to predict the properties of melt spun polypropylene filament. Splicing techniques assemble yarns on spinning bobbins into larger yarn packages, the modeling of this process was attempted by Ünal and Cheng et al (Ünal, Özdil, and Taşkın 2010; Ünal et al. 2010; K. P. S. Cheng and Lam

2003). Texturing techniques endow man-made fiber with flat geometry and smooth surface aesthetics and functional values without increasing its volume, resilience and changing original properties. Azimi et al. (Azimi et al. 2013) modeled the false twist texturing process in order to predict the crimp stability of stretch yarns and tenacity of set yarns that showed the applicability of ANN for modeling this process. Drawing of sliver is a very important operation for preprocessing of yarn spinning, the draw frame setting and sliver properties of this process were investigated by Farroq and Cherif (Farroq and Cherif 2008, 2012) using ANN technique.

In addition, modeling of fiber production for the preparation of the materials of yarn manufacturing was reported in the fields of kenaf degumming and acrylic fiber dry spinning. Degumming is necessary to pre-process of kenaf fibers for promoting its spinnability and dyeing abilities. Zheng et al. (Zheng et al. 2010) optimized the parameters of a kenaf bio-degumming treatment on the basis of an ANN model, the errors of the developed model for predicting the residual gum content and weight-loss ratio are 2.15% and 4.3% respectively. Dry spinning is a very widespread method for acrylic fiber manufacturing nowadays, while the complexities of factors' relationship in this process have hindered the management of fibers' quality stability. Vadood (Vadood 2014) employed ANFIS to predict the color index of acrylic fiber in the process, and further applied the Kohonen neural network for data clustering and genetic algorithm for ANFIS model parameter optimization. The mean square error of the final optimized model with testing data was only 0.06.

3.2.2 Factors and performances

It is easy to find out in Table 1 that the regular fiber properties are taken into account such as fiber length, strength, elongation and micronaire etc. are generally measured by three different systems, namely high-volume instrument (HVI) system, advanced fiber information system (AFIS) and fineness and maturity tester (FMT). But there are several specific properties of fiber materials, including the top oil content, top moisture regain etc., are investigated as well out of the regular testing of fiber from sliver or roving. Turhan and Toprakci (Turhan and Toprakci 2013) have tried to compare the difference between the accuracy of ANN for predicting yarn tenacity as well as hairiness of carded cotton ring spun yarns from HVI fiber measurement results and those from an AFIS, but after they optimized the architecture of their radial basis function ANN model using an experimental topology of a dataset, training parameters and neuron number, no significant difference was observed in the comparison between data derived from HVI and AFIS measurements. Another spinning process model established by Pynckel et al. using ANN in 1995 (Pynckels et al. 1995), as one of the earliest intelligent model in this area, has taken a wide range of fiber properties and process parameters to predict the spinnability (the breakage less than 5 times during the first 3 minutes of the ring- or rotor-spinning process). Their finding revealed that the poor performance of traditional techniques for modeling the textile manufacturing process is owing to the inaccurate suppose of factors in regard to independence. Like aforementioned that their relationships are not always linear as is being put forward, their analysis of the interdependence of the factors illustrated that the single correlation coefficients between the independent parameters are not negligible, so that traditional methods such as multiple regression will not give reliable results, the power of them is very limited in this domain.

Table 1. Fiber properties affecting spinning process that have been considered for modeling in previous works

Fiber properties					
F1	Mean diameter	F17	Top weight unevenness	F33	Top mean weight
F2	Strength	F18	Mean length(Hauteur)	F34	Spinning consistency index
F3	Elongation	F19	Recombed	F35	Upper half mean length
F4	Micronaire	F20	Fineness	F36	Foreign material
F5	Yellowness	F21	Maturity	F37	Length uniformity
F6	Brightness	F22	Grayness	F38	Upper quartile length
F7	Reflectance	F23	Color grade	F39	2.5% span length
F8	Bundle elongation	F24	Curvature	F40	Quadratic fiber fineness
F9	Sugar content	F25	Bundle tenacity	F41	CV of length
F10	Shirley nonlint content	F26	Wax content	F42	CV of the diameter
F11	Number of large neps	F27	Number of seed particles	F43	CV of the nep diameter
F12	1/8" gauge strength	F28	Number of trash particles	F44	CV of the number of neps
F13	Mean diameter of the neps	F29	Total trash	F45	Percentage of dust
F14	Neps	F30	Trash cent	F46	Percentage of short fibers
F15	Top oil content	F31	Trash area	F47	Percentage of mature fibers
F16	Top moisture regain	F32	Trash grade	F48	Standard fiber fineness for a maturity of 1

By contrast to the fiber properties are mainly derived from HVI, AFIS and FMT systems, the process parameters varied dramatically according to the applied process of yarn manufacturing as there are 68 process factors from 11 different processes or methods have been taken into account previously for yarn manufacturing process modeling using intelligent techniques. In Table 4, the frequency of factors considered or processes modeled is rough in line with the importance of them in the textile industry (for example, the use of ring spinning is more general than the rotor, air-jet and vortex in the spinning process, and the pretreatments or finishing processes like blending, drawing and splicing are less significant than yarn spinning on the yarn specification). However, a variety of researches only paid attention to the fiber properties in their models (e.g. (L. Cheng and Adams 1995; Zhu and Ethridge 1997; P. K. Majumdar and Majumdar 2004; Abhijit Majumdar et al. 2008; Mwasiagi, Huang, and

Wang 2008; Dayik 2009; Das et al. 2013)), or barely investigated the yarn count, a single process parameter input, coupled with fiber properties in their studies (e.g. (Zhu and Ethridge 1996; Chattopadhyay and Guha 2004; A Majumdar, Majumdar, and Sarkar 2005; Abhijit Majumdar, Majumdar, and Sarkar 2005; Nurwaha and Wang 2008; Abhijit Majumdar, Ciocoiu, and Blaga 2008; Abhijit Majumdar 2010; Nurwaha and Wang 2010; Ghosh and Chatterjee 2010; Nurwaha and Wang 2011, 2012; Ghosh 2014)). These models may work in specific simplified cases for finding the optimal material, but their effectiveness would be declined dramatically in the industry application as only one-side of the textile manufacturing is implemented, their simulation accuracy is hardly acceptable when any machine setting or process condition changed. While fortunately, a couple of tendencies can be found in Table 4 that the diversity of the yarn manufacturing process for modeling grew distinctly, and as a result, the complexities of constructed process models increased as well. More and more textile process models are issued with inputs from fiber properties and process parameters both, the variety of input as well as output in these models enhanced at the same time. This trend reveals the shortage of manufacturing data (and the hard for collecting data) in the early years in this area, and furthermore reflects the practice of the intelligent process model which is closer than ever to make a difference in the textile industry.

3.2.3 Relative importance of inputs and feature selection

The increasing variety of process factors and features studied for yarn manufacturing process modeling does not mean that infinitely expanding the inputs and outputs in a model can linearly improve the model performance, but conversely, this may result in more errors due to the waste of the computational resources such as training dataset and computation power in the arousing complexity of process model. Chattopadhyay and Guha (Chattopadhyay and Guha 2004) indicated that the information contained in factors or the contribution of input variables in the models as well as the correlation between factors with model targets are different, reducing the complexity of models by reducing the number of inputs should take the relative importance of these factors into consideration in case of losing a significant amount of information when unsuitable reduction implements. They proposed principal component analysis (PCA) in this study to deal with the input selection for improving the performance of an ANN model, such method was quite popular that also has been adopted by several other authors in their studies for selecting most relevant inputs of yarn manufacturing process modeling (Dayik 2009; Ghanmi, Ghith, and Benameur 2015; Doran and Sahin 2019). In particular, Doran and Sahin (Doran and Sahin 2019) have further compared PCA with analysis of variance technique (ANOVA, which also has been used in (Ghorbani, Vadood, and Johari 2016; Turhan and Toprakci 2013; Doran and Sahin 2019; Nurwaha and Wang 2008; Ezzatollah Haghighat et al. 2012a, 2012b; Moghassem and Fallahpour 2011; Demiryürek and Koç 2009; Subramanian, Venkatachalam, and Subramaniam 2007; Nurwaha and Wang 2012; Özkan et al. 2014; Demiryurek and Koc 2009; Azimi et al. 2013; Vadood 2014)) in feature selection for decreasing inputs dimensionality of ANN and SVM models, and their results illustrated that the models trained with input sets reduced by PCA were found to be the most successful among 117 models.

Table 2. Process parameters in spinning process that have been considered for modeling in previous works

Process parameters					
P1	Yarn design count	P25	Twist	P49	Torque-stop
P2	Blend ratio	P26	Tension	P50	Rotor type
P3	Humidity	P27	Navel type	P51	Rotor speed
P4	Ring size	P28	Ring traveler	P52	Extruder screw speed
P5	Traveler weight (traveler mass)	P29	Location of balloon control ring	P53	Spindle speed
P6	Traveler number	P30	Breaker speed	P54	Delivery speed
P7	Number of filament	P31	Gear pump gear speed	P55	Opening roller speed
P8	Spin tube(number of carves)	P32	Winding speed	P56	Roller covering hardness
P9	Draw	P33	Spinning speed	P57	Splicing air pressure
P10	Doublings	P34	Intermingling speed	P58	Opening air pressure
P11	Fore-spinning total doublings	P35	Intermingling pressure	P59	First nozzle pressure
P12	Ends retraction	P36	Back draft zone time	P60	Second nozzle pressure
P13	Ends preparation air volume	P37	Splicing air pressure time	P61	Nozzle material
P14	Roving (or sliver) count	P38	Material	P62	spindle cone angle
P15	Roving (or sliver) unevenness	P39	Jet orifice angle	P63	Distance between front roller nip and first nozzle inlet
P16	Roving (or sliver) twist	P40	Distance between back and middle rolls	P64	Count of core part
P17	Distance between the guiding needle and the spindle	P41	Drafting system angle	P65	Count of sheath part
P18	Nip gauge	P42	Break draft gauge	P66	Pretension
P19	Main draft	P43	Main draft gauge	P67	Draft ratio
P20	Spinning drafting	P44	Total draft	P68	Temperature
P21	Break draft	P45	Fore-spinning total draft	P69	Position of the jet orifices in the first nozzle
P22	Back zone setting	P46	Time of cycle	P70	D/Y
P23	Nozzle type	P47	Rotor diameter	P71	Setting overfeed
P24	Drawing ratio	P48	Doffing-tube nozzle		

Saliency test is another technique frequently applied in the prior researches for analysing the relative importance of inputs (P. K. Majumdar and Majumdar 2004; Mwasiagi, Huang, and Wang 2008; Mwasiagi, Wang, and Huang 2008; S. A. Malik et al. 2016). The implementation of it is to eliminate only one designated input from the model at a time, and observe the increment of error in model prediction, the higher error enhanced indicates the more important of the designated input variable in this model. In an ANN model of the vortex spinning process developed by Pei and Yu (Pei and Yu 2011), they opted to a similar but simpler way that performed single effect prediction of one specific parameter by fixing all other factors to evaluate the input importance in predicting model targets. Besides of the methods mention above, decision tree (or random forests) (Nurwaha and Wang 2011), partial derivative (Ghorbani, Vadood, and Johari 2016), multivariate test (Fattahi, Taheri, and Ravandi 2012), K-means algorithm (Mozafary and Payvandy 2014), grey incidence analysis and subjective and empirical approach (Yin and Yu 2007) have demonstrated their effectiveness in this issue as well. It is worth mentioning that the improvement of model performance with selected date reported in these studies ranged over 0.45%~47%, which would make a drastic difference in the industry application. The most common taken inputs and targets for modeling yarn manufacturing process, according to Table 4, are fiber (sliver or roving) properties of diameter, strength, elongation, micronaire, neps, length, upper half mean length, length uniformity, fineness, maturity, trash, short fiber content, process parameters of yarn design count, twist, blend ratio and the speed of certain machine parts (like roller, spindle, rotor etc.), the pressure of specific instruments (e.g. nozzle) and the distance between certain devices, yarn properties of strength, elongation, unevenness and hairiness, respectively.

Table 3. Process performance targeted in process modeling of yarn manufacturing in previous works

Process performance					
Y1	Linear density	Y8	Thin places	Y15	Count-strength product
Y2	Tenacity	Y9	Thick places	Y16	Total imperfections
Y3	Elongation	Y10	Neps	Y17	Bending&abrasion&appearance
Y4	Unevenness/ irregularity	Y11	Number of hairs	Y18	Color
Y5	Hairiness	Y12	Ends-down	Y19	RKM
Y6	Number of fibers in cross section	Y13	CV of count	Y20	Retained spliced diameter
Y7	Other irregularities	Y14	CV of strength	Y21	Leveling action point

Other than data mining for feature selection, the optimization of model architecture or parameters which have a significant influence on the model performance is widely discussed in the related literature as well. For example, learning rate, training functions, transfer functions, number of hidden layer and neurons, training stop conditions, assessment standards etc. of ANN, membership functions, rule sets, Fuzzy inference and Fuzzy number etc. of Fuzzy logic, kernel function of SVM and generations of GEP, great care should be taken in the determination of these parameters corresponding to every single specific case. The normal way authors employed was trial and error or topology following certain rules (e.g. the geometric pyramid rule for determining neuro number of ANN model), as the common options for most of the qualitative parameters are finite and have been deeply researched in many areas. But for certain process models possessing numerous quantitative parameters, the situation would be more complicated, where the advanced operations are needed. Genetic algorithm is a very powerful and popular optimization tool that had been used to optimize model structure and parameter in the previous studies (Sette, Boullart, and Van Langenhove 2000; Yang, Lu, and Li 2012; Vadood 2014). Moreover, Cheng and Adams (L. Cheng and Adams 1995) applied simulated annealing technique, Nurwaha and Wang (Nurwaha and Wang 2011) used grid search and pattern search methods, Doran and Sahin (Doran and Sahin 2019) attempted iterative single data algorithm, quadratic programming and sequential minimal optimization methods.

