Machining learning algorithms for process optimization and quality prediction of spinning in textile industries

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Abstract. In smart manufacturing, data-driven artificial intelligence algorithms are becoming increasingly important in improving decision-making by monitoring the control, analysis, and prediction of manufacturing processes in a production system. In the textile industry, there is a strong need for smart manufacturing technologies because various parameters could affect the quality dynamically. This study aims to optimize the parameters of spinning processes by developing machine learning algorithms and models which can predict the toughness and elasticity of threads. At first, meaningful variables are extracted from the shop floor data, and then a defect classification learning model is developed to predict defects in advance. In addition, a regression model is implemented for the prediction of toughness and elasticity of the textile. By transitioning from the traditional trial and error method to the data-based method for the spinning process, production costs and time can be reduced through optimal settings of the production parameters for the spinning of the desired threads.

Keywords smart manufacturing, data-driven prediction, textile industry, spinning process.

1 Introduction

The 4th Industrial Revolution resulted in industrial changes that have accelerated the transition into smart manufacturing. Smart manufacturing (SM) controls and manages production, helps the manufacturers with business decisions, and optimizes the manufacturing process [1]. A combination of the state-of-the-art technologies, such as Industrial Internet of Things (IoT), big data, cloud computing, and Artificial Intelligence (AI) drives the development of highly sophisticated manufacturing intelligence. It plays a pivotal role in SM by optimizing the manufacturing process. Recently, there has been an increase in applications of anomaly detection technology for predicting system failure and AI prediction models for quality control in the manufacturing industry.
The spinning process is a complicated manufacturing operation that involves a complex production plan. Fig.1. show an equipment of spinning process, which is the main topic of this research. The production plan needs to specify the number of yarns, the spinning

process system, and the preparation method, with a variety of options available for all, which introduces a lot of complexity into the production planning stage [3].

Figure 1. An equipment of spinning process in textile industry

Moreover, in the case of fiber industry, an appropriate production sequence is planned and various production parameters are defined, once the specific category of the final product is decided upon [3]. As a labor-intensive industry, on-site decision-making for the spinning process, heavily depends on the knowledge and the experience of the workers, which gives rise to the following problems.

i. Since the on-site decision making heavily depends on the experience of the workers, it is prone to human error and could potentially lead to increased cost, resulting in inconsistencies in quality control from the trial-and-error process.
ii. However, the defects and quality of the products cannot be examined after each sub manufacturing process and can only be examined after the entire process is completed.

To address these problems, this research attempts to predict the quality of the final products before the manufacturing process, using AI technology, by proposing a model to assist workers with decision making in setting configurations for sub manufacturing processes. Deep learning methodologies have been widely used for quality prediction tasks. In this research, among the many deep learning methodologies, the long short-term memory (LSTM) method has been applied to overcome the gradient vanishing problem. Section 3 presents the process of forecasting methods. Section 4, applications of the proposed methodology in real-life situations are presented.

2 Research Background

2.1 Spinning Process

The spinning process involves a series of sub processes, including polymerizing to create high molecular fibers, drying high-molecular polymer chips, melt spinning, forming fiber structure, cooling and drawing, and finally the process of taking up, to ultimately produce fibers that satisfy the required property values [4]. Fig. 2 illustrates a flowchart of a typical spinning process. There is a lack of standardization on the extent to which variables affect the property values of the spinning process, so the variables are often arbitrarily set, invariably being affected by the worker’s subjectivity. In addition, due to the long production hours, the process can only be executed once a day and defects can only be examined after all the processes have been completed, as mentioned earlier.

