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Online Monitoring-Based Prediction Model of Knitting Machine Productivity

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Abstract
Recently, Industry 4.0 introduced a breakthrough in the textile industry to meet customer demands. This study aimed to accurately estimate the production rate of a knitting machine through an online monitoring system using the Internet of Things (IoT) and machine learning (ML) concepts. Experimentally, a double knitting machine was attached with sensors for gathering data of the machine speed, yarn feeder speed and stitch length while other production variables remained constant. Two prediction models were introduced since correlation results revealed multicollinearity issues among the parameters measured. The second model achieved a prediction accuracy of 100 %. Thus, it presents a novel formula of production calculation.

Keywords
Online monitoring, internet of things, machine learning, multicollinearity, knitting machine productivity, prediction accuracy.

1. Introduction

Although computers have long been used in the textile industry, incorporating Artificial Intelligence (AI) into the production process improves its efficiency. Although Machine Learning (ML) has demonstrated success in the textile industry, its application is not considered mature yet; therefore, it needs improvement [1].

As other sectors are also adopting similar measures, leveraging AI presents the most practical approach to future-proofing the modern industry [2].The use of the internet of things (IoT) provides machine monitoring, less human effort and labor cost reduction [3]. The industrial IoT (IIoT) is used in textile condition and production monitoring. IIoT gathers data from various sensors to build a platform for remote controlling and monitoring of any type of production machines. [4]. This monitoring platform allows the manufacturing process to be designed on top of a robust data infrastructure that enables the acquisition, forwarding, merging, and storing of accumulating data. This implies that data should be fully available throughout the manufacturing process through appropriate interfaces. Hence, the data-driven solutions used to handle the data at all stages of the process are necessary due to the product and its manufacturing needs. Furthermore, the wide range of current technology, including IT systems and industrial standards, and business strategies makes it difficult for manufacturers to create a digital transformation plan [5]. However, in order to demonstrate the value that may be added by an online monitoring system, it is crucial to incorporate and examine this system in the textile production industry. Moreover, examining several manufacturing situations occurringin real life is important to bridge the gap between abstract and applied research. The main aim of this applied research is to fulfill the needs and limitations of the textile industry.

There are several studies that have been published in this context. Kusters et al. [6] presented a Textile 4.0 model plant. That research investigated the challenges facing the textile sector to move toward Industry 4.0, conceptualizing that the last century's fast transformation in technology, industry, and societal patterns and processes was a result of growing interconnectedness and intelligent automation; however, no practical application was conducted or infrastructure built, as the work highlights the significant implementation challenges. They exist due to uncertainty about the financial rewards and a lack of specialized knowledge; hence. Businesses are reluctant to begin their digital transformation process. Chen et al. [7] also introduced a proposal for improving textile production based on Industry 4.0. It addresses the barriers to industrial upgrading and makes policy recommendations for execution. Nevertheless, it lacks the characterization of a specific data infrastructure and application framework. Digitizing the textile production sector using IoT was introduced in [8] for effective monitoring of operations and production with an emphasis on how IoT technologies are interpreted and their potential application to the textile industry from both a technological and business standpoint. This assessment also contrasts ongoing work in the use of IoT in the textile industry to that in other industrial sectors. Data are extracted from machines and delivered to appropriate destinations through Message Queuing Telemetry Transport (MQTT) [9] for further processing, as shown by Dianisio et al. [10].Based on the measures, data kept on a cloud server may be seen from a computer dashboard and accessed remotely with increased security. One of the inferences that may be made is that the suggested gateway enables data to be saved and conveniently viewed from a smart phone application or a computer online interface. MQTT is a messaging protocol designed for IoT devices that operate on extremely high-latency networks of constrained capacity. It is the optimal protocol for machine-to-machine (M2M) communication because message queuing telemetry transport is designed for limited, high-latency settings [11].