3.2.4 Modeling techniques

Table 4 shows that the ANN is the first choice for most of the modeling studies of the yarn manufacturing process, and the simulation performance of these constructed ANN models showed that generally acceptable in testing period. ANN is an excellent machine learning tool for textile manufacturing process modeling by approximating the relationship of inputs and outputs, but a drawback of it that has been criticized often because of the so-called "black box" problem, limits its use in modeling certain textile manufacturing process. It hardly provides substantial physical information about the process itself but simply connects the inputs and output parameters. This flaw of ANN can be found in several comparative investigations as well. Abhijit Majumdar and his colleagues have built linear regression models with ANN models and ANFIS models for predicting yarn breaking elongation (Abhijit Majumdar, Majumdar, and Sarkar 2005) and yarn unevenness (Abhijit Majumdar, Ciocoiu, and Blaga 2008) respectively, their results demonstrated that the ANFIS models performed slightly better than ANN models in both of these two studies as the former can discover linguistic rules relating input to output variables and extract some physical information about the mechanism of the process benefiting from the Fuzzy principle by means of membership functions and linguistic rule sets. ANFIS takes the advantage of both ANN and Fuzzy logic in modeling, which is more appealing than the ANN for certain textile process modeling. Another type of hybrid model combining ANN and Fuzzy logic for predicting yarn tenacity, elongation, unevenness and hairiness can be found in the publications of Ghanmi et al. (Ghanmi, Ghith, and Benameur 2015, 2019), they developed ANN models separately to predict the yarn properties and further injected the obtained predicted results into Fuzzy system to introduce a new quality index.

The application of Fuzzy logic for modeling the yarn manufacturing process is diverse. In addition to the combinational use with ANN, it has been used directly as a single model as well for predicting the tensile strength and the yarn count of chemical fibers in melt spinning process (Kuo, Hsiao, and Wu 2004a) and the hairiness of polyester-viscose blended yarns in ring spinning process (Ezzatollah Haghighat et al. 2012b) respectively. Furthermore, Sette et al (Sette, Boullart, and Van Langenhove 2000) built rule sets automatically from the data by means of a Fuzzy efficiency-based classifier system (FECS) to predict the spinnability and yarn strength. This method defined several rule efficiencies and introduced them into the learning strategy of the system, which demonstrated high prediction accuracy and delivered additional qualitative information about the process behavior in the study. In quality studies of processes for manufacturing fine and expensive textile, the data are few and/or reported as imprecise quantities and/or the relationship between variables is defined vaguely, upon which Fattahi et al. (Fattahi, Taheri, and Ravandi 2012) proposed Fuzzy least squares regression for modeling the relationship of quality indexes of ring spun yarn and the fiber properties, roving properties as well as yarn design count. This proposed approach is announced that can be extended to other cases in textile engineering where the data availability and preciseness are short.

Studies comparing intelligent techniques for yarn manufacturing process modeling were also conducted among ANN, ANFIS, SVM and GEP. Unlike the ANN models which implement the empirical risk minimization principle, SVM implements the structural risk minimization principle which seeks to minimize an upper bound of the generalization error rather than minimize the training error. Ghosh (Ghosh 2014) found that the performances of the SVM model have better accuracies and reliabilities than the ones of ANN and ANFIS for predicting the strength, elongation, evenness and hairiness of ring spun yarn from fiber properties. The preferences of SVM than ANN to be suitable in this area are also illustrated in the comparative researches of (Ghosh and Chatterjee 2010; Nurwaha and Wang 2012; Doran and Sahin 2019). The accurate and dependable predictions of SVM models in these studies reflect their better potential to generalize and ability to handle noisy data. Yang et al. (Yang, Lu, and Li 2012) further found one more interesting phenomenon that in small data set and real-life production, the predictive power of ANN models appears to decrease, but SVM models remain stability of predictive accuracy to some extent, which is more suitable for noisy and dynamic industrial process. Nurwaha and Wang (Nurwaha and Wang 2012) compared not only ANN and SVM but GEP models as well in their study for predicting yarn count-strength-product from fiber properties and yarn count. Their results show that the lowest error was provided by the SVM model, followed by GEP model, and the ANN models did not generalize the training data effectively in the testing analysis. This result is generally in line with the studies of (Dayik 2009; Moghasssem, Fallahpour, and Shanbeh 2012), and the advance of GEP on ANN in this regard may be attributed by the better optimization of its parameters on the basis of genetic algorithm without complexity increasing though the latter can apply GA as well. It is worth to mention that another important advantage of GEP is its ability to generate equations that can be easily programmed even into a pocket calculator to use in future predictions.

Table 4. Process performance targeted in process modeling of yarn manufacturing in previous works

Ref.	Model inputs	Model targets	Modeling techniques	Data train: test	Testing accuracy
(L. Cheng and Adams 1995)	F2,F4,F5,F18,F20,F21,F22,F37,F46	Y15	ANN	84:85	R=0.850
(Zhu and Ethridge 1997)	F1,F2,F3,F4,F5,F7,F10,F12,F14,F18,F20 ,F21,F23,F29,F37,F38,F39,F41,F46	Y5	ANN	67:33	R ² =0.842
(Desai, Kane, and Bandyopadhyay 2004)	F2,F4,F39,F46 / P1,P25	Y4,Y19	ANN	40:25	t=0.0191; 0.6128
(Chattopadhyay and Guha 2004)	F20,F25,F29,F37,F39 / P1	Y2,Y4,Y13,Y14,Y15,Y16	ANN	14:6	RE=2.4%~19.1%
(P. K. Majumdar and Majumdar 2004)	F3,F4,F5,F7,F25,F35,F37	Y3	ANN		R=0.938
(A Majumdar, Majumdar, and Sarkar 2005)	F3,F4,F4,F7,F25,F35,F37 / P1	Y2	ANN; ANFIS	72:15	R=0.738;0.802
(Abhijit Majumdar, Ciocoiu, and Blaga 2008)	F14,F18,F20,F21,F27,F46 / P1	Y4			R=0.959;0.970
(Abhijit Majumdar et al. 2008)	F2,F4,F18,F46	Y2	Fuzzy logic	-	R ² =0.75
(Abhijit Majumdar 2010)	F18,F46,F21 / P1	Y5	ANFIS	36:18	R ² =0.946
(Mwasiagi, Huang, and Wang 2008)	F3,F4,F5,F7,F18,F21, F30,F31,F32,F34, F37,F46 / P1,P4, P5,P20,P25,P53	Y3		-	MSE<0.03
1) (Mwasiagi, Wang, and Huang 2008)	F2,F3,F4,F5,F18,F21, F32,F34,F37,F46 / P1,P4,P25,P53	Y2,Y3,Y4	ANN	-	R=0.975; 0.907; 0.915
(Mwasiagi, Huang, and Wang 2012)	F2,F3,F4,F5,F18,F21, F32,F34,F37,F46 / P1,P4,P25,P53			120:24	R=0.959;0.94; 0.939
(Üreyen and Gürkan 2008a)	F2,F3,F20,F35,F37 / P1,P14,P15,P25,	Y2,Y3			R ² =0.981; 0.889
(Üreyen and Gürkan 2008b)	F2,F3,F5,F35,F37,F40 / P1,P15,P25,	Y4,Y5	ANN	135:45	R ² =0.993; 0.951
(Dayik 2009)	F2,F3,F4,F14,F18,F29, F37,F46,	Y2	ANN;GEP	130:32	R ² =0.94;0.988
(Furferi and Gelli 2010)	F2,F18,F20 / P1,P25	Y2	ANN	98:50	RE=3.5%
(Ghosh and Chatterjee 2010)	F4,F8,F18,F25,F46 / P1; F4,F18,F46 / P1		ANN;SVM	87 for 10-folds	RE=3.5%~7.2%; 1.5%~5.6%
(Ghosh 2014)	F4,F8,F18,F25,F46 / P1	Y2,Y3;Y4,Y5	ANN;SVM; ANFIS	90 for 10-folds	RE=3.5%~7.2%;1.5 %~5.6%;3%~12.6%
(Ezzatollah Haghighat et al. 2012a)	P1,P5,P16,P21,P22,P25,P29,P41, P44,P53,P56	Y5	ANN	46:11	R=0.967

