Thesis

MODÉLISATION ET OPTIMISATION DES PROCÉDÉS DE FABRICATION TEXTILE À L'AIDE DES TECHNIQUES INTELLIGENTES

MODELING AND OPTIMIZATION OF TEXTILE MANUFACTURING PROCESSES USING INTELLIGENT TECHNIQUES

by

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Oral defense on 15/12/2020

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Abstract

Textile manufacturing plays an important role in the world economy. While the globally increasing competition is stressing the textile companies to promote the manufacturing flexibility, as a trend of intelligent manufacturing in Industry 4.0, the future development of the textile manufacturing process will increasingly rely on shorter cycle and higher quality. However, the complicated intricate relationship between the large-scale parameter variables from a variety of textile processes makes it seem incredibly difficult. In order to overcome these issues, intelligent techniques are employed in this thesis to promote textile manufacturing from the process modeling and optimization.

In this Ph.D. research, a thorough investigation and literature review regarding the previous studies on modeling and optimization of the textile manufacturing process using intelligent techniques. A series of the summarizations were determined in pros and cons, which provided a theoretical foundation and research direction for the subsequent studies. Three sub-studies thus were developed: A specific case study on textile ozonation process modeling using extreme learning machine (ELM), support vector regression (SVR) and random forest (RF) was developed, where the SVR models and RF models were found that both can well address the uncertain interrelationships of variables in the textile process modeling with less training data, but their requirement on training time is different. On the basis of the established RF models, a novel multi-criteria decision support system was then developed for textile optimization with the collaboration of the analytic hierarchy process (AHP) and the Deep Q-networks (DQN) algorithm, where the textile process is formulated as the Markov decision process (MDP) paradigm, and the application result showed that it can master the challenging decision-making tasks in the textile manufacturing process. To better address the growing complexity in this issue, the application of this developed system is further integrated into a multi-agent system for multi-objective optimization in the textile manufacturing process. The developed systems can optimize the textile process and help companies maintain competence in the trend of intelligent manufacturing in the textile industry.

Keywords: Process modeling; Production optimization; Reinforcement learning; Machine learning; Textile process; Artificial intelligence

MODÉLISATION ET OPTIMISATION DES PROCÉDÉS DE FABRICATION TEXTILE À L'AIDE DES TECHNIQUES INTELLIGENTES

Résumé

La fabrication textile joue un rôle important dans l'économie mondiale. Face à une concurrence mondiale croissante, les entreprises textiles tentent de promouvoir la flexibilité de fabrication en s'appuyant sur le concept de fabrication intelligente issu de l'industrie 4.0. Ainsi, le futur développement des processus de production textile reposera de plus en plus sur un cycle de fabrication plus court et une qualité supérieure. Cependant, les relations complexes entre les paramètres provenant des nombreux procédés textiles et la grande variété de produits rend le contrôle et l'optimisation de la fabrication très difficile. Afin de surmonter ces problèmes, des techniques intelligentes de modélisation des processus et d'apprentissage à partir de données expérimentales sont utilisées dans cette thèse pour optimiser la fabrication textile.

Dans cette thèse une étude approfondie de la littérature est menée sur les travaux précédents concernant la modélisation et l'optimisation du processus de fabrication textile à l'aide de techniques intelligentes. La synthèse de ces travaux, des avantages et inconvénients des différentes techniques, ont fourni une base théorique et une direction de recherche sur la méthodologie à suivre. Trois sous-études ont ainsi été développées. La première étude de cas spécifique porte sur la modélisation des processus d'ozonation des textiles à l'aide de réseaux neuronaux de type "extreme learning machine" (ELM), de régression par machines à vecteurs "support vector regression" (SVR) et de forêt d'arbres décisionnels "random forest" (RF). Les modèles SVR et RF ont montré les meilleures aptitudes à modéliser les interrelations incertaines des variables dans le processus textile avec un nombre réduit de données d'apprentissage, mais nécessite des temps d'exécution plus importants. Sur la base des modèles RF établis, un nouveau système d'aide à la décision multicritères a ensuite été développé, dans une deuxième étude, pour l'optimisation textile en combinaison avec une méthode de hiérarchie multicritère, "analytic hierarchy process" (AHP), et de l'algorithme Deep Q-networks (DQN). Le processus textile est alors formalisé comme un processus de décision markovien, "Markov decision process" (MDP). Le résultat obtenu par ce modèle montre qu'il est possible de contrôler les relations décisionnelles complexes qui régissent le processus de fabrication textile. Dans la troisième étude, afin de mieux répondre à la complexité croissante de ce problème en milieu industriel, le système développé est intégrée dans un système multi-agents pour l'optimisation multi-objectifs du processus de fabrication textile. Les différents systèmes proposés permettent d'optimiser le processus de fabrication textile et aider les industries textiles à converger vers une fabrication intelligente pour maintenir leur compétitivité.

Mots clés: Modélisation de processus; Optimisation de la production; Apprentissage par renforcement; Apprentissage automatique; Processus textile; Intelligence artificielle

Acknowledgement

This thesis was carried out at the GEMTEX (Laboratoire de Génie et Matériaux Textiles), ENSAIT (École Nationale Supérieure des Arts et Industries Textiles) in Lille, France. This thesis was supported by the China Scholarship Council (CSC, 201708420166). Both of the GEMTEX-ENSAIT and the CSC are gratefully acknowledged for supporting the preparation and completion of the thesis.

I would like to express my deepest gratitude to my supervisors, Prof. Xianyi Zeng, Prof. Sébastien Thomassey, and Prof. Kim Phuc Tran, thanks for their advices and ideas conceptualized the problems and the frameworks of the researches in this thesis, thanks for taking their valuable time to discuss with me and guide me when I feel confused and frustrated. I can barely work out this Ph.D. thesis without their warm help and support, it is my great honor to work with them and have all of them as my Ph.D. supervisors.

Part of the acquisition of data in the researches of this thesis was managed by Prof. Changhai Yi and Dr. Jie Xu from Wuhan Textile University, Wuhan, China. Their work was very significant to the studies in my thesis. Some helps came from the other Ph.D. students of GEMTEX-ENSAIT (Yanni Xu, Kaichen Wang, Kehui Song, Melissa Wagner, Chandadevi Giri, Mohammad Neaz Morshed, Ashik Md Faisol, Balkiss Hamad, Shenglei Xiao, Xiang Yan, Cheng Chi, Hao Shen, Xin Zhao, Shengchang Zhang) have benefited me a lot to improve my works from different directions. I thank to their help from the bottom of my heart.

Last but not the least I would like to thank my families and my fiancée (Mengru Li) for their selfless encouragement and support to me.

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List of abbreviations

Abbreviation	Explanation
ABC	Artificial bee colony
ACO	Ant colony optimization
AFIS	Advanced fiber information system
AHP	Analytic hierarchy process
AI	Artificial intelligent
ANFIS	Adaptive-Network-based Fuzzy Inference System
ANN	Artificial neural network
ANOVA	Analysis of variance technique
DE	Differential evolution
DNNs	Deep neural networks
DQN	Deep Q-networks
DRL	Deep reinforcement learning
DRL	Deep reinforcement learning
EA	Evolutionary algorithm
ELM	Extreme learning machine
ENRBF	Extended normalized radial basis function
ERBF	Exponential Radial basis function
FECS	Fuzzy efficiency-based classifier system
FIS	Fuzzy inference system
FMT	Fineness and maturity tester
GA	Genetic algorithm
GEP	Gene expression programming
GP	Genetic programing
HVI	High-volume instrument system
IoT	Internet of Things
KNN	K-nearest neighbors
LM	Levenberg-Marquardt
LOO	Leave-one-out process
MAE	Mean absolute error
MARL	Multi-agent reinforcement learning system
MCDM	Multi-criteria decision-making
MCI	Mean of capability index
MDP	Markov decision process
ME	Mean error
MLR	Multiple logarithm regression
MOSPO	Multi-objective swarm particle optimization
MSE	Mean square error
NPF	Needle penetration force
NSGA-Ⅱ	Non-dominated sorting genetic algorithm- Ⅱ
PCA	Principal component analysis
PSO	Particle swarm optimization
R	Correlation coefficient
R^2	R-square

RBF	Radial basis function networks
RE	Relative error
RF	Random forest
RL	Reinforcement learning
RMSE	Root mean square error
RT	Regression trees
SA	Simulated annealing
SICS	Synergetic immune clonal selection
STE	Strength transfer efficiency
STE	Strength transfer efficiency
SVM	Support vector machine
SVR	Support vector regression

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General introduction

With the globally increasing competition in the textile industry, the manufacturers are forced to promote the product quality, process efficiency, and process environmental issues as a whole. This is highly complex due to the intricate relationship involved in a large number of parameter variables from a variety of processes. Traditional techniques can hardly make remarkable promotions in these regards. Thus, some innovative methods are demanded to solve these issues and optimize the textile processes.

In the background of Industry 4.0, manufacturing processes are expected to be more intelligent with quick reactivity to the market and adaptation to the big data environment. In this situation, intelligent techniques are regarded as the key techniques simulating human reasoning and perception, permitting to model and analyze with various data, and then leading to smart and fast utilization of IoT (Internet of Things) and cloud computations, as well as data-driven product and market prediction and online traceability. Especially, intelligent techniques in the big data environment will enable to get through the information channel of the whole supply chain from very initial production stages to finished products. Concretely, intelligent manufacturing techniques have been developed to meet various personalized requirements of customers, deal with quickly and continuously arriving data generated from multiple connected devices, connected materials and connected operators. In general, intelligent manufacturing could be a promising direction to solve the aforementioned problems encountered in the textile manufacturing by intelligent process modeling and optimization with evolutionary data.

Artificial intelligence techniques are playing a vital role in industry development. They have attracted significant attention from both industry and academia, many successful applications of intelligent techniques for modeling, simulation and optimization of industry processes as well as supporting decision-making have been developed. These techniques are known as efficient data mining tools and can overcome the aforementioned complex problems encountered in various industrial processes.

Intelligent process modeling and optimization constitute the main axis of my thesis. Three inter-organizational investigations on modeling and optimization strategies were developed respectively to solve current issues in the textile manufacturing process. Specifically, from a case study on modeling a textile ozonation process, a modeling technique was proposed upon the comparison of multiple intelligent approaches. And two decision support frameworks based on deep reinforcement learning techniques were designed on the basis of the developed intelligent process model with the collaboration of the multi-criteria decision-making tool of the analytic hierarchy process, and the multi-agent system respectively. The feasibility and effectiveness of the developed model and corresponding proposed decision support frameworks were verified through the application in a textile ozonation process. According to the outcomes of this research, the decision-maker from the textile manufacturing industry can take advantages of the models and frameworks developed in this thesis to exploit their manufacturing dynamic data for modeling, simulation and optimization of the process, to address the complexities in the process promotion by assisting decision-making under uncertainties and efficiently finding the optimum process solution from the challenging high dimensional decision space, so that to enhance their competitiveness in the future of Industry 4.0 era.

The structure and organization of this thesis are introduced as shown in Figure 1.

As illustrated in Figure 1, Chapter 1 introduces the background of my Ph.D. research in general. We give a brief introduction to textile manufacturing and discuss the necessity of modeling and optimization using intelligent techniques. The formulated problems and the purposes of this Ph.D. thesis are also presented.

Chapter 2 makes a systematic literature review concerning the previous researches and applications of the modeling and optimization of the textile manufacturing process using intelligent techniques, paves the way for the research direction for the following sub-studies in this thesis. It summarizes the prior investigations on the intelligent techniques for modeling and optimization of the textile manufacturing process with a general outline in three clusters, i.e. applications in yarn manufacturing, fabric manufacturing and garment manufacturing, respectively. It compared many traditional algorithms and the analysis concluded that current methods are not eligible enough to handle the increasing complexities of large-scale data and high dimensional space of the modeling and optimization problems in the textile manufacturing process in the era of Industry 4.0.

Chapter 3 studies three intelligent modeling techniques, i.e. extreme learning machine (ELM), support vector regression (SVR) and random forest (RF), for modeling the textile ozonation process. The prediction performances among these algorithms in regard to the color properties of treated textiles in the ozonation with respect to the process parameters are comparatively investigated. The potential applicability of these models in the use of textile process modeling is estimated.

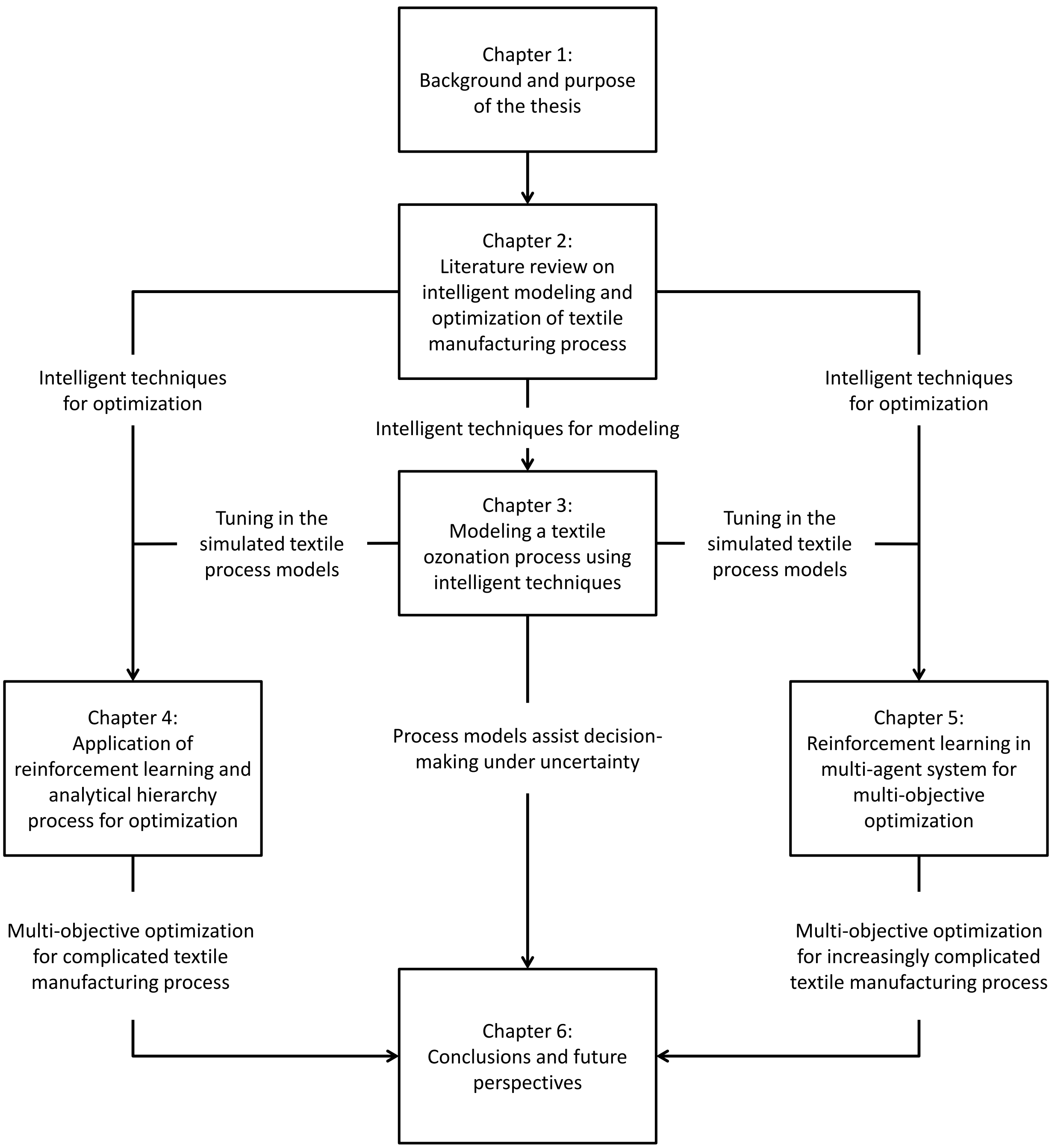


Figure 1. Structure of the thesis

According to the models comparatively studied in Chapter 3, a multi-criteria decision support system for the textile manufacturing process is established in Chapter 4. The developed decision support system combines the intelligent data-based models of random forest (RF) and a human knowledge-based multi-criteria structure of the analytic hierarchy process (AHP) in accordance with the objective and the subjective factors of the textile manufacturing process respectively. More importantly, the solution optimization of the textile manufacturing process is described as the Markov decision process (MDP) paradigm, and a deep reinforcement learning scheme, namely the Deep Q-networks (DQN) algorithm, is employed to cope with it. The textile ozonation process is taken as an application case study to estimate the effectiveness of this system for multi-objective optimization.

Multi-objective optimization of the textile manufacturing process is increasingly challenging because of the growing complexity involved in the development of the textile manufacturing process. Though significant improvement from certain successful applications has been reported, the use of traditional techniques failed to work with high-dimension decision space and required prior experts' knowledge as well as human intervention, Chapter 5 presents another paradigm of the Markov decision process with game theory into a multi-agent system that formulates the Multi-objective optimization problem as a Markov game. This proposed multi-agent reinforcement learning framework transforms the multi-objective optimization process into a Markov game, and introduced the deep Q-networks algorithm to train the multiple agents. A utilitarian selection mechanism is employed in the Markov game, which maximizes the sum of all agents' rewards (obeying the increasing ε-greedy policy) in each state to avoid the interruption of multiple equilibria and achieve the correlated equilibrium optimal solutions of the optimizing process. The constructed textile ozonation process model is applied as a case study and extended to the multi-agent reinforcement learning system to achieve the optimal solutions. The optimization performances of this system are evaluated in the comparison with multi-objective swarm particle optimization (MOSPO) and non-dominated sorting genetic algorithm-Ⅱ (NSGA-Ⅱ).

Based on the results gained from the chapters above, a list of conclusions of the thesis is derived in Chapter 6. The contribution of this thesis is summarized with a discussion on the perspectives of future researches.

1. Introduction

1.1. An overview of the textile manufacturing processes

Textile manufacturing plays an important role in the world economy and it is one of the most relocated industrial sectors. The objective of textile manufacturing is to convert fibers into intermediated products like yarns, fabrics, and finished products like garments and technical textiles. A general illustration of the whole textile manufacturing processes is displayed in Figure 2 with a focus on woven fabrics excluding the knitting and non-woven processes.

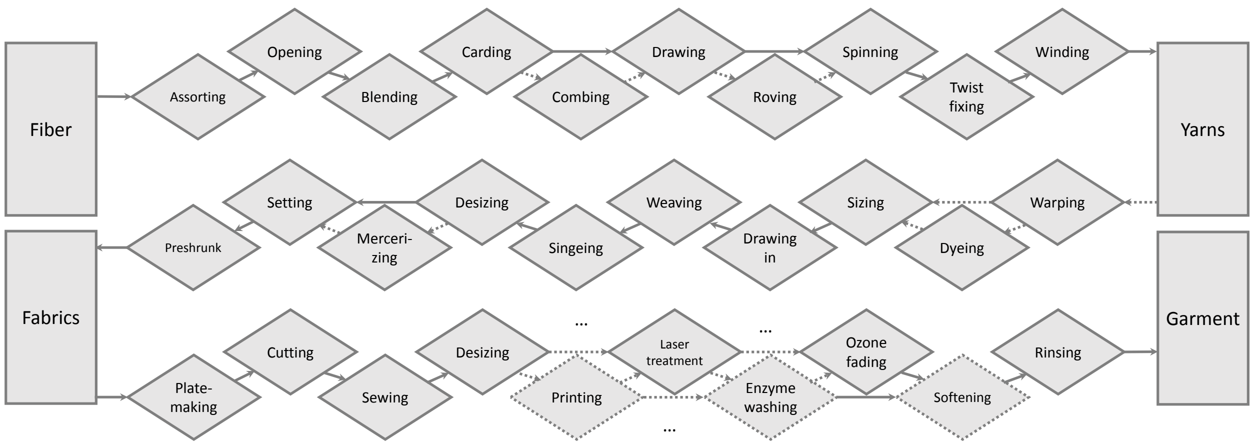


Figure 2. Principal processes of textile manufacturing from fiber to garment.

Among these, 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 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[1]. To achieve the most important properties of yarns including strength, elongation and evenness, the first half of these processes generally perform the functions of blending and removing impurities of the fibers to obtain the fiber slivers, while the second half of these operations mainly play the roles of mixing, straightening, orienting the fibers and drafting, twisting the slivers to strengthen and forming the yarns. The designed specification of yarns depends 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[2] has introduced the fundamental technology of spun yarn in detail with the coverage of the rudiments of staple-yarn technology, the manufacturing, the raw materials, and the production processes for short-staple, worsted, semi-worsted, woolen spinning, doubling, and specialty yarn, respectively. In where, some of the interesting advanced topics were also discussed ranging from new development in fiber preparation technology, carding technology to roller drafting, ring spinning, open-end rotor spinning, and 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 many preprocesses 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, promote the quality of fabrics in terms of stability, aesthetics, comfort, and 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 does not 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 of staple fiber and spun-laid of filaments, coupled with 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. Its principal operations include cutting and joining of at least two pieces of fabric. Similar to the fabrics, to improve the performance, there is a range of finishing processes for the garment as well. For example, as one of the most popular garment products, denim needs further treatments like desizing, color fading (laser, enzyme washing etc.), softening after the garment-making.

1.2. The necessity of modeling and optimization

Textile manufacturing is one of the typical traditional manufacturing sectors in which production is realized in small and medium enterprises with limited capacity on investment of advanced technologies. Under the arousing global competition, textile companies have to face the challenges of cost reduction and performance improvement. And 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 resources. Meanwhile, its future development heavily relies on product customization and shortened manufacturing cycles as the distributors and consumers are increasingly looking for variety and personalization. To approach the high degree of variability in materials, processes and parameters as well as the lack of precise control in practice, the manufacturers can barely conduct trial and error, and lean on the expertise and experience[3]. There is a strong need to develop novel methods to improve the textile manufacturing process.

Process modeling can make a difference in this regard for understanding the intricate relationships between various textile process parameters and performance properties, therefore to assist the decision-makers to find the optimal solutions of the process. The research in process engineering enables to incorporate more and more specificities of the industrial processes and then becomes increasingly practical and capable of improving the flexibility of the production operations and productivity. Although process engineering already deals with various generalized practical problems, it is still necessary to consider special issues on the running and cooperation of the textile manufacturing processes.

Since the textile manufacturing is consist of a very long value chain of processes from raw materials to finished products, combinations of processes and parameters at different stages will be stochastic and immense when factors of the targeted performance vary in any respect. Taking the textile manufacturing processes summarized in Figure 2 as an 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 specific yarn products to satisfy the design requirements. Another example is garment finishing in which 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 with different production solutions. Therefore, it is clearly impossible to promote the textile manufacturing processes by only following generalized principles of other industries, but need to take the textile specificities into consideration.

On one hand, due to the complexity involved in the textile manufacturing processes with regard to multi-stage, multi-machine, and environment-dependent specification, the process decision-maker manages numerous inputs and outputs variables and always feed with a complex interdependence between variables. And the relationship between textile manufacturing process factors is extremely nonlinear and hardly-understood, the effects of these factors on corresponding product properties are unclear [4], the decision maker is unaware of the probabilities of future states of nature that are associated with alternative actions and therefore make decision under uncertainty. It is highly unlikely that an exact mathematical model will ever be developed. On the other hand, as the increasingly shortened manufacturing cycle and the growing product variety enhances the data-scale and the decision space in current issues, the statistical models are also rarely used in any branch of the textile industry because of their sensitivity to the rogue data[5]. 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 scarification on accuracy. These traditional models show their limitations in certain scenarios that can hardly even represent the vast volume of process parameter-related data, not mention to work in the practical textile manufacturing processes.

Currently, along with the progress of innovative digital technologies, such as Big Data, virtual reality, cloud computing and Internet of Things (IoT), the textile industry is progressively developing its intelligent manufacturing systems. In order to meet various personalized requirements of customers and deal with quickly and continuously arriving data generated from multiple connected devices, connected materials and connected operators in the era of Industry 4.0, textile manufacturing needs to be updated to an intelligent level to achieve flexible, smart and reconfigurable manufacturing processes to overcome aforementioned diverse challenges[6]. Certain underpinning technologies with learning capacity from past experiences are needed in this regard. And the artificial intelligence (AI) techniques which enables manufacturing systems to efficiently learn from experiences through data, is advantageous to deal with the complexity in the textile manufacturing process modeling with regard to uncertainty and imprecision related to human knowledge on products and processes, thereby allowing problems to be solved and adaptively cooperate with the production optimization in a timely fashion [7].

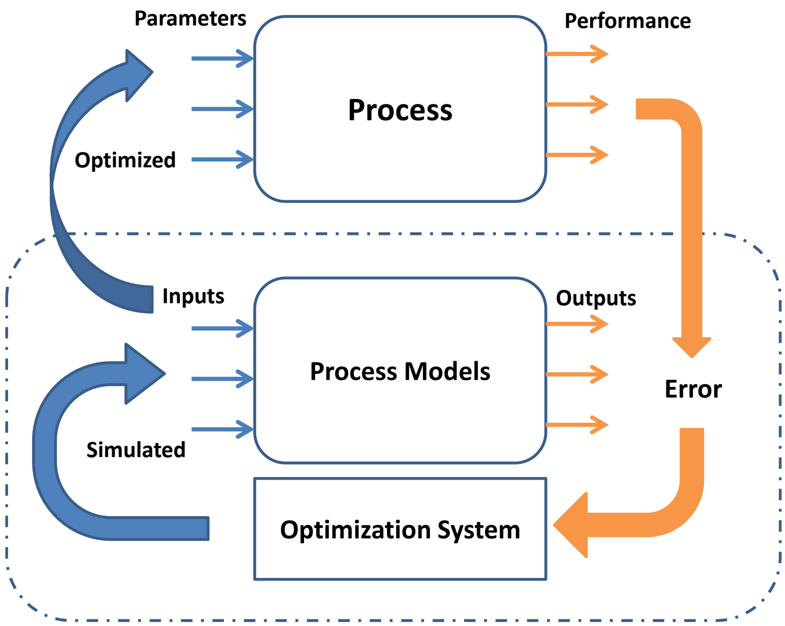


Figure 3. The basic structure of modeling and optimization for the textile process.

The AI techniques have attracted significant attention from both industry and academia, and have been investigated in many industrial applications. The use of intelligent techniques is strongly related to the nature of the present problems of interest. However, as illustrated in Figure 3, the modeling of a specific textile manufacturing process can only address one part of current issues that the performance results of process solutions can be properly simulated that reduce the time- and resource-intensive experimental effort and physics-based process simulation to tune the optimum operations on process parameter. For the second part of it, using traditional methods by virtual tuning on the basis of the constructed model for the textile process optimization will be inefficient due to the high-dimensional decision-space in this issue. More broadly, the optimization problems in the textile manufacturing process usually involve conflicting objectives as the overall performance of textile processes is normally governed by a few criteria [8], we have to take multi-objective optimization into account.