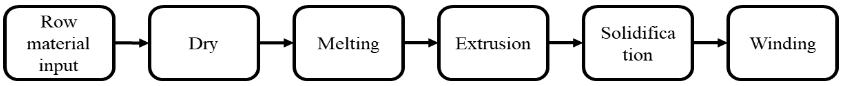

Figure 2. Steps of a Spinning Process

2.2 LSTM: Long Short-Term Memory Network

In recent years, the neural network (NN) has emerged as a powerful tool in the fields of data analysis and time series forecasting [5]. Deep learning technologies have been applied in load forecasting, with most depending on the recurrent neural network (RNN) or LSTM [6-10]. Farooq *et al*. [11] have conducted research on artificial neural networks (ANNs) for quality characteristics estimation. The ANN was fed with parameters that affect the quality and was trained, using a combination of the Marquardt-Levenberg algorithm and Bayesian regularization. The research revealed that NNs are effective in estimating the quality characteristics of yarns. Although RNN is one of the more powerful neural networks that can internally maintain input memory, there exist the challenges of a long training process and the Levenberg vanishing gradient problem [12]. LSTM is one variation of RNN that is widely used to resolve the vanishing gradient problem [13]. LSTM is a neural network with an architecture to store sequential short-term memory, which is later processed with a secondary RNN and is frequently used in the field of AI and deep learning [14]. Hu *et al*. [15], evaluated the prediction accuracy of an optimization algorithm, using CNN-LSTM, to develop a prediction model that can accurately predict yarn quality parameters. CNN was utilized to optimize the input values, and LSTM was used to figure out the correlation between the performance index and the machining parameters and to predict the yarn quality parameters. The research indicated that the prediction accuracy of CNN-LSTM model is heavily influenced by the process parameters and the optimization algorithm. LSTM leverages the input gate, output gate, and forget gate in the memory cell of the hidden layer to discard insignificant memories, thus retaining only significant ones [16]. The vanishing gradient problem is also prevented, considerably improving the performance in the processing of long sequence inputs compared to the conventional RNN [6].

3 Methodology

This section discusses the AI algorithm development methodology that predicts the strength and elongation of products, manufactured by the spinning process. Fig. 3 illustrates each step of the methodology, in detail.

3.1 Data Extraction and Processing

For this research, the data were provided by the Korea Fiber Research Institute and obtained from manufacturing processes. The data consisted of values of the process parameters and the measurements of strength and elongation. In total, 50 types of manufacturing data variables, were obtained during the spinning process. Among the 50 process variables, all the values with fixed constant value were excluded from the training of the model. Mathematical-statistical methods were utilized to derive the key factors of the process. In general, the t-test is one of the most commonly used mathematical-statistical methods to determine the correlation. However, due to the relatively large number of process variables in the spinning process, ANalysis Of VAriance (ANOVA) was utilized, which has been proven useful for analyzing multiple experimental groups. ANOVA analyzes the significant effects of a specific variable on the target variable when more than two groups exist in a study. ANOVA is an extension of the t-test for comparing means of two groups to situations where there are two or more levels of a categorical independent variable[17]. In experiments with two or more treatment groups and where the same individuals are subjected to multiple treatments or measured at different time points, the independence assumption between samples is violated. Therefore, such designs are analyzed using two-way repeated measures ANOVA (2-way ANOVA). Researchers in optometric research should carefully consider experimental design aspects and seek statistical advice to ensure the appropriate application of ANOVA[18]. To ensure the correct application of ANOVA, Armstrong[18] design and match the appropriate analysis that considered about single factor, multiple factor, sequential treatment, factor combination. In this case, there are various factors that influence the two response variables (strength and elongation), Multivariate ANOVA(MANOVA) is more effective than two-way ANOVA. Fig. 4 describes two-way ANOVA and MANOVA in detail. As such, ANOVA was utilized to analyze un-fixed variables of the spinning process and ‘n’ number of significant variable data were extracted as a result.

