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A CASE STUDY FOR PREVENTING ELECTRICITY OVER-CONSUMPTION USING DEEP LEARNING IN TEXTILE INDUSTRY

Hakan YURDOGLU, Omer GULEC *

Pamukkale University, Department of Management Information Systems, Denizli, Türkiye

Keywords

*Deep Learning,
LSTM,
Sliding Window Technique,
Electricity Consumption,
Textile Industry.*

Abstract

Resources are the most critical input in the manufacturing industry therefore, resource consumption is an essential issue to be minimized. On the other hand, consumption depends on several parameters thus, it is difficult to estimate. Recently, Machine Learning (ML) and Deep Learning (DL) are powerful Artificial Intelligence (AI) subdomains for future prediction in any area. In this paper, a DL-supported electricity prediction method is designed for the textile industry as a case study in order to prevent resource over-consumption while the machines are in the standby state. This method provides dynamic consumption thresholds of electricity consumption by sliding window technique based Long-Short Term Memory (LSTM) model that helps the machines to interrupt manufacturing in their decision. These calculated thresholds are also compared with the results of Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU) as the other DL methods and Automated Regressive Integrated Moving Average (ARIMA) as a traditional method and then the results have been analyzed how close they are to real-time electricity consumption data at standby. According to the results, the LSTM model successfully predicts electricity consumption levels, sends an interrupt signal to Programmable Logic Controller (PLC) unit when the consumption levels reach the threshold and therefore prevents resource over-consumption.

TEKSTİL ENDÜSTRİSİNDE DERİN ÖĞRENME KULLANARAK AŞIRI ELEKTRİK TÜKETİMİNİN ÖNLENMESİNE YÖNELİK BİR VAKA ÇALIŞMASI

Anahtar Kelimeler

*Derin Öğrenme,
UKSB,
Kayan Pencere Tekniği,
Elektrik Tüketimi,
Tekstil Endüstrisi.*

Öz

Endüstrinin en kritik girdileri kaynaklardır ve bu nedenle kaynak tüketimi endüstriyel süreçlerde en aza indirilmesi gereken önemli bir konudur. Öte yandan, kaynak tüketimi birçok parametreye bağlı olduğu için tahmin edilmesi zordur. Son dönemlerde, Makine Öğrenmesi (MÖ) ve Derin Öğrenme (DÖ) kavramları, herhangi bir alanda gelecek tahmini için kullanılan güçlü Yapay Zeka alt alanlarıdır. Bu çalışmada tekstil endüstrisi için bir vaka çalışması olarak, makinelerin bekleme durumunda aşırı kaynak tüketimini önlemek amacıyla DÖ destekli bir elektrik tahmin modeli tasarlanmıştır. Bu yöntem, makinelerin karar verme süreçlerini içeren ve aşırı tüketime nedeniyle üretimi kesintiye uğratmasına yardımcı olan Uzun-Kısa Süreli Bellek (UKSB) tabanlı kayan pencere tekniği sayesinde elektrik tüketiminin saatlik dinamik eşik değerlerini tahminlemektedir. Hesaplanan eşik değerleri, Tekrarlayan Sinir Ağları (TSA) ve Kapılı Tekrarlayan Birimler (KTB) gibi diğer Derin Öğrenme yöntemleri ve geleneksel bir yöntem olan Otomatik Regresif Entegre Hareketli Ortalama (ARIMA) yöntemi ile karşılaştırılmış, elde edilen sonuçların makinelerin bekleme durumundaki gerçek zamanlı elektrik tüketim verilerine ne kadar yaklaştığı analiz edilmiştir. Elde edilen sonuçlara göre, UKSB modeli elektrik tüketim seviyelerini başarılı bir şekilde tahmin etmekte, tüketim seviyeleri eşiğe ulaştığında Programlanabilir Mantık Denetleyicisi (PMD) ünitesine durma sinyali göndermekte ve bu sayede aşırı kaynak tüketimini engellemektedir.