There are just a few known successful real-world demonstrations of IIoT in textile production, despite the availability of communication protocols and machine learning capabilities. In this paper, a complete condition monitoring system was built on a knitting machine. Different sensors were integrated on the machine to monitor the motor speed, stitch length and etc. The data we recollected and stored using a data acquisition system. Machine learning was applied to the contributed dataset to produce a linear regression model for the estimation of machine production. Thus, the objective of this study was to predict the production rate of a double knitting machine using a prototype of an online monitoring device based on IoT and AI, potentially transforming industries through efficiency. In addition, the precision of this prediction model was evaluated.

2. Experimental work

A monitoring system was employed and tested on a "Knitel" machine from PAI LUNG (dial 2 tracks and cylinder 2 tracks), which has 96 feeds and a machine diameter of 30 inches at gauge 24. The machine produces polyester fabric. 100% polyester spun yarn, 70/1 Denier was used to produce interlock fabric of 70 g/m^2 weight. The real speed of the knitting machine and yarn feeder sensor rotation were 18 rpm and 1174 rpm in series. Additionally, the actual stitch length needed to produce 6.4 kg/h of fabric was 2.1 mm. This length value was acquired by experimentation and trial & error. The online monitoring system designed consisted of a proximity sensor and yarn feeder sensor, which was deployed in order to evaluate the stitch length value by counting the number of revolutions per minute of the knitting machine's toothed belt (MEMMINGER-IRO).With each revolution, a pulse width modulation (PWM) signal was captured by the yarn feeder sensor (LFA). The toothed belt was designed to provide a constant, synchronized, slip-free drive to all the yarn feeders on the feeder ring.

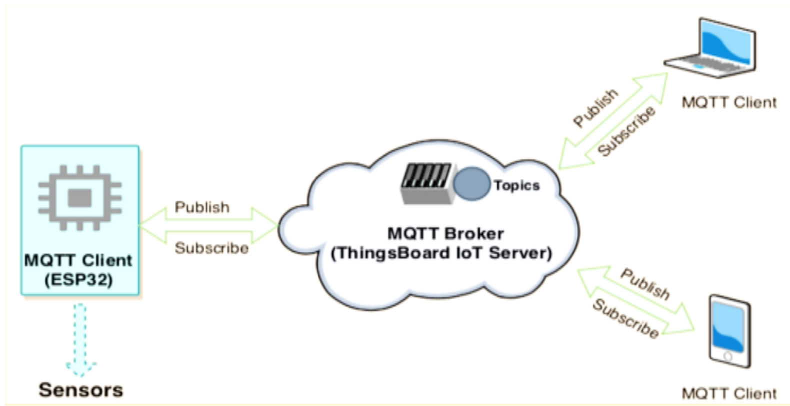


Fig. 1. ESP32 MQTT Client Connection

2.1. IoT Framework

In addition, the IoT system was deployed as it is based upon ESP32. It consists of a low-cost and low-power system on a chip microcontroller with built-in Bluetooth and Wi-Fi. ESP32 was used along with MQTT to convey the data to the server and store them for analysis. MQTT is an efficient, reliable and OASIS standard messaging protocol for IoT. It is designed as an extremely lightweight publish/subscribe messaging transport which uses little network traffic and has a small code footprint, making it perfect for connecting faraway devices. The MQTT interacts with HiveMQ, a form of cloud computing that offers a wide range of services through the Internet, including data storage, servers, databases, networking, and applications. IoT devices may be reliably and scalable connected to any cloud platform using the fully managed MQTT platform called HiveMQ. Figure 1 shows the connection of an MQTT broker server where ESP32 is assigned as the MQTT Client which acquires and processes the sensor's data and then publishes them to the MQTT Broker server. On the other hand, the MQTT Broker must have already subscribed the ESP32 MQTT Client. Moreover, the monitoring device, such as a phone or laptop, plays the role of another MQTT Client [9-11].