	(Ezzatollah Haghighat et al. 2012b)	P1,P5,P53		Fuzzy logic	-	R ² =0.931
	(Fattahi, Taheri, and Ravandi 2012)	F3,F4,F18,F21,F25,F35,F37,F46 / P1,P14, P15,	Y2,Y3,Y4,Y5	Fuzzy logic	-	MCI=0.66; 0.57;0.62;0.66
	(Zhao 2012)	P16,P18,P36,P53,P55	Y4	ANN	14:4	R=0.982
	(Das et al. 2013)	F2,F3,F20,F35,F37,F46	Y2,Y4	ANN	30:6	R=0.886;0.92
	(Ghanmi, Ghith, and Benameur 2015)	F2,F3,F5,F7,F20,F21,F29,F31,F35,F37, F46 / P1,P25	Y2,Y3,Y4,Y5	Neuro-Fuzzy	-	R ² =0.81
1)	(Pynckels et al. 1995)	F2,F3,F4,F5,F6,F9,F11,F13,F14,F18,F20 ,F26,F27,F29,F37,F41,F42,F43,F44,F45, F46,F47 / P1,P25,P27,P51,P55	Y12	ANN	1400:850	RE<5%
2)	(Pynckels et al. 1997)	F2,F3,F4,F5,F6,F18,F20,F21,F28,F29, F37,F47,F48 / P1,P8,P25,P30,P51	Y2,Y3,Y4,Y7,Y8,Y9, Y10,Y11		1200:182	RE<5%
	(Zhu and Ethridge 1996)	F1,F14,F18,F29,F38,F46 / P1	Y4	ANN	150:27	R ² =0.881
	(Sette et al. 1997)	F2,F3,F4,F5,F6,F18,F20,F21,F28,F29,F3 7,F47,F48 / P1,P8,P25,P30,P51	Y2,Y3	ANN	1200:182	RE<5.7%;3.5%
	(Sette, Boullart, and Van Langenhove 2000)	F2,F3,F4,F18,F37 / P1,P25,P27,P30,P51	Y2,Y12	Fuzzy logic	840:420 1944:216	RE=8.0%;5.9%
	(Zhu and Ethridge 1997)	F1,F2,F3,F4,F5,F7,F10,F12,F14,F18,F20 ,F21,F23,F29,F37,F38,F39,F41,F46	Y5	ANN	67:33	R ² =0.772
	(Chattopadhyay and Guha 2004)	F20,F25,F29,F37,F39 / P1	Y2,Y4,Y13,Y14, Y15,Y16	ANN	78:33	RE=2.7%~38.0%
	(A Majumdar, Majumdar, and Sarkar 2005)		Y2			R=0.964;0.959
2)	(Abhijit Majumdar, Majumdar, and Sarkar 2005)	F3,F4,F5,F7,F25,F35,F37 / P1	Y3	ANN; ANFIS	88:20	R=0.879;0.882
	(Nurwaha and Wang 2008)	F2,F3,F4,F5,F22,F35,F37,F46 / P1		ANFIS	21:13	MAE=79.8
	(Nurwaha and Wang 2010)	F2,F3,F4,F5,F35,F37,F46 / P1			-	RMSE= 5.2e-4
	(Nurwaha and Wang 2011)	F2,F3,F4,F5,F7,F22,F35,F37,F46 / P1	Y15	SVM	-	MAE=82.87
	(Nurwaha and Wang 2012)	F2,F3,F4,F5,F22,F35,F37,F46 / P1		ANN;SVM;GEP	-	MAE=89.7;82.9;93.7
	(Ghosh and Chatterjee 2010)	F4,F8,F18,F25,F46 / P1; F4,F18,F46 / P1	Y2,Y3;Y4,Y5	ANN;SVM	108 for 10-folds	RE=2.5%~4%; 1.7%~3.7%
	(Moghassem and Fallahpour 2011)			GEP		R ² =0.9672
	(Moghassem, Fallahpour, and Shanbeh 2012)	P40,P42,P54	Y2	ANN;GEP	38:10	R ² =0.93; 0.97
	(Ghanmi, Ghith, and Benameur 2019)	F2,F46 / P1,P14,P15,P25	Y2,Y3,Y4	Neuro-Fuzzy	-	RMSE=0.07
	(Ramesh, Rajamanickam, and Jayaraman 1995)		Y2,Y3		48 for 5-folds	ME=-1.91%; -0.29%
	(Rajamanickam, Hansen, and Jayaraman 1997)	P1,P2,P59,P60	Y2	ANN	35:4	ME=-2.04%
3)	(Y. C. Zeng, Wang, and Yu 2004)	P33,P59,P60,P63,P69	Y2	ANN	35:5	R ² =0.98
	(Subramanian, Venkatachalam, and Subramaniam 2007)	P1,P23,P61	Y2,Y3,Y4,Y5	ANN	2700:300	ME=-3.5%~6%
	(Özkan et al. 2014)	F2,F3 / P7,P34,P35	Y2,Y3	ANN	209:52	R=0.861;0.884
	(Thevenet, Dupont, and Jolly-Desodt 2003)	F7	Y18	ANN	-	E=0.53%
	(Demiryurek and Koc 2009)	P1,P2,P51	Y3	ANN	84:28	R=0.976
	(Demiryürek and Koç 2009)		Y4	ANN	87:25	R=0.98
4)	(Turhan and Toprakci 2013)	HVI(F2,F3,F20,F35,F37,F46) / P1; AFIS(F14,F18,F20,F41,F46) / P1,P2	Y2,Y5	ANN	30:10	R ² =0.85,0.85; 0.97,0.98
	(S. A. Malik et al. 2016)	P2,P25,P56,P67	Y2,Y3,Y4	ANN	40:8	R ² =0.99;0.99;0.96
	(Ghorbani, Vadood, and Johari 2016)	P47,P48,P49,P50	Y5	ANN	202:50	R=0.97
	(Gharehaghaji, Shanbeh, and Palhang 2007)	P25,P64,P65,P66	Y2,Y3	ANN	54 for 5- folds	R=0.88;0.967
5)	(Almetwally, Idrees, and Hebeish 2014)	P1,P24,P25	Y2,Y3	ANN	32:8	R ² =0.99;1
	(Doran and Sahin 2019)	F2,F3,F4,F5,F7,F13,F14,F18,F21,27,F28 ,F29,F30,F34,F36,F37,F38,F41,F45,F46, F47,(F18/F37) / P1,P26,P33,P64	Y2,Y3,Y4,Y8,Y9,Y10, Y11,Y19	ANN;SVM	193:34	R=0.95;0.95
	(Rafael Beltran, Wang, and Wang 2004)	F1,F18,F24,F25,F41,F42,F46 / P1,P4,P19,P25,P33	Y2,Y3,Y4,Y5,Y6,Y8, Y9,Y10,Y12,Y13,Y15	ANN	250 for 5-folds	R ² =0.554~0.995
	(R Beltran, Wang, and Wang 2006)	F1,F2,F18,F19,F24,F41,F42,F46 / P1,P4,P5,P25,P53,P67	Y2,Y3,Y4,Y6,Y8, Y9,Y10,Y12	ANN	98 for 5-folds	R ² =0.60~0.96
6)	(Yin and Yu 2007)	F1,F14,F15,F16,F17,F18,F33,F41,F42,F 46 / P1,P11,P14,P16,P20, P28,P33,P44,P45	Y2,Y3,Y4,Y12	ANN	69:8	R=0.982;0.969; 0.881;0.843
	(Khan et al. 2009)	F1,F18,F24,F41,F42,F46 / P1,P4,P6,P20,P25,P53	Y5	ANN	53:22	R ² =0.949
	(Yang, Lu, and Li 2012)	F1,F18,F41,F42,F46 / P1,P6,P25,P33,P67	Y2,Y3	ANN;SVM	20:6	R=0.96,0.58; 0.99,0.87
	(Mozafary and Payvandy 2014)	F2,F3,F14,F18,F20,F42 / P1,P2,P3,P9,P10,P14,P15,P25	Y4,Y8,Y9,Y10	ANN	1411:249	R=0.93
7)	(Pei and Yu 2011)	P17,P39,P59,P62	Y2	ANN	35:5	R=0.95
8)	(Kuo, Hsiao, and Wu 2004b)	P31,P32,P52	Y1,Y2	ANN	18:10	ME=-0.22%;0.13%

	(Kuo, Hsiao, and Wu 2004a)			Fuzzy logic	-	ME=-0.32%;-0.03%
9)	(K. P. S. Cheng and Lam 2003)	P1,P12,P13,P25,P46	(Y2+Y17)	ANN	-	R ² =0.97
	(Ünal, Özdil, and Taşkın 2010)	F1,F39 / P1,P25,P57,P58	Y2,Y3	ANN	76:22	R=0.88,0.86;
	(Ünal et al. 2010)	F1,F18,F36,F38,F39,F46 / P1,P25,P37,P57,P58	Y20	ANN	54:18	R ² =0.706
10)	(Azimi et al. 2013)	P25,P54,P68 P70,P71	Y2,crimp satility	ANN	39:9	R=91.5%;99.29%
11)	(Farooq and Cherif 2008)	P21,P26,P38,P42,P43,P54	Y21		161:8	R ² =0.9622
	(Farooq and Cherif 2012)	P10,P14,P21,P38,P42,P43,P44,P54	Y2,Y4(silver and yarn)	ANN	135 for 10-folds	MAE=6.6%; 6.76%;4.03%

Note that the overview of intelligent techniques for modeling the yarn manufacturing process concluded above is not meant to recommend any single technique, but collect and analyze the experiences from prior works to arouse inspiration for future researchers. The choosing of models in practice for the textile manufacturing process still needs to count the specifications of applied case in detail. For example, the model developed by Ghosh(Ghosh and Chatterjee 2010; Ghosh 2014) using different methods actually fed with different data sets and variables which were determined on the basis of their knowledge of the process and optimization trials.

3.2.5 Data and performance estimation

Depending on the discussions above, it is easy to find out that the availability and quality of data set play a key role in the modeling of the textile manufacturing process. However, the total number of data sets was found limited in most of the studies listed in Table 4 (for certain references divided data sets to training, validation and testing, the validation sets was counted as part of the train here), such phenomenon would restrict the development of their models (e.g. ANN) and consequently impede the industrial application of these models. While the short of data with quality is quite common in the textile industry as it consists of small and medium enterprises in general that relying heavily on product customization with variety, so it has to be tackled with technical approaches. Except for model selection and variable dimensionality reduction, pretreatment and distribution of the data can also make a difference to this end. The pretreatments of data include feature selection for variables reduction (using clustering tools such as k-means and PCA), data normalization for cleaning and denoising, and even introducing dummy data to complete the raw data.

The pretreatments of data could improve the models to express the targeted problems more appropriately. While the proper distribution of datasets for training and testing, on the other hand, is beneficial to realize the generalization ability of models. The overviewed yarn manufacturing process models illustrated in Table 4 generally were trained by 60%~90% of their data sets, and some of them have employed k-fold cross validation to ensure the exploration of data. Where k-fold cross-validation is a technique randomly separating data into k disjoint sets, and using one of the k subsets to test the model trained by other k-1 subsets in turns for k times, the average error corresponding to k trials can better assess the expected generalization accuracies of models, which makes this method very practical for modeling with a small dataset.

The performance estimation of models was expressed in many ways as illustrated in Table 4, such as correlation coefficient (R), R-square (R²), mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), mean error (ME) and relative error (RE). The calculations of them are based on:

$$R(e, p) = \frac{\sum_{i=1}^n (e_i - \bar{e})(p_i - \bar{p})}{\sqrt{\sum_{i=1}^n (e_i - \bar{e})^2 \cdot \sum_{i=1}^n (p_i - \bar{p})^2}} \quad (1)$$

$$R^2 = \left(\frac{\sum_{i=1}^n (e_i - \bar{e})(p_i - \bar{p})}{\sqrt{\sum_{i=1}^n (e_i - \bar{e})^2 \cdot \sum_{i=1}^n (p_i - \bar{p})^2}} \right)^2 \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |e_i - p_i| \quad (3)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (e_i - p_i)^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (e_i - p_i)^2} \quad (5)$$

$$ME = \frac{1}{n} \sum_{i=1}^n (e_i - p_i) \times 100\% \quad (6)$$

$$RE = \frac{1}{n} \sum_{i=1}^n \frac{e_i - p_i}{e_i} \times 100\% \quad (7)$$

where e_i is the real targets, whereas p_i is the predicted output of the model. Particularly, Desai et al.(Desai, Kane, and Bandyopadhyay 2004) used a test statistic variable t, Fattahi et al.(Fattahi, Taheri, and Ravandi 2012) applied mean of capability index (MCI), Thevenet et al(Thevenet, Dupont, and Jolly-Desodt 2003) employed an error

estimator of E in their studies respectively. Actually, evaluating a model with only the prediction accuracy is not enough, the detailed information of predicted results should be observed from multiple different directions. While any single estimation index above can barely give overall observations of the results, therefore, applying multiple estimations is more recommended in related modeling investigations.

3.3 Fabric manufacturing process

Different from modeling the yarn manufacturing that mostly was conducted on spinning processes, the attention of intelligent modeling studies in fabric manufacturing was more addressed on the related treatments such as fabrics dyeing and finishing. This may reflect that in general the understanding of the fabric manufacturing processes including weaving and knitting, compared with the related fabric processes, have been well constructed with mechanisms and theories. In terms of weaving, the accessible models in this area were released for predicting sizing performances, warp breakage rate, weft insertion velocity and compressed air consumption in air-jet weaving, the air permeability of rapier woven fabric, as well as strength transfer efficiency of warp and weft yarns in projectile woven fabrics. In terms of knitting, the modeling investigations were established to tackle the predictions of knitted fabrics' spirality, bursting strength and bagging bend height. The developed models of dyeing and finishing processes varied significantly in regards to applied materials and methods, but the predictive targets were generally focused on the color and functional performances, as the aims of these processes simply obtain the fabrics' aesthetics and functional values. Furthermore, many papers in the literature have applied the intelligent modeling techniques to map material and process parameters to nonwoven fabrics' properties such as the compression, air permeability, tensile and bulk density of needle-punched nonwoven as well as the fiber diameter in melt-blow and spun-bonding nonwoven processes.

The general information of fabric manufacturing process modeling using intelligent methods summarized from reviewed literature are listed in Table 5. It is clear that ANN and fuzzy logic dominate the application of intelligent techniques in this area. Meanwhile, it is noted that modeling chemical process such as textile dyeing and finishing has attracted more attention in the previous studies.

Table 5. Information of fabric manufacturing process modeling using intelligent methods

Process	Intelligent methods	Model inputs	Model outputs	performance	Reference
sizing	Fuzzy	steam pressure, nip pressure, sizing speed	Exit moisture, size add-on	-	(Dorrity et al. 1994)
	Neuro - Fuzzy	Speed, exit moisture, size add-on	Number of end breaks	-	(Kim and Vachtsevanos 2000)
	Neuro - Fuzzy	Temperature, low nip pressure, high nip pressure, sizing speed	Size add-on	RMSE=0.0222	(Zhang et al. 2015)
	ANN	Size add-on and the properties of sized yarn (abrasion resistance, abrasion resistance irregularity, hairiness beyond 3 mm, breaking strength, breaking strength irregularity, breaking elongation, breaking elongation irregularity)	Warp breakage rate in weaving process	R= 99.5%	(Yao, Guo, and Zhou 2005)
Weaving	Fuzzy	Weft yarn count, yarn twist.	Weft yarn insertion velocity	-	(Dayik and Colak 2004)
	ANFIS	Weft yarn count, fabric width, loom speed, reed count	Compressed air consumption	R=0.998	(Hussain, Jabbar, and Ahmed 2014)
	ANFIS	Strength of constituent yarns, fabric count, float length	Strength transfer efficiency of warps and wefts	R=0.951; 0.924	(Z. A. Malik and Malik 2010)
	ANN	Weave float, warp type, filament fineness of warp and weft, filling type, fabric density, shed closing angle, loom speed	Air permeability	MAE=1.05% ; 0.42%	(S. A. Malik et al. 2017)
Knitting	Fuzzy and ANN	Yarn parameter of yarn type and machine parameters of course count, gauge and binding	Residual bagging bend height	Fuzzy: R=0.676 ~ 0.821 ANN: R=0.991	(Jaouachi, Louati, and Hellali 2010)
	ANN	Twist liveliness, yarn type, yarn linear density, tightness factor, the number of feeders on the knitting machine	Spirality	R=0.976	(Murrells et al. 2009)
	Fuzzy	knitting stitch and yarn count	Spirality	R=0.991	(Shahid, M. A., Hossain 2015)
	Fuzzy	Knitting stitch length, yarn count and yarn tenacity	Bursting strength	R ² =0.961	(Hossain, Choudhury, et al. 2016)
	ANFIS	Yarn tenacity, knitting stitch length and fabric density	Bursting strength	R=0.996	(Jamshaid, Hussain, and Malik 2013)
Dyeing	ANN	K/S values of undyed fabrics, dye fixed ratio, percentage shades, NaCl concentrations, Na ₂ CO ₃ concentration, and K/S value of dyed samples after rinsing	Depth of shade in dyeing process	Error=1%	(Sentilkumar and Selvakumar 2006)
	ANN	Machine operating temperature, dyeing time, dye liquor	Color strength	RMSE=1.66e ⁻⁴	(Kuo and Fang 2006)