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Yazar Kimliği / Author ID (ORCID Number)

H. Yurdoglu, 0000-0003-3320-2429
O. Gulec, 0000-0002-7657-3230

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* İlgili yazar / Corresponding author: omer@pau.edu.tr, +90-258-296-2807

A CASE STUDY FOR PREVENTING ELECTRICITY OVER-CONSUMPTION USING DEEP LEARNING IN TEXTILE INDUSTRY

Hakan YURDOGLU, Omer GULEC †
Pamukkale University, Department of Management Information Systems, Denizli, Türkiye

Highlights

- Resources are the most critical input for the manufacturing industry therefore resource consumption should be minimized.
- Deep Learning is a powerful subdomain of artificial intelligence to predict resource consumption over time-series data taken from textile machines.
- The proposed model prevents electricity over-consumption using LSTM and Sliding Window technique.
- This study offers a different perspective from other studies focusing on the energy consumption of machines in their standby state.

Purpose and Scope

This paper proposes a Deep Learning-supported electricity prediction method for the textile industry as a case study in order to prevent resource over-consumption while the machines are in stanby state. The proposed study offers a new perspective to the existing literature by focusing on the standby electricity energy consumption of textile machines and emphasizes that standby energy consumption is an overlooked area and long waiting times can lead to huge costs. The results of this study have the potential to contribute to the studies in the field of energy efficiency, as well as to reduce the energy costs of enterprises and achieve their sustainability goals.

Design/methodology/approach

In this paper, an LSTM-based sliding window (SW) supported DL model is proposed in order to predict standby electricity threshold values for preventing resource over-consumption in the textile industry. Within the scope of this case study, an AI application that processes the electricity consumption values of the mercerization machine in a textile company between 2021 and 2023 with an SW-supported LSTM-based method has been developed. The proposed method predicts upcoming 4-hour consumption thresholds of electricity, learning from the past 96-hour time series that helps the machines to stop manufacturing if needed by sending an interrupt signal to the PLC unit when the consumption levels reach these thresholds. The proposed model was developed on real-time data taken from the textile machines, the training and testing of the model were provided with this data, the predictions of the model were compared with the real-time data, the errors of the model were eliminated and it was optimized to obtain more realistic predictions. In order to measure the efficiency of the proposed LSTM model on electricity consumption time-series data of the textile machines, the results are compared with the results of Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU) and Automated Regressive Integrated Moving Average (ARIMA) methods for the same dataset then the results are analyzed.

Findings

The realtime results show that the proposed model successfully predicts threshold levels of electricity values for preventing over-consumption of the textile machines on their standby state. Additionally, the proposed model is a powerful tool for controlling the productivity of these textile machines.

Originality

As in this case study, to the best of our knowledge, there exists no LSTM based DL supported electricity consumption model using SW technique in the literature for the textile manufacturing industry, in order to prevent over-consumption of electricity of the machines in their standby state by sending an interrupt signal to the Programmable Logic Controller (PLC) unit when the consumption levels reach the predicted thresholds. The real-time data is taken from mercerization machines of a textile company during their manufacturing processes.

1. Introduction

In today's world, factories and their processes are getting smarter day by day thanks to recent intelligent technologies. The most important factors to be "smart" for factories are the automation of their processes, the possibility of unmanned production, the inclusion of robots in the processes, the development of sensor technologies and most importantly the decision-making of the machines (González García et al., 2019). These learning and decision-making processes of the machines are called Machine Learning (ML) and Deep Learning

† Corresponding author: omer@pau.edu.tr, +90-258-296-2807

(DL) which are the subdomains of the Artificial Intelligence (AI) domain (Forootan et al., 2022).

In order to produce their products, factories need different resources in various processes. The very first need is energy which is a critical parameter for the industry due to its expense therefore, the resources should be used optimally. This is an essential but difficult issue in predicting the energy need in the industry to be considered (Wang et al., 2020). On the other hand, the resource over-usage may cost much hence it should not be higher than the price of each product. To overcome this problem, there are many consumption prediction methods have been proposed in the literature.

Predicting energy consumption may lead to an increase in manufacturing processes. In the literature, there are several ways to save energy. Recently, one of the most emerging ways of energy saving in industrial processes is minimizing energy consumption using AI-supported technologies. Related to this, DL methods are the main solutions to predict energy consumption that help the enterprise for managing all processes. Besides, while the resource consumption data is in a continuous form, these prediction methods need to be considered in the time series domain. Therefore, long short-term memory (LSTM) is a powerful DL method that is working well on periodic data for forecasting long-term trends (Fagerstrom et al., 2019).