2.2. Data Acquisition

For data collection of the online monitoring system proposed, the device gathers and populates the data through MQTT. In this work, we used our prototype of the monitoring device designed to gather the machine speed and yarn feeder sensor count. As a result, the production rate was calculated. Figure 2 shows an illustration of the prototype of the monitoring device designed. It shows the circular knitting machine in operation while the monitoring system captures the sensors' data and stores them in the cloud. This monitoring device consists of proximity sensor and yarn feeder sensor in addition to IoT embedded sensors in order to gather the revolutions of the machine speed and the yarn feeder sensor. As a result, the production rate was calculated. Figure 3 displays the architecture of the data migration process, where the MQTT broker is the interaction between server and machine. It explains the IoT components and how production data are sent from the

Fig. 2.Online monitoring device deployment on the circular knitting machine Where: (1) The proximity sensor, (2) The yarn feeder sensor, and (3) IoT components

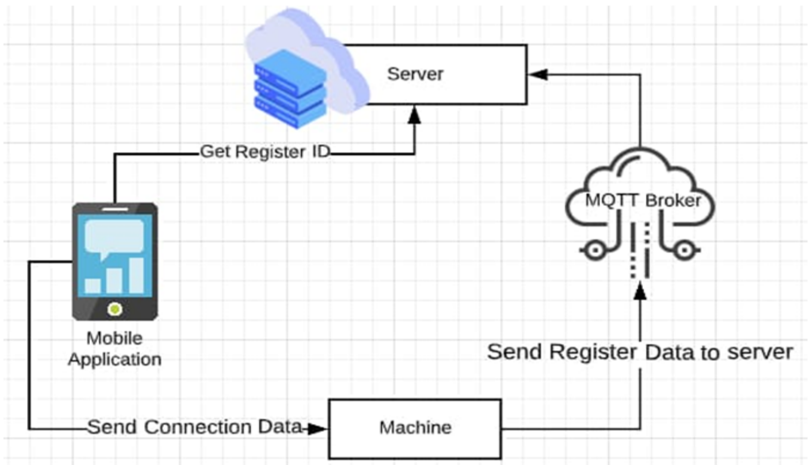


Fig. 3.MQTT Broker interaction with the machine

	n_1(rpm)	n_2(rpm)	L(mm)	P(kg/h)
Mean	18.00	1174.63	2.11	6.26
Std	2.82	182.78	0.05	0.97
Min	1.00	21.00	0.68	0.11
25%	19.00	1237.00	2.10	6.59
50%	19.00	1238.00	2.10	6.59
75%	19.00	1238.00	2.13	6.59
Max	21.00	1362.00	2.68	7.26

Table 1.Statistical data of measured parameters and the production rate

machine to the server using the ESP32 and MQTT broker. The server then stores and analyses the data and displays them in tables and on graphs. Finally, the server transmits information to the mobile application so that managers can use it to monitor the productivity and control the machine through this application, as well as fix problems and resolve issues.

This arrangement's primary objective is to forecast a product or intermediary product performance using the process setup during machine running. It is accomplished by gathering information from all equipment involved and tracking the product. This makes it possible to identify the settings and conditions that a work piece is exposed to inside each phase. It is feasible to create prediction models utilizing ML approaches, such as regression or deep neural networks, by gathering large data sets over time and assessing key performance indicators (KPIs) that measure the performance of the output. More than 6000 data points were recorded using the test system. The statistical data of the machine revolutions, yarn feeder sensor revolutions, stitch length and the production rate are denoted as n_1, n_2, L and P, respectively, as shown in Table 1. Hence, the purpose of this study was to estimate the production rate P based on the online monitoring parameters (n_1, n_2, and L). Indeed, the speed of the yarn feeder sensor stabilizes after three rotations, causing the variations observed, primarily due to sensor speed fluctuations. These fluctuations subsequently influence the standard deviation forn_2.Therefore, the output of the problem is P and the preliminary input dataset is formed from n_1, n_2 and L, where all other production factors, such as the yarn count, machine efficiency, and number of needles and feeders, are constant. The training set is 4000 and the test set - 2000.

3. Method concepts and Results

This section presents the developed concepts of machine production estimation using the online monitoring facilities. Linear regression is used to predict the machine production.