The simulation-based multi-objective optimization offers the decision-makers with trade-off solutions between several conflicting objectives, but the development of it is criticized that takes time[9]. It will no longer be a problem with the development of the internet, big-data environment and especially intelligent techniques [7] as the required time of intelligent optimization based on process models can be considerably reduced, which brings new opportunities to optimize the manufacturing process. Related AI techniques, especially the machine learning algorithms, have been applied in many sectors and shown their effectiveness in complicated multi-objective optimization problems with multi-input and multi-output variables, and high-dimension searching space [10], [11]. The applications of multi-objective optimization in the textile industry in recent years have drawn increasing attention [12]–[15], but at present, there is a limited complete study to solve a complex process optimization problem in the textile manufacturing domain.

Hence, a systematic study of modeling and optimization of the textile manufacturing process is desperately needed. But different from previous works using classical models relied on physical laws or simplified assumptions, and substantial numerical expertise, or considerable computation times, intelligent techniques would perform a vital function in this time.

1.3. Problem discussion and purpose of the thesis

As discussed above, the textile manufacturing industry is a traditional sector relied on small and medium enterprises in general. In order to survive in the competitive global market, textile manufacturing enterprises have to promote their process. But it is highly complex not only due to the intricate relationship involved in a large number of parameter variables from a variety of processes [16] but also resulted from the stochastic high dimension decision space involved in the textile process optimization problem with respect to multiple objectives. Based on intelligent techniques, the construction of process models and the development of a decision support system upon virtual process models to optimize the textile process solutions remains an open challenge [13].

This thesis aims to inform theory and practice on the modeling and optimization of the textile manufacturing process through intelligent techniques to enable the manufacturing enterprises to optimize the textile process with trade-off solutions between several conflicting objectives, to be competent to provide collaborative, customizable, flexible and reconfigurable services to end-users. The literature review shows that the modeling and optimization of the textile manufacturing process have been well investigated in many subfields, while the prior investigations either simplify the case by omitting certain non-essential details to achieve manageable equations on the basis of scarification on the accuracy or require prior experts' knowledge and human intervention. More importantly, the traditional approaches can hardly manage the high dimensional computation when the optimization of the textile manufacturing process increasingly considering multiple objectives.

2. Literature review

The next generation of industry, as known as Industry 4.0, holds the promise of increased flexibility in manufacturing, along with mass customization, better quality, and improved productivity. Therefore, it enables the manufacturers to cope with the challenges of producing increasingly individualized products with a shorter manufacturing cycle and higher quality[7]. An intelligent process is one of the basic elements in such a smart manufacturing environment. In order to globally improve the process for the development of an intelligent manufacturing system, it is necessary to properly address the uncertainties and imprecision among process variables in terms of the complex and non-linear relationship between the input process parameters and output performance parameters.

2.1. Intelligent techniques used for textile process modeling

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. The analytical models or mathematical models are usually based on certain idealized assumptions, so their applicability is largely governed by the viability of these assumptions[17][18]. Due to the increasing complexity in the development of intelligent textile manufacturing, none of the physical or chemical laws will be available that can figure out the picture of a process taking all the factors into consideration. The application of the textile manufacturing process nowadays incorporates a wide range of variables from the performance assessment and the corresponding effects from the process parameters are unclear, where the practical features cannot be fully reflected by the classical models, and the introduction of data-based intelligent models becomes a necessity.

The process modeling using intelligent techniques has been conducted in many areas, and the applied techniques comprise artificial neural network (ANN), Fuzzy logic, support vector machine (SVM), gene expression programming (GEP), etc.

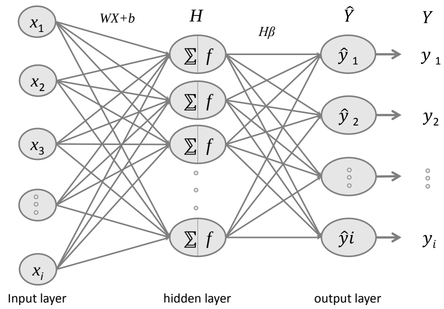


Figure 4. An example of artificial neural network architecture.

ANN is a widely investigated artificial intelligence approach in the textile sector[19]. The research of ANN for textile process modeling is very popular, which could be attributed to its excellent capacity to map the extremely nonlinear relationship between the factors and performances of the process. It is developed 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[20]. 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 4.), 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 [21]).

As there are a variety of textile properties rely on subjective evaluation, and human knowledge may help the interpretation of textile variables and their relationships in certain cases, especially when the data is limited, Fuzzy logic is also very popularly applied in this topic. Fuzzy logic was developed by Prof. Lotfi A. Zadeh in 1965 as an extension of crisp logic[22]. 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 to1 to define uncertainty. For instance, when the temperature higher than 40℃ indicates “hot”, as an input and output variable, there would be intermediate states named in linguistic terms like “quite 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 ≤40℃ 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 [23]. Fuzzy techniques are usually applied in order to solve control problem by formulating linguistic rules, but the use of it for modeling, optimization and decision-making support in the textile manufacturing industry is also very popular as the data and relations among variables might not crisp in this domain due to the involvement of human subjectivity and a large number of qualitative descriptions [14].

Aside from the ANN and Fuzzy logic, applications of the hybrid models combining their fuzzification technique and the learning capability are also widely accessible in textile researches. This is because of the compatibility of these hybrid methods on data and human knowledge can well reveal both of the subjective and objective factors in the textile manufacturing process. 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 the adaptive-network-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. 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. It is able to work under uncertain noisy and simulate complex nonlinear mappings which right fits the advantages of both ANN and Fuzzy logic.

Unlike most of the aforementioned models which implement the empirical risk minimization principle, the Support vector machine (SVM) implements the structural risk minimization principle which seeks to minimize an upper bound of the generalization error rather than the training error. It is assumed that has better potential to generalize and the ability to handle noisy data, so that has been considered in the process modeling of many textile scenarios. 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 [24]. 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 [25], [26]. 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[27]. Authors reported that it is not a black-box and explores the inter-relationship between input and output variable [28][18], and is better than ANN in terms of precision so that the uses of it can be found in certain related studies as well. 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 they 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 [29].

2.2. Modeling yarn manufacturing process

The textile manufacturing process generally is composed of three pillars: yarn manufacturing, fabric manufacturing, and garment manufacturing.

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 the ring-, rotor-spinning and the air-jet spinning to the 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.

Table 1. Fiber properties affecting textile 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

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 imply the input and output respectively of the sorted different yarn manufacturing process models introduced in reviewed 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 literature. 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, and 11) Drawing, respectively.

Table 2. Process parameters in the 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		

2.2.1 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 the textile manufacturing sector were reported [30]–[32]. 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. The 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 [33]. Air-jet spinning is essentially a pneumatic-spinning method, which consists of 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.

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

Table 4. Information about modeling the yarn manufacturing process using intelligent methods in previous works

	Ref.	Model inputs	Model targets	Modeling techniques	Data train: test	Testing accuracy
1)	[31]	F2,F4,F5,F18,F20,F21,F22,F37,F46	Y15	ANN	84:85	R=0.850
	[34]	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
	[35]	F2,F4,F39,F46 / P1,P25	Y4,Y19	ANN	40:25	t=0.0191; 0.6128
	[36]	F20,F25,F29,F37,F39 / P1	Y2,Y4,Y13,Y14,Y15,Y16	ANN	14:6	RE= 2.4%~19.1%
	[17]	F3,F4,F5,F7,F25,F35,F37	Y3	ANN		R=0.938
	[37]	F3,F4,F4,F7,F25,F35,F37 / P1	Y2	ANN; ANFIS	72:15	R=0.738;0.802
	[38]	F14,F18,F20,F21,F27,F46 / P1	Y4			R=0.959; 0.970

	[39]	F2,F4,F18,F46	Y2	Fuzzy logic	-	R^2=0.75
	[40]	F18,F46,F21 / P1	Y5	ANFIS	36:18	R^2=0.946
	[41]	F3,F4,F5,F7,F18,F21,	Y3		-	MSE<0.03
	[42]	F30,F31,F32,F34, F37,F46 / P1,P4, P5,P20,P25,P53	Y2,Y3,Y4	ANN	-	R=0.975; 0.907; 0.915
	[43]	F2,F3,F4,F5,F18,F21, F32,F34,F37,F46 / P1,P4,P25,P53			120:24	R=0.959;0.94; 0.939
	[44]	F2,F3,F20,F35,F37 / P1,P14,P15,P25,	Y2,Y3	ANN	135:45	R^2=0.981; 0.889
	[45]	F2,F3,F5,F35,F37,F40 / P1,P15,P25,	Y4,Y5			R^2=0.993; 0.951
	[28]	F2,F3,F4,F14,F18,F29, F37,F46,	Y2	ANN;GEP	130:32	R^2=0.94;0.988
	[46]	F2,F18,F20 / P1,P25	Y2	ANN	98:50	RE=3.5%
	[47]	F4,F8,F18,F25,F46 / P1; F4,F18,F46 / P1	Y2,Y3;Y4,Y5	ANN;SVM	87 for 10-folds	RE= 3.5%~7.2%; 1.5%~5.6%
	[48]	F4,F8,F18,F25,F46 / P1		ANN;SVM ; ANFIS	90 for 10-folds	RE= 3.5%~7.2%; 1.5%~5.6%; 3%~12.6%
	[49]	P1,P5,P16,P21,P22,P25,P29,P41, P44,P53,P56	Y5	ANN	46:11	R=0.967
	[50]	P1,P5,P53		Fuzzy logic	-	R^2=0.931
	[51]	F3,F4,F18,F21,F25,F35,F37,F46 / P1,P14, P15,	Y2,Y3,Y4,Y5	Fuzzy logic	-	MCI=0.66; 0.62; 0.66
	[52]	P16,P18,P36,P53,P55	Y4	ANN	14:4	R=0.982
	[53]	F2,F3,F20,F35,F37,F46	Y2,Y4	ANN	30:6	R=0.886; 0.92
	[54]	F2,F3,F5,F7,F20,F21,F29,F31,F35,F37 ,F46 / P1,P25	Y2,Y3,Y4,Y5	Neuro-Fuzzy	-	R^2=0.81
1) & 2)	[30]	F2,F3,F4,F5,F6,F9,F11,F13,F14,F18,F 20,F26,F27,F29,F37,F41,F42,F43,F44, F45, F46,F47 / P1,P25,P27,P51,P55	Y12	ANN	1400:850	RE<5%
	[55]	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%
	[56]	F1,F14,F18,F29,F38,F46 / P1	Y4	ANN	150:27	R^2=0.881
2)	[57]	F2,F3,F4,F5,F6,F18,F20,F21,F28,F29, F37,F47,F48 / P1,P8,P25,P30,P51	Y2,Y3	ANN	1200:182	RE<5.7%; 3.5%
	[58]	F2,F3,F4,F18,F37 / P1,P25,P27,P30,P51	Y2,Y12	Fuzzy logic	840:420 1944:216	RE= 8.0%; 5.9%
	[34]	F1,F2,F3,F4,F5,F7,F10,F12,F14,F18,F 20, F21,F23,F29,F37,F38,F39,F41,F46	Y5	ANN	67:33	R^2=0.772
	[36]	F20,F25,F29,F37,F39 / P1	Y2, Y4, Y13, Y14, Y15, Y16	ANN	78:33	RE= 2.7%~38.0%
	[37]	F3,F4,F5,F7,F25,F35,F37 / P1	Y2	ANN; ANFIS	88:20	R=0.964; 0.959

	[59]		Y3			R=0.879; 0.882
	[60]	F2,F3,F4,F5,F22,F35,F37,F46 / P1		ANFIS	21:13	MAE=79.8
	[61]	F2,F3,F4,F5,F35,F37,F46 / P1			-	RMSE= 5.2e-4
	[62]	F2,F3,F4,F5,F7,F22,F35,F37,F46 / P1	Y15	SVM	-	MAE=82.87
	[63]	F2,F3,F4,F5,F22,F35,F37,F46 / P1		ANN;SVM ;GEP	-	MAE=89.7; 82.9; 93.7
	[47]	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%
	[18]	P40,P42,P54	Y2	GEP	38:10	R^2=0.9672
	[64]			ANN;GEP		R^2=0.93; 0.97
	[65]	F2,F46 / P1,P14,P15,P25	Y2, Y3, Y4	Neuro-Fuzzy	-	RMSE=0.07
3)	[32]	P1,P2,P59,P60	Y2,Y3	ANN	48 for 5-folds	ME=-1.91%; -0.29%
	[66]		Y2		35:4	ME=-2.04%
	[67]	P33,P59,P60,P63,P69	Y2	ANN	35:5	R^2=0.98
	[68]	P1,P23,P61	Y2,Y3,Y4,Y5	ANN	2700:300	ME= -3.5%~6%
	[69]	F2,F3 / P7,P34,P35	Y2,Y3	ANN	209:52	R= 0.861;0.884
4)	[70]	F7	Y18	ANN	-	E=0.53%
	[71]	P1,P2,P51	Y3	ANN	84:28	R=0.976
	[72]		Y4		87:25	R=0.98
	[73]	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
	[74]	P2,P25,P56,P67	Y2,Y3,Y4	ANN	40:8	R^2=0.99; 0.99; 0.96
	[75]	P47,P48,P49,P50	Y5	ANN	202:50	R=0.97
5)	[76]	P25,P64,P65,P66	Y2,Y3	ANN	54 for 5- folds	R=0.88;0.967
	[77]	P1,P24,P25	Y2,Y3	ANN	32:8	R^2=0.99; 0.99
	[78]	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
6)	[79]	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
	[80]	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
	[81]	F1,F14,F15,F16,F17,F18,F33,F41,F42, F46 / 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

	[82]	F1,F18,F24,F41,F42,F46 / P1,P4,P6,P20,P25,P53	Y5	ANN	53:22	R^2=0.949
	[83]	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
	[84]	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)	[85]	P17,P39,P59,P62	Y2	ANN	35:5	R=0.95
8)	[86]	P31,P32,P52	Y1,Y2	ANN	18:10	E= -0.22%;0.13%
	[87]			Fuzzy logic	-	ME=-0.32%;-0.03%
9)	[88]	P1,P12,P13,P25,P46	(Y2+Y17)	ANN	-	R^2=0.97
	[89]	F1,F39 / P1,P25,P57,P58	Y2,Y3	ANN	76:22	R=0.88,0.86;
	[90]	F1,F18,F36,F38,F39,F46 / P1,P25,P37,P57,P58	Y20	ANN	54:18	R^2=0.706
10)	[91]	P25,P54,P68 P70,P71	Y2,crimp satility	ANN	39:9	R= 91.5%; 99.29%
11)	[92]	P21,P26,P38,P42,P43,P54	Y21	ANN	161:8	R^2=0.9622
	[93]	P10,P14,P21,P38,P42,P43,P44,P54	Y2,Y4(sliver and yarn)		135 for 10-folds	MAE=6.6%; 6.76%;4.03%

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. [70] 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. [77] and Doran and Sahin [78] compared ANN with the multilinear regression model and the SVM model for modeling the 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 [84] 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 [85] 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.[86], [87] applied Fuzzy logic and ANN respectively to predict the properties of melt-spun polypropylene filament. Splicing techniques assembles yarns on spinning bobbins into larger yarn packages, the modeling of this process was attempted by Ünal and Cheng et al. [88]–[90]. 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. [91] 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 [92], [93] using the 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. [94] 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 [95] 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.

2.2.2 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 [73] have tried to compare the difference between the accuracy of ANN for predicting yarn tenacity as well as the 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 [30], as one of the earliest intelligent models 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 with 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.

By contrast to the fiber properties that 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 in the previous researches modeling yarn manufacturing process 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. [17], [28], [31], [34], [39], [41], [53]), or barely investigated the yarn count, a single process parameter input, coupled with fiber properties in their studies (e.g. [36]–[38], [40], [47], [48], [56], [59]–[63]). These models may work in specific simplified cases for finding the optimal material, but their effectiveness would be declined vitally 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 illustrated in Table 4, the diversity of the yarn manufacturing process for modeling grew distinctly, and consequently the complexities of constructed process models increased as well. More and more textile process models are issued with inputs from both of fiber properties and process parameters, the variety of input and output in these models is 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 is closer than ever to make a difference in the textile industry.

2.2.3 The relative importance of inputs and feature selection

The increasing variety of process factors and features studied for yarn manufacturing process modeling does not imply 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 [36] indicated that it is different the information contained in factors or the contribution of input variables in the models as well as the correlation between factors with model targets, diminishing the complexity of models by reducing the number of inputs should consider the relative importance of these factors 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 the relevant inputs of yarn manufacturing process modeling [28], [54], [78]. In particular, Doran and Sahin [78] have further compared PCA with analysis of variance technique (ANOVA, which also has been used in [18], [49], [50], [60], [63], [68], [69], [71]–[73], [75], [78], [91], [95]) 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.

The saliency test is another technique frequently applied in the prior researches for analyzing the relative importance of inputs [17], [41], [42], [74]. 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[85], 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) [62], partial derivative [75], multivariate test [51], K-means algorithm [84], grey incidence analysis and subjective and empirical approach [81] have demonstrated their effectiveness in this issue as well. It is worth mentioning that the improvement of model performance with selected data 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 the 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.

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. The genetic algorithm is a very powerful and popular optimization tool that had been used to optimize the model structure and parameter in the previous studies [58], [83], [95]. Moreover, Cheng and Adams[31] applied a simulated annealing technique, Nurwaha and Wang [62] used grid search and pattern search methods, Doran and Sahin[78] attempted iterative single data algorithm, quadratic programming and sequential minimal optimization methods. As the optimization of the textile manufacturing process would be discussed further in the following chapters, the details about the optimization techniques would not be given here.

2.2.4 Modeling techniques applied in yarn manufacturing

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 indeed, showed that is generally acceptable in the 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 [59] and yarn unevenness [38] 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. [54], [65], 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 the melt spinning process [87] and the hairiness of polyester-viscose blended yarns in ring spinning process [50] respectively. Furthermore, Sette et al. [58] built rule sets automatically from the data using 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. [51] proposed Fuzzy lease 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 implements 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 [48] 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 [47], [63], [78]. 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. [83] 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 stable of predictive accuracy to some extent, which is more suitable for noisy and dynamic industrial process. Nurwaha and Wang[63] compared not only ANN and SVM but the 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 the 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 [28], [64], and the advance of GEP on ANN in this regard may be attributed by the better optimization of its parameters based on a 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.

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 the applied case in detail. For example, the model developed by Ghosh[47], [48] using different methods fed with different data sets and variables which were determined the basis of their knowledge of the process and optimization trials.

2.2.5 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 is 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 de-noising, 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 (R^2), 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:

$$R(e,p) = \frac{\sum_{i=1}^{n}(e_i - \bar{e})(p_i - \bar{p})}{\sqrt{\sum_{i=1}^{n}(e_i - \bar{e})^2 \cdot \sum_{i=1}^{n}(p_i - \bar{p})^2}} \tag{2.1}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(e_i - \bar{e})(p_i - \bar{p})}{\sqrt{\sum_{i=1}^{n}(e_i - \bar{e})^2 \cdot \sum_{i=1}^{n}(p_i - \bar{p})^2}}\right)^2 \tag{2.2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i - p_i| \tag{2.3}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(e_i - p_i)^2 \tag{2.4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(e_i - p_i)^2} \tag{2.5}$$

$$ME = \frac{1}{n}\sum_{i=1}^{n}(e_i - p_i) \times 100\% \tag{2.6}$$

$$RE = \frac{1}{n}\sum_{i=1}^{n}\frac{e_i - p_i}{e_i} \times 100\% \tag{2.7}$$

where e_i is the real targets, whereas p_i is the predicted output of the model. Particularly, Desai et al. [35] used a test statistic variable t, Fattahi et al. [51] applied mean of capability index (MCI), Thevenet et al. [70] employed an error estimator of E in their studies respectively. 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.

Table 5. Information about modeling fabric manufacturing process using intelligent methods in previous works

Process	Intelligent methods	Model inputs	Model outputs	performance	Ref.
Sizing	Fuzzy	steam pressure, nip pressure, sizing speed	Exit moisture, size add-on	-	[96]
	Neuro - Fuzzy	Speed, exit moisture, size add-on	Number of end breaks	-	[97]
	Neuro - Fuzzy	Temperature, low nip pressure, high nip pressure, sizing speed	Size add-on	RMSE=0.0222	[98]
	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%.	[99]
Weaving	Fuzzy	Weft yarn count, yarn twist.	Weft yarn insertion velocity	-	[100]
	ANFIS	Weft yarn count, fabric width, loom speed, reed count	Compressed air consumption	R=0.998	[101]
	ANFIS	Strength of constituent yarns, fabric count, float length	Strength transfer efficiency of warps and wefts	R=0.951; 0.924	[102]
	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%	[103]
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	[104]
	ANN	Twist liveliness, yarn type, yarn linear density, tightness factor, the number of feeders on the knitting machine	Spirality	R=0.976	[105]
	Fuzzy	knitting stitch and yarn count	Spirality	R=0.991	[106]

	Fuzzy	Knitting stitch length, yarn count and yarn tenacity	Bursting strength	R^2=0.961	[107]
	ANFIS	Yarn tenacity, knitting stitch length and fabric density	Bursting strength	R=0.996	[108]
Dyeing	ANN	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	Depth of shade in dyeing process	Error=1%	[109]
	ANN	Machine operating temperature, dyeing time, dye liquor concentration and the bath ratio	Color strength	RMSE=$1.66e^{-4}$	[110]
	ANN	Dye concentration, salt concentration, and alkali concentration	Color strength and fastness	R = 0.992	[111]
	Fuzzy			R = 0.977	[112]
	Fuzzy	Dye concentration with dyeing time and process temperature	Color strength	R=0.998	[113]
	Fuzzy	Dyeing time, alkali concentration and washing temperature	Color fastness	R = 0.992	[114]
	ANN	Type of treatment, the replication of washing, and the dyes type targets	CIELab values	R=0.96	[115]
	Fuzzy	Dyes concentration, temperature and time	Colour yield	MSE=0.0018~ 0.0478	[116]
	Fuzzy and ANN			-	[117]
	Fuzzy			MSE=2.333	[118]
Finishing	ANN	Reactive dyes, reducing agents, o.w.f%, original *L**, concentration of the reducing agents and caustic, process temperature, the presence of the leveling agent	CIELab values	R=97.66%	[119]
		fabric parameters, dyeing agents and finishing processes		R>0.89	[120]
	ANN	The fabric specifications of composition, density, mass, thickness, linear density, yarn twist and crimp and two applied laser parameters (DPI and pixel time)	K/S values and CIELab values	MSE =39.538; 0.256; 0.036; 0.032	[121]
				MSE=0.218; 0.057; 0.019; 0.064	[122]
				MSE =6.348; 0.165; 0.03; 0.087	[123]
		Pixel time, DPI and grayscale		MSE=16.492; 0.146; 0.003; 0.033	[124]
		Treating time, temperature, pH, mechanical agitation and fabric yarn twist		MSE=$1.5e^{-3}$; $9.9e^{-6}$; $2.8e^{-9}$; $6.2e^{-7}$; $4.3e^{-8}$; $1.9e^{-5}$;	[125]
	ANN	Fabric type, method, chemicals and concentration	Water-oil repellent and	-	[126]

			wrinkle resistant		
	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	[127]
	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	[128]
	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%	[129]
	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	[130]
	Neuro - Fuzzy	(variables above) + composition, warp count and summit density		R=0.9957; 0.9964	[131]
Non-woven	ANN	Fabric weight, needling density and blend ratio	Tensile properties	-	[132], [133]
			Compression properties	-	[134]
	ANN	Web area density, punch density, and depth of needle penetration	Bulk density and tensile properties	R=0.907; 0.986; 0.982	[135]
	ANN	Polymer flow rate, initial polymer temperature and initial air velocity	Fiber diameter	R^2 = 0.9424	[136]
		Polymer flow rate, initial air velocity and die-to-collector distance		Error=0.013%	[137]
	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	[138]
	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%	[139]

2.3. Modeling 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 processes such as textile dyeing and finishing has attracted more attention in the previous studies.

2.3.1 Modeling weaving process

The 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 desired 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. [96] 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 later extended by Kim and Vachtsevanos [97] 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 the sizing process on the modeling performance, Zhang et al. [98] 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, backpropagation and radial basis function (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. [99] 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 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 to almost all kinds of yarns at a very high speed. Dayik and Colak [100] introduced a fuzzy model for predicting the weft yarn insertion velocity from weft yarn count and twist. However, Hussain et al. [101] pointed out that the high productivity of the 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 the 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 [102] 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 the 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 [103]. 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.

2.3.2 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 product at a 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. To understand the role of the knitting process in this phenomenon, Jaouachi et al. [104] 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 the ANN model.

The spirality phenomenon arising from many process factors can hardly be explored without modeling tools. Murrells [105] 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 were applied to test the models. The results show that the correlation coefficients 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 [106] 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. [107] further used this fuzzy expert system to predict the bursting strength of knitted fabric based on of knitting stitch length, yarn count and yarn tenacity. The differences from modeling spirality in the 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. [108] 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 the regression model in this issue because of a higher correlation coefficient of predicted values versus actual values in terms of 0.996＞0.991.

2.3.3 Modeling dyeing process

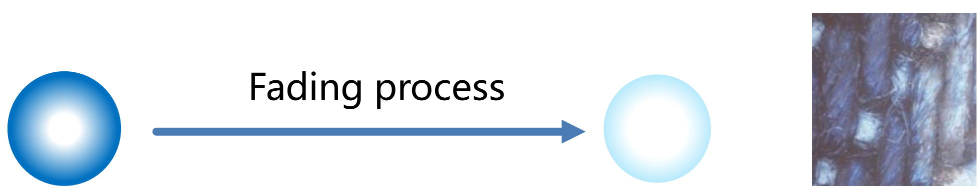
The dyeing process introduces color to the textile including fabrics, while the use of intelligent techniques used in most of the previous studies was dedicated to alternate Kubelka-Munk theory for color recipe matching [115]. Sentilkumar and Selvakumar [109], as well as Kuo and Fang [110] made a difference 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 terms of 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[111]. 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 predicts more accurately than the Fuzzy model in this case [112]. The attempt of the fuzzy model was extended to the dyeing process of different cotton knitted fabrics [113]. 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.