		concentration and the bath ratio			
	ANN	Dye concentration, salt concentration, and alkali concentration	Color strength and fastness	R = 0.992	(Hossain, Hossain, and Choudhury 2015)
	Fuzzy			R = 0.977	(Hossain, Choudhury, and Mamat 2017)
	Fuzzy	Dye concentration with dyeing time and process temperature	Color strength	R=0.998	(Hossain, Hossain, et al. 2016)
	Fuzzy	Dyeing time, alkali concentration and washing temperature	Colorfastness	R = 0.992	(Hossain et al. 2014)
	ANN	Type of treatment, the replication of washing, and the dyes type targets	CIELab values	R=0.96	(Balci, Oğulata, et al. 2008)
	Fuzzy			MSE=0.0018~0.0478	(Tavanai, Taheri, and Nasiri 2005)
	Fuzzy and ANN	Dyes concentration, temperature and time	Colour yield	-	(Nasiri, Shanbeh, and Tavanai 2005)
	Fuzzy			MSE=2.333	(Nasiri and Berlik 2009)
	ANN	Reactive dyes, reducing agents, owf%, original L*, concentration of the reducing agents and caustic, process temperature, the presence of the leveling agent	CIELab values	R=97.66%	(Balci, Oğulata, et al. 2008)
		fabric parameters, dyeing agents and finishing processes		R>0.89	(Balci and Oğulata 2009)
				MSE =39.538; 0.256; 0.036; 0.032	(Kan and Song 2016)
		The fabric specifications of composition, density, mass, thickness, linear density, yarn twist and crimp and two applied laser parameters (DPI and pixel time)		MSE=0.218; 0.057; 0.019; 0.064	(Hung et al. 2011)
	ANN		K/S values and CIELab values	MSE =6.348; 0.165; 0.03; 0.087	(Hung et al. 2012)
		Pixel time, DPI and grayscale		MSE=16.492; 0.146; 0.003; 0.033	(Hung et al. 2014)
		Treating time, temperature, pH, mechanical agitation and fabric yarn twist		MSE=1.5e ⁻³ ; 9.9e ⁻⁶ ; 2.8e ⁻⁹ ; 6.2e ⁻⁷ ; 4.3e ⁻⁸ ; 1.9e ⁻⁵ ;	(Kan et al. 2013)
	ELM, SVR, and RF*	Color, pH, temperature, water pick-up and treating time	K/S values and CIELab values	R = 0.9063; 0.9777; 0.9847	(He et al. 2020)
Finishing	ANN	Fabric type, method, chemicals and concentration	Water-oil repellent and wrinkle resistant	-	(Sema, Çoban, and Ünal 2011)
	ANN	The weight of scratching material in percentage to the weight of stone wash, acidic enzyme treated and neutral enzyme treated fabrics respectively, the duration of process, and the softener	Fabric hand	R=0.991	(FEKI, MSAHLI, ZENG, & KOEHL, 2016)
	ANN and Fuzzy	Parameters of multiple finishing processes and the instrumental tactile characteristics	compression and surfaces properties	RMSE=0.02~2.39; 0.01~2.71	(Schacher et al. 2011)
	ANN	Substrate strength, flame gas-air mixture, flame temperature, rameuse temperature, polyurethane granulometry, coagulation duration, and reticulation duration	thermal insulance, dimensional stability, ultimate tensile stress, pilling resistance grade	Error<5.5%	(Furferi, Governi, and Volpe 2012)
	Neuro - Fuzzy	Fiber nature, fabric weight, thickness, construction, weft density, warp density, weft count, fiber count, air permeability, porosity, and surface roughness, electrical power, treatment speed	contact angle; capillarity height	R=0.9917; 0.9998	(Jelil et al. 2013)
	Neuro - Fuzzy	(variables above) + composition, warp count and summit density		R=0.9957; 0.9964	(Abd Jelil et al. 2013)
	ANN	Fabric weight, needling density and blend ratio (Debnath and Madhusoothanan 2008)	Tensile properties	-	(Debnath, Madhusoothanan, and Srinivasmoorthi 2000), (Debnath, Madhusoothanan, and Srinivasamoorthy 2000)
			Compression properties	-	(Debnath and Madhusoothanan 2008)
Non-woven	ANN	Web area density, punch density, and depth of needle penetration	Bulk density and tensile properties	R=0.907; 0.986; 0.982	(Rawal et al. 2009)
	ANN	Polymer flow rate, initial polymer temperature and initial air velocity	Fiber diameter	R ² = 0.9424	(Chen, Wang, and Huang 2005)
	ANN	Polymer flow rate, initial air velocity and die-to-collector distance		Error=0.013%	(Chen, Li, and Huang 2005)
	ANN	Fiber length, fiber count, total pore volume, basis weight uniformity, thickness, basis weight, and fiber volume density	Fabric air permeability, strength, elongation	Error=-0.78%, -0.88, and -0.84	(Chen et al. 2006)
	ANN	Polymer melt index, the polymer flow rate, initial polymer temperature, the initial air temperature, and the initial air velocity	Fiber diameter	Error=-0.135%	(Chen et al. 2008)

*ELM: extreme learning machine; SVR: support vector regression; RF: random forest.

3.3.1 Modeling weaving process

Sizing (or slashing) process is a very necessary procedure in the textile manufacturing industry that directly affects the productivity in weaving. It enforces the warp yarns to resist the loading of weaving by adding a homogeneous liquid mix of chemicals, binders and lubricants in the most efficient manner. To achieve the desirable settings of size add-on, exit moisture and stretch is a challenging issue in sizing operation. In order to control the moisture content of sizing to combat the warp weaken problem because of over-drying, Dorrity et al. (Dorrity et al. 1994) released the first attempt of sizing process modeling in 1994 using Fuzzy theory based on trials conducted with 37's cc 50/50 polyester-fiber/cotton warp yarns with 9000 ends. Steam pressure, nip pressure and speed are inputted to the model for predicting exit moisture and add-on of sizing warps. This investigation was latter extended by Kim and Vachtsevanos (Kim and Vachtsevanos 2000) in a Neuro-Fuzzy model. This proposed Neuro-Fuzzy model combines the fuzzy inference engine through polynomial neural network architecture which has some similarities in common with an ANFIS model. Both of these two models applied a genetic algorithm to optimize the model parameters.

Due to the influences of outliers and noise data in sizing process on the modeling performance, Zhang et al. (Zhang et al. 2015) also proposed the combined structure of fuzzy and neural networks on the basis of non-Euclidean distance clustering to predict the slashing process quality index, i.e. the size add-on, from the temperature, low nip pressure, high nip pressure and sizing speed. Their algorithm partitioned the input space into many local regions first, and then determines the fuzzy rule number by validity function depending on the separation and the compactness among clusterings. After training by a hybrid learning algorithm of the gradient descent and the least-squares method, this model was tested with an accurate predictive performance of RMSE=0.0222. A comparison of this model with grip partition, BP and RBF neural networks show that the proposed method has lower computation complexity and faster convergence time. As mentioned that the sizing operation enforce the warps to smooth the weaving process, this is owing to the decrement of warp breakage rate in weaving ensures the weaving productivity. Yao et al. (Yao, Guo, and Zhou 2005) took size add-on and the properties of sized yarn (such as abrasion resistance, abrasion resistance irregularity, hairiness beyond 3 mm, breaking strength, breaking strength irregularity, breaking elongation, and breaking elongation irregularity) to predict the warp breakage rate in weaving process by a back-propagation ANN model. The correlation coefficient of model predicted data and actual data from the testing data set is $R=99.5\%$.

Other than warps, weft yarn affects the weaving productivity dramatically at the same time and the weft insertion system plays a key role in this issue. Air-jet weft insertion system is commonly applied almost for all kinds of yarns at a very high speed. Dayik and Colak (Dayik and Colak 2004) introduced a fuzzy model for predicting the weft yarn insertion velocity from weft yarn count and twist. However, Hussain et al. (Hussain, Jabbar, and Ahmed 2014) pointed out that the high productivity of air-jet weaving machine relies heavily on the energy consumption of compressed air production for weft insertion. Upon which they developed models relating air-jet weaving parameters of weft yarn count, fabric width, loom speed and reed count to the compressed air consumption using response surface regression and ANFIS comparatively. Some 108 fabric samples are used for training (100) and testing (8) the models respectively. It was found that ANFIS model was slightly better than the response surface regression model with a higher Pearson correlation (between actual and model predicted air consumption) of $R=0.998$ and $R=0.986$ respectively.

The crossing of yarns from warp and weft directions forms woven fabrics in a stable structure, the strength of fabrics from the warp or weft direction in this structure is clearly not only the accumulation of yarns because of the existence of crossing abrasion of yarns. Malik and Malik (Z. A. Malik and Malik 2010) termed the percentage of cumulative strength of longitudinal yarns in warp or weft direction which is transferred to the fabric after weaving as strength transfer efficiency (STE) of yarns in that direction. They developed a predictive model for predicting STE from the strength of constituent yarns, the fabric count and the float length using ANFIS technique based on the input-output data sets of 264 woven fabric samples (234 samples and 30 samples were used to develop and validate the prediction models respectively). Their models were found that are capable of predicting the warp and weft yarns strength transfer efficiencies accurately ($R=0.951$ for warps and 0.924 for wefts).

Air permeability is a very significant quality index concerning the textile comfort and functional performance of certain technical fabrics like protective garments, filters, airbags and parachutes. The air permeability of the polyester woven barrier fabrics has been predicted from the weave float, warp type, filament fineness of warp and weft, filling type, fabric density, shed closing angle and loom speed by using an ANN model trained by backpropagation algorithm with 82 data patterns (S. A. Malik et al. 2017). The model performance derived from 28 testing data patterns was MAE=3.7%. They have further analyzed the importance of certain factors from the input space in this cited paper, and extended the constructed ANN model work with different deducted input sets. The results illustrated that the model with inputs excluding warp yarn type and filling type, as well as the one excluding weave float have gained better performance with respect to MAE=1.05% and 0.42% respectively. The relative importance of model inputs, according to their analysis, ranges from weft filament fineness, fabric density, weave float, warp filament fineness, shed closing angle, warp type, loom speed to filling type.

3.3.2 Modeling knitting process

The popularity of knitted fabrics can easily find out from the daily use of apparel like shirts, sweaters, undergarments and sportswear etc. This is owing to the knitting process that introduces properties of the elasticity, drape, wrinkle resistance, comfort, softness and easy-care to this sort of textile products at low cost. However, specific structural problems like bagging and spirality phenomenon remain a handicap of the fabric during and after use. Residual bagging bend height is one of the primary assessments of fabrics' bagging phenomenon. In order to understand the role of knitting process in this phenomenon, Jaouachi et al (Jaouachi, Louati, and Hellali 2010) have tried to map the yarn parameter of yarn type and machine parameters of course count, gauge and binding to the residual bagging bend height of knitted fabric using Fuzzy logic and ANN technique respectively. Samples out of 24 were used to validate the models predicted values and the R value of tested samples was found that ranging from 0.676 to 0.821 for fuzzy models with different membership functions and 0.991 for ANN model.

The spirality phenomenon arising from many process factors can hardly be explored without modeling tools. Murrells (Murrells et al. 2009) employed an ANN model and a standard multiple linear regression model to predict the spirality of 100% cotton single jersey fabrics with given inputs of twist liveliness, yarn type, yarn linear density, tightness factor, the number of feeders on the knitting machine, the machine gauge, the rotational direction of the machine and whether the fabrics had been piece dyed or not. 66 fabric samples produced from regular ring spun yarns, low torque ring spun yarns and plied yarns were used. Among which, data measured from 13 samples was applied to test the models. The results show that the correlation coefficients (R) between the actual and predicted degree of spirality were slighter higher for ANN model of 0.976 compared with 0.970 for the regression model. By contrast, Shahid and Hossain (Shahid, M. A., Hossain 2015) proposed a fuzzy expert system, rather than ANN models, to deal with the knitting process modeling for spirality prediction. But in this study only two variables from 16 samples were considered, namely knitting stitch and yarn count. Four triangular linguistic fuzzy sets of very low, low, medium and high were chosen for input parameters in the input space, while 5 more linguistic rules (very very low, very very high, low medium, high medium and very high) were additionally introduced to the output triangular membership function. The validation results derived from 9 testing datasets illustrated a very high predictive accuracy (R=0.991).