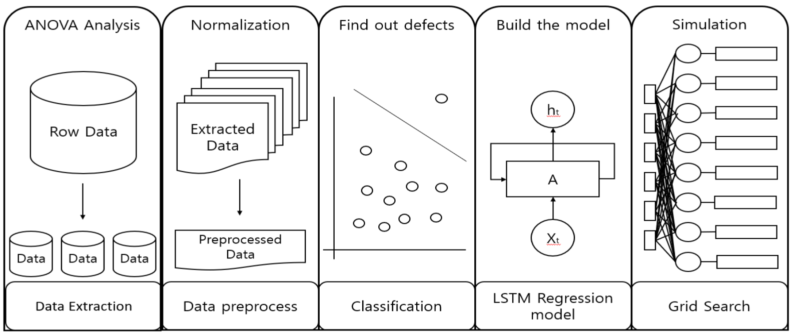

Figure 3. Methodology for algorithm development

Based on the result of the variance analysis, data with low significance were excluded and the remaining key variables were preprocessed in the form of a standard normal distribution with mean 0 and variance 1 with anomalies excluded.

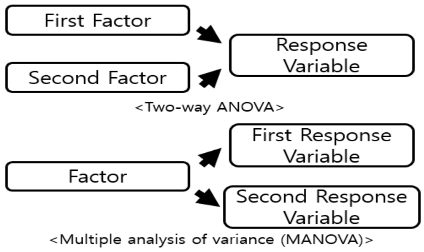

Figure 4. ANOVA and MANOVA

3.2 Classification Model for Defect Regression Model Implementation

Removing anomalous data points is the preliminary step in implementing regression model. To accurately predict the strength and elongation of yarns, defective yarn data were regarded as outliers. After eliminating all data that were classified as outliers using a classification model, the remaining data were used for the training of the regression model. Several different models, proven to be useful for the classification task, were compared to build a defective data filtering model. The four methods used to implement the classification model were: eXtreme Gradient Boosting (XGBoost), Multi-Layer Perceptron (MLP), Random Forest (RF), and K-Nearest Neighbor (KNN). As this research distinguishes the models for predicting the strength and the elongation of the yarn, the classification model for each target value of these variables was accordingly chosen to show the best results for each. As the primary evaluation metrics for the classification model, accuracy, precision, recall, and F1 score were utilized.

3.3 Proposed Algorithm

This research built a model, using a Keras-based LSTM algorithm, in the Tensorflow 2.0 and Python 3.9.1 environment. Mean squared error was utilized to calculate the loss value for the optimization of the LSTM model and the prediction model was designed to predict two types of outputs, strength and elongation. The LSTM method used in the research stems from RNN, which is a type of deep learning algorithm, whereby dropout, batch size, epoch to store, and pass on the data were set from the previous steps for error correction in the hidden layer. The internal hidden layer of the regression prediction model consisted of a dense layer and LSTM layer; the dropout rate, to prevent overfitting; the batch size, to determine the input size for error correction; and the epoch, to state the total number of training iterations for optimization, which were all optimized through a series of trial and errors. Table 1 shows the optimal values for the parameter tuning.

Table 1. Parameter tuning values

Layer	Dropout	Batch size	Epoch
LSTM, Dense	0.2	16	50

Once the training for the newly implemented regression model was complete, the process simulation data were fed into the model for examination of the prediction results. The process simulation data were derived through a grid search analysis with the unique value of each significant variable.

4 Case Study

The selected factory for this research uses a melt spinning process and has two production lines. Each of the two hoppers consists of two extruders, A and B. Hence, there are four tanks: extruder #1 A, extruder #1 B, extruder #2 A, extruder #2 B. The above methodology was applied to a real-life site.

4.1 Data Variable Extraction

As mentioned earlier, there were 50 types of spinning data. After excluding the variables with fixed values, only 14 variables remained. Table 2 categorizes these 14 variables, based on the relevant process.