3.1. Correlation analysis between the production rate and measured parameters

A statistical analysis method is used in order to predict the machine production based on the monitoring data. The correlation between the available data sets should be determined to exclude highly correlated variables. The multicollinearity concept is an effective way to detect the correlation between multiple variables. A typical approach to detect the multicollinearity features is using Pearson's correlation matrix [12]. The correlation matrix is provided in Figure 4, which shows the correlation between the independent variables n_1, n_2 and the L and production rate, where the correlation coefficients (r) determine the degree of correlation. When the r value rises, the features are positively correlated; while on the other hand, the features are negatively correlated when it rises negatively. The results show that the n_2, n_1 and L are correlated with P by (100%, 99% and 2.1%) respectively. In addition, the correlations between the independent variables (n_1 and n_2), (n_1 and L) and (n_2 and L) are (99%, -7.2% and 2.1%) in order.

In a multiple regression equation, multicollinearity occurs when one or more independent variables have a high correlation with one another. The statistical significance of an independent variable is affected by the multicollinearity issue, which is a problem. Statistical indicators like R^2 (coefficient of determination), tolerance, and VIF (Variance Inflation Factors) are used to significantly measure the degree of multicollinearity [13, 14]. These results imply that there is a high correlation between (n_1, n_2). The following equations are used to calculate the degrees of multicollinearity between independent variables:

$$\text{Tolerance}=1-R_i^2 \tag{1}$$

$$\text{VIF}=1/(1-R_i^2) \tag{2}$$

According to statistical outcomes shown in Table 2, it is clear that there is a multicollinearity problem between (n_1 and n_2), where the VIF (50.251) value is higher than 10. Furthermore, R^2 between (n_1 and n_2) is high (0.980) with the lowest tolerance of (0.020), which proves the multicollinearity issue. Conversely, the relation between the other variables is normal, where the lowest R^2 values (0.005) and (0.000) are found between (L&n_1) and (L&n_2) respectively. In addition, there are high correlation values (0.995) and (1.000) between (L&n_1) and (L&n_2) in order. Besides, the lowest VIF values of (1.005) and (1.000) are found between (L&n_1) and (L&n_2) in series.

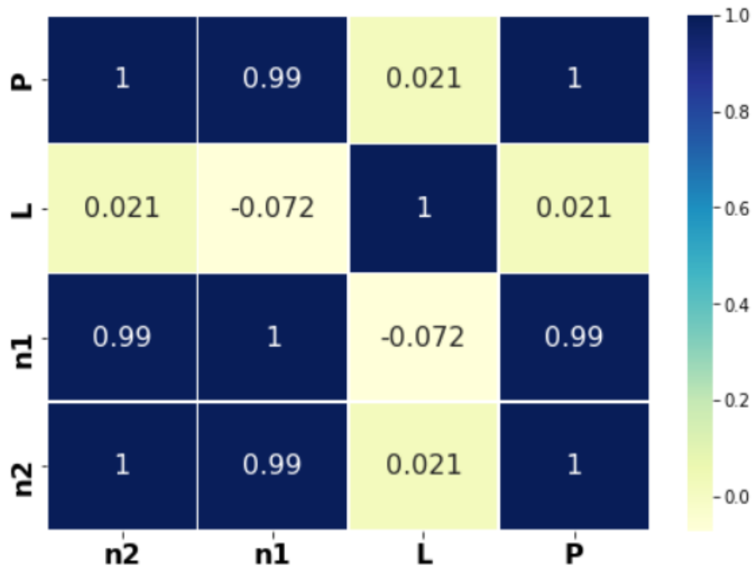


Fig. 4. Pearson's correlation matrix

Independent Parameter	n_1&n_2	L&n_1	L&n_2
R_i^2	0.980	0.005	0.000
Tolerance	0.020	0.995	1.000
VIF	50.251	1.005	1.000

Table 2. Statistical measure of degrees of multicollinearity

All of these outcomes highlight the multicollinearity between independent variables (n_1 and n_2), which affects the accuracy of the prediction model. Hence, the recommended solution to overcome this problem is to delete one of these independent variables.