Hossain et al. (Hossain, Choudhury, et al. 2016) further used this fuzzy expert system to predict the bursting strength of knitted fabric on the basis of knitting stitch length, yarn count and yarn tenacity. The differences from modeling spirality in knitting process consist of data used and data range distributed on membership functions in this model (in particular the fuzzy linguistic sets for yarn tenacity excluded very low, and 10 fuzzy sets from 1.1 to 1.10 were instead of the linguistic rules for output). The model was found to be very powerful in knitted fabric bursting strength prediction ($R^2=0.961$). Jamshaid et al. (Jamshaid, Hussain, and Malik 2013) have compared the models of regression and ANFIS for investigating the effects of the knitting process on fabrics' bursting strength, where the input variable comprising yarn tenacity, knitting stitch length and fabric density. Out of total knitted samples, the validation results from 8 samples revealed that the ANFIS model performed slightly better than regression model in this issue because of a higher correlation coefficient of predicted values versus actual values in terms of $0.996 > 0.991$.

3.3.3 Modeling dyeing process

The dyeing process introduces color to the textile including fabrics, while the use of intelligent techniques used in most of the previous studies was dedicated to alternate Kubelka-Munk theory for color recipe matching (Balci, Ogulata, et al. 2008). Sentilkumar and Selvakumar (Sentilkumar and Selvakumar 2006), as well as Kuo and Fang (Kuo and Fang 2006) made a difference in this issue. Sentilkumar and Selvakumar proposed an ANN dyeing process model for predicting and the depth of shade in the dyeing process using a backpropagation ANN. The constructed model has six input parameters (K/S values of undyed fabrics, dye fixed ratio, percentage shades, NaCl concentrations, Na_2CO_3 concentration, and K/S value of dyed samples after rinsing) and two outputs in terms of the time for primary exhaustion and time for dye fixation. Binary sigmoid activation function was used in a three hidden layers net which possessed 9 neurons in each hidden layer and was chosen from an optimization of net structure based on a series of attempts and experiments. It was trained and tested by 45 and 6 sets of data respectively and the performance was presented as only 1% average error.

Color strength is the basic and most vital property of dyed fabrics, and the control of it in the dyeing process to be stable without variance is a big issue. In order to optimize the performance of color strength in the one-bath-two-section dyeing process for nylon/lycra blended knitted fabrics with acid dyestuff, Kuo and Fang have constructed an intelligent model of it by means of ANN technique. The processing parameters of machine operating temperature, dyeing time, dye liquor concentration and the bath ratio were used as input variables. They used the ANOVA to arrange the optimal condition, significant factors and the percentage contributions, and employed the Taguchi quality method as well as GA to design the parameters and optimize the back-propagation ANN architecture respectively. The obtained ANN model predictive error in RMSE can be as low as 0.000165531.

Apart from modeling the bursting strength of knitted fabrics, Hossain et al. additionally proposed the use of fuzzy logic in the textile dyeing area. They developed several different fuzzy models for predicting the color strength and fastness of knitted

fabrics from dyeing process parameters respectively. The constructed Fuzzy model of exhaust dyeing of viscose/lycra blended fabric using reactive dyes was feed by dye concentration, salt concentration, and alkali concentration as input variables to predict the fabrics' color strength. This model performed very well in the evaluation that $R = 0.992$ from the actual and predicted color strengths(Hossain, Hossain, and Choudhury 2015). However, this model was later compared with ANN models trained by the same parameters and data in another publication of them, which showed that the ANN model predict more accurately than the Fuzzy model in this case(Hossain, Choudhury, and Mamat 2017). The attempt of the Fuzzy model was extended to the dyeing process of different cotton knitted fabrics (Hossain, Hossain, et al. 2016). They changed inputs to the dye concentration with dyeing time and process temperature, and designed different linguistic rules for input and output variables. The prediction performance was tested up to $R=0.998$.

Colorfastness reflects the ability of dyed fabrics to resist color characteristics change or transfer its colorant to adjacent materials. The higher colorfastness of dyed fabrics, the more possibility its color will not run or fade with washing and wearing. The fuzzy model Hossain et al. (Hossain et al. 2014) established for predicting color fastness takes dyeing time, alkali concentration and washing temperature as inputs, and the mean relative error as well as the correlation coefficient of predicted values from this fuzzy model are found to be 2.43%, and 0.992 respectively in the evaluation analysis. The colorfastness predictive model proposed by Balci et al., 2008 (Balci, Oğulata, et al. 2008) involves CIELab values(i.e. L^* , a^* , b^* , C , h° values etc.) in addition, which is based on the nylon 6.6 fabric in dyeing process with 1:2 metal-complex acid dye followed by one of the treatments in the group of syntan, syntan/cation, full backtan using a Levenberg-Marquardt (LM) trained ANN (one hidden layer with 30 nodes). The net input variables consist of the type of treatment, the replication of washing, and the dyes type targets. The experimental data were divided into three groups as 65% for training, 35% for testing and 5% for cross validation. According to a comparison between the trained ANN model and a set of regression models, it was found that ANN predicts more accurately than regression models for predicting fastness, however dissimilar to the literatures mentioned above, performed poorer for predicting the color parameters of CIELab.

The color yield of dyed fabrics known as the K/S values derived from the aforementioned Kubelka-Munk theory was studied by Tavanai et al(Tavanai, Taheri, and Nasiri 2005) by modeling a polyethylene terephthalate high temperature disperse dyeing process using fuzzy regression. The inputs of this model are comprised of disperse dyes concentration, temperature and time. This model was trained with an ANN model and a statistical regression model by using 95 sets of the same experimental parameters data Additionally,. The testing results obtained from the rest data of 25 samples indicated that the predictive power of the ANN model leads the model performance followed by fuzzy regression, while the statistical regression approach did not meet the required conditions to be accepted(Nasiri, Shanbeh, and Tavanai 2005). They also have attempted to promote the Fuzzy model in this case by means of the covariance matrix adaptation evolution strategy for model parameter optimization (Nasiri and Berlik 2009).

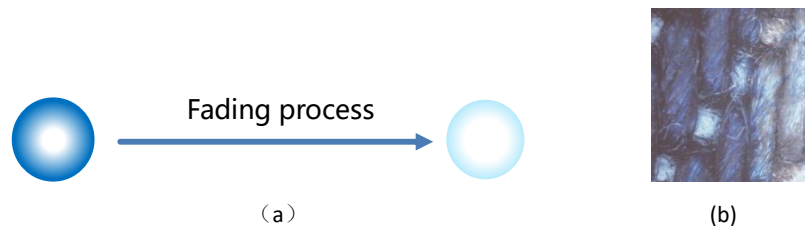


Figure 3. (a)Ring dye effect in fading process; (b) Inner cotton exposed denim.

3.3.4 Modeling finishing process

Finishing processes perform an increasingly significant function in textile manufacturing in recent years as a range of novel designed finishing methods promoted the aesthetics and functions of the textile products which have attracted a growing number of young customers' attention and obtained a considerable share of the fashion market. Taking denim finishing as an example, the indigo color which is regarded as the nature of denim usually contaminates the warp yarn only, but the property of "ring" dyeing effect of it resulted from the partial penetration was found a vintage style with a worn look when longtime abrasion or repeated washing removes the dyes and exposes the inner layer undyed cotton(J. N. Etters 1993; J. Etters 1995). Figure 3(a) illustrates the faded "ring" dye effect, and (b) gives a real denim sample that inner undyed cotton exposed.

Upon the presentation of the finishing process above, it is clear that the color properties of treated textiles must be targeted in many related process modeling studies. Balci et al., (Balci, Oğulata, et al. 2008) reported an application of LM trained ANN to the alkali reductive stripping process for predicting L^* and ΔE of stripped cotton fabrics. An optimization process was conducted to find the numbers of inputs, nodes and the estimation criteria for stopping training). Eight inputs in terms of the reactive dyes and reducing agents, o.w.f. %, original L^* , the concentration of the reducing agents and caustic as well as process temperature and the presence of the leveling agent were defined to feed the model (85 nodes in single hidden layer) with $MSE=0.01$ for stopping training predicting L^* , whereas 2 more parameters of a^* and b^* were inputted additionally to

predict ΔE using 70 nodes in the single hidden layer with MSE=0.001. The achieved R between the actual and predicted was 97.66% and 97% for these two models respectively.

They have also comparatively studied the ANN and Linear regression models for finding the effect of fabric parameters, dyeing agents and finishing processes on fabric's CIELab values in the chemical finishing process (Balci and Oğulata 2009). The chemical finishing applications such as softening, water repellent, durable press, cationic, micro silicone and macro silicone processes were studied in the laboratory condition in order to achieve the data for modeling. It was a feed-forward and backpropagation mixed ANN model that structure optimized through a topology, contained two hidden layers with 6 and 4 nodes in the first and second layer respectively. After training with 75% randomized data, cross validating with 10% data and testing with 15% data, it presented a high competition with more powerful prediction than linear regression models which was constructed by a new set of data. Correspondingly, the correlation coefficient was $R > 0.89$ for the ANN model whereas $R < 0.83$ for the linear regression models.

Process modeling applied to textile color finishing process was limited, which situation was changed until last years that a series of researches were delivered by Hong Kong Polytechnic University. They have investigated the effects of laser treatment on K/S values and CIELab values of weaving fabrics (Hung et al. 2011, 2012, 2014) and knitting fabrics (Kan and Song 2016) respectively as well as the effects of cellulase treatment on the K/S values and CIELab values of cotton denim fabric (Kan et al. 2013).

As shown in Table 5, a topology was used in all of these five studies in common that aims at finding the effect of changes in number of hidden layer and nodes on the performance of nets applied to each case above. In the meantime, they have investigated the relative importance of input variables by specifically rule out one of the variables in the net and comparing the decreased performance of affected nets.

Table 5. Topology of artificial neural network applied in the studies of (Hung et al. 2011; Kan and Song 2016; Kan et al. 2013).

Number	N1	N2	N3	N4	N5	N6	N7	N8	N9
Hidden layer	1	1	1	1	1	2	2	2	2
Nodes	10	15	20	25	30	10-5	10-10	15-10	20-10

Laser treatments are dry processes for denim and other colored textiles, which fits manufacturers' and designers' demands on controllability and sustainability, and more vitally the efficiency and high repeatability on denim color stripping process. C. Kan and Song (Kan and Song 2016) modeled the effect of laser on knitted fabric by inputting the fabric specifications of composition, density, mass, thickness, linear density, yarn twist and crimp and two applied laser parameters (DPI and pixel time) in various nets (illustrated in Table 5.) to output K/S values and CIELab values. The performance of trained nets was introduced as MAE, MSE and RMSE. It is found that DPI and pixel time was more important than other inputs to affect the knitted fabrics' color performance in laser treatment, and the predicting performance of the smallest MSE least to 39.538, 0.256, 0.036, 0.032 for K/S values and CIELab L, a, b values respectively in this study.

In terms of laser treatment on woven fabrics (similar networks but omitting the input of linear density from the model mentioned above), they pointed out that DPI is more significant than pixel time to affect the color properties in laser treatment, and the predicting accuracy of ANN was clearly proved in a comparison with the linear regression model in this study as the MSE result of latter was 5 to 55 times (0.218, 0.057, 0.019, 0.064 versus 23.668, 3.461, 0.100, 2862 for K/S and CIELab values respectively) to the former for predicting varied color properties (Hung et al. 2011). A similar work was conducted on six colored cotton-spandex fabrics with the same model architectures as well. They (Hung et al. 2012) claimed that the optimized tested MSE of established ANN model was 6.348, 0.165, 0.03, 0.087 in this issue. And the analysis revealed that thought the process performance of the laser process was determined importantly by process parameters, fabric thickness dominated the color fading effect if fabric parameters were taken into consideration. They have further tried to simplify the input variables of the ANN model in the related study by treating denim fabrics using the laser (Hung et al. 2014). The input only involved laser process parameters of pixel time, DPI and grayscale. The grayscale was found to be the most important factor in this model among the three input variables, and the MSE of tested prediction of an optimized model on K/S and CIELab values were 16.492, 0.146, 0.003 and 0.033 respectively.

Cellulase is an enzyme for degrading the surfaced dyed cotton (or other cellulose materials) on fabrics that have been used in denim washing sectors for years. Meanwhile, it is one of the most commonly used methods to achieve color fading effect as well as fabric softness for cotton denim. Modeling the process and predicting the color properties of K/S value and CIELab values depending on the inputs of cellulase treating time, temperature, pH, mechanical agitation and fabric yarn twist level using ANN, the work projected by Kan et al. (Kan et al. 2013) illustrated the potential of ANN in the modeling of the denim cellulase process. On the basis of the saliency test of parameters and the identical topology used in the previous studies, this optimized model constructed by researchers from Hong Kong Polytech University successfully verified the predicted accuracy of the ANN models in the case as well.

Color fading conventionally was achieved by chemical methods which not only highly consume water and power, but leave a heavy burden to the environment as well. The ozone treatment was increasingly proposed in this domain for its efficiency and environment friendly characteristics(He et al. 2018; He, Li, Zuo, and Yi 2019; He, Li, Zuo, Xu, et al. 2019). The complicated and nonlinear relationship between the ozone process parameters and color fading effects of reactive dyed cotton in ozone treatment was model by He et al(He et al. 2020) using extreme learning machine (an algorithm for single-hidden layer feedforward ANN), support vector regression and random forest comparatively. The models were inputted by the color of treated textile and the process parameters of pH, temperature water pick-up and treating time. The predictive performances of the optimized models with testing data were shown to be $R = 0.9063, 0.9777$ and 0.9847 .