While the industrial processes are being adopted by Industry 4.0 with the support of Industrial Internet of Things (IIoT), the textile industry benefits more from ML and DL techniques recently in supply chain decision-making, product quality, production scheduling, product engineering and such areas (Arora and Majumdar, 2022). Not only today but also in the future, IoT and IIoT will be in touch with AI technologies for smart industries (Milic et al., 2023). Therefore, in this paper, an LSTM-based Sliding Window (SW) supported DL model is proposed in order to predict electricity threshold values for preventing resource over-consumption in the textile industry. Within the scope of this case study, an AI application that processes the electricity consumption values of the mercerization machine in a textile company between 2021 and 2023 with an SW-supported LSTM-based method has been developed. If the electricity consumption values reach the predicted threshold values, the proposed model sends an interrupt signal to the PLC of the machine.

This study offers a different perspective from other studies focusing on the energy consumption of machines. Generally, while the energy consumption of the machines is examined during active operation, the energy consumption situation is ignored while the machines are in the standby state. This study emphasizes the importance of the energy consumed while the processes are paused and draws attention to a potential that can cause great costs. Considering the situations where the waiting time can be long, it is important to examine the energy consumption not only during active operation but also while waiting. How long the machine spends in the standby state is a critical factor in determining energy costs and increasing operating efficiency. Therefore, this study shows that taking certain precautions as a result of analyses on standby energy consumption can avoid large-scale costs. Optimizing energy consumption and managing it efficiently, especially when waiting is required, can reduce the costs of textile enterprises and contribute to their sustainability goals.

The proposed model aims to prevent excessive use of electrical energy in the production processes of the textile company, where resources are valuable and resource use is critical. The proposed model was developed on real-time data taken from the textile machines, the training and testing of the model were provided with this data, the predictions of the model were compared with the real-time data, the errors of the model were eliminated and it was optimized to obtain more realistic predictions. In order to measure the efficiency of the proposed LSTM model on electricity consumption time-series data of the textile machines, the results are compared with the results of Neural Networks (RNN) and Gated Recurrent Units (GRU) as the DL methods and Automated Regressive Integrated Moving Average (ARIMA) as a traditional method for the same dataset then the results are analyzed.

To the best of our knowledge as in this case study, there exists no LSTM-based DL-supported electricity consumption model using the SW technique in the literature for the textile manufacturing industry, in order to prevent electricity over-consumption by sending an interrupt signal to the Programmable Logic Controller (PLC) unit when the consumption levels reach the predicted thresholds for the machines are in the standby state. The proposed model also provides continuous prediction values as the time series while adding real-time data to its training process.
The contributions of this study are;

- The proposed DL model predicts the electricity consumption thresholds of a mercerization machine in a textile enterprise using LSTM method while the machines are in the standby state.
- Using SW technique allows the model to learn from the predicted thresholds therefore, the learning process stays continuous.
- The proposed model sends an interrupt signal to the PLC unit of the textile machine even if its electricity consumption reaches the predicted thresholds therefore it prevents the machines from energy over-

consumption by the predicted thresholds.

- With this developed model, even when the machine is in the standby state, it also helps to find out a possible malfunction whether it consumes more than it should.
- The proposed model can help textile enterprises to reduce energy resource and machine maintenance costs and to contribute to their sustainability goals.

The rest of the paper is organized as follows. Literature survey on energy, ML, DL, LSTM, SW and the textile industry are summarized in Section 2. Problem definitions and the proposed model of the current study are given in Section 3. The experimental results of the study are given in Section 4. Finally, Section 5 concludes the study.

2. Literature Survey

The smartening of industrial machines is possible when artificial intelligence and IoT fields become an inseparable whole under the Industry 4.0 concept. Machine learning and deep learning are artificial intelligence subdomains that are frequently preferred in the IoT ecosystem.

In the industry, the resources are valuable therefore, energy consumption is a key factor to be minimized. To this end, Yucesan et al. (2021) proposed a daily natural gas consumption prediction framework on the data in the case of Turkey using regression, time series, ML and metaheuristics. Malakouti et al. (2022) proposed a novel ML algorithm to predict wind turbine power by randomized trees, light gradient boosting machine and the LSTM method. Similarly, Ikeda and Nagai (2021) proposed an optimization method for central energy (power, air conditioning and hot water) and storage systems of buildings using ML and metaheuristics. Besides, the price of energy is an essential issue to be considered in economics. To this end, Yang et al. (2022) suggest an improved model for predicting electricity prices using ML techniques.