3.2. Linear Regression Model

This is the relation between one or more independent variable (predictors or regressors) and a dependent (response) variable. In this case, the output variable P and the predictors are (n_1, n_2 and L).Figure 5 shows the relation between the production rate and measured parameters, where Figure 5 (a, b) shows a strong correlation between the production rate and (n_1 and n_2) in series, which is presented in a straight line. Furthermore, both figures show the best fit of the data set, which indicates that the production rate increases with the rising of (n_1 and n_2). Conversely, Figure 5 (c) shows a weak correlation between the production rate and stitch length in a certain range of the data set.

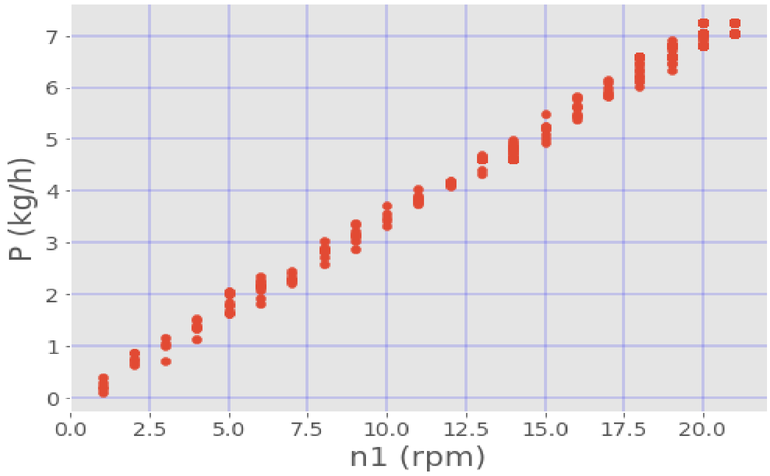
The linear regression method of ML is adopted, which fits a straight line reducing the outcome error between observed and expected values. There are simple linear regression calculators that use a "least squares" method to discover the best-fit line for a set of paired data. A typical linear regression model output is shown in equation (3) [15, 16].

$$Y_i=f(X_i,\beta)+e_i \tag{3}$$

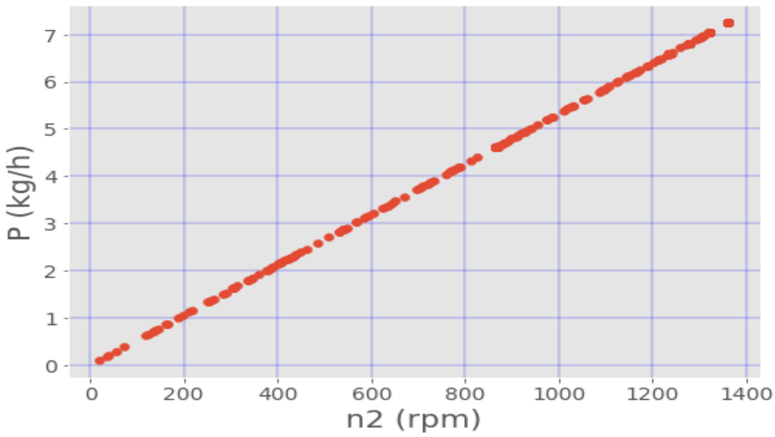
Where X_i, β and e_i are the independent variable, unknown parameters and error terms, respectively.