Not only color properties matter, but physical functional performances are also very important for certain finishing process. For instance, the crease resistance finishing is one of the many types of fabric finishing that improve wrinkle resistance and smooth appearance of fabrics made from cellulose or related fibers which have a tendency to wrinkle badly after washing and tumble dring and also during wearing. The water and oil repellency treatments form the thin hydrophobic film on fiber surface so that proof the water or oil. Sema et al.(Sema, Çoban, and Ünal 2011) trained an ANN model to predict the properties of water-oil repellent and wrinkle resistant of blended woven fabrics obtained from finishing processes according to the fabric type, method, chemicals and concentration applied. As the input they used involves quantitative variables, the outputs variables were transformed from numerous values to linguistic ones to be bad, mean, good and best in this study as well. The results were concluded as that the ANN performed well with linguistic transformation of variables but specifically not satisfactorily for the wrinkle recovery angle owing to the lacks of homogeneity of sample size in each output class.

Feki et al.(FEKI, MSAHLI, ZENG, & KOEHL, 2016) described an ANN model structure optimized by a multilayer perception pruning algorithm for predicting denim fabric hand from stonewash parameters. It is a method based on variance sensitivity analysis and followed by pruning hidden neurons (pruning separately for four sensory descriptors as smooth, fluffy, full and soft). K-fold cross validation was used in the net training and validating process. There were only one hidden layer and five inputs (the weight of scratching material in percentage to the weight of stone wash, acidic enzyme treated and neutral enzyme treated fabrics respectively, the duration of the process, and the softener) in this network which variables were transferred by sigmoid. The optimum of 15 nodes in the hidden layer for "smooth" evaluated at the end present a high correlation coefficient of determination of 0.991.

Schacher et al. (Schacher et al. 2011) have modeled the relationship between finishing treatments' parameters and the instrumental tactile characteristics of treated textiles using ANN and Fuzzy techniques. The considered finishing processes include bleaching or dyeing, enzymatic bio-polishing, softening, emerizing and calendaring. The instrumental tactile characteristics comprising linearity of the pressure-thickness curve, compressional energy, compressional resilience, thickness at 50 pa, thickness at 5000 pa, coefficient of friction, mean deviation of coefficient of friction, frictional roughness and geometrical roughness. It was concluded that the performances of the proposed models were acceptable with the mean relative percent error $<10\%$ in general, and the fuzzy models performed slightly better than neural models.

Polyurethane-based coating process promotes the "hand effect" of fabrics, and makes their uniform substance, shade, stretch, softness and appearance similar to natural leather. Furferi et al. (Furferi, Governi, and Volpe 2012) developed an ANN predictive model of a particular coating process to map the coating process parameters (substrate strength, flame gas-air mixture, flame temperature, rameuse temperature, polyurethane granulometry, coagulation duration, and reticulation duration) to the most relevant quality index of coated product(thermal insulance, dimensional stability, ultimate tensile stress, and pilling resistance grade). 90 sets of data were used to train, and the performance of trained model with 18 more testing data showed that the maximum error in foresting was about ± 10 with an average error of less than 5.5%.

Plasma treatment of fabric, owing to the energetic species in gas plasma such as ions, electrons, radicals, metastables and UV photons, can enable a variety of generic surface process including surface activation by bond breaking to create reactive sites, dissociation of surface contaminants (cleaning), material volatilization and removal (etching), and deposition of conformal coatings (polymerization). Jelil et al (Jelil et al. 2013) launched an investigation on the modeling of plasma fabric surface treatment using ANN and Fuzzy techniques. The ANN model approximated the inputs of fabric features (fiber nature, fabric weight, thickness, construction, weft density, warp density, weft count, fiber count, air permeability, porosity, and surface roughness) and plasma parameters (electrical power, treatment speed) to the targets of water contact angle and capillarity. The fuzzy sensitivity criterion was used to select the most relevant input parameters (electrical power, treatment speed, fiber nature, fiber count, air permeability and surface roughness) to reduce the complexity of ANN model and improve its performance. They compared the training algorithms and the ways of single output and multiple outputs. The tested results showed that the training algorithm of Bayesian Regularization is more suitable in this case and it is better to predict each target singly by separate ANN models rather than multiple outputs using a single model. ($R=0.9917: 0.9876$ for contact angle and $0.9998: 0.9994$ for capillarity respectively). The model reported in another publication of Jelil (Abd Jelil et al. 2013) additionally researched the woven fabric features of composition, warp count and summit density in the input data set. Finally, the

optimized model possess 7 input variables in terms of electrical power, treatment speed, composition, air permeability, fiber count, construction and summit density.

3.3.5 Modeling nonwoven manufacturing process

The nonwoven manufacturing processes consist of web forming and web consolidation, where the web forming methods include dry laid (carding or air laying), wet laid (for materials like cellulose acetate) and polymer-based (spun-bonding and melt-blown etc.), while the web consolidation generally is implemented by chemical (such as spun-bonding) as well as mechanical (e.g. needle-punching) means. Intelligent models have been presented to simulate the nonwoven processes of needle-punched, spun-ponding and melt-blown in literatures.

Needle-punching is a well-known nonwoven process of converting fibrous webs into self-locking or coherent structures using barbed needles. The barbed needles pull the fibers from the surface of the web and reorientate them in the thickness direction leading to a complex three-dimensional structure. The structural coherence of a needle-punched fabric depends upon the frictional characteristics and interaction of constituent fibers. Debnath et al. (Debnath, Madhusoothanan, and Srinivasmoorthl 2000) have tried to predict the tensile properties (tenacity and initial modulus) of needle-punched, jute and polypropylene fibers blended nonwoven fabrics from fabric weight, needling density and blend ratio. Authors compared the methods of multiple regressions and ANN in their case trained with 15 sets of training data collected from experimental samples, and their testing results derived from 3 further verification experiments indicated that ANN models gave less absolute percentage error than the regression model for both predicting fabric tenacity and initial modulus, even when the selected input variables are beyond the range over which the model was trained. They reported a similar comparative investigation for predicting the air permeability of these needle-punched nonwoven fabrics later and about the same result of ANN dominating empirical model was obtained (Debnath, Madhusoothanan, and Srinivasamoorthy 2000), but an attempt of studying the effect of hidden layers in this work additionally revealed that the constructed ANN model with three hidden layers shows less prediction error followed by the one with two hidden layers, empirical model and ANN with one hidden layer respectively. In another study, Debnath and Madhusoothanan (Debnath and Madhusoothanan 2008) turned their researches on modeling the needle-punching process to predict the compression properties of polyester/jute/polypropylene blended nonwoven fabrics. The targeted compression properties of nonwoven are Initial thickness, percentage compression, percentage thickness loss, and compression resilience. 25 and 4 sets of samples were applied to train and test an ANN model, the correlation of R^2 in the ANN training process could be up to 0.999 while the tested result was a little unstable with certain data because of the lack of learning during training phase. Rawel et al. (Rawal et al. 2009) predicted the bulk density and tensile properties of needle-punched nonwoven by means of ANN mapping the process parameters of web area density, punch density, and depth of needle penetration to targets. The model was trained based upon 21 sets of experimental data, and the verification of developed model working on 6 sets of unseen data inferred that the ANN models have achieved a good level of generalization that is further ascertained by the acceptable level of mean absolute error obtained between predicted and experimental values of fabric bulk density and tensile strength in the machine direction and cross-machine direction.

Melt-blowing is an important one-step technology for converting polymer resin into the nonwoven fabric of microfibers directly. The fiber diameter plays a significant role in the engineering performances of melt-blown nonwoven fabric. Chen et al. (Chen, Wang, and Huang 2005) established an ANN model feed by process parameters of polymer flow rate, initial polymer temperature and initial air velocity to predict the fiber diameter. 90 nonwoven samples were divided into a training set and a testing set with 60 and 30 samples, respectively. The optimized ANN model has 3 hidden layers (5-2-3) and illustrates good predictive performance in terms of $R^2 = 0.9424$ between measure and predicted fiber diameters of tested samples. The advancement of an intelligent model in regard to ANN has been shown additionally in a further report of Chen (Chen, Li, and Huang 2005), where physical, statistical model was developed and compared with ANN for predicting fiber diameter of melt-blown nonwoven fabric from the polymer flow rate, initial air velocity and die-to-collector distance. It was found that only 0.013% of the average error was made by the ANN model, whereas 9.744% and 0.074 were taken by physical model and statistical model respectively. Chen et al. (Chen et al. 2006) have also attempted to study the structure-property relations of nonwoven fabrics (web forming by dry laid for and web bonding by thermal bonding respectively) by ANN technique using a limited number of samples. They proposed a variable selection approach on the basis of human knowledge and Euclidean distance, and consequently selected the nonwoven fabrics' structural parameters of fiber length, fiber count, total pore volume, basis weight uniformity, thickness, basis weight, and fiber volume density to predict fabric air permeability, strength and elongation separately. The average error of constructed ANN models with 18 tests was -0.78%, -0.88, and -0.84 respectively.

Aside from melt-blowing, spun-bonding is also known as a one-step technology for nonwoven production. Chen et al. (Chen et al. 2008) simulated the drawing of spun-bonding nonwoven process using an ANN model to predict the fiber diameter. Considered input variables are the polymer melt index, the polymer flow rate, initial polymer temperature, the initial air temperature, and the initial air velocity. Leave-one-out cross-validation was used in their study on the basis of 26 sets of samples. The estimated average error was -0.135%, which is far lower than the baseline method of nonlinear regression with 2.683%.

3.4 Garment manufacturing process

Garment manufacturing contains four principal processes following cutting, sewing, finishing, and packing. The complex system deals with the configuration of numerous operations and resources in facing of various uncertainties (Y. Xu, Thomassey, and Zeng 2018). Intelligent techniques have been applied to garment manufacturing process modeling for years. Guo et al. (Guo et al. 2011) have overall reviewed the applications of artificial intelligence in the apparel industry from the perspectives of design, manufacturing, retailing and supply chain management. In terms of the apparel manufacturing, they have generally summarized the related works before 2011 that applied intelligent modeling techniques to schedule the production, make marker, and deal with sewing issues etc. While regarding the applications of intelligent techniques for modeling garment processes as the procedures in the textile manufacturing process as a whole, the present section would particularly focus on the modeling of cutting, and sewing (the works about garment finishing processes have been drawn into the fabric section above) operations only. Table 6 demonstrated the basic information of the previous applications of modeling garment manufacturing process reviewed in this section.

Table 6. Information of garment manufacturing process modeling using intelligent methods

Process	Intelligent methods	Model inputs	Model outputs	performance	Reference
Cutting	ANN	Number of fabric layers, cutting blade speed, number of sizes, marking lengths, and cutting times	Cutting time	Error=0.786 %	(Ozel and Kayar 2008)
	Neuro-Fuzzy	machine speed and the fabric sewability	foot pressure and thread tension	-	(Stylios and Sotomi 1995, 1996)
	ANN	Fabric bending stiffness, thickness and weight	pucker grade	R=0.884	(Stylios and Parson-Moore 1993)
Sewing	ANN	Fabric composition, structure, thread density, thickness yarn count, weight, formability, extensibility, rigidity	Seam pucker, needle damage, fabric distortion, overfeeding	-	(C. Hui and Ng 2005)
	ANN	Linearity of extension curve, tensile energy, fabric extension; tensile resilience, ratio of weft extension to warp extension, shear rigidity, shear hysteresis, bending rigidity, bending hysteresis, thickness	seam pucker, seam flotation, seam efficiency	R=0.790, 0.849, 0.881	(C. L. Hui and Ng 2009)
	*RT and KNN	Fabric formability, fabric elasticity, bending rigidity, shear rigidity, shear hysteresis, tensile resilience	seam pucker, seam flotation,	RMSE=0.693, 0.897; 0.561, 0.569	(Pavlinic et al. 2006)
	ANN	Fabric width, folding length of joint, seam design, seam type	Seam strength	-	(Onal et al. 2009)
	ANN	No. of fabric layers, needle size, weave pattern, fabric weight	Needle penetration force	R=0.989	(Ezzatollah Haghghat, Etrati, and Najar 2013)
	Fuzzy logic and ANN	No. of fabric layers, needle size, fabric weight		R ² =0.968; 0.944	(E. Haghghat, Najar, and Etrati 2014)
	ANN	fabric layer, stitch density, needle size, fabric area density, thread linear density, and thread type,	strength loss in threads	R=0.83~0.94	(Midha et al. 2010)
Others	ANN	Linearity of extension curve, tensile energy, fabric extension; tensile resilience, ratio of weft extension to warp extension, shear rigidity, shear hysteresis, bending rigidity, bending hysteresis, thickness, friction coefficient, mean deviation of friction coefficient, geometric roughness, linearity of compression curve, compression energy, compression resilience, fabric weight	laying, cutting, overall handling, interplay shifting, structural jamming, seam slippage, needle damage, seam pucker, ease of pressing, dimensional performance, appearance retention	-	(Gong and Chen 1999)

*RT: regression trees; KNN: K-nearest neighbors (KNN) methods.