Besides, in the literature, there are many models used for electricity consumption prediction such as autoregressive integrated moving average (ARIMA), autoregressive moving average (ARMA) and linear regression models (Lee et al. 2022). In addition, Albuquerque et al. (2022) compared traditional models with ML models for the prediction of electricity consumption using a high-dimensional dataset. According to their work, ML models such as Random Forest outperforms the benchmark models. Oprea et al. (2021) proposed an unsupervised ML technique in order to detect anomalies in the time series of electricity consumption values by analyzing large datasets of smart meters in Ireland. For smart farming, Shine et al. (2018) analyzed the performance of ML techniques such as random forest, decision tree, ANN and support vector machines on electricity and water consumption of Irish dairy farms. Mirandola et. Al. (2021) reviews the performance of ML methods such as Gradient Boosting (GB), Random Forest (RF), Kernel Ridge and Artificial Neural Networks (ANN) for the prediction of energy consumption in metal forming and radial-axial ring rolling processes. Awan et al. (2022) proposed a supervised ML-based energy consumption prediction model using regression, regression trees and ANN for cut-off grinding of oxygen-free copper which has high energy consumption rates in the industry.

For predicting the long-term values of time series data, LSTM-based methods have been widely used in the literature. Fagerstrom et al. (2019) proposed an LSTM-based algorithm for early detection of septic shock namely LiSEP LSTM using Keras and TensorFlow. LiSEP LSTM has been trained with the health data containing vital signs and laboratory data received from 59 thousand of patients that predicts upcoming septic shock up to 40 hours before. Alazab et al. (2020) proposed a multidirectional LSTM model for predicting the stability of a smart grid. The results have been compared with Gated Recurrent Units (GRU), traditional LSTM and Recurrent Neural Networks (RNN) methods which have 99% accuracy compared to the other methods. Wang et al. (2020) proposed a novel model using LSTM for predicting energy consumption periodically on a cooling system. Their proposed model outperforms the other models such as ARMA, ARFIMA and BPNN.

In time series SW technique is also useful for several cases. To this end, Bhatt et al. (2022) proposed an SW-supported DL model for solar irradiance forecasting that is useful for controlling, managing and optimizing the power generation in microgrids. Chen et al. (2022) proposed an LSTM model supported by SW to predict rainfall distribution levels in two cities, Rize and Konya, in Turkey using monthly data in 41 years range. Similarly, Kulanuwat et al. (2021) designed an LSTM model using SW technique for anomaly detection on hydrological time series data. Sun et al. (2022) proposed a Support Vector Machine (SVM) based SW-supported model for predicting desert locust presence in Somalia, Ethiopia and Kenya using the data from 2000 to 2020.

Sensor technologies have a close relationship with the textile industry, especially in body sensor networks. For instance, Fang et al. (2021) developed ML assisted wearable waterproof textile sensor for monitoring pulse and cardiovascular condition. Vu and Kim (2018) provided an ML-supported model of human motion recognition by wearable textile sensors. Similarly, the textile industry also benefits from artificial intelligence technologies day by day. Consequently, demand for the products needs to be predicted for better manufacturing. Therefore, Yasir et al. (2022) investigated the significance of endogenous and exogenous indicators of demand forecasting for the textile industry using ML models such as linear regression (LR), support vector regression (SVR) and LSTM. Medina et al. (2022) proposed an ML model including regression, SVR and KNN in order to predict demand forecasting in the textile industry. Güven and Şimşir (2020) designed an ML model using color parameters including ANN and SVR for demand forecasting in the textile industry. Majumdar et al. (2022) developed a Genetic Algorithm (GA) supported hybrid ML-based model to predict cotton properties using ANN.

3. Material and Method

3.1. Deep Learning Model

Deep Learning (DL) is a branch of ML that can solve complex problems by mimicking the human brain and this structure is called Artificial Neural Networks (ANN) which is a common algorithm for DL. Besides, Convolutional Neural Network (CNN), RNN, LSTM, Wavelet Neural Network (WNN), Deep Belief Neural Network (DBN), Radial Basis Function (RBF) algorithms are the members of the DL domain (Forootan et al., 2022).