3.3. Data Prediction Results

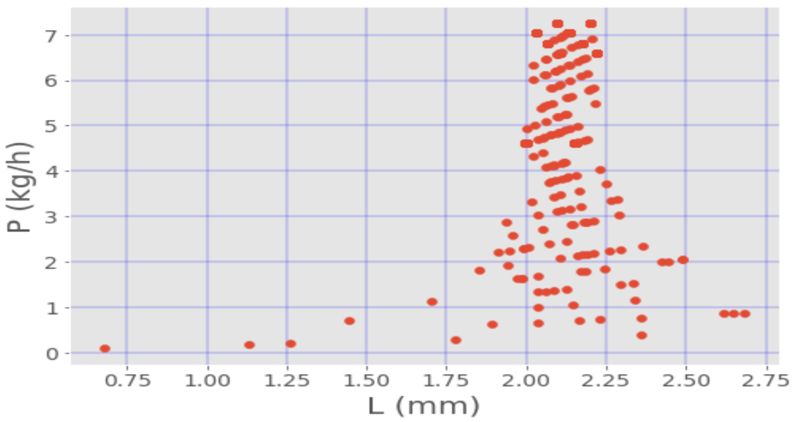
Prediction results of the recommended solutions to overcome the multicollinearity problem in estimating



a) Relation between the production rate and machine speed



b) Relation between the production rate and yarn feeder revolution



c) Relation between the production rate and stitch length

Fig. 5. Relation between the production rate and measured parameters

the production rate are obtainedin two ways. The first procedure is deleting n_2 and the prediction of the production rate using n_1 and L, which is represented by the linear regression equation of the model (4).The second procedure is deleting n_1 and the prediction of production rate using n_2 and L, which is represented by the model's linear regression equation (5).

$$P_1=0.345(n_1)+1.5525(L)-3.224 \tag{4}$$

$$P_2=0.005(n_2)-(7.44E-16)*(L)-(4.09E-14) \tag{5}$$

Figure 6 shows the regression hyper-plane of the dataset after training. The count of the machine revolution n_1 and the stitch length L are on the x-axis and y-axis, respectively. The production rate is on the z-axis. The coefficients of n_1 and L are 0.345 and 1.5525, respectively. The intercept of the hyper-plane is -3.224. The intercept is the y-axis anticipated mean value when all the x-axis is equal to 0. The model creates a regression equation with the x-axis as the only predictor to begin with. The predicted mean value of the y-axis at that value is the intercept in the event that the x-axis occasionally equals 0, which has significance.

Figure 7 shows the regression hyper-plane of the dataset after training. The count of the machine revolution n_2 and the stitch length L are on the x-axis and y-axis, respectively. The production rate is on the z-axis. The coefficients of n_2 and L are 0.005 and (7.44E-16), respectively. The intercept of the hyper-plane is -(4.09E-14). The intercept is the y-axis anticipated mean value when all the x-axis is equal to 0. The model creates a regression equation with the x-axis as the only predictor to begin with. The predicted mean value of the y-axis at that value is the intercept in the event that the x-axis occasionally equals 0, which has significance.

After that, model evaluation is made through statistical indicators such as the mean absolute error (MAE) and mean absolute percentage error (MAPE), as well as the accuracy of the test data. Results of prediction precision are shown in Tables (3 and 4) for prediction using (n_1 and L) and using (n_2 and L), respectively. Table 3 shows precision results which represent a high level of accuracy of predicting the production rate (kg/h). The findings show that the accuracy reaches 99.73 % with an MAE of 0.029 and standard deviation of 0.002. The least value of MAPE is 0.65 %. In addition, Table 4 shows precision results which represent a high level of accuracy of predicting the production rate (kg/h). The findings show that the accuracy reaches 100% with an MAE of 0 and standard deviation of 0. The least value of MAPE is 0 %. Thus, this prediction