3.4.1 Modeling cutting process of garment manufacturing

Cutting process cut fabrics into pieces depends on maker making. It importantly influences the following processes in terms of efficiency and quality. There is a range of technical factors and indirect factors of cutting time ranging from size distribution and fabric's type to the workmanship and wastage etc. Ozel and Kayar (Ozel and Kayar 2008) established a model to estimate the cutting time of apparel manufacturing using the ANN system. They took the data of different marking length and the fabric lays quantities, cutting blade speed, size distribution to training the model. The structure of the ANN model was 7-14-1 where the number of hidden nodes was determined from studying the factors of training process such as convergence rate and error criteria etc. The constructed model was very acceptable with only 0.786% percentage error in the testing phase.

3.4.2 Modeling garment sewing process

Sewing operation performs the key function during garment production affecting the clothing quality. The sewing machinery dominates the performance of the sewing operation. Stylios and Sotomi (Stylios and Sotomi 1995, 1996) proposed a neuro-fuzzy system to control the sewing machines. In particular, this system is constituted by a back propagation ANN model for predicting the sewability of applied fabric from its relevant physico-mechanical properties, and then the main neuro-fuzzy

program was inputted by the machine speed and the estimated fabric sewability to control the foot pressure and thread tension of sewing machine on the basis of the fuzzy logic linguistic rules suggested by human operators determined from experimental data. Where the neural network in the main program was used to optimized the input and output membership functions. The implementation of this process model on an industrial sewing machine has successfully shown its effectiveness for improving the sewing quality.

A seam is the basic requirement in the construction of garments. Seam pucker is a common problem in garment manufacturing because of the improper sewing operations. Stylios and Parson-Moore (Stylios and Parson-Moore 1993) predict the seam pucker approximately of pucker grade in accordance with the AATCC standards by neural networks from the fabric properties of bending stiffness, thickness and weight. The distribution of data for model training and testing was 25:11, and the correlation coefficient of 0.884 was obtained from the comparison of actual with predicted pucker grade from the testing dataset. This accuracy probably is relatively unacceptable in certain applications nowadays, but this work is still very meaningful in the garment manufacturing filed as it addressed an early attempt of applying intelligent techniques to model sewing process and deal with seam pucker problem.

Sewing performance is not only assessed by seam pucker, but also the needle damage, fabric distortion, as well as the overfeeding of fabric during the sewing operation, announced by Hui and Ng (C. Hui and Ng 2005). Upon which they employed an extended normalized radial basis function (ENRBF, an algorithm developed by Xu(L. Xu 1998)) neural networks to predict these four sewing performance properties of specific fabrics. Regarding the data, they input the model by measured fabric properties with respect to the composition, structure, thread density, yarn count, weight, thickness, formability, extensibility, and rigidity, while for the outputs of model are related to the aforementioned sewing performance properties assessed by the experts. There were 94 sets of data were used to train the ENRBF model as well as a baselined back propagation neural networks model (P. C. . Hui et al. 2007). It is shown that in the testing experiment with 15 sets of samples, both of the trained neural networks models performed well, but the ENRBF one was slightly better, especially for predicting the seam performances of pucker and needle damage individually. Hui and Ng (C. L. Hui and Ng 2009) have also compared the multiple logarithm regression (MLR) with the ANN for predicting seam pucker, seam flotation and seam efficiency from the properties of the woven fabrics (Linearity of extension curve, tensile energy, fabric extension; tensile resilience, the ratio of weft extension to warp extension, shear rigidity, shear hysteresis, bending rigidity, bending hysteresis, thickness), it is concluded that the ANN model was more accurate than MLR, but both models were effective. Seam flotation was targeted in a sewing process model developed by Pavlinic et al(Pavlinic et al. 2006) as well with the seam pucker. But different from the ANN models above, they employed regression trees and K-nearest neighbors (KNN) methods. From the given parameters of fabric mechanical properties, the obtained root of mean squared error (RMSE) of constructed models is 0.693, 0.897 and 0.561, 0.569 for regression tree and KNN models predicting seam puckering and seam flotation respectively. The KNN model was regarded as more appropriated, and the $R^2=0.943$, 0.815 for the target seam performances were further provided to show its prominence.

Seam strength is one of the most important characteristics evaluating the seam quality. It is worth mentioning that Onal et al. (Onal et al. 2009) have launched a study predicting the seam strength of notched webbings for parachute assemblies. They broadened the application of sewing process modeling in the textile industry although it was not applied to the garment manufacturing. Seam factors in regard to the fabric width, folding length of joint, seam design and seam type were considered as input variables in the model construction, and seam strength of webbing was the only output. The ANN was compared with Taguchi's design of experiment method for the prediction accuracy on the basis of 60 training data and 10 testing data. It was shown that ANN was better than the Taguchi's approach.

Other than seam performances, the assessment of fabrics' sewability is also one of the center factors affecting the garment quality. Predicting needle penetration force (NPF) in the sewing process can invade the needle breakage and consequently promote the process efficiency and product quality. Related works have been reported by Haghghat et al comparatively using ANN and multiple linear regression(MLR) (Ezzatollah Haghghat, Etrati, and Najar 2013), as well as fuzzy logic and ANN (E. Haghghat, Najar, and Etrati 2014). The considered input variables are composed of the No. of fabric layers, needle size, weave pattern, and fabric weight in the comparison of ANN and MLR, and the parameters of networks were discussed with regard to different structures, learning functions, loss functions and transfer functions. The optimized ANN model (structure in 4-8-1, learn by gradient descent function, assessed by mean squared error, transferred by Tansig function) has higher average R-value ($0.989 > 0.901$) and lower average MSE ($1.720 < 10.594$) than the MLR model in the comparison of testing results. In the work comparing fuzzy logic and ANN for NPF prediction, weave pattern was omitted from the input variables, and 5-folds cross validation of experimental data derived from 100 samples was conducted to train and test the models. It is indicated that both of the fuzzy logic model and ANN model predicted with high accuracy though the latter was slightly better than the former (in terms of average $R^2=0.968 > 0.944$).

In addition to the NPF, thread tension is also mentioned above that the affects the sewability in the sewing process. Midha et al. (Midha et al. 2010) have tried to predict the strength loss in threads during high speed sewing by an ANN model. They collected 68 samples of sewing thread tenacity loss with records of fabric layer, stitch density, needle size, fabric area density,

thread linear density, and thread type, to train and test the model by means of 4-folds cross validation. The average prediction performance of the networks for cross validation data illustrates that MSE ranges from 17.63 to 20.56 and the maximum and minimum errors are 58.23 and 0.07 %, respectively. R^2 in the four partitions is 0.94, 0.83, 0.83, and 0.85, respectively.

3.4.3 Other issues in garment manufacturing process

The performance of the garment manufacturing process can be observed not only by cutting and seam properties. Gong and Chen (Gong and Chen 1999) listed a series of fabric performance in the garment manufacturing process from varied areas (laying, cutting, overall handling, interplay shifting, structural jamming, seam slippage, needle damage, seam pucker, ease of pressing, dimensional performance, appearance retention) to be the prediction targets in the development of ANN models. 32 different samples diverting from 18 parameters in terms of composition, fabric weights and mechanical performances were used to train the model. Meanwhile, another ANN model was established with 15 selected inputs additionally for comparison. It is demonstrated that ANN is possible to predict fabric performance in clothing manufacturing and garment appearance according to fabric mechanical properties, and highly related parameters can be eliminated from the input without deteriorating the convergence and generalization ability of the ANN.

4. Limitations, challenges and future perspectives

The foregoing sections demonstrate the versatile role of intelligent techniques in modeling the textile manufacturing process. It is also clearly illustrated that related publications on the sector are produced in increasing numbers from the research community. However, compared with other industries with higher automation levels, the textile industry has attracted relatively little attention from the research community of the intelligent techniques. Though previous studies facilitate the applications of intelligent models in the textile manufacturing industry, various limitations and research challenges still exist, where lies in the future work directions as well.

- (1) Despite the application of intelligent techniques to the textile industry for process modeling existed since 1993, and a growing number of the related studies are reported, the current investigations of the textile manufacturing process modeling are still over fundamental and far from being implemented at the industrial level. On the one hand, this topic is dependent on the interdisciplinary contributions, but researchers working in artificial intelligence and in the textile engineering may lack expertise from the other. On the other hand, the textile manufacturers from small and medium enterprises remain skeptical about the benefits of intelligent techniques and data analytics as they look at the cost and benefit tradeoff to be able to exploit it. Therefore, the significance of process modeling in the textile manufacturing industry should be roused by deepening related research to actual applications.
- (2) The reviewed articles covered the range of textile manufacturing from the yarn processes to the garment processes. However, most of the research articles addressed the modeling problem only in a single process, where the variety of textile manufacturing process was omitted. The investigated problem was assumed not affected by the upstream activities, and the influences of a target process on the downstream procedure are not considered. Limited studies have addressed the problems considering integrated multiple processes of the textile manufacturing, the constructed textile process models lack the accounting of the relationship between processes in the way how they really work in the chain. Future works should pay more attention to multiple complete processes and realize the modeling not only in a single treatment but taking the associated upstream or downstream processes into account as well.
- (3) The application of the process model basically is to assist the manufacturing decision-maker to search the optimum solutions using a virtual simulation of the process instead of real experimental exploration. The predictive power of the intelligent process model can make a difference in the decision-making sector when it is applied with advanced optimization algorithms. But most of the previous studies only focused on process modeling, barely formulated the constructed model into a systematic problem of optimization or decision-making. It is suggested to the extent the investigation of process modeling to the overall practical problems such as optimization and decision-making.
- (4) It is evident from the review that the data for textile process modeling is quantitatively limited. This could be attributed to the complexity and variety of the textile manufacturing processes. While on the other hand, certain developed models are found that similar in many aspects (e.g. modeling the yarn spinning process). Regarding these two issues, it is necessary to integrate a sharing platform where the textile process data could be accumulated increasingly from different contributors and the repeated efforts could be avoided but to work out on studies more innovative. Additionally, regarding the lack of data for modeling the textile manufacturing process, future works should pay more attention to the feature-extraction procedures, and methods of data pretreatment (such as clustering technique of PCA) or the modeling techniques which can stably work with small data.

- (5) Though it is difficult to determine the appropriate intelligent techniques in the case of textile process modeling, the previous researches mostly took ANN as their premium choice. The finite comparative studies were conducted also with the concentration only on the techniques of ANN, fuzzy theory etc. comparing with linear regression models. In fact, the novel methods are constantly developed in recent years that are worth to be noted in the investigations of textile process modeling.
- (6) There were more than 128 articles reviewed in this paper and the established models were firstly related to the yarn manufacturing process (70 articles). Comparatively, only 45 and 13 articles explored the fabric manufacturing processes and garment manufacturing process, the research will probably shift attention to the areas such as knitting, nonwoven and garment processes in future works.

5. Conclusions

Textile manufacturing industry is complex because of the involvement of a variety of processes and a large number of variables. In order to understand the intricate relationships between textile process parameters and the process performance properties, researches have paid a lot of attention to the intelligent techniques for process modeling as the traditional methods can hardly manage the complexities from numerous factors, while the intelligent techniques can directly learn from data and accurately simulate the interrelated impacts of process variables on process performances. In this study, the literatures investigating the process modeling of textile manufacturing are systematically reviewed. The structure of it is in line with the procedure of textile processes from yarn to fabrics, and to garments. The analysis and discussion of the previous studies are conducted from the different applications in a different process. The factors and performance properties considered in process modeling are collected in comparison. The considerations of the previous studies in terms of inputs' relative importance, feature selection, modeling techniques, data distribution and performance estimations are analyzed and summarized. On the basis of the summaries of more than 128 related articles from the point of views of textile engineering and artificial intelligence, the limitations, challenges and future perspectives in this issue are also concluded.

Acknowledgments

This research was supported by the funds from National Key R&D Program of China (Project NO: 2019YFB1706300), and Scientific Research Project of Hubei Provincial Department of Education, China (Project NO: Q20191707).

The first author would like to express his gratitude to China Scholarship Council for supporting this study (CSC, Project NO. 201708420166).

Reference

- Al-Dunainawi, Y., Abbod, M. F., & Jizany, A. (2017). A new MIMO ANFIS-PSO based NARMA-L2 controller for nonlinear dynamic systems. *Engineering Applications of Artificial Intelligence*, 62, 265-275.
- Balci, O., & Oğulata, R. T. (2009). Prediction of the changes on the CIELab values of fabric after chemical finishing using artificial neural network and linear regression models. *Fibers and Polymers*, 10(3), 384-393.
- Balci, O., Oğulata, S. N., Sahin, C., & Oğulata, R. T. (2008). Prediction of CIELab data and wash fastness of nylon 6, 6 using artificial neural network and linear regression model. *Fibers and Polymers*, 9(2), 217.
- Balci, O., Oğulata, S. N., Şahin, C., & Oğulata, R. T. (2008). An artificial neural network approach to prediction of the colorimetric values of the stripped cotton fabrics. *Fibers and polymers*, 9(5), 604-614.
- Baumgarte, U. (1987). Developments in vat dyes and in their application 1974–1986. *Coloration Technology*, 17(1), 29-38.
- Behera, B. K., & Muttagi, S. B. (2005). Comparative analysis of modeling methods for predicting woven fabric properties. *Journal of Textile Engineering*, 51(1), 1-9.
- Beşdok, E. (2004). A new method for impulsive noise suppression from highly distorted images by using Anfis. *Engineering Applications of Artificial Intelligence*, 17(5), 519-527.