LSTM is a very effective algorithm in DL space that can successfully predict values on time series data (Garg and Alam, 2020). In other words, In other words, LSTM is an artificial neural network belonging to the RNN family, where the traditional feed-forward neural network receives data only from the input node and the data only proceeds from the input layer to the hidden layer and finally to the output layer (Agga et al., 2022). To be more specific, an LSTM cell is given in Figure 1. According to the figure, an LSTM cell is formed by an input gate (i), a forget gate (f) and an output gate (o). The input gate includes $tanh$ function ranging from -1 to 1 and it takes the input data (x_t) and previous cell output (h_{t-1}) and C_{t-1} values for processing. Similarly, the forget gate includes σ and $tanh$ as the activation functions. The output gate determines the output data (Chen et al., 2022; Alazab et al., 2020; Yasir et al., 2022).

The gates of an LSTM cell can be summarized as follows (Rani et al., 2022; Sundar and Patchaiammal, 2022);

1. Forget Gate: It is responsible for the decision about the information that should be kept or removed from the cell state.
2. Input Gate: In this gate, the input data is decided by the sigmoid function where $tanh$ function is used for the connection of possible values of input data. Both sigmoid and $tanh$ functions update cell state.
3. Output Gate: It is the final part of the cell where the sigmoid function decides the cell state to be passed as the output.

All of the equations used in Figure 1 are given in Equation [1 – 6] where σ is the sigmoid function, b is the bias value for the gates and W is the weight.

$$i_t = \sigma\,(W_i.[h_{t-1}, x_t] + b_i) \tag{1}$$

$$f_t = \sigma\,(W_f.[h_{t-1}, x_t] + b_f) \tag{2}$$

$$o_t = \sigma\,(W_o.[h_{t-1}, x_t] + b_o) \tag{3}$$

$$\tilde{C}_t = tanh\,(W_C.[h_{t-1}, x_t] + b_C) \tag{4}$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t \tag{5}$$

$$h_t = o_t \otimes tanh\,(C_t) \tag{6}$$

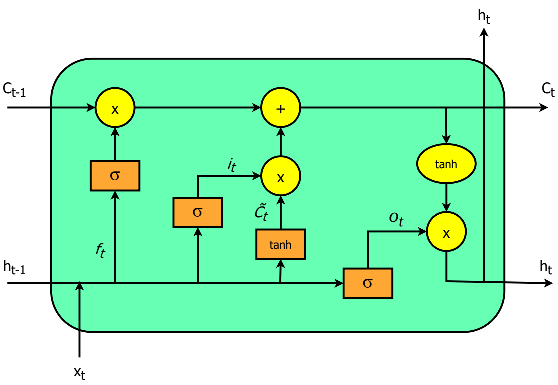

Figure 1. An illustration of LSTM cell

3.2. Sliding Window Approach

The Sliding Window (SW) is a useful technique for predicting values in ANN-based networks, LSTM in this study, that process a fixed range of previously observed values as input data and predicts the next values of the time series as output data then includes this predicted value to the next input data while removing same fixed size of values from initial data (Vafaeipour et al., 2014) which is also known as Rolling Window technique. To be more clear, an illustration of the Sliding Window technique is given in Figure 2. According to the figure, the data from t_0 to t_n is used for training and the predicted values from t_n to t_{n+x} is generated according to this range. The size of the window is therefore $s_w = t_n - t_0 = n$ and the size of prediction is $s_p = t_{n+a} - t_n = a$. In the next step, the predicted values are included in the data. Therefore, for sliding the window to the right, the initial values from t_0 to t_a will be removed in order to save window size where it is calculated as $s_{sw} = t_a - t_o = a$ after sliding. With this technique, the upcoming values can be predicted by learning from the previous values on time series data.