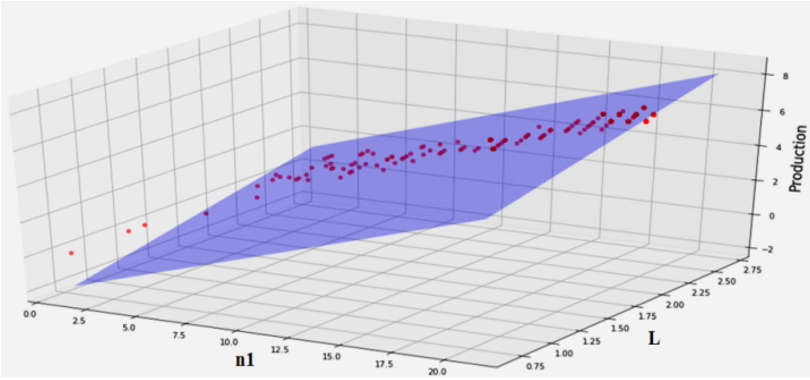


Fig. 6. Regression hyper-plane for first prediction model

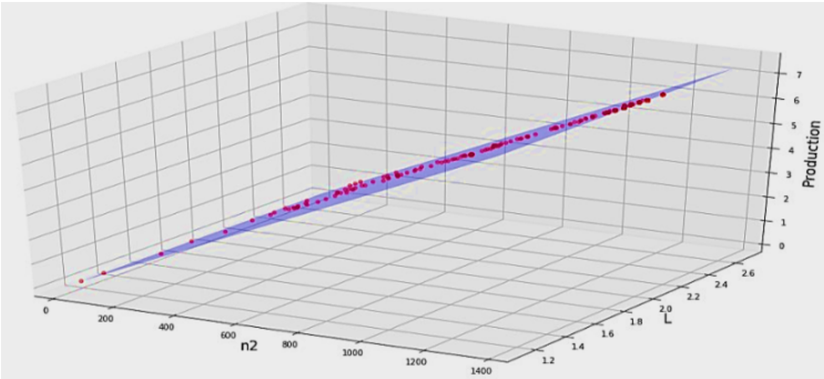


Fig. 7. Regression hyper-plane for second prediction model

MAE	Standard deviation of MAE	MAPE	Accuracy
0.029	0.002	0.65%	99.73%

Table 3. Results of prediction precision using (n_1 and L)

MAE	Standard deviation of MAE	MAPE	Accuracy
0	0	0	100%

Table 4. Results of prediction precision using (n_2 and L)

model for determining the production rate using (n_2 and L) introduces a novel formula in the knitting industry. Thus, it is recommended to calculate the production rate (kg/hr) using predictors (n_2 and L) or (n_1 and L) due to high precision results.

4. Conclusion

In this research, ML and IoT are combined to construct a prototype of an online monitoring system for circular knitting machines, and to forecast their output rate. A variety of sensors were used to collect readings from the environment. These data were sent to the MQTT as a first stage of data saving in a cloud system. The heights of the histogram show the density distribution of the data for the tested variables. A regression model was built between the condition monitoring sensors' data and the machine production. A multicollinearity study was done between all test data. The correlation matrix shows that n_2 has a high correlation with n_1, proven by values of theR^2, tolerance and VIF between independent variables. Therefore, a linear regression model was built to predict the production (P) using two prediction models: the first using uncorrelated-monitored data (n_1 and L) and second model using (n_2 and L). Both models achieved a high level of accuracy of predicting the production rate (kg/h), as evidenced by the regression outcomes. For the first model, the accuracy reached 99.73 %, while the MAE showed a mean loss of 0.029 with the least values of MAPE, which are0.65 % and a standard deviation of 0.002. Moreover, the second model reached a high accuracy level, which reached 100 %, while the MAE showed a mean loss of 0 with the least values of MAPE. which are 0 % and standard deviation of 0.As a consequence of the high accuracy results, it is recommended to compute the production rate (kg/h) using predictors (n_2 and L) or (n_1 and L), while other manufacturing factors remain unchanged. As a result, calculating the production rate using the second prediction model utilizing the stitch length and a yarn feeder sensor presents a novel formula. In conclusion, this research pioneers an innovative production calculation approach previously unexplored within the knitting industry.

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Declaration of Conflicting Interests

Author declares there is no conflict of interest.

Abbreviations

IoT	Internet of Things
IIoT	Industrial IoT
AI	Artificial Intelligence
M2M	Machine-to-Machine
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
PWM	Pulse width modulation
R^2	coefficient of determination
VIF	Variance Inflation Factors
KPIs	Key performance indicators

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