Table 2. Non-fixed variables

No	Process	Variable	UNIT	Value
1	Extrusion Process	Mesh #1 type	-	#30, #36
2		Mesh #2 type	-	#30, #36
3		Mesh #3 type	-	#30, #36
4		Mesh #4 type	-	#30, #36
5		Spinbeam Temp	℃	254, 256, 258, 260, 262
6		Mainfold A Temp	℃	254, 256, 258, 260, 262
7		Mainfold B Temp	℃	254, 256, 258, 260, 262
8		Pack front pressure	Mpa	54, 69
9		Pack end pressure	Mpa	54, 69
1	Winding Process	FR speed	m/min	4000 ~ 4400
1	Bundling Process	Migration pressure	Kg/cm^2	1.2, 1.8
1	Heat Treatment Process	GODET R/O B temperature	℃	90, 100, 105
1	Drawing Twist Process	GODET R/O A SPEED	m/min	1000 ~ 3675
2		GODET R/O B SPEED	m/min	4105 ~ 4520

If the P-value is less than 0.05, it can be said that there is significance. This means that the significance level is 95% or higher, thus hinting that the independent variable has statistically significant effects on the dependent variable. Table 3 summarizes the degrees of freedom, squared sum, mean of squared sum, and p-value. In extracting significant variables, a total of eight independent variables remained after filtering. MANOVA was utilized to verify the significance of effects of these eight independent variables on strength and elongation. As illustrated in Table 4, all variables, except drawing ratio, were confirmed as significant. However, because the drawing ratio also had an influence on strength and elongation in the two-way ANOVA analysis, it was also selected as a significant variable for the regression model.

Table 3. Suggested significant variables

Variable	Value	Sum_sq	Mean_sq	F	PR(>F)
Spinbeam Temp	Strength	27.0066	13.5033	3.0945	$4.610038e^{-2}$
	Elongation	1047.7134	523.8567	392.3657	$5.912841e^{-2}$
Mainfold temp	Strength	4.446084	2.2230	0.5094	$6.011138e^{-1}$
	Elongation	1047.7134	9.0743	9.0743	$1.329997e^{-1}$
GODET R/O A speed	Strength	180.3400	6.9361	1.5895	$3.326776e^{-2}$
	Elongation	1113.1336	32.0665	32.0665	$3.487900e^{-2}$
GODET R/O B speed	Strength	1.0002	0.2500	0.0573	$9.938931e^{-1}$
	Elongation	82.9456	15.5314	15.5314	$4.909281e^{-1}$
GODET R/O B temp	Strength	623.6853	47.9757	10.9945	$5.06930e^{-21}$
	Elongation	619.3138	35.6817	35.6817	$2.52557e^{-21}$
Drawing ratio	Strength	21.5961	3.5993	0.8248	$5.550908e^{-1}$
	Elongation	25.2373	3.1504	3.1504	$4.801639e^{-1}$
FR speed	Strength	1.8033	0.4508	0.1033	$9.813244e^{-1}$
	Elongation	15.2008	2.8463	2.8463	$2.351307e^{-1}$
Yarn count	Strength	1.7693	0.4423	0.1013	$9.819756e^{-1}$
	Elongation	36.756109	6.882529	6.882529	$2.081831e^{-1}$
Residual	Strength	2356.3457	4.363603	NaN	NaN
	Elongation	720.9667	1.335124	NaN	NaN

Table 4. MANOVA analysis

Variable	Pillai's trace Value	F Value	Pr < F
Spinbeam Temp	0.2009	24.1278	P < 0.001
Mainfold Temp	0.2009	24.1278	P < 0.001
GODET R/O speed A	0.2217	25.5734	P < 0.001
GODET R/O temp A	0.2315	24.8567	P < 0.001
GODET R/O speed B	0.1153	38.8318	P < 0.001
GODET R/O temp B	0.1215	41.2002	P < 0.001
FR speed	0.1163	39.2073	P < 0.001
Drawing ratio	0.0001	0.0421	P < 0.959

4.2 Data Preprocessing

The data, used in this research were in float type. Based on the variance analysis results, insignificant variables and missing values were all removed. To improve the training process of the model, scaling techniques of normalization and standardization were utilized. During the preprocessing stage, standardization was set to transform data into a Gaussian standard distribution, where the mean is 0 and the variance is 1.