- Blackburn, R. S., Bechtold, T., & John, P. (2009). The development of indigo reduction methods and pre-reduced indigo products. *Coloration Technology*, 125(4), 193-207.
- Brinkworth, B. J. (1972). Interpretation of the Kubelka-Munk coefficients in reflection theory. *Applied Optics*, 11(6), 1434-1435.
- Chavan, R. B. (2015). 3-Indigo dye and reduction techniques A2 - Paul, Roshan *Denim* (pp. 37-67): Woodhead Publishing.
- Choudhury, A. K. R. (2017). Environmental impacts of denim washing.
- Dhouib, S., Khedher, F., & Sakli, F. (2015). A new approach to predict the fabric shrinkage in denim garments after finishing treatments. *Journal of the Textile Institute Proceedings & Abstracts*, 107(3), 364-375.
- Dias, F. M., Antunes, A., & Mota, A. M. (2004). Artificial neural networks: a review of commercial hardware. *Engineering Applications of Artificial Intelligence*, 17(8), 945-952.
- Doğan, D., & Türkdemir, H. (2005). Electrochemical oxidation of textile dye indigo. *Journal of Chemical Technology and Biotechnology*, 80(8), 916-923.
- Downey, L. (2007). A short history of denim. *Levi Strauss & Co., San Francisco, USA*.
- Eren, H. A., Avinc, O., Erişmiş, B., & Eren, S. (2014). Ultrasound-assisted ozone bleaching of cotton. *Cellulose*, 21(6), 4643-4658. doi: 10.1007/s10570-014-0420-2
- Eren, H. A., & Ozturk, D. (2010). The evaluation of ozonation as an environmentally friendly alternative for cotton preparation. *Textile Research Journal*, 81(5), 8. doi: 10.1177/0040517510380782
- Etters, J. (1993). Indigo dyeing of cotton denim yarn: correlating theory with practice. *Coloration Technology*, 109(7-8), 251-255.
- Etters, J. (1995). Advances In Indigo Dyeing: Implications for the Dyer, Apparel Manufacturer and Environment. *Textile Chemist & Colorist*, 27(2).
- Fan, J., & Hunter, L. (1998). A worsted fabric expert system. II. An artificial neural network model for predicting the properties of worsted fabrics. *Textile Research Journal*, 68(10), 763-771.
- Fan, J., & Hunter, L. (1998). A worsted fabric expert system: Part I: System development. *Textile Research Journal*, 68(9), 680-686.
- FEKI, I., MSAHLI, F., ZENG, X., & KOEHL, L. (2016). *MODELING FABRIC HAND OF A TEXTILE PROCESS USING A MULTILAYER PERCEPTRON PRUNING ALGORITHM*. Paper presented at the Uncertainty Modelling in Knowledge Engineering and Decision Making: Proceedings of the 12th International FLINS Conference.
- Gazzah, M., Jaouachi, B., Schacher, L., Adolphe, D., & Sakli, F. (2014). *MODELING THE BAGGING BEHAVIORS OF DENIM FABRICS AS FUNCTION OF MECHANICAL PROPERTIES*. Paper presented at the International Conference of Applied Research in Textile.
- Gharehaghaji, A. A., Shanbeh, M., & Palhang, M. (2007). Analysis of two modeling methodologies for predicting the tensile properties of cotton-covered nylon core yarns. *Textile Research Journal*, 77(8), 565-571.
- Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1): MIT press Cambridge.
- Haghighat, E., Mohammad Etrati, S., & Shaikhzadeh Najar, S. (2013). Modeling of needle penetration force in denim fabric. *International Journal of Clothing Science and Technology*, 25(5), 361-379.
- Haghighat, E., Mohammad Etrati, S., & Shaikhzadeh Najar, S. (2014). Evaluation of Woven Denim Fabric Sewability based on Needle Penetration Force. *Journal of Engineered Fabrics & Fibers (JEFF)*, 9(2).
- Haghighat, E., Najar, S. S., & Etrati, S. M. (2014). The Prediction of Needle Penetration Force in Woven Denim Fabrics Using Soft Computing Models. *Journal of Engineered Fabrics & Fibers (JEFF)*, 9(4).
- He, Z., Li, M., Zuo, D., & Yi, C. (2018a). Color fading of reactive-dyed cotton using UV assisted ozonation. *Ozone: Science & Engineering*(just-accepted).
- He, Z., Li, M., Zuo, D., & Yi, C. (2018b). The effect of denim color fading ozonation on yarns. *Ozone: Science & Engineering*, 1-8.
- Huang, S.-C., & Huang, Y.-F. (1991). Bounds on the number of hidden neurons in multilayer perceptrons. *IEEE transactions on neural networks*, 2(1), 47-55.

- Hung, O., Song, L., Chan, C., Kan, C., & Yuen, C. (2011). Using artificial neural network to predict colour properties of laser-treated 100% cotton fabric. *Fibers and polymers*, 12(8), 1069-1076.
- Hung, O., Song, L., Chan, C., Kan, C., Yuen, C., & Zhang, Y. (2011). *Prediction of laser-treated knitted fabric colour properties based on a new elman neural network*. Paper presented at the Future Computer Sciences and Application (ICFCSA), 2011 International Conference on.
- Jang, J.-S. (1993). ANFIS: adaptive-network-based Fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, 23(3), 665-685.
- Jang, J.-S., & Sun, C.-T. (1993). Functional equivalence between radial basis function networks and Fuzzy inference systems. *IEEE transactions on Neural Networks*, 4(1), 156-159.
- Jelil, R. A., Zeng, X., Koehl, L., & Perwuelz, A. (2013). Modeling plasma surface modification of textile fabrics using artificial neural networks. *Engineering Applications of Artificial Intelligence*, 26(8), 1854-1864.
- K, L., D, M., F, P., & J, L. (2006). Color measurement in L*a*b* units from RGB digital images. *Food Research International*, 39(10), 1084-1091.
- Kan, C. (2015). Washing techniques for denim jeans *Denim* (pp. 313-356): Elsevier.
- Kan, C., & Song, L. (2016). An artificial neural network model for prediction of colour properties of knitted fabrics induced by laser engraving. *Neural processing letters*, 44(3), 639-650.
- Kan, C. W., Cheung, H. F., & Chan, Q. (2016). A study of plasma-induced ozone treatment on the colour fading of dyed cotton. *Journal of Cleaner Production*, 112, 3514-3524. doi: 10.1016/j.jclepro.2015.10.100
- Kan, C. W., Wong, W. Y., Song, L. J., & Law, M. C. (2013). Prediction of Color Properties of Cellulase-Treated 100% Cotton Denim Fabric. *Journal of Textiles*, 2013, (2013-03-19), 2013.
- Khalil, E. (2015). Sustainable and Ecological Finishing Technology for Denim Jeans. *AASCIT Communications*, 2, 159-163.
- Khalil, E., & Islam, M. M. (2015). Wrinkle Finish on Denim by Resin Treatment: A Review. *AASCIT Communications*, 2, 82-87.
- Khalil, E., & Sarkar, J. (2014). Effect of Industrial Bleach Wash and Softening on the Physical, Mechanical and Color Properties of Denim Garments. *IOSR Journal of Polymer and Textile Engineering*, 1(3), 46-49.
- Kuo, C.-F. J., Hsiao, K.-I., & Wu, Y.-S. (2004). Using Fuzzy theory to predict the properties of a melt spinning system. *Textile Research Journal*, 74(3), 231-235.
- Majumdar, P. K., & Majumdar, A. (2004). Predicting the breaking elongation of ring spun cotton yarns using mathematical, statistical, and artificial neural network models. *Textile Research Journal*, 74(7), 652-655.
- Malek, S., Khedher, F., Jaouachi, B., & Cheikrouhou, M. (2017). Determination of a sewing quality index of denim fabrics. *The Journal of The Textile Institute*, 1-13.
- Mas, J. F., & Flores, J. J. (2008). The application of artificial neural networks to the analysis of remotely sensed data. *International Journal of Remote Sensing*, 29(3), 617-663.
- Meksi, N., & Mhenni, M. (2015). Indigo dyeing technology for denim yarns *Denim* (pp. 69-105): Elsevier.
- Mercer, H. (2010, February 17). The Rise and Fall of the U.S. Denim Manufacturing Industry: 1960-2010. Denims and Jeans. USA.
- Moller, M. F. (1993). A scaled conjugate gradient algorithm for fast supervised learning. *Neural networks*, 6(4), 525-533.
- Moosavi, S. H. S., & Bardsiri, V. K. (2017). Satin bowerbird optimizer: A new optimization algorithm to optimize ANFIS for software development effort estimation. *Engineering Applications of Artificial Intelligence*, 60, 1-15.
- Nicholson, S. K., & John, P. (2004). Bacterial indigo reduction. *Biocatalysis and Biotransformation*, 22(5-6), 397-400.
- Paul, R. (2015). 1 - Denim and jeans: An overview *Denim* (pp. 1-11): Woodhead Publishing.
- Ramesh, M., Rajamanickam, R., & Jayaraman, S. (1995). The prediction of yarn tensile properties by using artificial neural networks. *Journal of The Textile Institute*, 86(3), 459-469.
- Roessler, A., Crettenand, D., Dossenbach, O., Marte, W., & Rys, P. (2002). Direct electrochemical reduction of indigo. *Electrochimica Acta*, 47(12), 1989-1995.
- Sandberg, G. (1989). *Indigo textiles: technique and history*: A & C Black; Lark Books.

- Sarkar, J., Khalil, E., & Solaiman, M. (2014). Effect of Enzyme Washing Combined With Pumice Stone on the Physical, Mechanical and Color Properties of Denim Garments. *International Journal of Research in Advent Technology*, 2(9), 65-68.
- Seefelder, M. (1994). Indigo in culture, science and technology: ecomed.
- Senthilkumar, M., & Selvakumar, N. (2006). Achieving expected depth of shade in reactive dye application using artificial neural network technique. *Dyes and pigments*, 68(2-3), 89-94.
- Sette, S., & Van Langenhove, L. (2003). An overview of soft computing in textiles. *Journal of The Textile Institute*, 94(1-2), 103-109.
- Shahid, A., & Hossain, I. (2015). Modeling the spirality of cotton knit fabric using Fuzzy expert system. *Turkish Journal of Fuzzy Systems*, 6(2), 056-067.
- Slah, M., Amine, H. T., & Faouzi, S. (2006). A new approach for predicting the knit global quality by using the desirability function and neural networks. *Journal of the Textile Institute Proceedings & Abstracts*, 97(1), 17-23.
- Soud, H., Babay, A., & Sahnoun, M. (2012). Fabric Quality Optimization by Using Desirability Function and Neural Networks. *Journal of Computer Technology and Application*, 3(1), 356-364.
- Soud, H., & Cheikhrouhou, M. (2011). Slub Yarn Quality Optimization by using Desirability Function and Neural Networks. *Journal of Applied Sciences*, 11(17).
- Suzuki, K. (2011). Artificial Neural Networks - Industrial and Control Engineering Applications.
- Tieckelmann, R. H., Bull, R. A., & Kurschner, L. M. (1991). Wet processing of denim: Google Patents.
- Uddin, M. G. (2014). Indigo ring dyeing of cotton warp yarns for denim fabric. *Chemical and Materials Engineering*, 2(7), 149-154.
- Vanschoren, J., Van Rijn, J. N., Bischl, B., & Torgo, L. (2014). OpenML: networked science in machine learning. *ACM SIGKDD Explorations Newsletter*, 15(2), 49-60.
- Wong, T.-T. (2015). Performance evaluation of classification algorithms by k-fold and leave-one-out cross validation. *Pattern Recognition*, 48(9), 2839-2846.
- Wu, L., Yick, K.-l., Ng, S.-p., Yip, J., & Kong, K.-h. (2012). Parametric design and process parameter optimization for bra cup molding via response surface methodology. *Expert Systems with Applications*, 39(1), 162-171.
- Yang, L., & Kruse, B. (2004). Revised Kubelka-Munk theory. I. Theory and application. *Journal of the Optical Society of America A Optics Image Science & Vision*, 21(10), 1933-1941.
- Zanaganeh, M., Mousavi, S. J., & Shahidi, A. F. E. (2009). A hybrid genetic algorithm–adaptive network-based Fuzzy inference system in prediction of wave parameters. *Engineering Applications of Artificial Intelligence*, 22(8), 1194-1202.
- Zervent Ünal, B. (2012). The prediction of seam strength of denim fabrics with mathematical equations. *Journal of The Textile Institute*, 103(7), 744-751.