Color fastness reflects the ability of dyed fabrics to resist color characteristics change or transfer its colorant to adjacent materials. The higher color fastness of dyed fabrics, the more possibility its color will not run or fade with washing and wearing. The fuzzy model Hossain et al. [114] 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 color fastness predictive model proposed by Balci et al., 2008 [115] also involves CIELab values(i.e. L^*, a^*, b^*, *C*, *h° values, etc.*) 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 literature 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. [116] 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 parameter 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 [117]. They also have attempted to promote the Fuzzy model in this case using the covariance matrix adaptation evolution strategy for model parameter optimization in the work of [118].



(a) (b)

Figure 5. (a) Ring dye effect from fading process; (b) Inner cotton exposed denim.

2.3.4 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 [4], [140]. Figure 5 (a) illustrates the ring dye effect from the fading process, 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. [119] reported the application of LM trained ANN to the alkali reductive stripping process for predicting L^* and ΔE of striped cotton fabrics. Optimization 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 [120]. 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 layers 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 [122]–[124] and knitting fabrics [121] respectively as well as the effects of cellulase treatment on the K/S values and CIELab values of cotton denim fabric [125].

As shown in Table 6, a topology was used in all of these five studies in common that aims at finding the effect of changes in the 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 6. The topology studies of [121], [122], [125] applied to optimize the artificial neural network structure.

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 treatment is a dry process for denim and other colored textiles, which fits manufacturers' and designers' demands on controllability and sustainability, and more vitally the efficiency and high repeatability of the denim color stripping process. C. Kan and Song [121] 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 (pixel time and dot per inch, i.e. DPI) in various nets (illustrated in Table 6.) 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 prediction 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 prediction 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[122]. Similar work was conducted on six colored cotton-spandex fabrics with the same model architectures as well. They [123] claimed that the optimized tested MSE of the 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 [124]. 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. [125] 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.

Not only color properties but also physical functional performances play important roles in the 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 tend to wrinkle badly after washing and tumble drying and also during wearing. The water and oil repellency treatments form the thin hydrophobic film on the fiber surface so that proof the water or oil. Sema et al. [126] 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 the linguistic transformation of variables but specifically not satisfactorily for the wrinkle recovery angle owing to the lack of homogeneity of sample size in each output class.

Feki et al. [127] 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 was 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. [128] 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.

The 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. [129] 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 the 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 the 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. [130] 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 [131] additionally researched the woven fabric features of composition, warp count and summit density in the input data set. Finally, the optimized model possesses 7 input variables in terms of electrical power, treatment speed, composition, air permeability, fiber count, construction and summit density.

2.3.5 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 literature.

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 re-orientate 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. [132] 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 [133], 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 [134] 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 the training phase. Rawel et al. [135] predicted the bulk density and tensile properties of a needle-punched nonwoven through 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 the 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. [136] 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 about ANN has been shown additionally in a further report of Chen [137], where a 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. [138] 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. [139] simulated the drawing of the 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 based on 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%.

2.4. Modeling 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 various uncertainties [141]. Intelligent techniques have been applied to garment manufacturing process modeling for years. Guo et al. [142] have overall reviewed the applications of artificial intelligence in the apparel industry from the perspectives of design, manufacturing g, retailing and supply chain management. In terms of 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 7 demonstrated the basic information of the previous applications of modeling garment manufacturing process reviewed in this section.

Table 7. Information about modeling garment manufacturing process using intelligent methods in previous works

Process	Intelligent methods	Model inputs	Model outputs	performance	Ref.
Cutting	ANN	Number of fabric layers, cutting blade speed, number of sizes, marking lengths, and cutting times	Cutting time	Error=0.786 %	[143]
Sewing	Neuro-Fuzzy	machine speed and the fabric sewability	foot pressure and thread tension	-	[144], [145]
	ANN	Fabric bending stiffness, thickness and weight	pucker grade	R=0.884	[146]
	ANN	Fabric composition, structure, thread density, thickness yarn count, weight, formability, extensibility, rigidity	Seam pucker, needle damage, fabric distortion, overfeeding	-	[147] [148]
	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	[149]
	*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	[150]
	ANN	Fabric width, folding length of joint, seam design, seam type	Seam strength	-	[151]
	ANN	No. of fabric layers, needle size, weave pattern, fabric weight	Needle penetration force	R=0.989	[152]
	Fuzzy logic and ANN	No. of fabric layers, needle size, fabric weight		R^2=0.968; 0.944	[153]
	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	[154]

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, frition coefficient, mean deviation of frition 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	-	[155]

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

2.4.1 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 [143] established a model to estimate the cutting time of apparel manufacturing using the ANN system. They took the data of different marking lengths 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 the 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.

2.4.2 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 [144], [145] 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 physic-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.

The seam is the basic requirement in the construction of garments. Seam pucker is a common problem in garment manufacturing because of improper sewing operations. Stylios and Parson-Moore [146] predict the seam pucker approximately of pucker grade umder 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 field as it addressed an early attempt of applying intelligent techniques to model the sewing process and deal with seam pucker problems.

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 [147]. Upon which they employed an extended normalized radial basis function (ENRBF, an algorithm developed by Xu [156]) neural networks to predict these four sewing performance properties of specific fabrics. Regarding the data, they input the model by measured fabric properties for the composition, structure, thread density, yarn count, weight, thickness, formability, extensibility, and rigidity, while for the outputs of the 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 [148]. 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 [149] 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. [150] as well with the seam pucker. But different from the ANN models above, they employed regression trees and KNN methods. From the given parameters of fabric mechanical properties, the obtained root of MSE 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 seam quality. It is worth mentioning that Onal et al. [151] 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 garment manufacturing. Seam factors concerning 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 Haghighat et al. comparatively using ANN and MLR [152], as well as fuzzy logic and ANN [153]. 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 about 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 a 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. [154] 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 using 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.

2.4.3 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 [155] 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.

The intelligent techniques have been applied to textile process modeling since 1993, leading to a great number of successful results published. However, the current investigations failed to integrate the interdisciplinary strengths in their applications so that the developed models either lacks the practicality or too basic. One reason could be that the researchers working on AI and textile manufacturing lack expertise from the field of each other, but more importantly, it is owing to the high complexity in the textile manufacturing industry about the variety of process and its parameters which impedes the cooperation of different disciplines in every detail.

Besides, the data used in these prior works were limited and noisy. This situation did not seem to be clearly noticed though it is a common issue in various subfields of the industry. For example, most of the researches took ANN as their first choice simply depended on its popularity, but ignored the features of the textile products and textile processes and their connection to the nature of modeling techniques, which have resulted in the developed models were poor of generalization ability. Another basic characteristic of the textile product is that the textile properties rely on both subjective and objective evaluations on the whole. The qualitative analysis performs a function as same as the quantitative analysis for modeling a textile process in certain scenarios, but the researchers paid little attention to this in their works.

Furthermore, instead of real experimental exploration, the development of a process model basically enables to assist the process optimization by providing a digital simulation of the process. However, only a small group of previous studies formulated the constructed model into a systematic problem of optimization or decision-making. It is suggested to devote more efforts to the complete investigation involving both process modeling and optimization in the overall practical problems.

Therefore, the significance of process modeling in textile manufacturing should be better roused by adapting commonly used approaches and tools to specific applications of the textile process optimization problems.

2.5. Intelligent techniques used for textile process optimization

Process managers work to improve the design of process and devote to enhance the operation of the process so as to realize the largest production, the greatest profit, the minimum cost, the least energy and resource consumption, and so on. These practical engineering applications can be formulated as optimization problems. The goal of process optimization basically is to achieve the desired performances from the operation of the process parameter. The realization of it, in general, is setting up of objective of the problem to be maximized or minimized to find the values of the variables in the process that yield the best value of the performance criterion, in addition, there may exist conditions to constrain the objective function and involve multiple objectives in the optimization problem [157]. Depending on the process model, textile manufacturers can conveniently estimate the performance of a proposed process solution to virtually tune the optimum operations on process parameters. However, it is extremely challenging to properly find the optimal solution of the production scheme with optimal parameter setting by trial and error from the numerous possibilities. The employment of intelligent optimization techniques is identified as playing a key role in this issue.

The intelligent optimization algorithms applied in prior studies mainly focused on an evolutionary algorithm (EA), particle swarm optimization (PSO), ant colony optimization (ACO), simulated annealing (SA), synergetic immune clonal selection (SICS), and artificial bee colony (ABC), etc.

Evolutionary algorithms including genetic algorithms (GA) and differential evolution (DE) are the most popular optimization methods in the textile manufacturing area. The formulation of them is in accordance with the mechanism of natural learning evolution and the natural selection process. The individuals update in a population by learning from each other in a generation according to different heuristics. The general implementation of the first is to generate the initial population of individuals randomly, and then iteratively repeats the steps of selection, crossover and mutation (at each iteration, select individuals from the current population termed as parents according to their fitness and produce children from them by crossover and mutation of their "chromosome" for the next generation.) to retain the optimal individual and eliminates the poor ones, and finally "evolves" the population and directs the search process approximate to the optimal individuals. GA and DE are very similar in the operations that both allow each successive generation of solutions to "evolve" from the strengths of the previous generations. While different, the method of DE can be applied much more easily than the GA to the real-valued problems over a continuous space. The idea behind the method of DE is that the difference between two vectors yields a difference vector which can be used with a scaling factor to traverse the search space [158].

The development of the particle swarm optimization (PSO) algorithm was inspired by the social behavior of animals and birds. It mimics the choreography of a bird swarm that flies through the search space. In this algorithm, according to the population size, a group of particles representing the birds swarm is specified with random generation of initial position and velocity flying in the search space. Each particle represents a candidate solution (the fitness value of each particle is calculated from objective function), stores its individual best performance, and keeps track of the best performance of the swarm at the same time. The velocity update and position update are the primary mechanisms that assure the new generations of particles accelerate towards the best position in the search space from iterations until minimum error is achieved [159].

Ant colony optimization (ACO) was introduced by Dorigo on the principle of foraging behavior of ants to find the shortest route from their nest to the food source [160]. The chemical trial of pheromone, the medium of ants in communication, is left on the ground with various probabilities to guide the group towards the target position. The pheromone decomposed over action time and the quantity of this chemical substance is determined by the amount of food found as well as the number of ants using it so that high level of pheromone would be left over short route because of less the action time taken in comparison and more ants would come to strengthen the pheromone level. In the ACO algorithm, artificial ants are introduced to represent the solutions, and the solutions are chosen according to a probabilistic rule depends mainly on the state of the pheromone. In the pheromone updating process, either the pheromone evaporates to decrease the bad solution, or each ant deposits a certain amount of pheromone to obtain a good solution. This process is iterated until the algorithm satisfies stopping criteria.

Simulated annealing (SA) is a point by point search method. It arbitrarily generates a number of points representing various solutions in the search space with a high initial temperature, and compared it with the points generated in the next iteration in the neighbor of it in terms of the function values, then selects the better one and rejects the other one. The iteration goes continuously by generating new points randomly in the neighborhood of the current points and accept or reject the points. This process terminates when it is no longer improves the solution or the maximum number of trails reached [161].

Artificial bee colony (ABC) is based on the intelligent foraging behavior of honey bees [162]. It comprises four phases, that is, initialization phase, employed bee phase, onlooker bee phase and scout bee phase. In the first phase, settings of different control parameters and vectors of the population of foods are initialized. The initial solutions are then subjected to repeated cycles which indicate the search process of the employed, onlooker and scout bees. In the next phase, searching for the neighboring food sources with more nectar content is performed by the employed bees. These neighbor food sources remain present in their memory which is further employed for evaluation of the fitness values. The fitness value is calculated for each new food source and subsequently, a greedy selection process is applied. During the onlooker bee phase, information about the food sources is being shared with the onlooker bees waiting in the hive and further food sources are chosen probabilistically by them. Scout bee phase deals with searching the new solutions in place of the abandoned solutions while making the scouts free. The employed bees, whose solutions cannot be improved, are set as scout bees and are abandoned. These scout bees further search for new solutions randomly which results in more exploitation of the poor food source and gets abandoned. Thus, the negative feedback of such behavior leads to balanced positive feedback.

2.6. Optimization of the textile manufacturing process

Textile manufacturing originates from the fibers (e.g. cotton) to final products (such as curtain, garment, and composite) through a very long procedure with a wide range of different processes filled with a large number of variables. Like the fact that a few criteria govern the quality of textile process performance and their significance with an overall objective is different, the optimization problems in this industry always take multiple objectives into account. The simultaneous optimization of multiple targets in a textile production scheme from the high dimensional space is challenging.

There are a variety of works on the textile process multi-objective optimization from the last decades. For example, Sette and Langenhove [163] simulated and optimized the fiber-to-yarn process to balance the conflicting targets of cost and yarn quality. Majumdar et al. [164] optimized the functional clothing in terms of ultraviolet protection factors and air permeability. Mukhopadhyay et al[165] attempted to optimize the parametric combination of injected slub yarn to achieve the least abrasive damage on fabrics produced from it. Almetwally [166] optimized the weaving process performances of tensile strength, breaking extension and air permeability of the cotton woven fabrics by searching optimal parameters of weft yarn count, weave structure, weft yarn density and twist factor.

These works generally used the prior techniques that combine the multiple objectives into a single weighted cost function, the classical approaches such as weighted sum, goal programming, min-max, etc. are not efficient as they cannot find the multiple solutions in a single run but times as many as the number of desired Pareto-optimal solutions. Pareto optimal solutions or non-dominated solutions are equally important in the search space that superior to all the other solutions when multiple objectives are considered simultaneously, and the curve formed by joining Pareto optimal solutions is the well-known Pareto optimal front [167].

The investigations and applications of the related algorithms and computational complexity theory are very popular in the textile manufacturing industry with regard to the multi-objective optimization that is feasible to approach the Pareto optimal solutions. Among these, evolutionary algorithms such as genetic algorithms (GA) and gene expression programming (GEP) are the ones that are most often taken into consideration in previous studies in the textile sector. Kordoghli et al. [168] schedule the flow-shop of a fabric chemical finishing process aiming at minimal make-span and arresting time of machine simultaneously using multi-objective GA. Nurwaha [169] optimized the electrospinning process performance in terms of fiber diameter and its distribution by searching for optimal solutions about the processing parameters including solution concentration, applied voltage, spinning distance and volume flow rate. The electrospinning process parameters were mapped to the performances by the GEP model, and a multi-objective optimization method was proposed based on GA to find the optimal average fiber diameter and its distribution. Wu and Chang [170] proposed a nonlinear integer programming framework on the basis of GA to globally optimized the textile dyeing manufacturing process. The results of their case study presented the applicability and suitability of this methodology in a textile dyeing firm and exactly reflected the complexity and uncertainty of application challenges in the optimal production planning program in the textile industry.

In terms of multi-objective optimization, the general GA systems developed in the works above may not efficient in certain cases as the elitist individuals could be over-reproduced in many generations and lead to early convergence. To this end, Deb [171] proposed a Non-dominated sorting genetic algorithm Ⅱ (NSGA-Ⅱ) that introduced a specialized fitness function and fast non-domination sorting as well as crowding distance sorting in the common GA system to promote solution diversity in the generations. Such a modified strategy has been widely applied in related textile studies. For instance, Ghosh et al. [53] optimized the yarn strength and the raw material cost of the cotton spinning process simultaneously with NSGA-Ⅱ on the basis of two objective function models in terms of artificial neural networks and regression equation. Similarly, Muralidharan et al. [172] described the combined use of NSGA-Ⅱ with response surface methodology for the design and control of color fast finish process to optimize five quality characteristics, i.e. shade variation to the standard, color fastness to washing, center to selvedge variation, color fastness to light and fabric residual shrinkage. Majumdar et al. [173] derived the Pareto optimal solutions using NSGA-II so as to obtain the effective knitting and yarn parameters to engineer knitted fabrics having optimal comfort properties and desired level of ultraviolet protection. Barzoki et al. [174] and Vadood et al. [175] employed this algorithm with artificial neural networks and Fuzzy logic respectively to optimize the properties of core-spun yarns in the rotor compact spinning process, where the investigated process parameters consist of the filament pre-tension, yarn count and type of sheath fibers, and the objectives were yarn tenacity, hairiness and abrasion resistance for the former but elongation and hairiness for the latter respectively.

Apart from the GA frameworks, applications reported of other heuristic or meta-heuristic algorithms for multi-objective optimization in the textile domain also have been presented with synergetic immune clonal selection (SICS), artificial bee colony (ABC) algorithm, ant colony optimization (ACO), and particle swarm optimization (PSO) [176], [177]. Meanwhile, simultaneous optimization using desirability function[178], in addition to the heuristic or meta-heuristic algorithms, was very popular in the textile manufacturing process multi-objective optimization applications as well[179], [180].

The previous researches of the textile process optimization were mostly realized by using the heuristic methods. Although the general optimization techniques such as genetic algorithm and grey relational analysis [181] have shown their effectiveness in certain scenarios, there still exist some drawbacks for coping with the high dimensional decision space in the textile processes optimization problem about the increasingly complicated multi-inputs and multi-outputs variables as well as multiple objectives. Commonly used heuristic methods like genetic algorithms are time-consuming so that they can hardly be applied in the context of industrial practice when the number of involved variables becomes very large, along with large change intervals [182].

More importantly, as mentioned that the textile manufacturing industry develops rapidly in these years to quickly reactive to the market and adapt to the big data environment, the developed textile process optimization system will be invalid when the process or applied scenarios vary in the future. These previous works failed to illustrate the capacities of their system for learning from the continuously arriving data to keep updated with the textile process development in this regard, thus are still far from being implemented in the practical applications. It is necessary to investigate on more innovative intelligent methods in the optimization problem of the textile manufacturing process.

2.7. Formulation of the research questions

From the literature review above, three patterns are identified on the research of intelligent modeling and optimization of the textile manufacturing process. These are given and elaborated in the following. On the basis of the identified patterns, the research directions for subsequent sub-studies are derived and research questions are also formulated.

• How to develop an intelligent algorithm appropriate for modeling a textile manufacturing process?

From the review of the literature above regarding the use of intelligent techniques for modeling the textile process, several drawbacks were summarized that researchers barely connect the features of an applied algorithm to that of the specific textile process, and the determination of modeling method was made groundlessly. As the modeling of a process is always problem-specific, taking the features of the targeted textile process into account, it is necessary to do a comparative study on different intelligent techniques to determine the appropriate one specifically. Thus, Chapter 3 provides a case study of modeling the textile ozonation process from the comparison of three different intelligent techniques, i.e. extreme learning machine (ELM), support vector regression (SVR) and random forest (RF), to show the procedures of determining an intelligent algorithm appropriate for modeling a textile manufacturing process.

- How to deal with the complex multi-objective optimization problem with reinforcement learning in the progressively developing textile process?

Based on the constructed model, process decision-makers can reduce the time- and resource-intensive experimental effort and physics-based simulation to tune the optimum operations on process parameters. While complexity in such an optimization problem could be enhanced dramatically when more processes and more variables as well as multiple objectives are considered. The classical intelligent techniques like heuristic methods could be inefficiency in some scenarios in this situation, and more importantly, they cannot adapt to the developing environment to learn from the continuously new arriving data form the dynamic textile manufacturing industry. Reinforcement learning is a novel machine learning technique that has been reported can make a difference in this issue. Consequently, it is taken into account in Chapter 4 to tackle these issues for the multi-objective optimization of the textile process.

- Is there further improvement we can do to address the increasing searching dimension of optimizing a textile process in the upcoming big data era with multi-agent reinforcement learning?

The literature review shows that researches have been failed to work with high-dimension decision space, especially in a dynamic environment with growing new data. It could be very challenging for the textile manufacturing companies in the upcoming big data era when new data are continuously generated from the interconnected elements. To address the increasing searching dimension, in Chapter 5, the third sub-study further formulate the textile process multi-objective optimization problem to a stochastic Markov game using multi-agent reinforcement learning algorithm.

Table 8. Research questions list.

	Research questions
Chapter 3	How to determine an intelligent algorithm appropriate for modeling a textile manufacturing process?
Chapter 4	How to deal with the complex multi-objective optimization problem with reinforcement learning in the progressively developing textile process?
Chapter 5	Is there further improvement we can do to address the increasing searching dimension of optimizing a textile process in the upcoming big data era with multi-agent reinforcement learning?

In summary, modeling and optimization of the textile manufacturing process using intelligent techniques is a salient direction for future research, but it is challenging because of the growing complexity in the textile process. The realistic optimization problems in the textile manufacturing industry normally are always related to multiple-objective or multi-criteria, which makes this situation to be more knotty. Based upon the above points, three research questions are posed as listed in Table 8, and the research questions are addressed in Chapters 3, 4 and 5 respectively.

Three sub-studies are implemented to solve the research questions in Chapter 3, 4, and 5, respectively. The sub-study in Chapter 3 explores the application of three intelligent modeling techniques, i.e. ELM, SVR and RF, to model the textile ozonation process. The prediction performances among these algorithms in regard to the color properties of treated textiles in the ozonation with respect to the process parameters are comparatively investigated. In Chapter 4, the complex multi-objective optimization problem in the textile manufacturing process is formulated as the Markov decision process (MDP) paradigm, and a deep reinforcement learning algorithm is employed collaboratively with RF and the analytic hierarchy process (AHP) in a multi-criteria decision support system to cope with it. To better address the increasing complexity in the Multi-objective optimization of the textile manufacturing process, Chapter 5 presents another paradigm of the Markov decision process with game theory into a multi-agent system that formulates the Multi-objective optimization problem as a Markov game. The constructed RF models of the textile ozonation process are applied as a case study to evaluate the developed systems in Chapter 4 and 5.

3. Modeling a textile process using intelligent techniques: a case study for color fading ozonation

Intelligent tools are playing a significant role in many applications of textile manufacturing process modeling. However, since modeling textile manufacturing processes is always problem-oriented, the development of a model needs to connect the features of an applied algorithm to that of the specific textile process, the comparative study on different proposed methods is necessary in this regard. This chapter presents a case study for modeling a textile ozonation process, where different intelligent techniques are comparatively investigated. The model development of other processes from the textile manufacturing industry can follow the same scenario.

Textile products with faded effect, worn look, or vintage style are Increasingly attracting a growing number of young customers' attention and have gained a considerable share of the fashion market[183]. However, such a faded effect generally was achieved by chemical treatments (hydrogen peroxide/chlorine bleaching, for example) which are not only highly water and power consuming, but also release a wide range of toxic substances to the environment [184]. Ozone is an excellent gaseous oxidant with an environmentally friendly nature that can be rapidly decomposed into O_2 after its application without emitting additional pollution. It is able to react with a large number of organic and inorganic substances in water due to a series of intermediates or by-products such as hydroxyl radicals (which reacts with no selectivity) may be generated in the reaction between ozone and water [185]. More significantly, ozone could be applied directly in the form of gas without a water bath to color fade the objective products (with water content), which can dramatically decrease the water consumption in the sector. Therefore, ozone is regarded as a perfect alternative to traditional oxidizing agents and bleaching agents [186]. In recent years, studies regarding color fading dyed textiles using ozone instead of the conventional processes have been increasingly reported by taking advantage of the application of ozone, namely ozonation [183], [187]–[190].

Although color fading ozonation of textiles has a promising prospect in the industry, it is facing certain plights. The color fading performance of dyed cotton was found that affected by many different factors from the properties of textile material to the color fading process. Such as the application form of ozonation, as well as the process parameters of temperature and time, etc.[191]–[193]. How these factors affect the color fading process separately has been reported, while to understand their overall impacts simultaneously, the complex and nonlinear relationship between the factors of material properties as well as technical parameters of ozonation and color fading effects must be taken into consideration. Therefore, this chapter takes the textile ozonation process as an example to comparatively investigate the intelligent techniques for process modeling.

As ANN is assumed that difficult to be applied in the textile cases when training data is limited though it was widely proposed for textile process modeling because of its popularity, this case study proposed ELM and SVR instead of ANN for modeling the textile ozonation process as they are more manageable than the ANN and have higher generalization performance with less training data, which is very significant for the color fading effect prediction in this case study. Since RF can accurately predict with small dimensions feature vectors by taking advantage of the interaction of variables and the evaluation of the significance of each variable, it is potential to figure out the complicated interrelationships of the process parameters and colorimetric variables, in this case, thus is introduced in the comparative study with ELM and SVR for modeling the textile ozonation process.

3.1. Experimental

3.1.1 Material

Desized grey cotton fabrics ($^{3}/_{1}$ twill; 325.7g/m^2; supplied by Shunfu, Hubei, China) was dyed by three bifunctional fluorotriazine azo reactive dyes named Reactive Blue FL-RN (RB-RN), Reactive Red FL-2BL (RR-2BL) and Reactive Yellow FL-2RN (RY-2RN) (provided by Color Root, Hubei, China; commercial quality, purity of dyes: 92%,) respectively. Chemical material of Sodium hydroxide and hydrogen chloride (analytical grade, supplied by Sinopharm Limited, China) were used in the ozonation.

3.1.2 Apparatus

Ozone employed in this work was generated by a corona discharge ozone generator, CF-G50 (Guolin, China), that fed by pure and compressed dry oxygen (≥99.9%, 1Mpa, 12L/min) from an oxygen cylinder. Ozone was flowed to the reactor (made of glass, the structure is exhibited in Figure 6), and in each single color fading ozonation experiment, samples would be distributed evenly on the sample desk (made of air-permeable steel net). Ozone was imported with a gas flow of 2 L/min and dosage of 137±3 mg/L ·min (tested by UV meter NS-xmd614, Naishi, China) throughout the treatment. The exhaust from the reactor would be collected and decomposed by a heater (≥230℃) before evacuating to the atmosphere.

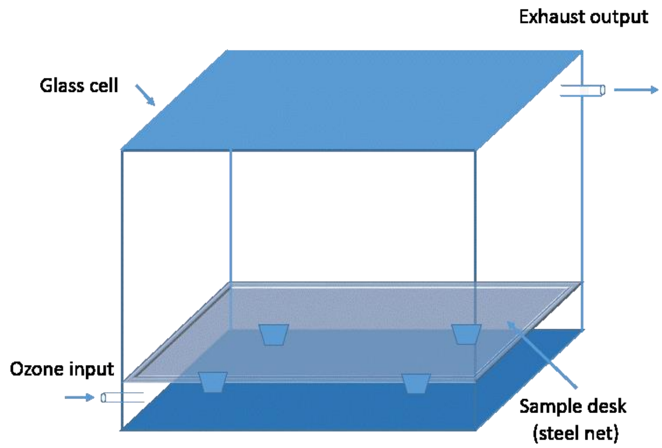


Figure 6. The reactor setup of ozonation.

3.1.3 Methods

(1) Ozonation processes

Three dyed cottons in different colors were treated respectively by the color fading ozonation following the steps: wetting the fabrics by deionized water (pH=7, or using sodium hydroxide and hydrogen chloride respectively when specific pH is required) to obtain certain pick-up water content. After ozone treating, samples were rinsed by deionized water before naturally drying up.