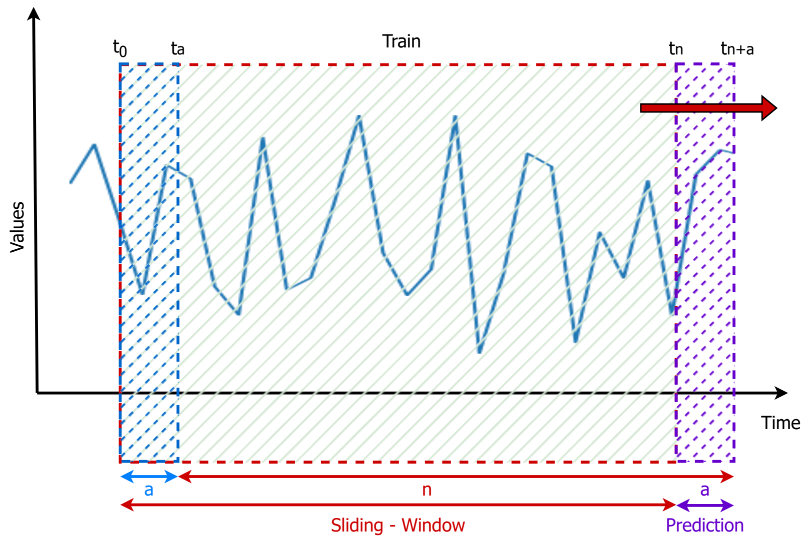

Figure 2. An illustration of the sliding window technique

3.3. Proposed Method

According to the data taken from the textile machines, LSTM is chosen for resource consumption prediction in a textile factory due to its memory layer for the time series of electricity usage. In this case study, the LSTM model is used with the SW technique in order to calculate the predicted thresholds of each resource consumption value based on prior information. These thresholds are predicted by the LSTM model after learning the resource consumption values of the last 96-hour time series. The flowchart of the proposed method is given in Figure 3.

When the proposed model initializes, the electricity consumption values are obtained from the mercerization machine. In the first step, as in every ML model, the proposed model analyzes the data and cleans it. In the second step, the proposed model is training the past 96-hour time series in order to predict upcoming 4-hour electricity consumption threshold values using the LSTM model and SW technique.

In the third step, these predicted values are stored in the PLC unit of the textile company. When these 4-hour time series begin, the PLC unit checks the real-time electricity consumption values against the predicted thresholds. If the real-time consumption values reach the predicted threshold values in this 4-hour time span, the proposed model sends an emergency signal to the PLC unit to interrupt the process. If the consumption values do not reach the predicted thresholds after a 4-hour time span, the proposed model includes these 4-hour electricity consumption values at the end of the data without sending an interruption signal.

In the last step, the proposed model removes the initial 4-hour values from the beginning of the data after including the 4-hour prediction values. This makes the window slide from the beginning to the end while it saves fixed window size which is a 96-hour time span. In fact, if the consumption values reach the predicted consumption values or not, the model includes the real-time consumption values at the end of the data in order to learn from the past values using the SW technique. Therefore, learning, training and prediction steps become the continuous processes of the proposed model.

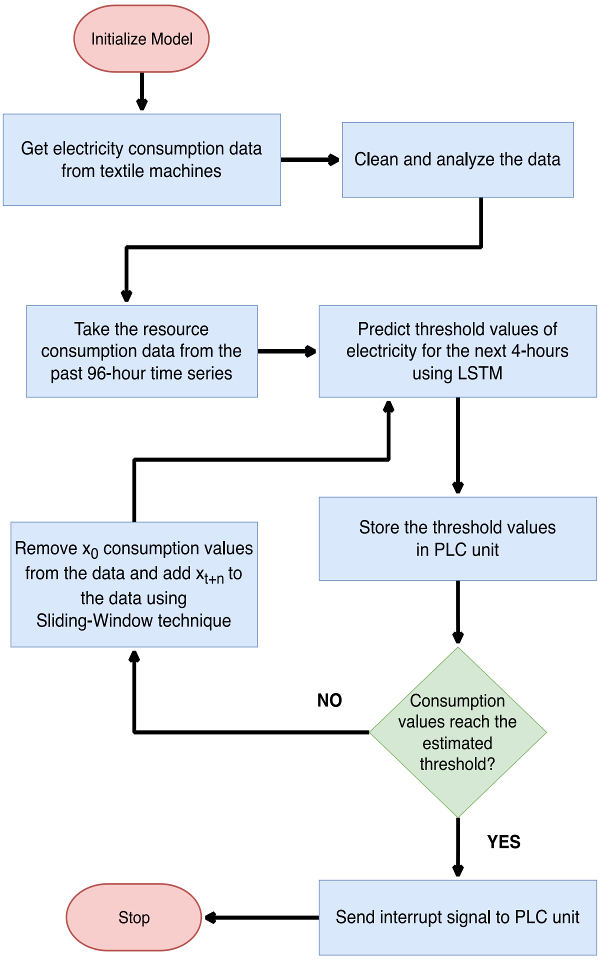

Figure 3. Flowchart of the proposed LSTM model

Figure 4. Mercerization machine 117 which executes the proposed LSTM model in the case study