4.3 Classification Model for Defect Removal

Prior to implementing the regression model, the field datasets were preprocessed to remove any defects in strength and elongation, so that the model would be trained only on relevant data. To separate defective data, a classification model was built with defect set to have strength and elongation of 0 value each. As two-way ANOVA between the normal products and the defects aggravates the issue of imbalanced data, the range for a product value was divided into 0.3 units. Four classification models: XGBoost, MLP, RF, and KNN, were compared to select the best, the one with the highest accuracy in this case. The performance results are displayed in Table 5. For strength and elongation, XGBoost and MLP models were selected classification, respectively.

Table 5. Classification performance by suggested model

	Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
Strength	XGBoost	0.9833	0.8333	0.8293	0.8312
	MLP	0.8750	0.5991	0.5851	0.5912
	RF	0.9833	0.8293	0.8333	0.8312
	K-NN	0.8750	0.7646	0.7486	0.7559
Elongation	XGBoost	0.3500	0.3125	0.1896	0.2350
	MLP	0.7167	0.5485	0.5556	0.5482
	RF	0.6333	0.5538	0.5747	0.5508
	K-NN	0.3500	0.2500	0.1896	0.2131

4.4 Implementation of the Regression Model with LSTM

A quality estimation regression model was first built to predict the quality of the spinning process and then trained on field data. The quality estimation model was implemented based on the LSTM method, and the parameters were tuned to obtain the most optimized results for the field data. This method has been proven to show better performance in handling the vanishing gradient problem during backpropagation. As such, the r2-scores of the regression models, trained with field data for strength and elongation were 0.7002 and 0.6992, respectively. The results of the training are illustrated in the graphs of Fig. 5 which shows that the prediction results follow approximately 70% of the actual field data.

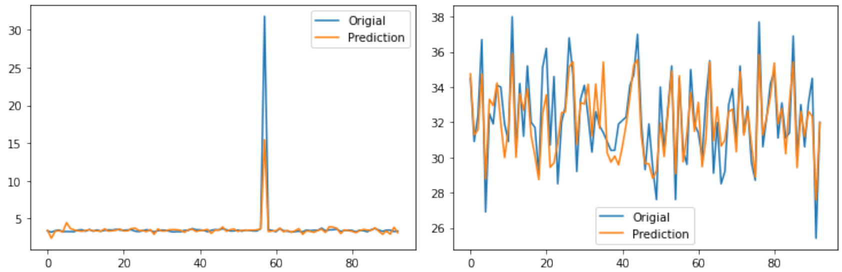

Figure 5. Strength and elongation prediction

4.5 Process Optimization

One of the main reasons for implementing the prediction model is to facilitate on-site decision making without depending on the worker. The model attempts to set up a process that can output the desired values in advance, by predicting the final values of strength and elongation even before executing the process. As such, the process simulation data were generated to verify the usefulness of leveraging the prediction model as a tool to assist decision making for workers.

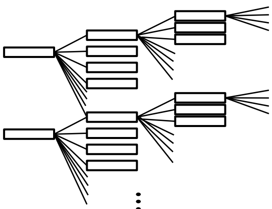

Figure 6. Predictions of strength and elongation

The structure of the process simulation data is shown in Fig. 6. The process simulation data consist of combinations of unique values of each process variable. Therefore, all possible process scenarios that can occur on-site were transformed into input data format. In total, 238,140 datasets were generated. From these, the defective data values were removed for training and 231,050 datasets were used.
As shown in Fig. 7, measuring the similarity of the density distributions between the field dataset and the prediction results indicates that the variance is higher, and the distribution is more uniform in the simulation datasets than in the field datasets. This could be attributed to the fact that all possible scenarios of the process have been considered, thus resulting in a generally higher variance.