Ozonation at different pH (1, 4, 7, 10, 13), temperature (0, 20, 40, 60, 80℃) with variable pick-ups (water content of sample, 0, 75%, 150%) for different treating time (0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60 min) were investigated on the three dyed cotton fabrics (blue, red, yellow) respectively. Besides of pH which was set up depending on the method mentioned above (using sodium hydroxide and hydrogen chloride respectively in the water pick-up step), the temperature of ozonation was controlled by a water bath around the reactor (including the inlet tubes), and the pick-up of the sample was calculated by the Equation (3.1).

$$Pick\text{-}up\ (\%) = \frac{W_s - W_0}{W_0} \times 100\% \tag{3.1}$$

where w_s was the weight of the wet pickup sample, w_0 was the weight of the sample before wetting.

(2) Analytical

Based on Kubelka-Munk theory[194], it is known that *K/S* value can indicate the color depth of samples. While L^* a^* b^* values (or CIELab), an international standard widely used for color measurements, is capable of illustrating the color variation of textile samples. Normally, the color of the final textile product agreeing with specific *K/S* and L^* a^* b^* values is in the acceptance tolerance of the consumer [120]. Consequently, these values tested by Datacolor 110 spectrophotometer (Datacolor, USA) were used to characterize the color variation of dyed textiles in the color fading ozonation.

3.2. Algorithm and structure of process modeling

ANN is a widely used artificial intelligence approach in the textile sector [19]. It is inspired by the bionic simulation of the human brain that interconnected numerous neurons in different hidden layers to process the complex information of specific input-output relation [13]. In particular, ELM is a novel algorithm for single-hidden layer feedforward neural networks (SLFNs, the structure of it is illustrated in Figure 4) which randomly chooses the input weight matrix ($\boldsymbol{W}$) and analytically determines the output weights (β) of SLFNs. ELM not only learns much faster with a higher generalization performance than the traditional gradient-based learning algorithms but it also avoids many difficulties faced by gradient-based learning methods such as stopping criteria, learning rate, learning epochs, local minima, and the over-tuned problems [195]. It has been successfully applied to forecast sales behavior in the fashion retailing [196]. The implementation of it is comparatively more manageable, and its high generalization performance can help us simulate more different solutions in the textile ozonation process model, so that is worth being taken into account in this case study.

SVM is a popular machine learning tool for classification and regression based on statistic learning theory, first identified by Vladimir Vapnik and his colleagues in 1992 [24]. 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 [25], [26]. The excellent use of SVR has been issued for predicting yarn properties

[47], [62], PU-coated cotton fabrics qualities [197] and wool knitwear pilling propensity [198]. Gosh claimed that SVM is more suitable than the ANN in the textile applications because of the better generalization capability and higher predictive power [63]. And it can be a good tool to overcome some difficulties such as the nonlinear relationships of variables in the textile ozonation process.

RF is a predictive model composed of a weighted combination of multiple regression trees. It constructs each tree using a different bootstrap sample of the data, and different from decision tree splitting each node using the best split among all variables, RF using the best among a subset of predictors randomly chosen at that node [199]. In general, combining multiple regression trees increases predictive performance. It can lead to accurate prediction results by taking advantage of the interaction of variables and the evaluation of the significance of each variable [200]. Its application in the textile field has been reported for fabric surface defect detection [201] and the prediction of photovoltaic properties of phenothiazine dyes [202]. It shows outstanding performance even for feature vectors with small dimensions, which can be a relevant solution to address the limitation of data in the present case study for modeling the textile ozonation process.

3.2.1 Extreme Learning Machine

ELM is an algorithm of SLFNs randomly chooses the input weight matrix ($\boldsymbol{W}$) and analytically determines the output weights (β). According to Figure 4, we can take K hidden nodes SLFNs as an example, using activation function $\boldsymbol{f}(x)=(f_1(x),f_2(x),\ldots,f_k(x))$ to learn N samples (X_i, Y_i), where $X_i=[x_{i1}, x_{i2},\ldots,x_{in}]^T \in R_n$ and $Y_i=[y_{i1}, y_{i2},\ldots,y_{in}]^T \in R_m$. The ideal approximation of the SLFNs to these samples is zero error, which turns out

$$\sum_{j=1}^{N} \left\| \hat{Y}_j - Y_j \right\| = 0 \tag{3.2}$$

where $\hat{Y}$ is the actual output value of SLFNs. Taking the weights $\boldsymbol{W}$, β and bias b into consideration, we have

$$\textstyle\sum_{i=1}^{K} \boldsymbol{\beta} \cdot f_i\left(\boldsymbol{W_i} \cdot X_j + b_i\right) = Y_j, j = 1, \ldots, N \tag{3.3}$$

where $W_i = [w_{i1}, w_{i2}, \ldots, w_{im}]^T$ and $\boldsymbol{\beta_i} = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$, $i=1,\ldots K$ are the weight vector for inputs and activated nodes respectively. b_i is the threshold of i_{th} hidden node. The compact expression of equation (3.3) in terms of vectorization could be

$$\boldsymbol{H}\beta = \boldsymbol{Y} \tag{3.4}$$

where $\boldsymbol{H}(W_1, \ldots, W_j, b_j, \ldots, b_j, X_1, \ldots, X_i) = f(\boldsymbol{W_j} \cdot X_i + b_j)$ (i=1,…,N and j=1,…K) is the hidden layer output matrix of the neural network, the j th column of it is the j th hidden node output in regard to the inputs of $X_1, \ldots, X_i$. While $\beta = [\beta_1, \beta_2, \ldots, \beta_K]^T$ and $\boldsymbol{Y} = [\boldsymbol{Y}_1, \boldsymbol{Y}_2, \ldots, \boldsymbol{Y}_N]^T$ are the matrix of output weights and targets respectively.

As the input weights ($\boldsymbol{W}$) are randomly chosen, as well as the biases (b) in ELM algorithm, the output weights (β) which connect the hidden layer and output layer could be simply determined by finding the least-square solution to the given linear system. According to Huang [203], the smallest norm least-squares solution of the linear system (3.4) among all the solutions is

$$\hat{\beta} = \boldsymbol{H}^{\dagger}\boldsymbol{Y} \tag{3.5}$$

where $H^{\dagger}$ is the Moore-Penrose generalized inverse of the matrix H [204]. In this chapter, A multi-output ELM regression function developed by Huang's group was used in this study with an optimal trial of the varied activation functions (i.e. Sigmoid, Sine, and Hardlim, given in equations (3.6)-(3.8)) and the number of hidden nodes (from 1 to 200) in the use of ELM.

$$Sigmoid(x) = \frac{1}{1 + e^{-x}} \tag{3.6}$$

$$Sine(x) = sin(x) \tag{3.7}$$

$$Hardlim(x) = 1 \;\; if\ x \geq 0; \; = 0 \;\; otherwise \tag{3.8}$$

3.2.2 Support Vector Regression

Compared with neural networks, SVR assures more generalization on the foundation of structural risk minimization, and generally performs better with less training samples. When we have training data $\{(x_l, y_l), \ldots, (x_l, y_l)\} \subset \mathbb{R}^n \times \mathbb{R}$ for a SVR model, the targeted function $g(x)$ should be as plat as possible and has ε deviation in maximum from the actual targets y_i for all the training data in the form of :

$$g(x) = \langle w, x \rangle + b \;\; with \;\; w \in \mathbb{R}^n, b \in \mathbb{R} \tag{3.9}$$

where x is the n-dimensional input vectors, w is the weight vector and b is the bias term. Flatness in (10) means small w, and the way achieving it is recommended to minimize the Euclidean norm, i.e. $\frac{1}{2}\|w\|^2$ [205], which turns out to a convex optimization problem:

$$\begin{aligned} & minimize \quad \frac{1}{2}\|w\|^2 \\ & subject\ to \quad \begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon \\ \langle w, x_i \rangle + b - y_i \le \varepsilon \end{cases} \end{aligned} \tag{3.10}$$

This is a feasible optimization problem when the function $g(x)$ actually exists and approximates all pairs (x_i, y_i) with ε precision, and slack variables ξ_i, ξ_i^* (referring to upper and lower constraints on the outputs of the system.)were introduced to deal with the otherwise infeasible constraints of it [24],

$$\begin{aligned} & minimize \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ & subject\ to \quad \begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \qquad \ge 0 \end{cases} \end{aligned} \tag{3.11}$$

where C is a constant greater than 0, determines the trade-offs of $\frac{1}{2}\|w\|^2$ and the sum of permitted errors. It is found that dual formulation makes it easy to solve this optimization problem [206], a standard dualization method utilizing Lagrange multipliers has been proposed:

$$\begin{aligned} L = {} & \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) - \sum_{i=1}^{l}\alpha_i(\varepsilon + \xi_i - \langle w, x_i \rangle + \\ & b) - \sum_{i=1}^{l}\alpha_i^*(\varepsilon + \xi_i^* + y_i - \langle w, x_i \rangle - b) - \sum_{i=1}^{l}(\eta_i\xi_i + \eta_i^*\xi_i^*) \end{aligned} \tag{3.12}$$

where L is the Lagrangian and η_i, η_i^*, α_i^*, α_i^* are the Lagrange multipliers which have to satisfy positivity constraints of ≥ 0. The partial derivatives of L with respect to the variables (w, b,ξ_i, ξ_i^*) have to vanish for optimality.

$$\partial_b L = \sum_{i=1}^{l}(\alpha_i^* - \alpha_i) = 0 \tag{3.13}$$

$$\partial_w L = w - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\, x_i = 0 \tag{3.14}$$

$$\partial_{\xi_i^{(*)}} L = C - \alpha_i^{(*)} - \eta_i^{(*)} = 0 \tag{3.15}$$

here $\xi_i^{(*)}$ refers to ξ_i and ξ_i^*. Substituting (3.13), (3.14) and (3.15) into (3.12), the dual optimization problem is given by

$$maximize \quad \begin{cases} -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\langle x_i,x_j\rangle \\ -\varepsilon\sum_{i=1}^{l}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{l}y_i(\alpha_i-\alpha_i^*) \end{cases} \tag{3.16}$$

$$subject\ to \quad \sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0 \ \ and \ \ \alpha_i,\alpha_i^*\in[0,C]$$

As the dual variables η_i, η_i^* can be reformulated on the basis of (16) as $\eta_i^{(*)}=C-\alpha_i^{(*)}$, Equation (15) turns to

$$w=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)\,x_i, thus\ g(x)=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)\,\langle x_i,x\rangle+b \tag{3.17}$$

This is so-called *Support Vector expansion*. In SVM training algorithm, the next necessary step is to make it nonlinearly, which was suggested to be achieved by a mapping $\emptyset$ *(x)* from $\mathbb{R}^n$ to a higher dimensional feature space using kernel function $K(x,x_i)=\langle\emptyset(x_i),\emptyset(\mathrm{x})\rangle$, therefore (18) becomes

$$\begin{gathered} w=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)\,\emptyset(x_i), \\ g(x)=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)\,k(x_i,x)+b \end{gathered} \tag{3.18}$$

It is different from the linear case as *w* means the flatness is no longer explicitly given. In this nonlinear case, the optimization problem refers to finding the flattest function in feature space, rather than in input space. The standard SVR is

$$g(x)=\sum_{i=1}^{N}(\alpha_i-\alpha_i^*)\,k(x_i,x)+b \tag{3.19}$$

where N (< the total number of input-output pairs) is the number of input data having nonzero values of $\alpha_i^{(*)}$. The kernel function $k\ (x_i,\ x)$ corresponds to a linear dot product of the nonlinear mapping. As we are disposing of a case of the process modeling containing multiple outputs, we applied a multi-output least-squares support vector regression (MLS-SVR) toolbox developed by Xu et al. [207]. Particularly in this study with an optimal trail on kernel functions of:

$$Linear: \quad K(x,x_i)=x^Tx_i+C \tag{3.20}$$

$$Sigmoid: \quad K(x,x_i)=tanh(\alpha x^Tx_i+C) \tag{3.21}$$

$$Polynomial: \quad K(x, x_i) = \langle x, x_i \rangle^p \tag{3.22}$$

$$Radial\ basis\ function\ (RBF): \quad K(x, x_i) = e^{\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right)} \tag{3.23}$$

$$Exponential\ Radial\ basis\ function\ (ERBF): \quad K(x, x_i) = e^{\left(-\frac{\|x-x_i\|}{2\sigma^2}\right)} \tag{3.24}$$

There is also an optimization process (using leave-one-out, LOO) of the parameters of γ, λ and p in the toolbox from where $\gamma \in \{2^{-5}, 2^{-3}, \ldots, 2^{15}\}$ and $\lambda \in \{2^{-10}, 2^{-8}, \ldots, 2^{10}\}$ (are two positive regularized parameters controlling the bias-variance trade-off), $p \in \{2^{-15}, 2^{-13}, \ldots, 2^{3}\}(=\frac{1}{2\sigma^2}$, is a parameter of RBF that sets the spread of the kernel) [207].

3.2.3 Random Forest

RF is an ensemble-learning algorithm depending on the bagging method that combines multiple independently-constructed decision tree predictors to classify or predict certain variables[200]. In RF, successive trees do not rely on earlier trees; they are independently using a bootstrap sample of the dataset, and therefore a simple unweighted average over the collection of grown trees $\{h(x, \Theta_k)\}$ would be taken for prediction in the end.

$$\bar{h}(X) = \frac{1}{K}\sum_{k=1}^{K} h(\boldsymbol{x}, \Theta_k) \tag{3.25}$$

where k=1, …,K is the number of trees, x represents the observed input vector, Θ is an independent identically distributed random vector that the tree predictor takes on numerical values. RF algorithm starts from randomly drawing ntree bootstrap samples from the original data with replacement. And then grow a certain number of regression trees in accordance with the bootstrap samples. In each node of the regression tree, a number of the best split (mtry) randomly selected from all variables are considered for binary partitioning. The selection of the feature for node splitting from a random set of features decreases the correlation between different trees and thus the average prediction of multiple regression trees is expected to have lower variance than individual regression trees [208]. Regression tree hierarchically gives specific restriction or condition and it grows from the root node to the leaf node by splitting the data into partitions or branches according to the lowest Gini index:

$$I_G\left(t_{X(X_i)}\right) = 1 - \sum_{J=1}^{M} f\left(t_{X(X_i)},\ j\right)^2 \tag{3.26}$$

where $\boldsymbol{f}(\boldsymbol{t}_{\boldsymbol{X}(\boldsymbol{X_i})},\ \boldsymbol{j})$ is the proportion of samples with the value x_i belonging to leave j as node t [209]. In the present study, Multivariate RF developed by Raziur Rahman et al. [210]was employed with an optimal topology of three parameters in terms of ntree (the number of trees in the forest), minleaf (minimum number of samples in the leaf node) and mtry (the randomly selected features considered for a split in each regression tree node).

3.2.4 Modeling structure

In the present study, the ozonation process model is expected to be capable of predicting (or outputting) the color qualities of ozone-treated samples in terms of *K/S* and *L*, a*, b** values by giving 5 variables including not only the specific color of treated fabric but also the process parameters of pH, temperature, pick-up and treating time. In other words, the anticipated model of color fading ozonation of reactive-dyed cotton realizes the complex and unclear relation of color fading ozonation parameters and its effectiveness on reactive-dyed cotton fabric in certain respects.

(a)

(b)

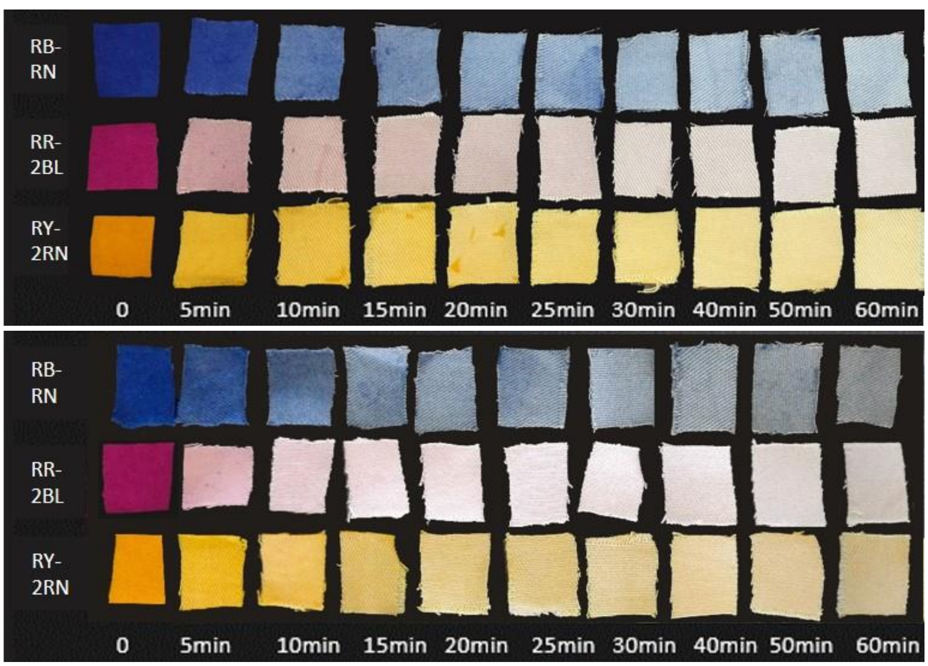


Figure 7. The illustration of the real ozone-treated cotton samples from (a) the front side, and (b) the back side

For instance, the real samples used in the ozonation, particularly, at pH7, 20℃ with 150% pick-up over different time from 0 to 60min can be observed in Figure 7. Corresponding *K/S*, L^*, a^*, b^* values of these exhibited samples are listed in Table 9. It is clear that each treated sample has an obvious difference from others in regard to color properties as treated by different ozonation processes, which on the other hand revealed how complex the process parameters influence the color of dyed cotton fabric in ozonation. Table 10 illustrates the variation including the minimum, maximum, average and standard deviation of the dataset we used in the process modeling.

Table 9. *K/S*, L^*, a^*, b^* values of samples shown in Figure 7.

		Time(min)									
		0	5	10	15	20	25	30	40	50	60
RB-RN	K/S	8.12	3.70	2.17	1.63	1.24	1.17	0.89	0.85	0.66	8.12
	L*	6.13	14.89	21.90	26.12	29.50	29.93	33.44	33.80	36.66	6.13
	a*	-2.86	-4.47	-5.18	-5.68	-5.57	-5.27	-5.25	-5.19	-4.76	-2.86
	b*	4.48	11.38	15.46	16.85	18.83	19.59	21.40	22.16	23.62	4.48
RR-2BL	K/S	1.10	0.95	0.70	0.66	0.52	0.57	0.51	0.39	0.39	1.16
	L*	22.66	25.93	29.74	30.26	33.05	31.96	33.79	36.04	36.43	21.68
	a*	-32.59	-37.32	-39.25	-40.16	-41.17	-41.82	-43.19	-42.44	-43.49	-32.39
	b*	12.84	13.69	12.84	12.49	12.05	11.82	12.38	11.23	11.69	13.41
RY-2RN	K/S	6.60	3.70	2.90	2.20	1.81	1.58	1.16	1.11	0.87	6.60
	L*	8.02	8.49	9.80	10.82	11.60	13.19	13.96	14.14	15.43	8.02
	a*	20.41	15.35	12.99	11.47	9.59	8.62	7.31	6.52	5.56	20.41
	b*	-17.99	-28.27	-32.09	-37.32	-40.95	-41.58	-47.94	-48.92	-52.39	-17.99

Table 10. The maximum, minimum, average and standard deviation of parameters.

Parameters	Minimum	Maximum	Average	Std. dev.
Color	0(Blue)	1(Yellow)	0.5(Red)	-
pH	1	13	7	3.463
Temperature	0	80℃	40℃	24.91
Pick-up	0	150%	75%	58.78
Time	0	60min	30min	20.77
K/S	0.10	22.82	7.18	7.94
L^*	0.99	65.27	33.52	17.61
a^*	-58.99	53.68	-1.81	32.75
b^*	-90.53	88.04	3.88	42.34

Table 11. The correlation coefficients of data for modeling.

	pH	Temperature	Pick-up	Time
K/S	0.0383	0.0648	-0.4862	-0.7913
L^*	-0.0579	0.1146	-0.1557	-0.3137
a^*	0.0248	0.1490	-0.4500	-0.7430

b*	-0.0302	-0.0155	-0.0184	-0.0461

612 sets of experimental data were used to construct the process modeling. Among this, 459 experimental datasets (75%) were distributed to train and validate the models, while 153 datasets (25%) were used to test. The correlation of these data was estimated by Spearman coefficients (for pH, Temperature, Pick-up and Time only as the original color of the fabric is not a continuous variable). The results illustrated in Table 11 reveal that treating time is slightly more relevant than pick-up, but both of these are the most relevant variables in the ozonation process comparing with temperature and pH.

K-fold cross-validation (k=10) was used in process modeling. It is a popular statistical approach for estimating predictive models. Taking k=10 as an example as it was the one we used in the modeling study, in which case 459 training sets of data would be divided randomly and equally into 10 disjoint folds, 9 folds of it would be split into training subset while the rest 1-fold would be used as validating subset. This procedure would be repeated 10 times with varied training and the testing dataset at each time to validate the trained models. In order to evaluate the performance of models in validation, Mean Square Error (MSE) would be used based on:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(e_i - p_i)^2 \tag{3.27}$$

where e_i is the real experimental results, whereas p_i is the predicted output of the specific model. Additionally, four statistical performance criteria, including mean absolute error (MAE), root mean square error (RMSE), correlation coefficient (R) and mean relative absolute error (MRAE) are used in this study for indicating the predictive performance of the obtained models.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i - p_i| \tag{3.28}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(e_i - p_i)^2} \tag{3.29}$$

$$R(e,p) = \frac{\sum_{i=1}^{n}(e_i - \bar{e})(p_i - \bar{p})}{\sqrt{\sum_{i=1}^{n}(e_i - \bar{e})^2 \cdot \sum_{i=1}^{n}(p_i - \bar{p})^2}} \tag{3.30}$$

$$MRAE = \frac{1}{n}\sum_{i=1}^{n}\frac{|e_i - p_i|}{e_i} \tag{3.31}$$

The models' development and construction were carried out using MATLAB R2015b for multi-output ELM and MLS-SVR, but R studio for MRF respectively on a laptop (Core i7-4710, 2.5GHz, 16GB RAM). All of the original data was regularized to the range of [0, 1] before using.

3.3. Results and discussion

3.3.1 Modeling training

(1) ELM models

ELM models with hidden nodes from 1 to 200 activated by Sigmoid, Sine, and Hardlim functions are investigated respectively (the corresponding validation MSE is illustrated in Figure 8 with a detailed demonstration of the trained ELM models possessing nodes from 1 to 140 in detail). The overfitting situation of ELM activated by Sigmoid and Sine is easy to be observed that starts from the ones with nodes around 100. More specifically, it is noted that Sigmoid trained ELM models performed similarly to the ones trained by Sine since MSE of these models both dropped as well as minimized at the ones with around 50 nodes (MSE$\approx$0.052) following by a dramatic enhancement. By contrast, validation MSE of Hardlim activated models performed generally stable with the growing number of nodes in the ELM model, but strictly a minimum of MSE$\approx$0.069 (larger than Sigmoid and Sine) at the one with 97nodes still can be discovered in Figure 8. Similar comparative results of the use of these activation functions in ELM can be found as well in the work of Rampal Singh, and S. Balasundaram [211].

The use of activation functions in an artificial neural network is to convert an input signal of the node to an output signal by mapping non-linear properties. It is very important for an ELM model to learn and achieve the complicated mapping of input and output data by activating the nodes with a certain activation function. The graph of the activation functions we used is given in Figure 9. It is noted that Sigmoid and Sine has something in common with their S-shaped curve and both are infinitely differentiable function which makes them easy to be understood and applied. However, on the other hand, it may also result in their similar proximity and disadvantage in the ELM models as we can see their similar performance variation and the overfitting situation with the increasing nodes in Figure 8. Hardlim performed least compared with Sigmoid and Sin in terms of their activated ELM models in this issue probably is owing to its oversaturation.

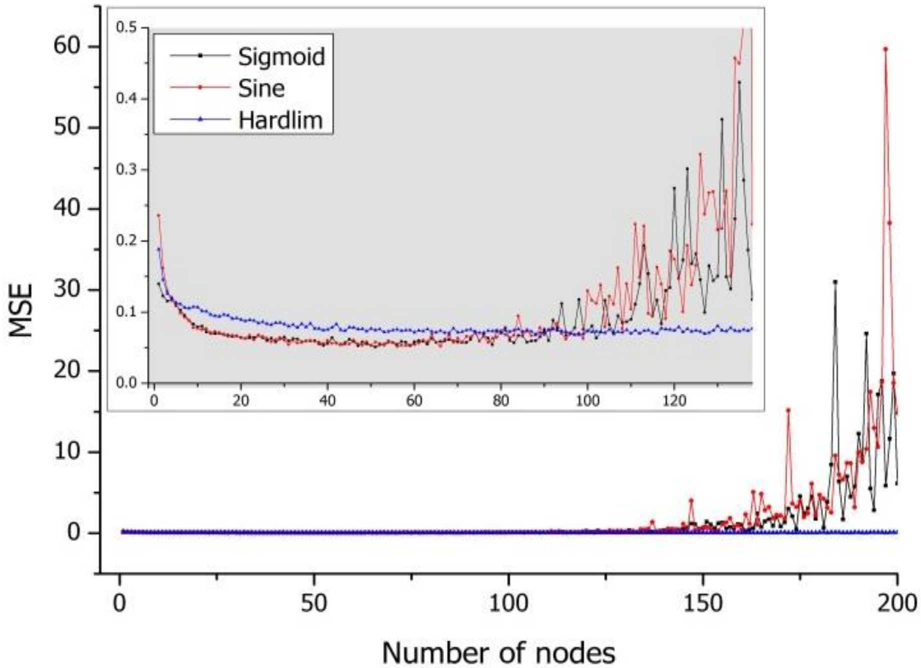


Figure 8. Validation MSE of ELM models activated by different functions

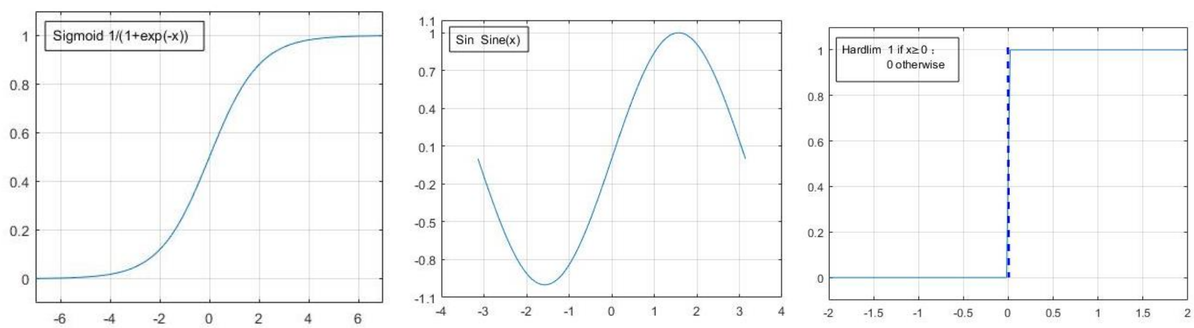


Figure 9. Activation functions of ELM.