The electricity consumption values obtained from a sample mercerization machine which is numbered 117 in the enterprise as shown in Figure 4, have been analyzed by Entes MPR63 energy analyzer. The electricity signals taken from the energy analyzer have been transferred to Siemens S7-1200 PLC devices. After that, these PLC devices transmit electricity information over CAT-6 ethernet cable using network switches and Profinet communication protocol to the main network of the enterprise. Then, the data collected through the application written with .NET technology is transferred to the server which has the MSSQL databases where the electrical energy consumption values of all machines are stored. Finally, the DL model proposed in this case study is also executed on this server to predict upcoming electricity threshold values. After predicting the next 4-hour electricity consumption values, this threshold data has been sent back to the PLC unit in order to compare electricity consumption values. If the consumption values reach the threshold value, the proposed method sends the interrupt signal to the PLC unit. The PLC unit and energy analyzer are given in Figure 5, respectively.

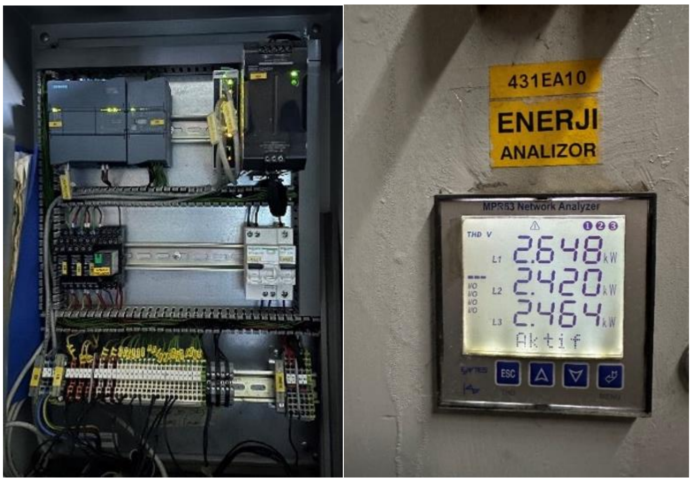

Figure 5. Siemens S7-1200 PLC unit (left)

Table 1. Data set of electricity consumption values

Date	Total Electricity Consumption Values (kWh)	Unit Electricity Consumption Values (kWh)	Standby Time (min)
01.01.2021 00:00	3.99989	0.01674	238.90000
01.01.2021 04:00	3.99989	0.01692	236.40000
01.01.2021 08:00	2.99987	0.01265	237.20000
01.01.2021 12:00	3.99994	0.01696	235.80000
01.01.2021 16:00	2.99991	0.01254	239.20000
...	...	...	...
23.03.2023 20:00	13,00000	0.30374	42.80000
24.03.2023 00:00	24.00000	0.26667	90.00000
24.03.2023 04:00	30.00000	0.24000	125.00000
24.03.2023 08:00	25.00000	0.11236	222.50000
24.03.2023 12:00	17.00000	0.35343	48.10000

Date	Weekly Electricity Consumption Values (kWh)
03.01.2021	0.01421
10.01.2021	0.10472
17.01.2021	0.07343
24.01.2021	0.16620
31.01.2021	0.10874
...	...
19.02.2023	0.12097
26.02.2023	0.06737
05.03.2023	0.11580
12.03.2023	0.09221
19.03.2023	0.27037

Date	Normalized Electricity Consumption Values
01.01.2021 00:00	0.01289
01.01.2021 04:00	0.01321
01.01.2021 08:00	0.00538
01.01.2021 12:00	0.01329
01.01.2021 16:00	0.00519
...	...
23.03.2023 20:00	0.53867
24.03.2023 00:00	0.47075
24.03.2023 04:00	0.42190
24.03.2023 08:00	0.18806
24.03.2023 12:00	0.62970