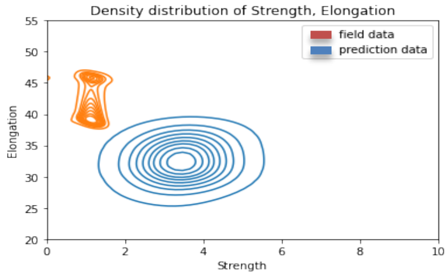

Figure 7. Density distribution

As shown in Fig. 8, because all possible scenarios have been considered for the simulation data, the correlation analysis indicates that the correlation complexity between significant variables has been reduced. However, the effects of each variable on strength and elongation are still reflected in the field data, implying a similar correlation.

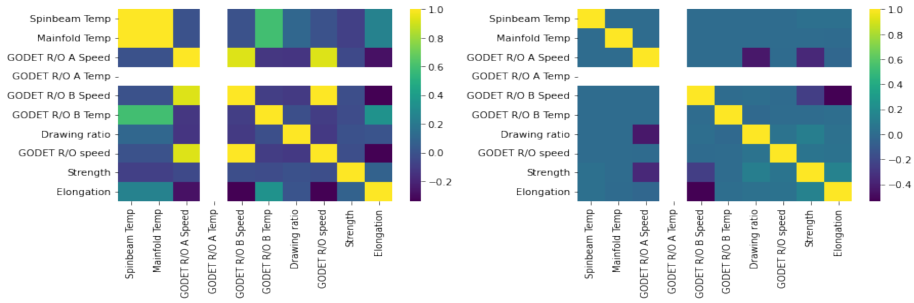

Figure 8. Correlation analysis between field and simulation data

5 Conclusion

Today, achieving manufacturing productivity and intelligence requires the interoperability and scalability of data-driven technological systems. This has become an important issue. To optimize products and production processes, it is necessary to establish a systematic system that spans the entire lifecycle of the product. The purpose of this study was to achieve the development of the necessary data for the system and the algorithms that constitute the system to achieve systematic system construction throughout the entire lifecycle of the product. This paper proposes a methodology to optimize the fiber spinning process setting. The first contribution of this study lies in utilizing the characteristics of the spinning process data and conducting analysis to identify significant data. In textile processes, uncertainty has traditionally been addressed by relying solely on the expertise of workers or through a trial-and-error approach to adjust optimal process settings such as temperature and speed. However, this paper identifies the variables that impact the yield and quality of textile processes through data analysis. This allows for the efficient resolution of problems that were previously dependent on workers' expertise, by leveraging data-driven approaches. Furthermore, analyzing and extracting data that influences quality can aid in the collection and accumulation of necessary data for the digital transformation of textile processes, contributing to the digitization process. The second contribution of this study involves designing various process scenarios to produce yarns with the desired quality. The strength and elongation values were then predicted based on the results obtained from these scenarios. The deep learning technique in LSTM was proven to be effective in analyzing all possible process scenarios that can occur from spinning. The proposed model had a prediction accuracy of approximately 70% and 69% for strength and elongation, respectively. In the field, knowledge about process setting variables is primarily based on the experience of production. However, the proposed predictive model in this paper allows for obtaining knowledge about process settings in unexplored environments, providing support to workers' decision-making. The algorithm can replace results that were previously obtained through the knowledge of experienced workers or through trial and error. The predictive model can support workers' decision-making by providing desired quality process settings that can be achieved, and workers can utilize the generated list of settings to configure the process. This way, the predictive model assists workers in their decision-making process and enables them to set up the process using one of the recommended configurations. Further improvements in future research, can include optimization of the prediction model so that the process would no longer need to rely solely on the experience of the workers. In addition, setting initial process configurations through predicted process results could help overcome the limitations of continuous manufacturing.

Acknowledgement. This research was supported by the MOTIE(Ministry of Trade, Industry and Energy), Korea, under the Virtual Engineering Service Platform program (P0022335) supervised by the Korea Institute for Advanced Technology(KIAT).

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