(2) SVR models

Multi-output SVR models with kernel functions of Linear, Sigmoid, Polynomial, RBF and ERBF were trained and developed using MLS-SVR toolbox. The corresponding results of minimum validation MSE are 0.05678, 0.00932, 0.08613, 0.00493 and 0.0092 respectively (as demonstrated in Figure 10). It is worth noting that models trained with linear kernel and polynomial kernel are found that performed far poorly than the others. Performance of the ones with Sigmoid kernel and ERBF kernel are very close in a quite low level though the validation MSE of them is nearly two times than the SVR model with RBF kernel (which performed utmost in the comparison in this issue when its parameters are optimized to γ = 32768, λ = 9.7656e^{-4} and p = 0.125. For more information regarding the LOO optimization process used in the toolbox for these kernel parameters see [207]). The kernel function is to transform the data as input into the required form to facilitate a non-linear decision surface to be a linear equation in higher dimensions where the computational power of the learning machine is heightened. The type of kernel function used would influence many of the characteristics of the SVR model. A wide range of kernels exist and it is hard to explain their individual characteristics, but it is well known that RBF kernel is recommended to be tried first in an SVR model since it not only possesses certain similar parameters and behaviors of Linear and Sigmoid but also has fewer hyper parameters than Polynomial to complex the model. RBF is assumed as having computational advantages over other kernels depending on its easier and faster to compute the kernel values[212]. The lowest MSE it achieved, in this case, validates its preferential suitability to be employed in this study, and it should be attributed to that we have not too many features in the model but with comparatively large numbers of observations.

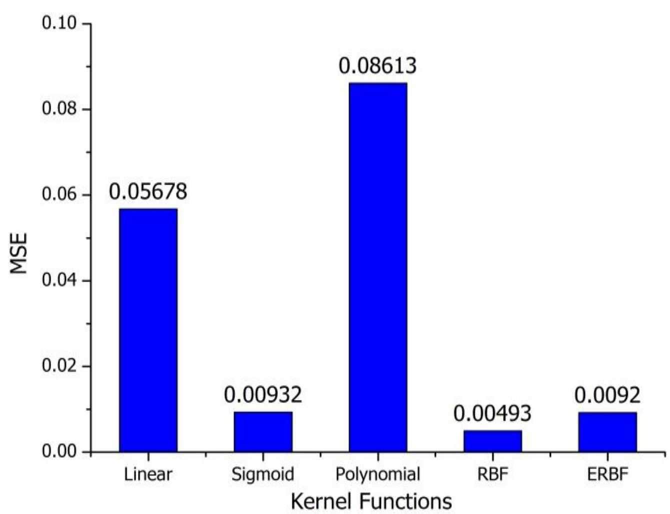


Figure 10. Validation MSE of SVM models with varied kernel functions

(3) RF models

RF models with different *mtry* (from 1 to 5), *minleaf* (from 1 to 10) and *ntree* (from 1 to 100) are trained and developed respectively, and the validation MSE of these models are given in Figure 11 with a detailed demonstration of the ones *mtry* =1 and *ntree* ranging from 1 to 100 excluding those which validation MSE higher than 0.026. In Figure 11, the number of *mtry* in each regression tree node is found that plays a very significant role in affecting the models' prediction accuracy of the color properties of ozone-treated cotton fabrics. The falling curves of MSE with the growing number of *mtry* may reveal that the five inputs we used to construct these RF modes, i.e. (1) color of dyed cotton and (2) pH, (3) temperature, (4) pick-up, (5) treating time of ozonation process, have a very clear independent relation with each other. As a result, RF models with five randomly selected features generally lead the low validation MSE in this comparison. It is also found that *ntree* played another significant role in RF models as MSE of these models decreased dramatically when the number of trees increased in the forest from 1 to 30. In general, these models perform steadily when there are more than 30 regression trees in the forest construction no matter what are the *mtry* or *minleaf* employed, but to save time and cost less in the model training process, 10 trees forest is sufficient and may be more recommended to be used in the color fading ozonation of dyed textile prediction model for further experiments. However, different from the *mtry* and *ntree*, minimum number of samples in the leaf node, i.e. *minleaf* seems to be preferable to be less though it is relatively uninfluential. Depending on the observation of the detailed-depicted MSE plots of 1-*mtry* RF models in Figure 11, we can see that the average MSE of achieved RF models generally enhanced when the number of leaves increased from 1 to 10.

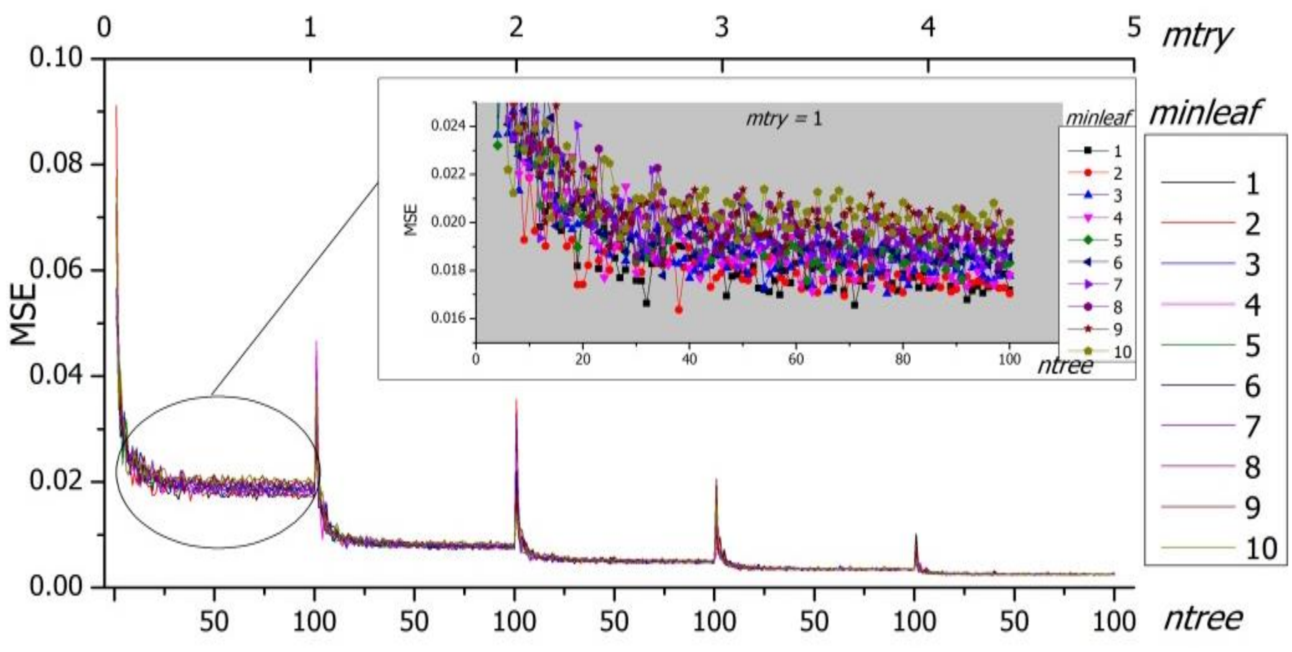


Figure 11. MSE of RF models with varied number of features, leaves and trees

3.3.2 Prediction performance

The quality of a model is not only determined by its ability to learn from the data but also its ability to predict unseen data, which two are so-called learning capacity and generalization ability of a model. Models are seldom good in both of these two capacities. According to the analysis above, we obtain ELM models trained with activation function of Sine and Sigmoid with 50 nodes, and SVR models worked with RBF kernel function as well as the RF with 5 randomly selected features, 10 trees and 2 minimum number of samples in the leaf node as the optimized models in the application of modeling color fading ozonation of dyed textile that worth to be used in further experiments.

Table 12. Prediction performance of optimized models.

Parameters	ELM (Sigmoid)	ELM (Sine)	SVR	RF
Training time(s)	0.0312	0.0936	0.9360	21
Average error (%)	0.1527	0.1549	0.1530	0.149
Maximum error (%)	0.3752	0.3700	0.3503	0.302
Minimum error (%)	0.0300	0.0029	0.0304	0.038
MSE	0.0172	0.0173	0.0043	0.0036
MAE	0.0894	0.0921	0.0429	0.0295
RMSE	0.1311	0.1315	0.0656	0.0601
R	0.9052	0.9063	0.9777	0.9847
MRAE	0.0197	0.0168	0.0109	0.0062

To estimate and compare these optimized models, the prediction test using the testing dataset (which has not been used in the training and validation processes) is carried out. Table 12 presents a comparison of the prediction performance of ELM, SVR and RF models. It is found that, in general, ELM models using activation functions of Sigmoid (MSE=0.0172) and Sine (MSE=0.0173) do not make any big difference in regard to their prediction performance, but both of it are slightly poorer comparing with SVR and RF models. However, ELM models are the fastest-trained ones in the comparison, which means ELM model is still worth to being applied in certain resource-limited cases especially while limited training time is concerned. The most accurately-predicted model we can see according to the finding in Table 11 is RF as it leads the least testing error with higher R (0.9847) and less MSE (0.0036), MAE (0.0295), RMSE (0.0601) and MRAE (0.0062). However, it is also noted that the training RF model requires a much longer time than the others (21s). As a result, it is worth taking the SVR models into account as it achieved the second lowest error (R=0.9777, MSE =0.0043, MAE=0.0429, RMSE =0.656, MRAE=0.0109) with a more acceptable shorter training time (0.9360s).

Table 12 demonstrates the overall performance of the constructed models in terms of certain estimation evaluation indexes, but the detail of these predictions is neglected. As known that the constructed models possess four outputs, i.e. K/S, L*, a*, b* values of reactive-dyed cotton fabrics treated in the color fading ozonation. How these predictive models work in detail with them is unclear. To reflect the real prediction performance (using testing data) of each trained model on predicting every single output separately, the predicted results range from output1 (k/s value) to output4 (b^*) versing real experimental data (target 1 to 4) is illustrated in Figure 12 (a) (b) (c) (d) respectively.

In Figure 12, the predicted values of models generally agree with the actual values, though the predictive errors varied in different levels for different models. As we can see that the gap of models' prediction performance is not that significant in Table 12 (taking MSE as an example, Sigmoid activated ELM=0.0172, Sine activated ELM=0.0173, SVR=0.0043, RF=0.0036), while the distribution of errors in terms of each single output prediction is observed that has a larger gap in the real application. In Figure 12 (a) and (c), certain predicted data of ELM models can be clearly seen that is far different from the real target data in a certain range, which situation would result in a big mistake in certain prediction application where the good overall performance of the average of multiple outputs may hinder the discovery of a wrong prediction on a specific single output. According to the linear fitting correlation coefficients of predicted data versing real experimental data (demonstrated in Figure 7) listed in Table 8, the testing result obtained reveals that SVR (R^2=0.9505) model and RF model (R^2=0.9555) are actually more stable and suitable than ELM models (R^2=0.8025 and 0.8007 for Sigmoid and Sine activated respectively) in modeling color fading ozonation of dyed textile, in terms of overall prediction performance, and more importantly predicting multiple outputs without deviation on a certain single output. This may attribute to the features of data we used concerning color fading ozonation of dyed textiles. While on the other hand, it could also attribute to a disadvantage of ELM that it completely relies on increasing the number of nodes to promote the prediction performance, which makes it risky to be applied in a complicated issue such as the present investigation. The result also reveals that both of SVR and RF can well deal with the interaction of variables and are comparatively more stable in multi-variable nonlinear modeling.

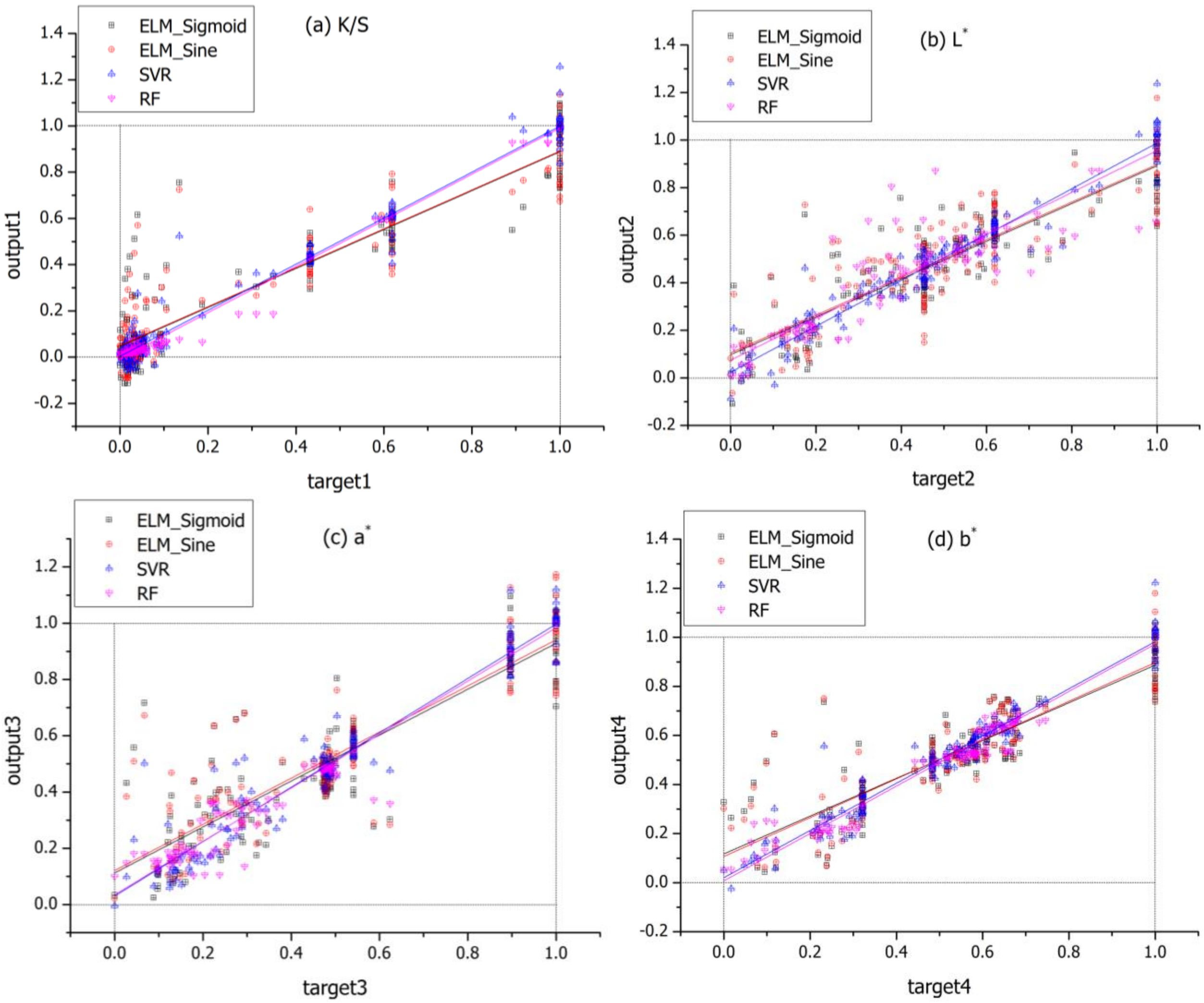


Figure 12. Predicted data outputted by ELM (trained by Sigmoid and Sine respectively), SVR and RF versus experimental data

Table 13. Correlation coefficients of data in Figure 12.

R^2	ELM (Sigmoid)	ELM (Sine)	SVR	RF
Target 1 - K/S	0.8474	0.8596	0.9683	0.9954
Target 2 - L^*	0.7944	0.7517	0.9442	0.8816
Target 3 - a^*	0.7903	0.8048	0.9380	0.9719
Target 4 - b^*	0.7778	0.7868	0.9513	0.9731
Average	0.8025	0.8007	0.9505	0.9555

3.4. Conclusions

In this chapter, we used three modeling techniques i.e. ELM, SVR and RF, to model the ozonation process for predicting the color properties of treated textiles. The potential applicability of these models in the use of process modeling in the related textile process was estimated. Based on the results, it is concluded as follow:

(1) Ozonation is a novel technology developed in recent years to be employed to achieve the color fading effect of textile with high performance not only in the respect of efficiency and quality but also relating to environmental sustainability. The applicability of intelligent techniques for modeling the textile ozonation process was verified.

(2) The complexity and nonlinearity of the factors and impacts of color fading ozonation on reactive-dyed cotton were analyzed on the basis of models. The effects of ozonation in terms of pH, temperature, water pick-up, treating time of the process and dyed colors of fabrics on the color fading performance in terms of K/S, L^*, a^*, b^* values of reactive-dyed cotton were modeled using ELM, SVR and RF respectively.

(3) SVR and RF are both potential applicable candidates for modeling the textile ozonation process of dyed textiles, as the predicted results of them on the ozonation process showed a good agreement with the actual data collectively, as well as individually.

(4) Taking the training time and cost as a consideration, the SVR model would be more recommended than RF to be applied in the real use, while the RF model would be more recommended in the cases with more tolerance on training time cost and higher requirement on prediction accuracy.

(5) Comparatively, ELM models performed poorer in the prediction and were very unstable in terms of predicting certain individual output in multi-variable process modeling.

4. Optimizing textile manufacturing process using deep reinforcement learning based intelligent system

According to the study in Chapter 3, it is known that taking advantage of models learning from data based on artificial intelligence [213], an intelligent model integrated decision support system can make a difference to optimize the textile manufacturing process virtually. The applications of decision support systems for optimizing textile processes have been reported with various techniques: genetic algorithm [53] and fuzzy technology [214], [215] etc. But along with the development of the industry and the growing complexity in textile manufacturing, those classical approaches are no longer efficient in some scenarios. This is because, in recent years, a growing number of textile manufacturing problems were come up with multi-input and multi-output with high dimensional decision space [141], and instead of a single standard, multi-criteria is increasingly taken into consideration in these problems as evaluating the performance of a textile manufacturing [216]. in the meantime, massive quantities of new data will be generated from the development of textile manufacturing, but the adaptation to the progressive environment of a textile process optimization system is still absent.

Reinforcement learning (RL) is a machine learning approach using a well understood and mathematically grounded framework of MDP that has been broadly applied to tackle the practical optimization and decision-making issues in the industry. For example, the pricing optimization [217]–[221], the chemical reactions condition optimization [222], and the production or workflow scheduling [223], [224], as well as the energy management associated problems [225], [226]. Furthermore, using the temporal difference based RL methods to reduce the dimension of data in feature selection has been reported by Mehdi et al. [227] , and Jasmin et al. [228] have applied the RL to approach the economic dispatch problem. Even if RL has been criticized in literature for their complexity of implementation, tuning and parallelization capabilities [229][230], the flexible nature of RL enables it to pre-compute offline, making online evaluation fast in large systems with high-dimension. It is worth investigating the application of it in the textile industry process as the characteristics of it is advantageous to the industry process that to well handle the large-scale stochastic multiple-input multiple-out and high-dimensional decision space [231], which could be a good solution for optimizing the textile manufacturing process. Related applications of RL for decision-making have been reported [232][233], however, at present, there is no complete study to solve a complex production problem, especially in the textile manufacturing industry. This sub-study formulates the textile manufacturing process optimization problem into a Markov decision process (MDP) paradigm and applies deep reinforcement learning (more specifically, the Deep Q-networks, DQN) instead of current methods to collaboratively approach the optimization problems in the textile manufacturing process.

As the factors of the textile manufacturing process consist of both objective and subjective effects, the intelligent data-based models of RF and human knowledge-based multi-criteria structure of AHP are proposed collaboratively with DQN in the developed optimization system. Here, the proposal of the ensemble learning approach of RF for modeling textile process lies in the excellent approximation ability RF shown in Chapter 3 to deal with the complex and uncertain impacts of textile process variables on its performance, whereas the application of AHP, a multi-criteria decision making (MCDM) tool, regards to the fact that there are a few criteria govern the quality of textile process performance and their significance with an overall objective is different.

In summary, previous work addresses the optimization problems in the textile manufacturing process using methods different from the ones we are proposing in this chapter. Their approaches were found either performed not well relatively, or barely address high complexity to an open environment. In the proposed framework, the RL would be cooperatively applied with RF models and AHP to optimize the solutions of the textile manufacturing process against multi-criteria.

4.1. Problem formulation

Suggest a textile manufacturing process P involves a set of parameter variables $\{v_1, v_2 \ldots v_n\}$, and the performance of this process is evaluated by multi-criteria of $\{c_1, c_2 \ldots c_m\}$. Decision making needs to figure out how those parameter variables affect the process performances in terms of each criterion, and whether a solution of P $\{v_{1i}, v_{2j} \ldots v_{nk}\}$is good or not relating to $\{c_1, c_2 \ldots c_m\}$.

Suppose there is a model maps $v_1, v_2 \ldots v_n$ of the process to its performance in accordance with $\{c_1, c_2 \ldots c_m\}$, then the performance of the specific solution could be presented by:

$$f_i(v_1, v_2 \ldots v_n) \mid c_i, \qquad for \quad i = 1, \ldots m \tag{4.1}$$

When the domain of $v_j \in V_j$ is known, and the multi-criteria $\{c_1, c_{2\dots}\ c_m\}$ problem could be somehow represented by C, and the Equation (4.1) could be simplified to (4.2), and so that the objective of decision-makers is to find (4.3):

$$f\,(v_1, v_2 \dots v_n)\ \big|\ C, \qquad v_j\ \in\ V_j \tag{4.2}$$

$$argmax_{v_j \in V_j}\big[\ f\,(v_1, v_2 \dots v_n)\ \big|\ C\big] \tag{4.3}$$

Equation (4.3) aims at searching for the optimal solution of variable settings, while the traditional operation in this area usually relied heavily on trial and error.

4.2. Methodology

4.2.1 Analytic Hierarchy Process

As the most frequently used and widely discussed MCDM from the recently developed discipline of operation research, AHP has been proven to be an extremely useful decision-making method in the textile industry from the issued applications of AHP estimating the quality of fibers [234] and fabrics [235], the functional clothing design [164], rotor spinning machine setting [216], and the maintenance strategy evaluation [236], though certain reports have come up with their concerns on the theoretical basis of AHP [237]–[239]. The popular application and discussion of AHP in the textile industry are owing to its involvement of both objective and subjective factors that agree with the characteristic of the decision-making problem in the textile manufacturing process.

The multi-criteria decision making (MCDM) problem presented in Equation (4.3) could be summarized as a single objective optimization problem by structuring a hierarchy of criteria in terms of weights or priorities:

$$\begin{aligned} &argmax_{v_j \in V_j}\,[\,f\,(v_1, v_2 \dots v_n)\ \big|\ C] \\ &= argmax_{v_j \in V_j} \sum_{i=1}^{m} w_i f_i(v_1, v_2 \dots v_n) \end{aligned} \tag{4.6}$$

where w_1 to w_m are weights of criterion c_1 to c_m respectively.

The AHP is a MCDM method introduced by Saaty [240] that uses a typical pair-wise comparison method into extract relative weights of criteria and alternative scores and turns a multi-criteria problem to the paradigm of Equation (4.6). Above all, it constructs a pairwise comparison matrix of attributes using a nine-point scale of relative importance, in which number 1 denotes an attribute compared to itself or with any other attribute as important as itself, the numbers of 2, 4, 6 and 8 indicate intermediate values between two adjacent judgments, whereas the numbers 3, 5, 7 and 9 correspond to comparative judgments of 'moderate importance', 'strong importance', 'very strong importance' and 'absolute importance' respectively. A typical comparison matrix (C_m) of $m \times m$ could be established for m criteria as demonstrated below:

$$C_m = \begin{bmatrix} 1 & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & 1 \end{bmatrix} \tag{4.7}$$

where a_{ij} represents the relative importance of criterion c_i regarding criterion c_j. Thus $a_{ij} = \frac{1}{a_{ji}}$ and $a_{ij} = 1$ when $i = j$. Note that a consistency index (CI) is introduced in AHP with consistency ratio (CR) on the basis of the principal eigenvector (λ_{max}) to validate the consistency in the pairwise comparison matrix:

$$CI = \frac{\lambda_{max} - m}{m - 1} \ and \ CR = \frac{CI}{RCI} \tag{4.8}$$

where RCI is a random consistency index and the values of it are available in[237]. Afterward, the relative weight of the i_{th} criteria (w_i) would be calculated by the geometric mean of the principal eigenvector, i_{th} row (GM_i), of the above matrix, and then normalizing the geometric means of rows:

$$GM_i = \left\{ \prod_{j=1}^{m} a_{ij} \right\}^{\frac{1}{m}} \ and \ w_i = \frac{GM_i}{\sum_{I=1}^{m} GM_i} \tag{4.9}$$

4.2.2 Reinforcement learning for Multi-criteria optimization

The traditional optimization techniques such as genetic algorithm and grey relational analysis [181] have been reported that made sense in certain previous studies of textile optimization application, but the effectiveness and efficiency of these traditional tools would be unacceptable in the industry 4.0 era with the massive quantities of data as well as the high complexity grown of the textile manufacturing process. As we know that heuristic method like the genetic algorithm is time-consuming that can hardly be applied in the context of industrial practice, when the number of variables is very large, along with large change intervals [182]. By contrast, reinforcement learning (RL) is a machine learning approach using a relatively well understood and mathematically grounded framework of MDP that has been broadly applied to tackle the practical decision-making issues in the industry.

Reinforcement learning (RL) is a machine learning algorithm that sorts out the Markov decision process (MDP) in the formula of a tuple:$\{S, A, T, R\}$, where S is a set of environment states, A is a set of actions, T is a transition function, R is a set of reward or losses. An agent in an MDP environment would learn how to take action from A by observing the environment with states from S, according to corresponding transition probability T and reward R achieved from the interaction. The Markov property indicates that the state transitions are only dependent on the current state and current action is taken, but independent to all prior states and actions[241]. As known that a textile manufacturing process has a number of parameter variables as $P\ \{v_1, v_2 \ldots v_n\}$, if the probable value of v_j is $p(v_j)$, the parameter of the process defining the environment space φ from $\prod_{j=1}^{n} p(v_j), v_j \in V_j$ impacting the performance of the textile process with regards to criteria $\{c_1, c_2 \ldots c_m\}$. These parameter variables are independent to each other and obey a Markov process that models the stochastic transitions from a state S_t at time step t to the next state S_{t+1}, where the environment state at time step t is:

$$S_t = [s_t^{v_1}, s_t^{v_2} \ldots s_t^{v_n}] \in \varphi \tag{4.10}$$

RL trains an agent to act optimally in a given environment based on the observation of states and the feedback from their interaction, acquiring rewards and maximizing the accumulative future rewards over time from the interaction [241]. Here, the agent learns in the interaction with the environment by taking actions that can be conducted on the parameter variables $\in P\ \{v_1, v_2 \ldots v_n\}$ at time step t. More specifically, in a time step t, the action of each single variable v_j could be kept (0) or changed up (+) / down (-) in the given range with specific unit u_j. So there are 3^n actions totally in the action space and, for simplicity, the action vector A_t at time step t could be:

$$A_t = \left[a_t^{v_1}, a_t^{v_2} \ldots a_t^{v_n}\right], \quad \text{where } a_t^{v_j} \in \{-u_j, 0, +u_j\}, v_j \in V_j. \tag{4.11}$$

The state transition probabilities, as mentions that, are only dependent on the current state S_t and actionA_t. It specifies how the reinforcement agent takes action A_t at time step t to transit from S_t to next state S_{t+1} in terms of $T\ (S_{t+1} \mid S_t,\ A_t)$. For all $a_t^{v_j} \in \{-u_j, 0, +u_j\}, v_j \in V_j$, $T\ (S_{t+1} \mid S_t,\ A_t) > 0$ and $\sum_{S_{t+1} \in \varphi} T\ (S_{t+1} \mid S_t,\ A_t) = 1$. The reward achieved by an agent in an environment is specifically related to its transition between states, which evaluates how good the transition agent conducts and facilitates the agent to converging faster to an optimal solution.

4.2.3 Deep-Q-network algorithm

The RL performs a vital function in the MDP problem. However, the basic RL algorithms in most of the studies, such as the Q-learning and the SARSA (0/λ), are based on a memory-intensive tabular representation (i.e. Q-table) of the value, or instant reward, of taking an action *a* in a specific state *s* (the Q value of state-action pair, a.k.a Q(s, a)). The tabular algorithms would restrict the application of the RL in realistic large-scale cases when the amounts of states or actions are tremendous. Because in these situations, not only the tables come short of recording all of the Q(s, a), but presenting computational power would be overwhelming as well.

The deep neural networks (DNNs) is another widely applied machine learning technique that is quite good at coping with the large-scale issues and has recently been combined with the RL to evolve toward deep reinforcement learning (DRL). Deep-Q-network is a DRL developed by Mnih et al. [242] in 2015 as the first artificial agent that is capable of learning policies directly from high-dimensional sensory inputs and agent-environment interactions. It is an RL algorithm proposed based on Q-learning which is one of the most widely used model-free off-policy and value-based RL algorithms.

(1) Q-learning

The Q-learning learns through estimating the sum of rewards *r* for each state S_t when a particular policy π is being performed. It uses a tabular representation of the $Q^{\pi}(S_t, A_t)$ value to assign the discounted future reward *r* of state-action pair at time step *t* in Q-table. The target of the agent is to maximize accumulated future rewards to reinforce good behavior and optimize the results. In Q-learning algorithm, the maximum achievable $Q^{\pi}(S_t, A_t)$ obeys Bellman equation on the basis of an intuition: if the optimal value $Q^{\pi}(S_{t+1}, A_{t+1})$ of all feasible actions A_{t+1} on state S_{t+1} at the next time step is known, then the optimal strategy is to select the action A_{t+1} maximizing the expected value of $r + \gamma \cdot max_{A_{t+1}} Q^{\pi}(S_{t+1}, A_{t+1})$.

$$Q^{\pi}(S_t, A_t) = r + \gamma \cdot max_{A_{t+1}} Q^{\pi}(S_{t+1}, A_{t+1}) \tag{4.12}$$

According to the Bellman equation, the Q-value of the corresponding cell in Q-table is updated iteratively by:

$$Q^{\pi}(S_t, A_t) \leftarrow Q^{\pi}(S_t, A_t) + \alpha\left[r + \gamma \cdot max_{A_{t+1}} Q^{\pi}(S_{t+1}, A_{t+1}) - Q^{\pi}(S_t, A_t)\right] \tag{4.13}$$

where S_t and A_t are the current state and action respectively, while S_{t+1} is the state achieved when executing A_{t+1} in the set of S and A in any given MDP tuples of $\{S, A, T, R\}$. $\alpha \in [0, 1]$ is the learning rate, which indicates how much the agent learned from new decision-making experience ($Q^{\pi}(S_{t+1}, A_{t+1})$) would override the old memory ($Q^{\pi}(S_t, A_t)$). r is the immediate reward, $\gamma \in [0, 1]$ is the discount factor determining the agent's horizon.

The agent takes action on a state in the environment and the environment interactively transmits the agent to a new state with a reward signal feedback. The basic principle of Q-learning RL essentially relies on a trial and error process, but different from humans and other animals who tackle the real-world complexity with a harmonious combination of RF and hierarchical sensory processing systems, the tabular representation of Q-learning is not efficient at presenting an environment from high-dimensional inputs to generalize past experience to new situations [242].

(2) DQN: innovative combination of deep neural networks and Q-learning

Q-table saves the Q value of every state coupled with all its feasible actions in an environment, while the growing complexity in the problem nowadays indicates that the states and actions in an RL environment could be innumerable (such as Go game). In this regard, DQN applies DNNs instead of Q-table to approximate the optimal action-value function. The DNNs feed by the state for approximating the Q-value vector of all potential actions, for example, are trained and updated by the difference between Q-value derived from previous experience and the discounted reward obtained from the current state. While more importantly, to deal with the instability of RL representing the Q value using nonlinear function approximator [243], DQN innovatively proposed two ideas termed experience replay [244] and fixed Q-target. As known that Q-learning is an off-policy RL, it can learn from the current as well as prior states. Experience replay of DQN is a biologically inspired mechanism that learns from randomly taken historical data for updating in each time step, which therefore would remove correlation in the observation sequence and smooth over changes in the data distribution. Fixed Q-target performs a similar function, but differently, it reduces the correlations between the Q-value and the target by using an iterative update that adjusts the Q-value towards target values periodically.

Specifically, the DNNs approximate Q-value function in terms of Q-(s, a; θ_i) with parameters θ_i which denotes weights of Q-networks at iteration i. The implementation of experience replay is to store the agent's experiences e_t= (S_t, A_t, r_t, S $_{t+1}$,) at each time step t in a dataset D_t = {e_1,…e_t,}. Q-learning updates were used during learning to samples of experience, (S, A, r, S') ~ $U(D)$, drawn uniformly at random from the pool of stored samples. The loss function of Q-networks update at iteration i is:

$$L_i(\theta_i) = \mathbb{E}_{(S,A,r,S') \sim U(D)}\left[\left((r + \gamma \cdot \max_{A'} Q(S', A';\, \theta_i^-) - Q(S, A; \theta_i)\right)^2\right] \tag{4.14}$$

where θ_i^- are the network weights from some previous iteration. The targets here are dependent on the network weights; they are fixed before learning begins. More precisely, the parameters θ_i^- from the previous iteration is fixed as optimizing the i_{th} loss function $L_i(\theta_i)$ at each stage and are only updated with θ_i every R steps. To implement this mechanism, DQN uses two structurally identical but parametrically differential networks, one of it predicts Q$(S, A; \theta_i)$ using the new parameters θ_i, the rest one predicts $r + \gamma \cdot \max_{A'} Q(S', A';\, \theta_i^-)$ using previous parameters θ_i^-. Every R steps, the Q network would be cloned to obtain a target network $\hat{Q}$, and then $\hat{Q}$ would be used to generate Q-learning target $r + \gamma \cdot \max_{A'} Q(S', A';\, \theta_i^-)$ for the following R updates to network Q.

The DQN is a typical and classic DRL algorithm that played a key role in the applications of production scheduling, playing video games, and the Computer Go [223], [242], [245], etc. Given the advantages that the DQN can offer when confronted with decision making in the textile process optimization, this algorithm would be adopted in the construction of the proposed decision support system.

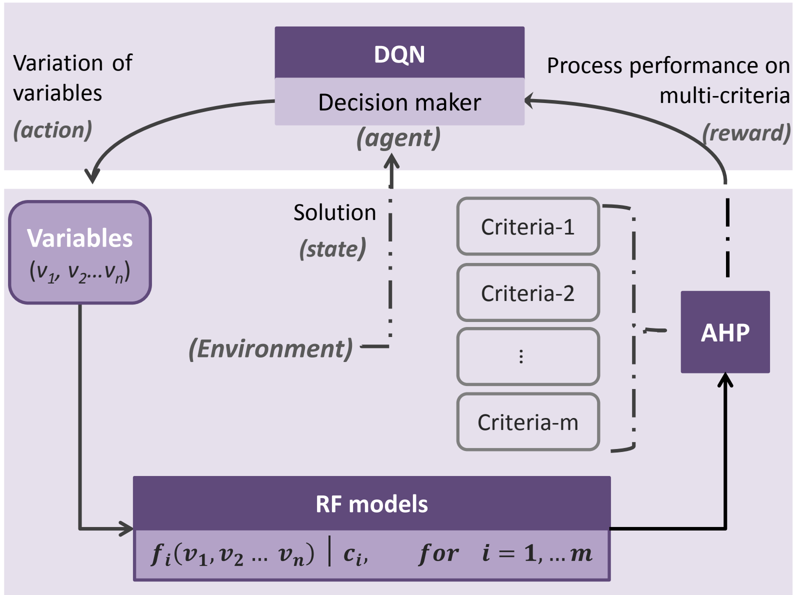


Figure 13. The MDP structure of textile manufacturing process multi-criteria optimization in the proposed framework

4.3. System framework

Figure 13 illustrates the textile manufacturing process optimization problem in the paradigm of RL, where the decision-maker plays the role of agent to traverse and explore the state space, the environment includes all the targeted process parameter variables, the adjustment of parameter variables indicates the action, the solution combined of all the parameter variables represents the state, and the objective function denotes the reward. The objective of the developed decision support system is to optimize the textile process with regards to its parameter variables on the basis of the multi-criteria objective function which has fundamentally been formulated in Equation (4.3). Therefore, here the feedback from the environment depending on a reward function is in accordance with the objective function.

Machine learning library of Scikit-learn is employed to develop the RF models [246], where the sub-sample size of it is always the same as the original input sample size but the samples are drawn with a replacement if *bootstrap* is used (or else the whole dataset would be used to build each tree). RF algorithm starts from randomly drawing a number of samples from the original data and grows corresponding regression trees (*n_estimators*) in accordance with the drawn samples. In each leaf node of the regression tree, respectively given the minimum number of samples required to be at a leaf node (*min_samples_leaf*) and to split an internal node (*min_samples_split*) as well as the maximum depth of the tree (*max_depth*), a number of the best splits (*max_features*) randomly selected from all variables are considered for binary partitioning. The selection of the feature for node splitting from a random set of features decreases the correlation between different trees and thus the average prediction of multiple regression trees is expected to have lower variance than individual regression trees [208]. A hyperparameter tuning process using a grid search with 3-fold cross-validation is conducted in this study for optimizing the RF models, and the applied parameter grid with 3960 combinations is demonstrated in Table 14.

The pseudo-code of the proposed multi-criteria decision support system based on DQN reinforcement learning, RF models, and AHP are illustrated in Algorithm 1, and an episodic running within the algorithm is graphically displayed in Figure 14. Apart from the aforementioned parameters, it is also necessary to provide an experience dataset (D_e) regarding the textile process modeling and the expected process performance or optimization targets (P) to the system construction. To balance the exploration and exploitation of states at the learning period and optimizing period respectively, we initialize the first state of every episode randomly from each sub-state $s_t^{v_i}$ where parameter variables $v_j \in V_j$, and more importantly, apply increasing ε-greedy policy at the meantime.

In fact, the algorithm given above can work without episodes, as the target of an RL trained agent is to find the optimized solution, in terms of state in the environment with minimum error tested by RF models and AHP evaluations, however, the lack of exploration of the agent in an environment may cause local optimum in a single running. So we initialize the first state randomly and introduce an episodic learning process to the agent for enlarging the exploration and preventing local optimum. On the other hand, we apply the increasing ε-greedy policy as well. The ε-greedy policy helps the agent find the best action (maximum Q value) in the present state to go to the next state with a possibility of ε that may also randomly choose an action with a possibility of $1-\varepsilon$ to get a random next state. While, as illustrated in Algorithm 2, increasing ε-greedy is employed with an increment given in each time step from 0 until it equals to ε_{max}. This benefits the agent to explore the unexplored states without staying in the exploitation of already experienced states of Q-networks, and plentifully exploit them when the states are traversed enough.

Table 14. Parameter grid used in the hyperparameter tuning process

Parameter of RF	Options and implication
bootstrap	True or False : sampling data points with or without replacement
n_estimators	200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000
min_samples_leaf	1, 2, 4
min_samples_split	2, 5, 10
max_depth	10, 20, 30, 40, 50, 60, 70, 80, 90, 100, None
max_features	'auto': *max_features* = *x* (the number of observed input vector) 'sqrt': max_features = $\sqrt{x}$

Algorithm 1: Multi-criteria decision support system main body:

Initialize: D_e (process experience data), C_m (comparison matrix of considered criteria),
P ($p_1, p_2 \dots p_m$, expected performance of process), E (number of episodes), N (number of time steps),
α (learning rate), γ (discount factor), R (the step updating DQN), D (replay memory size);

Phase 1: RF model construction
Split input and output of D_e to train and test RF models respectively;
For each output (process performance in regard to criterion c_i) **do**
RF model $f_i(v_1, v_2 \dots v_n) \mid c_i \leftarrow parameter\ tuning\ result\ with\ min\ error\ (see\ TABLE\ 13)$
End for

Phase 2: Multi-criteria summary
Initialize and check multi-criteria pairwise comparison matrix $C_m = \begin{bmatrix} 1 & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & 1 \end{bmatrix}$;
Geometric mean $GM_i = \left\{\prod_{j=1}^{m} a_{ij}\right\}^{\frac{1}{m}}$ and relative weight of criterion $w_i = \frac{GM_i}{\sum_{l=1}^{m} GM_i}$;
Transformation: $argmax_{v_j \in V_j}\, [f\,(v_1, v_2 \dots v_n) \mid C] = argmax_{v_j \in V_j} \sum_{i=1}^{m} w_i f_i(v_1, v_2 \dots v_n)$;

Phase 3: Optimization using DQN
Initial function Q with random weights θ:
Initial function $\hat{Q}$ with weights $\theta^- = \theta$;
Initialize state $s_0 = (v_1, v_2 \dots v_n)$
For episode =1, E **do**
For time step=1, N **do**
Choose an action a_t using ε-greedy policy
Execute action a_t , observe next state s_{t+1}
Estimate $f(s_t)$ and $f(s_{t+1})$ to observe r_t ($r_t = \sum_{i=1}^{m} \sqrt{{w_i}^2 (f_i(s_t) - p_i)^2} - \sum_{i=1}^{m} \sqrt{{w_i}^2 (f_i(s_{t+1}) - p_i)^2}$)
Store transition (s_t, a_t, r_t, s_{t+1}) in D
Sample random minibatch of transitions (s_t, a_t, r_t, s_{t+1}) from D
Set $y_i = \begin{cases} r_j & \text{if terminates at step } j+1 \\ r_j + \gamma max_{a'} \hat{Q}(s_{j+1}, a';\, \theta^-) & \text{otherwise} \end{cases}$
Perform a gradient descent step on $\left(y_i - Q(s_j, a_j;\, \theta)\right)^2$ with regard to θ
Every R steps reset $\hat{Q} = Q$
$s_t \longleftarrow s_{t+1}$

End For
End For

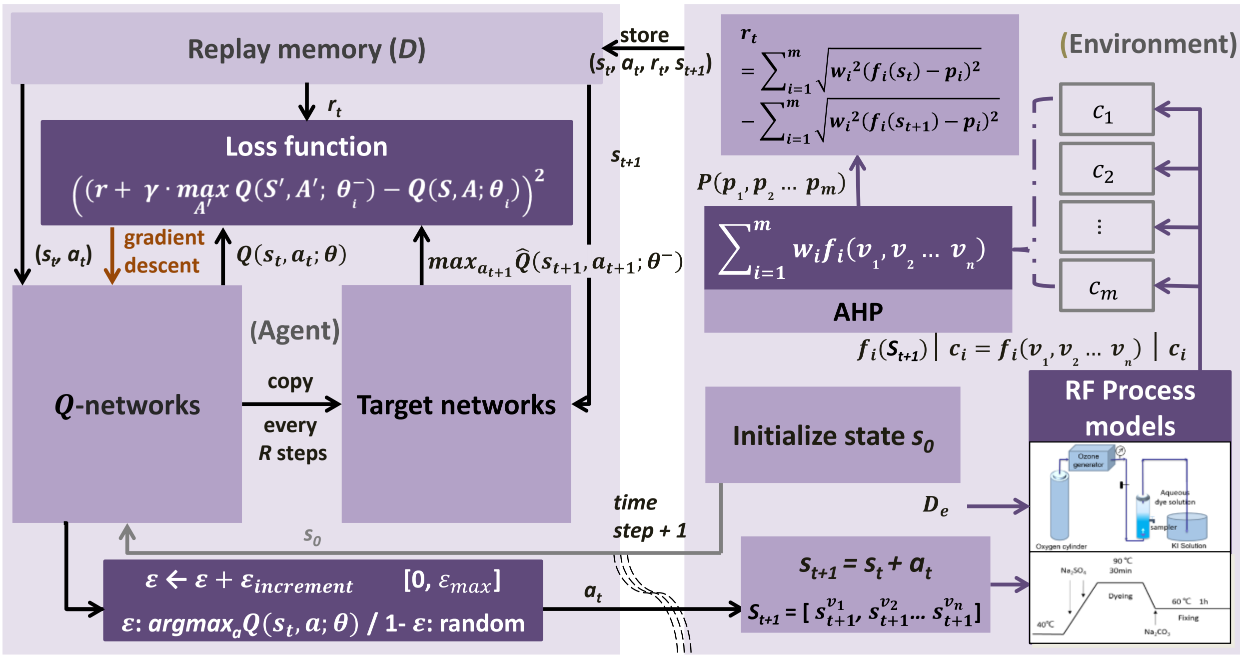


Figure 14. Flowchart of the algorithm implementing the deep reinforcement learning based multi-criteria decision support system for textile manufacturing process optimization

Algorithm 2: Choose an action using ε-greedy policy

Input: $\varepsilon_{increment}$, ε_{max}
$\varepsilon \leftarrow \varepsilon + \varepsilon_{increment}$ $(0 \leq \varepsilon \leq \varepsilon_{max})$;
If random(0,1) > ε
  Randomly choose action a_t from action space
Else
  Select a_t=argmax$_a Q(s_t, a; \theta)$
End if

4.4. Application

The application of the established decision support system to the ozonation process was performed to evaluate the performance of the proposed framework, the setup of the proposed framework would be attempted to solve a 4-targets optimization problem of color fading ozonation process. Specifically, the application study here only takes the yellow samples for RF model training and construction, which is different from the one developed in Chapter 3.

In terms of the experience dataset used to train and test RF models, it is different from the model developed in Chapter 3 that only the yellow samples are taken here for RF model construction. It includes 4 process parameters (water-content, temperature, *pH* and time) of the process and 4 process performance index known as *k/s*, L^*, a^*, and b^* of the treated fabrics. Where the *k/s* value indicates color depth, while L^*, a^*, and b^* illustrate the color variation in three dimensions (lightness, chromatic component from green to red and from blue to yellow respectively). Normally, the color of the final textile product in line with specific *k/s*, L^*, a^*, and b^* is within the acceptable tolerance of the consumer.

4.4.1 Modeling color fading ozonation process using the random forest

In terms of the RF model construction, 75% of the data was divided into the training group and the rest 25% was used to test models. In order to decrease the bias and promote the generalization of applied RF models in the system, we have trained 4 separate models for predicting 4 outputs (*k/s*, L^*, a^*, and b^*) respectively. The results of hyper-parameter tuning in regards to the context given in Table 14 are displayed in Table 15, and the final optimized models are tested (25% with unseen data) that can well predict the process performance with accuracies (R-square) of 0.996, 0.954, 0.937 and 0.965 respectively.

Table 15. The results of hyper-parameter tuning and performances of the RF models

	Bootstrap	n_ estimators	Min_ samples_ leaf	Min_ samples_ split	Max_ depth	Max_ features	R^2	MAE
k/s	True	2000	1	2	30	‘auto’	0.996	0.28
L^*	False	2000	1	2	None	‘sqrt’	0.954	0.77
a^*	False	2000	2	2	None	‘auto’	0.937	2.29
b^*	True	2000	1	5	100	‘auto’	0.965	2.87

4.4.2 Determining the criteria weights using the analytic hierarchy process

By means of combining experts’ judgment with our experience, a pairwise comparison matrix of the 4 decision criteria with respect to the overall color performance of the ozonation process treated textile product is provided in Table 16. λ_{max} of this comparison matrix is 4.1042 and known that the *RCI* for 4 criteria problem is 0.90, as a result, the *CR* calculated is 0.0386≤0.08 which implies that the evaluation within the matrix is acceptable.

Table 16. Pairwise comparison matrix of k/s, L*, a* and b* with respect to the overall color performance

	k/s	L^*	a^*	b^*	GM	w
k/s	1	3	5	5	2.9428	0.556
L^*	1/3	1	3	3	1.3161	0.249
a^*	1/5	1/3	1	2	0.6043	0.114
b^*	1/5	1/3	1/2	1	0.4273	0.081

4.4.3 Deep Q-Networks for optimal decision-making

We optimize the color performance in terms of *k/s*, L^*, a^*, and b^* of the textile in the ozonation process by finding a solution including proper parameter variables of water-content, temperature, *pH* and treating time that minimizes the difference between such specific process treated textile product and the targeted sample. Therefore, the state space φ, in this case, is composed by the solutions with four parameters (water-content, temperature, *pH* and treating time) in terms of $S_t = [s_t^{v_1}, s_t^{v_2}, s_t^{v_3}, s_t^{v_4}]$. In a time step *t*, the adjustable units of these parameter variables are 50, 10, 1 and 1 respectively in the range of [0, 150], [0,100], [1, 14] and [1, 60] respectively. As the action of a single variable v_j could be kept (0) or changed up (+) / down (-) in the given range with specific unit *u*, so there are 3^4 =81 actions totally in the action space and the action vector at time step t is $A_t = [a_t^{v_1}, a_t^{v_2}, a_t^{v_3}, a_t^{v_4}]$, where $a_t^{v_1} \in \{-50, 0, +50\}, v_1 \in [0, 150]$; $a_t^{v_2} \in \{-10, 0, +10\}, v_2 \in [0, 100]$; $a_t^{v_3} \in \{-1, 0, +1\}, v_3 \in [1, 14]$; $a_t^{v_4} \in \{-1, 0, +1\}, v_4 \in [1, 60]$.

The transition probability is 1for the states in the given range of state space above, but 0 for the states out of it. The reward *r* at time step *t* is expected to be in line with how close the agent gets to our target, and as the relative importance of these four performance criteria (0.556, 0.249, 0.114 and 0.081 respectively) is analyzed in AHP, we could set up the reward function as illustrated below to induce the agent to approach our optimization results:

$$r_t = \sum_{i=1}^{m} \sqrt{w_i^2 (f_i(s_t) - p_i)^2} - \sum_{i=1}^{m} \sqrt{w_i^2 (f_i(s_{t+1}) - p_i)^2} \tag{4.15}$$

As shown in the pseudo-code of DQN main body in Algorithm 1, optimization targets of textile ozonation process are needed to function the system (p_1, p_2, p_3, p_4, the color performance of the ozonation process in terms of *k/s*, L^*, a^*, and b^*), these targets in the present case study would be sampled by experts. In addition to the targets, the parameters of DQN such as step *R* for updating

Q-networks and replay memory size D, as well as the learning rate α and the discount rate γ for updating loss function, etc., are listed in Table 17. In particular, the R step for updating DQN here denotes that after 100 steps, the Q-networks would be updated at every 5 steps.

Table 17. DQN algorithm setting in textile ozonation process application study

R	D	α	γ	$\varepsilon_{increment}$	ε_{max}	E	N
5(>100)	2000	0.01	0.9	0.001	0.9	5	5000

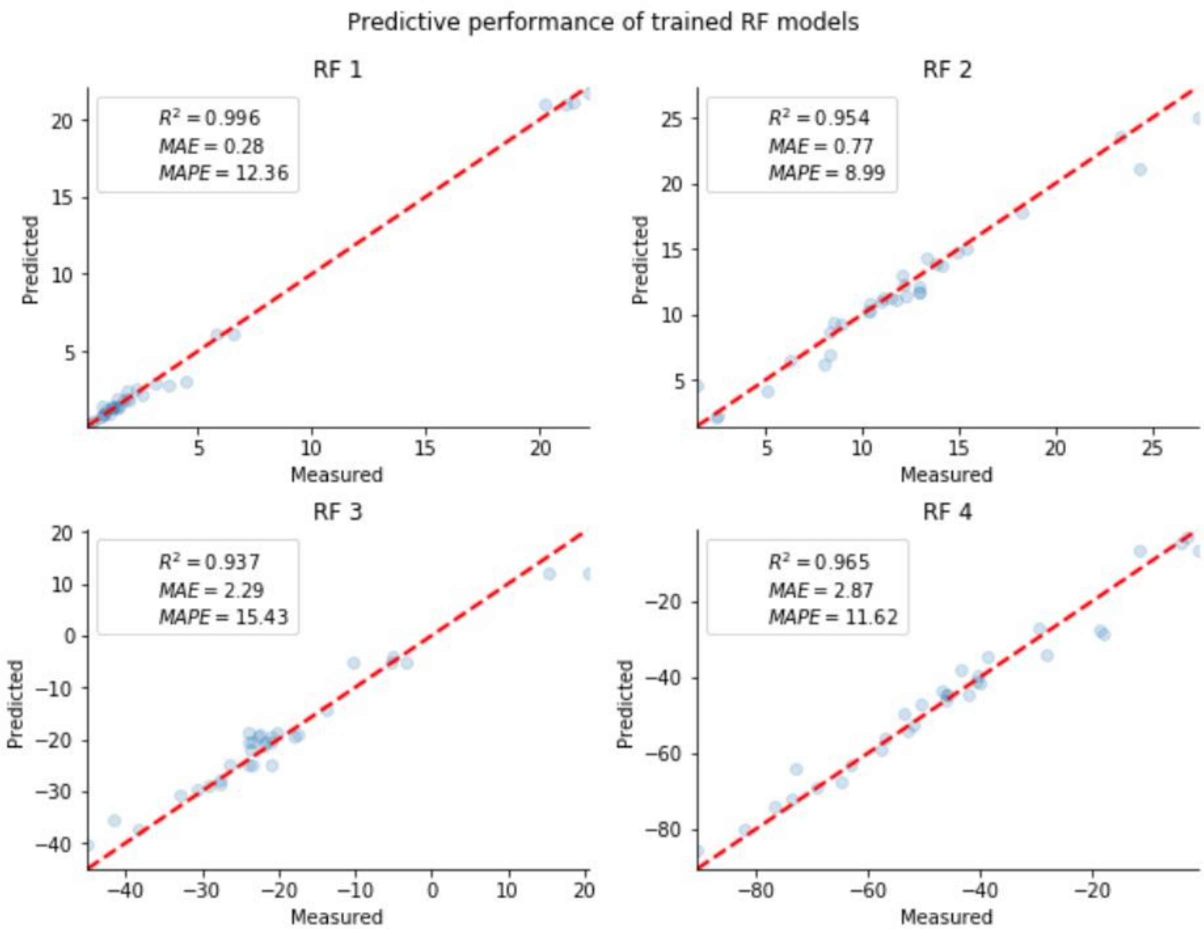


Figure 15. Predictive performance of the RF models trained in the case study for supporting decision making in the textile color ozonation process

4.4.4 Results and discussion

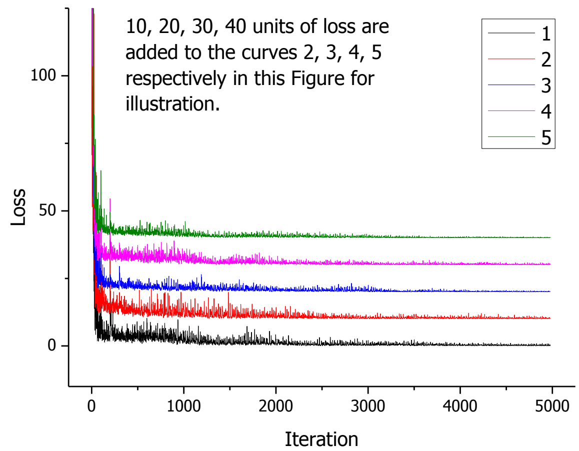
As mentioned that there are four RF models trained for predicting p_1, p_2, p_3, p_4 of the color performance of the ozonation process in terms of k/s, L^*, a^* and b^*, respectively. The predictive performance of these models displayed in Figure 15 indicates that the models work steadily in the algorithm of the present case study as it is found that the models predicted values are generally in accordance with the actual measured values through the predictive errors of different models varied slightly at different levels. This finding furthermore reflects that the RF approach is capable of modeling the textile manufacturing process and plays a significant role in our proposed decision support system.

In particular, the neural networks implemented by TensorFlow [247] are used in our case study to realize Q-networks which have been described in detail in the developed framework of Algorithm 1. The networks consist of two layers with 50 and 3^4 hidden nodes respectively, where the last layer corresponds to the actions. As demonstrated in Table 18, there are 5 experimental targets sampled by experts that were used in the present case study.

Table 18. The experimental targets sampled by experts we used in the case study application of proposed decision support system

	1	2	3	4	5
k/s	0.81	1.00	2.45	1.84	0.41
L^*	15.76	11.63	8.2	9.72	21.6
a^*	-20.84	-24.08	-18.73	-21.09	-36.48
b^*	-70.79	-54.1	-38.17	-42.78	-59.95

Figure 16 demonstrates the loss function of target Q-networks for each scenario. It is found that converged quickly to be steady after training by the action values feedback obtained from the environment in early time steps, which denotes that the representation of Q-value in this Q networks is stable and accurate. Relating to the dramatic falls at the beginning steps in each scenario, it is owing to the increasing ε-greedy policy employed in the algorithm which leads the agent to choose action randomly with a high probability in a range of beginning time steps, but increasingly choose the action with high value after that. On the other hand, in terms of the 5 episodes we employed in each scenario, it is found that the maximum unrepeated states that a DQN agent has been explored that are all occurred in the first episode in all the scenarios (Figure 17). This also reflects that the increasing ε has balanced the process of exploration and exploitation of states in the environment, and the rest episodes would benefit from the experience achieved before.



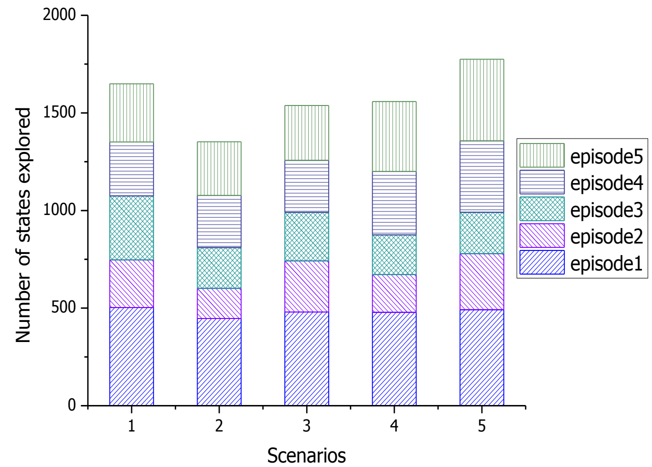


Figure 16. The loss function of Q-networks for each scenario with different targets

Figure 17. The number of states that the DQN agent has explored in each episode for different scenarios

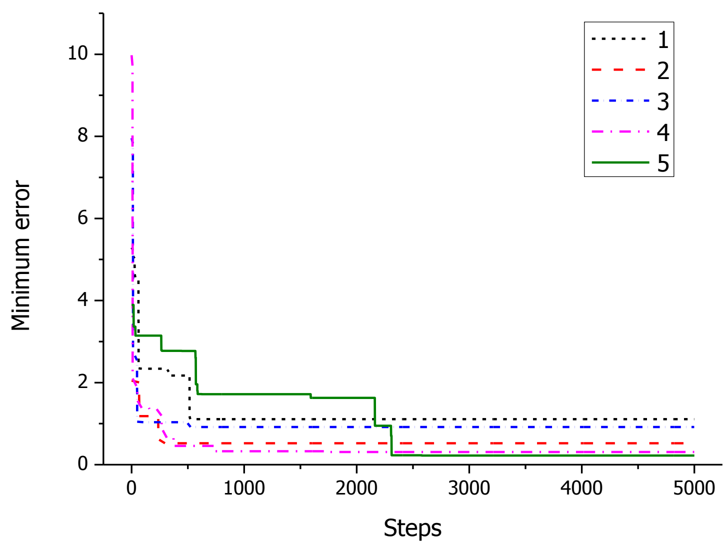
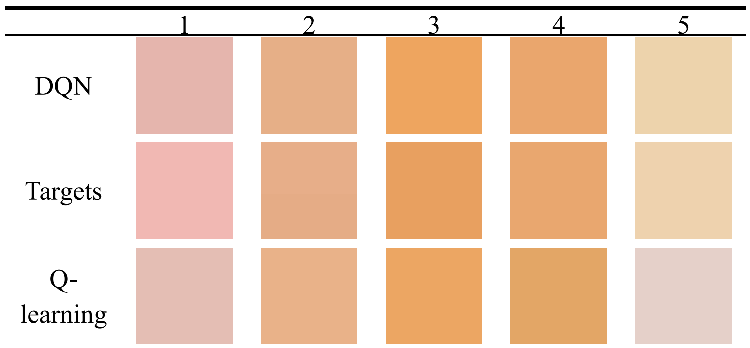


Figure 18. The minimum error of solutions that DQN agent achieved versus time steps

This case study implemented 5 episodic trails for each scenario with different targets in the proposed framework. We collect the minimum error of solutions (states) evaluated by RF-AHP during the DQN agent interacted with the environment time steps. While the initial state is randomly given in our proposed system for avoiding local optimum, only the ones with the best results are specifically illustrated in Figure 18 regarding the time steps. It is found that the reward function can effectively guide the agent to find the optimum in the environment, and the times steps taken in 3000 seem enough for the optimization. However, it is worth noting that the efficiency of the reward function in our proposed decision support system is still not fully illustrated by this case study. One main reason for this comes to the limited data of textile manufacturing processes and the costly computational power which hopefully would be solved in the Industry 4.0 era.

Table 19. simulated results of solutions with minimum errors obtained from DQN based and Q-learning based framework respectively



In order to show the advantage and effectiveness of DQN in our proposed decision support system, a comparison with Q-learning based on the same developed framework is conducted, and the simulated color performance of the results in terms of the solutions with minimum error obtained from two methods are comparatively demonstrated in Table 19 with the targets. Here the error is calculated by Equation (4.16), which are 1.06, 0.50, 0.88, 0.29, 0.22 and 1.13, 0.54, 0.91, 1.28, 1.76 in the DQN and Q-learning based decision support system for scenarios from 1 to 5 respectively.

$$error = \sqrt{0.556^2(k/s_s - k/s_t)^2 + 0.249^2(L_s^* - L_t^*)^2 + 0.114^2(a_s^* - a_t^*)^2 + 0.081^2(b_s^* - b_t^*)^2} \quad (4.16)$$

where $\boldsymbol{k/s_s}$, $\boldsymbol{L_s^*}$, $\boldsymbol{a_s^*}$, $\boldsymbol{b_s^*}$ are the properties of simulated color performance of the solution obtained from the decision support system, and $\boldsymbol{k/s_t}$, $\boldsymbol{L_t^*}$, $\boldsymbol{a_t^*}$, $\boldsymbol{b_t^*}$ are the targeted color performance.

4.5. Conclusions

Textile manufacturing is a traditional industry involving high complexities in interconnected processes with limited capacity on the application of modern technologies. Decision-making in this domain generally takes multiple criteria into consideration, which usually arouses more complexity. Traditional classical approaches are no longer efficient owing to the growing complexity with large-scale data and high dimensional decision space in some scenarios. In this chapter, a decision support system combining the random forest model, analytic hierarchy process and deep Q-Networks is proposed for optimizing the textile manufacturing process. This developed system tackles large scale optimization problems in high dimensional decision space with multi-criteria in the textile manufacturing process. Empirical data and human knowledge of the textile process are needed to build random forest models and evaluate criteria respectively. The dependence of the operations on data and knowledge of this system are in accordance with the characteristics of the complicated textile manufacturing process with respect to both objective and subjective factors in the decision making of an application. On the basis of the results obtained from this chapter, it is concluded:

(1) Decision making for optimizing the textile manufacturing process could be formulated into the Markov decision process paradigm of $\{S, A, T, R\}$ in the proposed algorithm.

(2) Taking advantage of the deep reinforcement learning by means of a deep Q-Networks algorithm, the proposed framework can effectively exploit the data on the basis of random forest models.

(3) AHP multi-criteria structure benefits the proposed framework to find the optimal textile manufacturing process solution with respect to multiple objectives.

(4) The application in optimizing the textile ozonation process showed that the developed system is capable of learning to master the challenging decision-making tasks and performed better than traditional methods.

5. Multi-objective optimization of the textile manufacturing process using deep reinforcement learning based multi-agent system

On the basis of the deep reinforcement learning algorithm, the proposed framework in Chapter 4 was applied to deal with the multi-objective optimization problems in the textile manufacturing process. For the further improvement of the established system to deal with the increasing searching dimension from the development of textile manufacturing industry in the upcoming big data era, this chapter would furthermore extent the investigation of the reinforcement learning algorithm to combine with the game theory in terms of a multi-agent system to cope with the formulated textile manufacturing process multi-objective optimization problems.

It is known that multi-objective optimization problem has been transformed into game-theoretic models to be well solved [248], [249], and recent developments of multi-agent system for optimizing multiple objectives based on game theory have shown its extreme capability of dealing with functions having high dimensional space [250], [251]. On the other hand, the multi-agent reinforcement learning (MARL) has been proposed in many contributions for robotics distributed control, telecommunications, traffic light control, and dispatch optimization etc. [252]–[254], but traditional MARL algorithms generally can hardly handle the large-scale problem, the applicability of it was therefore very limited [255]. While in recent years, the development of deep reinforcement learning (DRL) has achieved many outstanding results, which prompts a growing number of research efforts paying to the investigations of algorithms and applications of DRL in MARL environment [256]–[258]. Although studies reported the use of MARL and DRL for optimizing workflow scheduling, electronic auctions and traffic control problems with multiple objectives [259], very limited work solved a complex production problem, especially in the textile manufacturing industry.

Upon which, this chapter formulates the multi-objective optimization problems of the textile manufacturing process into a Markov game paradigm and collaboratively applying multi-agent deep-Q-networks (DQN) reinforcement learning instead of current methods to optimize the textile process in terms of multiple objectives.

5.1. System model

Consider the solution of a textile manufacturing process P is composed and determined by a set of parameter variables $\{v_1, v_2... v_n\}$, the impacts of these variables on the process performance could be varied a lot from n different respects with uncertainty, as the number of the processes and the related variables in the textile manufacturing industry is enormous and the influences of these variables on the targeted optimization performance are unclear. For example, the longer time was taken of a textile process generally would lead to the increment of production cost, and a tiny enhance of temperature used in the textile production process could significantly arouse the power consumption, but sometimes the enhanced temperature may promote the process efficiency so that decrease the production cost eventually. Therefore, it is necessary to study the interrelated effects of process variables on the process performance. From the engineering perspective, it is important to achieve a solution in the textile manufacturing process that can achieve good quality and avoid idle time, waste and pollutions at the same time. Models that incorporate the information of the process simulating the variation of multiple objective performances from the change of variable in the solutions are rather essential.

Suppose models exist that can map variables v_1, v_2... v_n of the process solution P to its performance in accordance with m objectives, the performance of a specific solution could be simulated by:

$$f_i\ (P) = f_i(v_1, v_2 \dots v_n) \quad for \quad i = 1, \dots m \tag{5.1}$$

When a decision-maker who wants to find a solution that satisfies m objectives of the process performances that the objectives are non-commensurable and no preference of the objectives related to each other is coming up with the decision-maker. The multi-objective problem could be defined as giving the n-dimensional variable vector $P = \{v_1, v_2... v_n\}$ in the solution space, finding a vector of p^* that optimizes a given set of m objective functions:

$$f\ (p^*) \ = \ \{\ f_1\ (p^*), f_2\ (p^*), \dots, f_m\ (p^*)\ \} \tag{5.2}$$

The solution space is generally restricted by a series of constraints, when the domain of $v_j \in V_j$ for $j = 1, \dots$, n is known, and representing the m objectives by M, the objective of the problem is to find (5.3):

$$argmax_{v_j \in V_j}[\ f\ (v_1, v_2 \ldots\ v_n)\ \big|\ M] \qquad for\ j\ =\ 1, \ldots, n \tag{5.3}$$

Equation (5.3) aims at searching for the optimal solution of variable settings, while there are always conflicting objectives that satisfying one single target but lead to unacceptable results to the others. A perfect multi-objective solution that simultaneously optimizes each objective function is almost impossible. To this end, this chapter proposes a self-adaptive DQN-based MARL framework where the *m* optimization objectives are formulated as *m* DQN agents that are trained through the self-adaptive process constructed upon a Markov game.

5.2. Methodology

5.2.1 Multi-objective optimization of the textile process as Markov game

We begin by formulating the single objective textile process optimization problem as a Markov decision process (MDP) in terms of a tuple :{ *S*, *A*, *T*, *R*}, where *S* is a set of environment states, *A* is a set of actions, *T* is the state transition probability function, *R* is a set of reward or losses. An agent in an MDP environment would learn how to take action from *A* by observing the environment with states from *S*, according to corresponding transition probability *T* and reward *R* achieved from the interaction. The Markov property indicates that the state transitions are only dependent on the current state and current action is taken, but independent of all prior states and actions [241]. While in the case of a multi-agent system, the joint actions are the result of multiple agents, the MDP is generalized to the Markov game of {S, A^1,…,A^m, T, R^1,…,R^m }, where *S* and *T* are similar to the MDP that are the finite set of environment states and the state transition probability function respectively in a Markov game, whereas differently, *m* is the number of agents, A^i for i =1,…, m are the finite sets of actions available to the agent *i*, R^i for i =1,…, m are the reward functions of the agent *i*.

As known that the solution of a textile manufacturing process is affected by a number of variables as *P* {v_1, v_2… v_n}, if the possible value of v_j is $h(v_j)$, the feasible values of the parameter in the process can define the environment space *S* from $\prod_{j=1}^{n} h(v_j), v_j\ \in\ V_j$ impacting the performance of the textile process with regard to the *k* objectives. These parameter variables are independent to each other and obey a Markov process that models the stochastic transitions from a state S_t at time step *t* to the next state S_{t+1}, where the environment state at time step *t* is:

$$S_t = [s_t^{v_1}, s_t^{v_2} \dots s_t^{v_n}] \in S \tag{5.4}$$

RL algorithm trains an agent to act optimally in a given multi-agent environment based on the observation of states and other agents as well as the feedback derived from the interactions, acquiring rewards and maximizing the accumulative future rewards over time from the interaction [241]. In our case, the agents learn in the interaction with the environment and other agents by taking action that can be conducted on the parameter variables $\in P$ $\{v_1, v_2 \dots v_n\}$ at time step t. Specifically, the action of an agent in a time step t of optimizing a textile manufacturing process in the Markov game could be adjusting variable v_j to keep (0) or change to up (+) and down (-) with a specific unit u_j subjected to the constraint. As a result, there are 3^n actions in total in the joint action space A and, for simplicity, the action vector A_t at time step t could be:

$$A_t = \left[a_t^{v_1}, a_t^{v_2} \dots a_t^{v_n}\right], \quad where\, a_t^{v_j} \in \{-u_j, 0, +u_j\}, v_j \in V_j \;\; for\; j = 1, \dots, n \tag{5.5}$$

We define $A = \prod_{i \in m, s \in S} A^i(s)$ for the joint action from overall the agent i's set of pure actions at state s. The m objectives of textile manufacturing process optimization are assigned to m agents in the Markov game. As known that apart from the benefits derived from the distributed nature of the multi-agent system such as parallel computation, the experience sharing from different agents also significantly improve the multi-agent algorithms. Therefore, it is assumed that agents can observe each other's action and rewards to select the joint distribution in our case, and the joint action is determined by the actions selected of each agent $(A^1, \dots, A^i, \dots, A^m)$.

The state transition probabilities, as mentions that, are only dependent on the current state S_t and actionA_t. It specifies how the reinforcement agents take action A_t at time step t to transit from S_t to next state S_{t+1} in terms of $T\ (S_{t+1} \,|\, S_t,\, A_t)$. For all $a_t^{v_j} \in \{-u_j, 0, +u_j\}, v_j \in V_j$, $T\ (S_{t+1} \,|\, S_t,\ A_t) > 0$ and $\sum_{S_{t+1} \in S} T\ (S_{t+1} \,|\, S_t,\ A_t) = 1$. The reward achieved by an agent in an environment is specifically related to its transition between states, which evaluates how good the transition agent conducts and facilitates the agent to converging faster to an optimal solution.

When the reinforcement agents perform joint action A_t at time step t to divert the system from S_t to next state S_{t+1} with transition probability T, each agent would earn reward $R_i(S_t, A_t)$ from (5.3) of the objective functions. This procedure would be repeated at time t+1 again, and finally converge agents' behaviors to a stationary policy. According to the study in the previous chapter, a random forests (RF) predictive model is applied to simulate the textile process in this proposed framework, and implement the objective functions (5.3) to earn the agents rewards. As illustrated in Figure 19 the textile manufacturing process multi-objective optimization problem in the paradigm of MARL, the optimization objectives are abstracted as RL agents, given feedbacks from the RF models integrated in the Markov game environment with state space formulated in Equation (5.4) that consist of all the parameter variables of the simulated textile process, the agents, are able to evaluate the values of its actions for adjusting the parameter variables with regard to the state (solution) and consequently improve its policy in the environment to optimize objectively gradually.

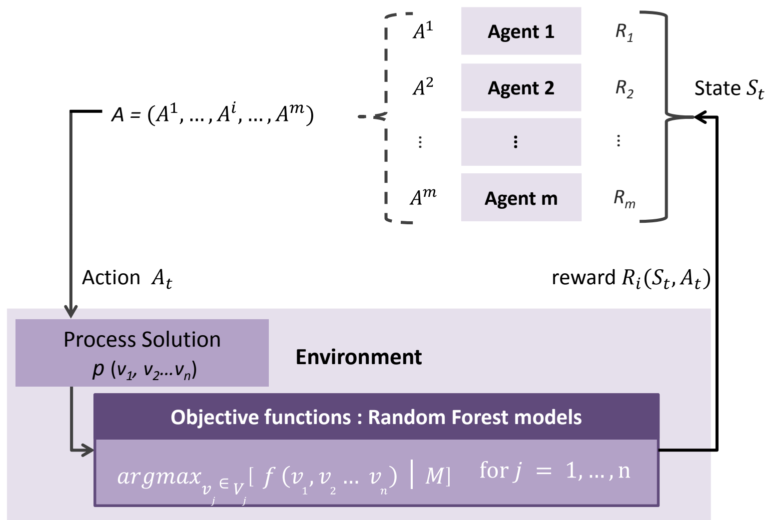


Figure 19. The Markov game for textile manufacturing process multi-objective optimization in the proposed framework

Stochastic games are neither fully cooperative nor fully competitive [252]. The performance of multi-objective optimization of our case in Markov game is determined by the agents' capability of gathering information about the other agents' behavior and the reward functions from the interaction to make a more informed decision thereafter. The rewards mechanisms along with the interaction among agents perform a significant function in this respect, so that the proposed system, similar to the study of [259], employs an utilitarian selection mechanism $h = argmax_{A \in \Delta(A(S))} \sum_{i \in M} Q_i(s, a)$ that maximize the sum of all agents' rewards in each state to avoid the interruption of multiple equilibria. Convergence to equilibria is a basic stability requirement of MARL, and the Nash equilibrium is a well-known solution concept for the stochastic game that a joint strategy leading to a status of no agent is incentive to change its strategy. But a correlated equilibrium with increased generality instead of Nash equilibrium is taken into consideration in this issue as it allows agents' strategies to be interdependent. It is a joint distribution of actions from which none of the agents has any motivation to deviate unilaterally. Consequently, the solutions of the textile manufacturing process multi-objective optimization problem are correlated equilibria.

Formally, given a Markov game, a joint stationary policy π leads to a correlated equilibrium when:

$$\forall i \in M, s \in S \Big| \sum_{a \in A^{-i}(s)} \pi_s \, Q_i^{\pi}(s,a) \geq \sum_{a \in A^{-i}(s)} \pi_s \, Q_i^{\pi}(s,a') \tag{5.6}$$

where $A^{-i}(s)$ is the set of action vector in state *s* excluding ones of agent *i*. The above inequality denotes that in state *s*, when it is recommended that agent *i* play *a*, it prefers to play *a*, because the expected utility of *a* is greater than or equal to the expected utility of a', for all a'.

Algorithm 3: DQN based MARL main body:

Input: game □, RF models for simulating *m* objective performance $f(f_1 \dots f_m)$, selection mechanism *h,* expected performance of process *P* ($p_1, p_2 \dots p_m$,), number of episodes *E* , number of time steps *N*, learning rate α, discount factor γ , the step updating DQN *F*, replay memory size *D*;

Initialize function Q with random weights θ;

Initialize function $\hat{Q}$ with weights $\theta^- = \theta$;

Initialize state $s_0 = (v_1, v_2 \dots v_n)$

For episode =1, *E* **do**

  For time step=1, *N* **do**

    Choose an action randomly or $a_t \in h$ using increasing *ε*-greedy policy

    Execute action a_t , observe next state s_{t+1}

    Estimate $f_1(s_t) \dots f_m(s_t)$ and $f_1(s_{t+1}) \dots f_m(s_{t+1})$ to observe r_t ($r_t = \sqrt{(f_i(s_t) - p_i)^2} - \sqrt{(f_i(s_{t+1}) - p_i)^2}$)

    Store transition (s_t, a_t, r_t, s_{t+1}) in *D*

    Sample random minibatch of transitions (s_t, a_t, r_t, s_{t+1}) from *D*

    Set $y_i = \begin{cases} r_j & \text{if terminates at step } j+1 \\ r_j + \gamma max_{a'} \hat{Q}(s_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$

    Perform a gradient descent step on $\left(y_i - Q(s_j, a_j; \theta)\right)^2$ with regard to θ

    Every *R* steps reset $\hat{Q} = Q$

    $s_t \leftarrow s_{t+1}$

  End For

End For

5.2.2 Deep Q-networks reinforcement learning algorithm

As described in Chapter 4 about the classical RL algorithms using the tabular expression, it is not only short at recording the Q(s, a), but also poor of generalization in the environment with uncertainty. The deep neural networks (DNNs) based Deep-Q-network (DQN) algorithm developed by Mnih et al. [242] is more suitable to tackle high dimensional problems in our case. Therefore, the multiple agents performing the Markov game would be trained by DQN algorithms as same as the one introduced in Chapter 4.

5.2.3 DQN based MARL for multi-objective optimization of the textile process

The pseudo-code of the DQN based MARL framework for multi-objective optimization of the textile manufacturing process is illustrated in Algorithm 3. Correspondingly, Figure 20 graphically depicts a single episodic running of Algorithm 1. To learn a correlated equilibrium strategy, the DQN agents interact with the textile solution environment and other agents iteratively on the basis of local updates of Q-values and policy at each state. As mentioned, the random forest models (RF) are constructed to simulate the objective performances of the textile process in the proposed framework. Along with suitable reward mechanisms designed according to objective functions (in our framework, the reward of an agent is given by the improvement of the objective performance from the current state compared with the last state), the convergence of the DQN-based algorithm in multi-agent settings can be guaranteed.

As the same as the reinforcement learning based framework established in Chapter 4, the algorithm developed here can work without episodes as the target of agents is to find the optimized solution, in terms of state in the environment with saticification of multiple objective performances in the textile process simulated by RF models, and the random initialization of the first state from each sub-state $s_t^{v_i}$, where parameter variables $v_j \in V_j$, are introduced with an episodic learning process to the agent for enlarging the exploration and preventing local optimum. Meanwhile, the employment of the increasing ε-greedy policy (Algorithm 2 introduced in Chapter 4 with a minor difference on the action selection mechanism among multiple agents) is also applied in this system to balance the exploration and exploitation of states at the learning period and optimizing period respectively.

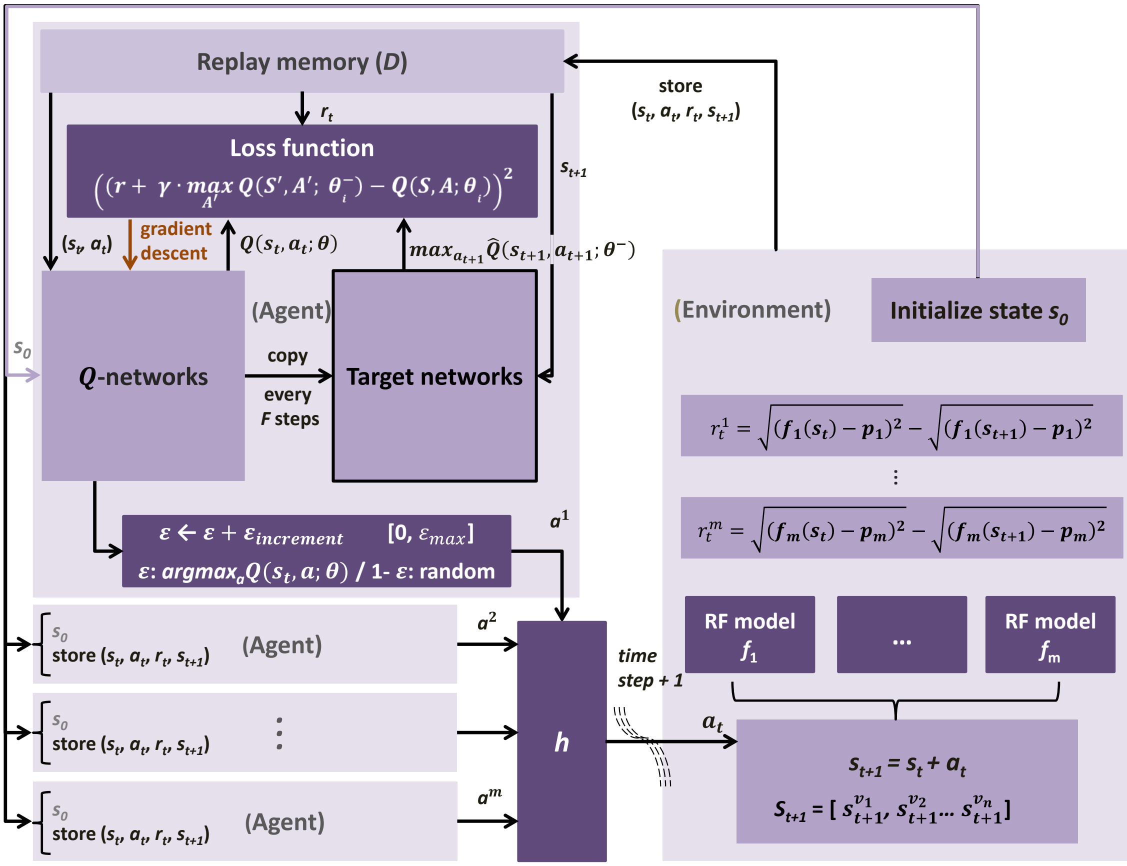


Figure 20. Flowchart of the algorithm implementing the DQN based multi-criteria decision support system for textile manufacturing process optimization

5.3. Application

5.3.1 Experimental setup

The application of textile ozonation process optimization is used in this chapter as well for estimating the multi-agent reinforcement learning (MARL) system in regard to multi-objective optimization. That is, optimizing the color performances in terms of *k/s*, L^*, a^*, and b^* of the textile in the ozonation process by finding a solution including proper parameter variables of water-content, temperature, *pH* and treating time, minimizes the difference between such specific process treated textile product and the targeted sample. Therefore, there are four agents in the Markov game, and the state space φ of it is composed of the solutions containing four parameters (water-content, temperature, *pH* and treating time) in terms of $S_t = [s_t^{v_1}, s_t^{v_2}, s_t^{v_3}, s_t^{v_4}]$. In a time step t, given the adjustable units of these parameter variables u = 50, 10, 1, 1 with regard to the constraint ranges of [0, 150], [0,100], [1, 14] and [1, 60] respectively, as the action of a single variable v_j could be kept (0) or changed up (+) / down (-) in the given range with specific unit u, so there are 3^4 =81 actions totally in the action space and the action vector every single agent at time step t is $A_t = [a_t^{v_1}, a_t^{v_2}, a_t^{v_3}, a_t^{v_4}]$, where $a_t^{v_1} \in \{-50, 0, +50\}, v_1 \in [0, 150]$; $a_t^{v_2} \in \{-10, 0, +10\}, v_2 \in [0, 100]$; $a_t^{v_3} \in \{-1, 0, +1\}, v_3 \in [1, 14]$; $a_t^{v_4} \in \{-1, 0, +1\}, v_4 \in [1, 60]$.

The transition probability is 1 for the states in the given range of state space above, but 0 for the states out of it. The reward *r* of an agent at time step *t* is expected to be in line with how close the agent gets to its target representing the related objective function. We set up the reward function as illustrated below to induce the agents to approach corresponding optimization objective results:

$$r_t = \sqrt{(f_i(s_t) - p_i)^2} - \sqrt{(f_i(s_{t+1}) - p_i)^2} \quad for \quad i = 1, \dots m \tag{5.9}$$

As demonstrated the pseudo-code of DQN based MARL main body in Algorithm 1, the expected color performances of ozonation process treated samples (p_1, p_2, p_3, p_4, in terms of *k/s*, L^*, a^*, and b^*) are sampled by experts as 0.81, 15.76, -20.84, and -70.79 respectively to function the system in the present case study. Therefore, there are four agents in this case with respect to their corresponding optimization targets. In addition to the targets, the parameters of DQN agents such as step *F* for updating Q-networks and replay memory size *D*, as well as the learning rate α and the discount rate γ for updating loss function, etc., are listed in Table 20. In particular, the *F* step for updating DQN here denotes that after 100 steps, the Q-networks would be updated at every 5 steps.

Table 20. DQN algorithm setting in textile ozonation process case study

F	D	α	γ	$\varepsilon_{increment}$	a_{max}	E	N
5(>100)	2000	0.01	0.9	0.001	0.9	1	5000

In order to reflect the effectiveness and efficiency of the proposed DQN-based MARL system for multi-objective optimization of the textile manufacturing process in this case study, multi-objective particle swarm optimization (MOPSO), and Non-dominated Sorting Genetic Algorithm Ⅱ (NSGA-Ⅱ) are considered as the baseline algorithms.

5.3.2 Results and discussion

In the case application, we trained four agents based on the DQN algorithm in a Markov game to optimize an ozone textile process with multiple objectives. As shown in Figure 21 that the increasing ε-greedy policy was used for agents to balance the exploration and exploitation of states. Where the exploration decays in the first 900 steps so that agents initially lack the information and policy explore possible actions, but increasingly follows its policy exploiting the available information by taking action selection mechanism h, rather than acting randomly. The effects of it are clearly illustrated on the convergences of DQN agents given in Figure 22 (for the illustration conveniences, 200, 400, and 600 units of loss are additional given to agent 2, agent 3, and agent 4 respectively). It denotes that the deep Q-networks adapts successfully to the stochastic environment that the representation of Q-value in this deep Q-networks for agents is stable and accurate and the agents act deterministically after 900 steps when the ε-greedy increased to the maximum.

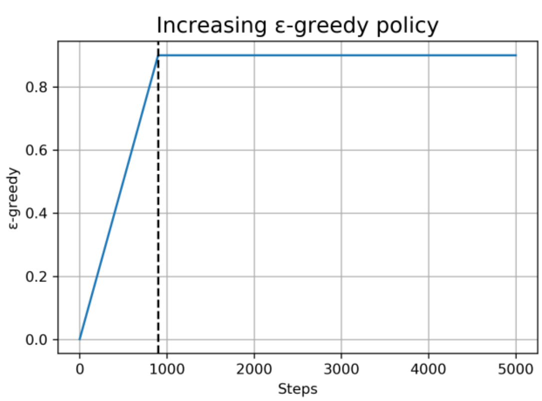


Figure 21. Increasing ε-greedy policy for choosing action

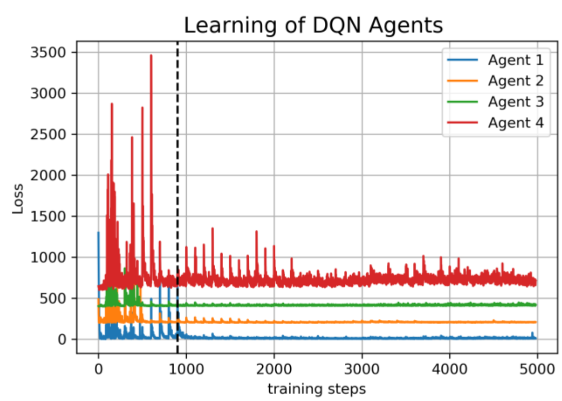


Figure 22. The loss function of DQN for four agents in the Markov game

The agents targeted at optimizing the solution of a textile ozone process to approach the fabric color performance of 0.81, 15.76, -20.84, and -70.79 in regard to k/s, L^*, a^*, and b^*. During the DQN agents interacted in the Markov game with 5000 steps, the minimum errors of each agent and their sum in total given by RF models are collected and displayed in Figure 23. The convergence diagrams of all the four agents and their sum in terms of minimum error, verify the effectiveness and efficiency of the designed reward function, and it seems that the solution with lower error can possibly be obtained along with growing time steps.

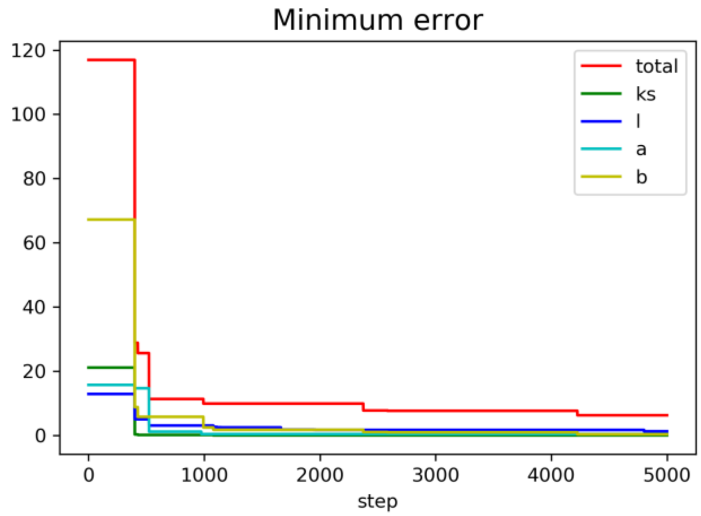
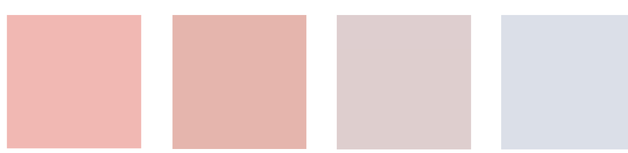


Figure 23. The minimum error of DQN agents and the sum of its versus time steps

The comparison of the constructed framework with baseline approaches in regard to optimized results is depicted in Figure 24. The multi-agent reinforcement learning (MARL) system proposed performed dominated the baseline methods of MOPSO and NSGA-Ⅱ in our case study to optimize the ozonation process solution and achieve the objective color on treated fabrics. The difference from these comparative results could be explained as that the meta-heuristic algorithms of MOPSO and NSGA-2 have been reported that may fail to work with smaller datasets [15] and take an impractically long time in iteration [260]. But more importantly, though they are effective to deal with low dimension multi-objective optimization problems, the increased stress of selection due to the growing dimension in the problem would decline the effects dramatically when the objectives are more than three.



Target MARL MOPSO NSGA-□

Figure 24. Comparison of baseline algorithms and the proposed multi-agent reinforcement learning framework with simulated results

5.4. Conclusions

Multi-objective optimization of the textile manufacturing process is increasingly challenging because of the growing complexity involved in the development of the textile manufacturing process. The use of intelligent techniques have been often discussed in this issue, although a significant improvement from certain successful applications is reported, the traditional methods fail to work with high-dimension decision space and require prior experts' knowledge as well as human intervention. Upon which, this chapter proposed a multi-agent reinforcement learning framework to transform the optimization process into a Markov game, and introduced the deep Q-networks algorithm to train the multiple agents. The Markov game is neither fully cooperative nor fully competitive, so that an utilitarian selection mechanism is employed in the Markov game that maximizes the sum of all agents' rewards (obeying the increasing ε-greedy policy) in each state to avoid the interruption of multiple equilibria and achieve the correlated equilibrium optimal solutions of the optimizing process. The results obtained from this chapter could be concluded as:

(1) The multi-objective optimization problem of the textile manufacturing process could be drawn in a multi-agent system.
(2) The formulation of optimizing the textile manufacturing process as a Markov decision process, and applying reinforcement learning can affectively solve the problem.
(3) Introducing multiple RL agents to search the optimal process solutions is capable to deal with the textile manufacturing multi-objective optimization problems into the game-theoretic model.
(4) Compared to the tabular RL algorithms applied in prior related works, the application of DQN in the multi-agent reinforcement learning system is more applicable and preferred to cope with the complicated large-scale realistic problems in the textile industry.
(5) The application case study result reflects that the proposed MARL system is possible to achieve the optimal solutions for the textile ozonation process and it performs better than the traditional approaches.

6. Discussion, conclusions and future perspectives

6.1. Summary of the thesis

This thesis studies the modeling and optimization of the textile manufacturing process using intelligent techniques. The results of the systematic literature review provided directions and a theoretical base for the research, and formulated the research questions of the thesis. Three sub-studies are conducted in this thesis to address the formulated research questions.

The first formulated research question is related to the process modeling of textile manufacturing. As a case study of the textile process model development, the first sub-study comparatively investigated the applicability of intelligent techniques of the extreme learning machine (ELM), support vector regression (SVR), and random forest (RF) for modeling the textile ozonation process to simulate the interrelationships of process parameters and process performances.

Depending on the results of the first sub-study, the well-constructed random forest (RF) model, illustrated excellent approximation ability and advancement than the other methods to simulate the complex and uncertain impacts of textile process variables on its performance, was therefore further implemented in an extension to the construction of decision support system. As a growing number of the textile manufacturing optimization problems were coming up with large-scale data and high dimensional decision space in recent years, and instead of a single standard, multi-criteria is increasingly taken into consideration in these problems, the second sub-study proposed a decision support framework for optimizing the textile manufacturing process by combining the developed model of RF with the human knowledge-based multi-criteria structure of analytic hierarchy process (AHP) and the deep reinforcement learning (DRL) algorithm. The proposal of the AHP, a multi-criteria decision making (MCDM) tool, involves the considerations of that the quality of textile process performance is governed by a few criteria and their significance with an overall objective is different. While formulating the textile manufacturing process optimization problem into a Markov decision process (MDP) paradigm and applying deep reinforcement learning (more specifically, DQN, the Deep Q-networks) instead of current methods to collaboratively approach the optimization problems in the textile manufacturing process, concerns the growing complexity in terms of large-scale data and high dimensional decision space in the textile manufacturing sector.

In order to cope with the challenges from future development of the textile manufacturing industry, the third sub-study, at last, developed a multi-agent reinforcement learning platform. It furthermore implemented the deep reinforcement learning technique in a multi-agent system, and the transformation of the textile manufacturing process optimization problem as Markov decision process was additionally combined with game theory to form the targeted multi-objective optimization problem as a Markov game paradigm. Multiple agents were trained by the deep reinforcement learning algorithm of DQN to deal with the formulated multi-objective optimization problems in the textile manufacturing process.

The textile process of ozonation is applied in the frameworks proposed in sub-study 2 and sub-study 3 to evaluate the effectiveness of the developed systems. Besides, the traditional multi-objective optimization algorithms of MOPSO and NSGA-Ⅱ were compared with the proposed platform in sub-study 3.

6.2. Discussion

- Research question 1: How to determine an intelligent algorithm appropriate for modeling a textile manufacturing process?

Table 21. Summary of sub-study 1

Sub-study	Sub-research question	Experiment outcome
Modeling a textile process using intelligent techniques: a case study for color fading ozonation	RQ1-1: What factors dominate the textile process modeling?	1-1: Converging fast with less training data，and performing well with multiple-input multiple-output.
	RQ1-2: Which approach is preferred for modeling the textile process?	1-2: Both the RF and SVR are potentially applicable. While the RF is more recommended when the training time is not significantly concerned.

The first research question is in regard to the modeling of the textile manufacturing process. It answered how to develop and what are the proper intelligent techniques for the textile process modeling by comparatively investigating the applications of extreme learning machine, support vector regression and random forest for modeling the textile ozonation process. Similar to the other researches reviewed, this sub-study on modeling the textile process also lacks training data, but involves multiple-inputs and multiple-output, which right reflect the current situation of the application of artificial intelligent techniques in the textile industry. These features dominate the preference of methods' performance in the textile manufacturing process modeling.

The model of a textile manufacturing process is always problem-specific and the novel methods are continuously developed in recent years. The comparison of the aforementioned novel methods for modeling a specific textile manufacturing process shows that both the SVR and RF are potential candidates as their predicted results on the modeled process had a good agreement with the actual output data entirely as well as individually. However, taking the training time and cost into consideration, the SVR model would be more recommended to be applied in real use, but RF would be more recommended in the cases where training time is not significantly concerned (e.g. academic research). In contrast, the ELM models performed poorer in the prediction and were very unstable in terms of predicting certain individual outputs in multi-variable process modeling.

- Research question 2: How to deal with the complex multi-objective optimization problem with reinforcement learning in the progressively developing textile process?

Table 22. Summary of sub-study 2

Sub-study	Sub-research question	Experiment outcome
Optimizing textile manufacturing process using deep reinforcement learning (DRL) based intelligent system	RQ2-1: How to optimize with multiple objectives in this issue?	2-1: Analytic hierarchy process, a based multi-criteria decision-making method which involves both objective and subjective factors, agrees with the characteristic of the decision-making problem in the textile chemical manufacturing process that can be us.
	RQ2-2: What advantages are brought to the textile manufacturing process optimization through DRL?	2-2: The flexible nature of RL enables it to pre-compute offline, making online evaluation fast in large systems with high-dimension. DRL is advantageous to the industry process that to well handle the large-scale stochastic multiple-input multiple-out and high-dimensional decision space.

The second research question addresses the multi-objective optimization problem in the textile manufacturing process on the basis of the model established (RF models developed in the first sub-study) with respect to the multi-input and multi-output. The optimization problems in the textile manufacturing process usually involve conflicting objectives as the overall performance of textile processes is normally governed by a few criteria, so that decision-making or optimization in this domain must take multi-criteria or multi-objective into account. It is found that the analytic hierarchy process (AHP), a based multi-criteria decision-making method, has been proven to be an extremely useful decision-making method in the textile industry from many issued applications. The objective and subjective factors of AHP agrees with the characteristic of the decision-making problem in the textile manufacturing process, so that the AHP can well formulate the multiple objectives into a single target and simplified the problem.

The flexible nature of RL enables it to pre-compute offline, making online evaluation fast in large systems with high-dimension. Deep reinforcement learning (DRL) is a recently developed method that can effectively work in a complex system. It is advantageous to the industry process that to well handle the large-scale stochastic multiple-input multiple-out and high-dimensional decision space. Therefore, the second sub-study applied a reinforcement learning algorithm to optimize the textile process, and the collaborative application of it with the constructed simulation models of RF and the multi-criteria decision-making method of AHP is investigated. The applied case study illustrated that the developed system is capable of learning to master the challenging decision-making tasks in the textile manufacturing industry and performed better than traditional methods.

- Research question 3: Is there further improvement we can do to address the increasing searching dimension of optimizing a textile process in the upcoming big data era with multi-agent reinforcement learning?

Table 23. Summary of sub-study 3

Sub-study	Sub-research question	Experiment outcome
Multi-objective optimization of textile manufacturing process using deep reinforcement learning based multi-agent system	RQ3-1: How to optimize with multiple objectives in this issue? RQ3-2: What advantages are brought to the textile manufacturing process optimization through multi-agent system?	3-1: The optimization objectives are formulated as DQN agents that trained through self-adaptive process constructed upon a Markov game employing a utilitarian selection mechanism which maximizes the sum of all agents' rewards in each state to achieve the correlated equilibrium optimal solutions of the optimizing process and avoid the interruption of multiple equilibria. 3-2: Apart from the benefits derived from the distributed nature of the multi-agent system such as parallel computation, the experience sharing from different agents also significantly improve the reinforcement learning of agents.

In order to better address the increasing complexity in the multi-objective optimization problem in the textile manufacturing process with respect to the large-scale data and high-dimensional decision space, the multiple optimization objectives in the problem are formulated as targets of the multiple DQN agents trained through self-adaptive process constructed upon a Markov game. A utilitarian selection mechanism is employed, which maximizes the sum of all agents' rewards in each state to achieve the correlated equilibrium optimal solutions of the optimizing process and avoid the interruption of multiple equilibria. This multi-agent reinforcement learning system can not only dramatically reduce the computation because of the distributed nature of the multi-agent system but also significantly enrich the reinforcement learning agents to learn the knowledge of the textile process from the experience sharing from different agents.

6.3. Contributions of the thesis

The contributions of this Ph.D. research are related to the modeling and optimization framework established based on the literature review. Specifically, one modeling technique was proposed from the comparison with multiple approaches on modeling a textile ozonation process, and two decision support frameworks applying deep reinforcement learning techniques were constructed with the collaboration of the developed model and multi-criteria decision-making tool as well as multi-agent system respectively. The contributions of this thesis are listed below:

(1) The prior applications of modeling and optimization of the textile manufacturing process were reviewed from the perspectives of different intelligent techniques and different textile processes, and the limitations of current methods were summarized with the future perspectives.

(2) The modeling of a textile ozonation process was investigated in terms of mapping the process parameters of pH, temperature, water pick-up, time (of the process) and original color (of textile) to the process performances of the color performance (K/S, L^*, a^*, b^* values) of treated textile using Extreme Learning Machine (ELM), Support Vector Regression (SVR) and Random Forest (RF) respectively. RF and SVR were found that perform better than ELM as the ELM models were very unstable in the case of predicting the certain individual output. Both RF and SVR are potentially applicable. The SVR may be more recommended to be used in the real application due to its balancer prediction performance with less training time, and

the RF would be more recommended in the cases which require more accuracy and has higher tolerance on the training time cost.

(3) Taking the RF process model to assist textile manufacturing optimizers to make a decision under uncertainties, a multi-criteria decision support system was presented. In terms of the widely existing multi-criteria diction-making problems in the field of textile manufacturing, the analytic hierarchy process (AHP) was proposed to cooperatively work with the reinforcement learning (RL) algorithm. The formulation of the textile manufacturing process optimization as a Markov decision process paradigm and the solution based on the RL algorithm was proposed for the first time to deal with decision-making issues in the textile industry.

(4) The application of DQN was proposed to train the RL agent. Compared to the tabular RL algorithms applied in prior related works, DQN is more applicable and preferred to cope with the complicated realistic high-dimensional problem in the textile industry. The effectiveness of this proposed multi-criteria decision-support system has been validated in the developed RF model of the textile ozonation process, which showed that it can master the challenging decision-making tasks in the textile manufacturing processes.

(5) Multi-objective optimization of the textile manufacturing process is increasingly challenging because of the growing complexity involved in the development of the textile manufacturing process. In the developed system above, the conflicts of objectives in a multi-objective optimization problem of the textile process were depicted by the expert estimation, which may hinder the application of it in cases without substantial numerical expertise. To this end, a multi-agent reinforcement learning framework was developed. It transforms the multi-objective optimization process into a Markov game, and introduced the deep Q-networks algorithm to train the multiple agents.

(6) A utilitarian selection mechanism is employed in the Markov game that maximizes the sum of all agents' rewards (obeying the increasing ε-greedy policy) in each state to avoid the interruption of multiple equilibria and achieve the correlated equilibrium optimal solutions of the optimizing process. The application result of this multi-agent reinforcement learning system on the RF model of the textile ozonation process reflected that the proposed system is possible to achieve the optimal solutions for the textile ozonation process and it performs better than the traditional approaches.

6.4. Limitation and perspectives in future research

From a comparative study, the random forest models of the textile manufacturing process were developed in this thesis to construct a decision support system with the collaborations of the analytic hierarchy process as well as the deep reinforcement learning algorithm, and a multi-objective optimization platform on the basis of a multi-agent reinforcement learning system, respectively.

However, the proposed models and optimization systems have some limitations. First of all, in this thesis, the validation of the model and decision-support system was only conducted on the textile ozonation process with experimental data, to see the realistic and practical effects of all these models and systems on the real industry, the development and implementation of them in the real industry with various applications would be one of the most interesting directions for future research.

In the comparative study, the intelligent modeling techniques considered were only limited in extreme learning machines, support vector regression, and random forest with a small range of the model parameters, which may impede the performance of the developed optimization systems when the modeling accuracy is not acceptable in certain other textile manufacturing cases.

The proposed multi-criteria decision support system can be generic to other applications for optimizing process parameters. However, the analytic hierarchy process approach of it relies heavily on experts' estimation, which may limit the generalization of it in certain areas, especially when there are a huge number of alternatives and alternative scores corresponding to each decision criterion are known objectively [66].

Moreover, for both of the DRL based multi-criteria decision support system and the multi-agent system based multi-objective optimization framework, it is well known that the practice and effectiveness of RF and DQN rely strongly on big data and computation power which is quite limited in the application of the textile industry nowadays. But the application of artificial intelligence techniques is growing in the textile manufacturing industry, such concerns could be properly addressed in the industry 4.0 era when it is able to take full advantage of the Internet of Things (IoT) environment. Following the development, the system can be fed with new data and scenarios continuously to learn the process in the online environment or more detailed simulation models that can better represent the complex interrelationships of the textile process variables are developed to retrain the RL agents, so that to keep updated the system with the development of the textile industry for the process optimization and even online adaptive parameter control. The proposed system trains the agent offline in a process simulator to obtain general knowledge of the process and assist decision-making, while the future use of it could be extended to online optimization and online optimal control of the textile manufacturing process for preventing long online computation times. Future research should devote more effort to test the proposed framework and broaden the application of it in more textile chemical manufacturing processes by collecting real empirical data and construct the corresponding MDP paradigm. Moreover, the future works could try to comparatively investigate more about other deep reinforcement learning algorithms in the textile manufacturing applications as the DQN is known needing an enormous amount of time-steps state fails at identifying which part is responsible for this speed-up, which may hinder its use in the future.

The verification of the two developed optimization systems was demonstrated through simulated results, the more efforts should be addressed to the development of a real-work system in the future.

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