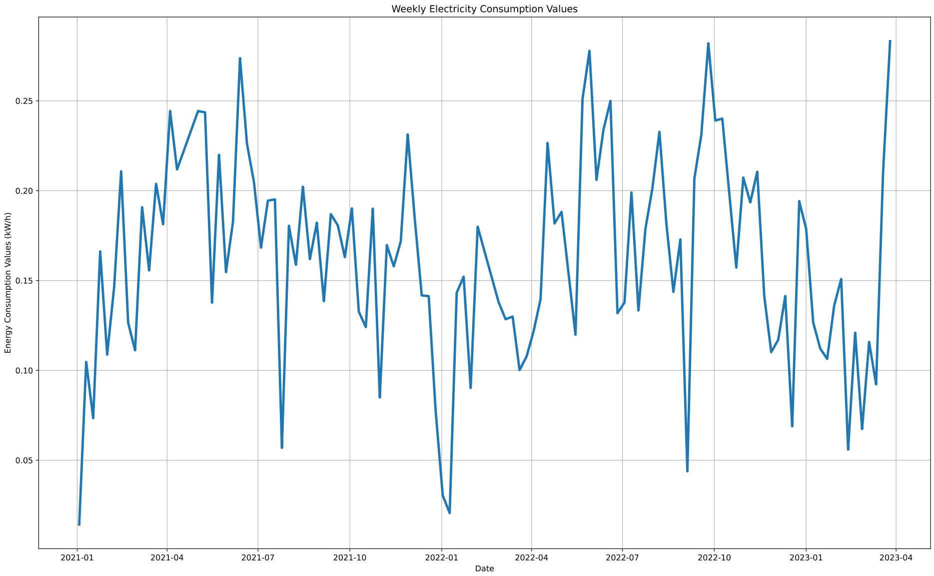

Figure 6. Weekly electricity consumption values of textile machines between january 2021 to April 2023

In this case study, the prediction model is developed with Python. Besides, several Python libraries are used for cleaning the data, mathematical calculations, training the model and predicting thresholds. To this end, Keras and Scikit-learn are used for teaching and training the LSTM model, Numpy and Pandas are used for statistical calculations and Matplotlib is used for generating the graphics. The data is taken from a mercerization machine, which is given in a weekly form between 01.01.2021 and 24.03.2023 in Figure 6, where the data consists of 15706 lines of electricity consumption values. For the SW technique on this time series data, the past 96 hours are processed with the model to predict the upcoming 4 hours. The dataset used in this case study is given in Table 1.

For the LSTM model, the number of epochs is 15, the learning rate is 0.005, the train size is 80% and the test size is 20% of the data. In order to determine these parameters, the trial and error method was used then the most suitable parameters were found in terms of performance, time and accuracy. However, Hyperparameter Tuning is not preferred in this study due to its time consuming, resource and computational requirements. Moreover, the Adam optimizer used in this study optimizes the training process by updating these hyperparameters. There are 2 hidden layers that are also used for the model. For a better model, Rectified Linear Unit (ReLU) is used as an activation function and Mean Absolute Error (MAE) is used as a loss function. In order to measure the efficiency of the proposed model, the prediction values are also generated using RNN and GRU models using the same data for comparison. All parameters of the proposed model are given in Table 2.

Table 2. LSTM model parameters

Deep Learning Model	LSTM with Sliding Window (SW)
Resource Type	Electricity
Type of Textile Machine	Mercerization
PLC	Siemens S7-1200
Energy Analyzer	Entes MPR63
Data Size	15706
Data Range	01.01.2021 to 24.03.2023 (812 days or 19488 hours)
Test Data Range	18.10.2022 to 24.03.2023 (162 days or 3768 hours)
Sliding Window Size	Past 96 hours
Prediction Size	Upcoming 4 hours
Number of Epochs	15
Learning Rate	0.005
SEED	123
Dropout Rate	0.1

Batch Size	128
Train Size	80%
Test Size	20%
Number of Hidden Layers	2
Activation Function	Rectified Linear Unit (ReLU)
Loss Function	Mean Absolute Error (MAE)
Optimizer	Adam
Comparison Models	RNN,GRU and ARIMA
Development Environment	Python
Packages	Scikit-learn, Keras, Pandas, Numpy, Matplotlib

4. Experimental Results

After the training process, the electricity consumption data between 18.10.2022 and 24.03.2023 are applied to the proposed LSTM model for the prediction where the range of the test data is 162 days or 3768 hours. In order to compare the predicted values with the actual values, the predicted values were converted to the original scales. Thus, the prediction values of the test data set will be reached on a real scale. In other words, the predicted values of the target variable based on the input data in the test data set of the model are reversed by the inverse scaling method. The real-time electricity consumption values and the predicted consumption threshold values of the proposed LSTM model are given in Figure 7.

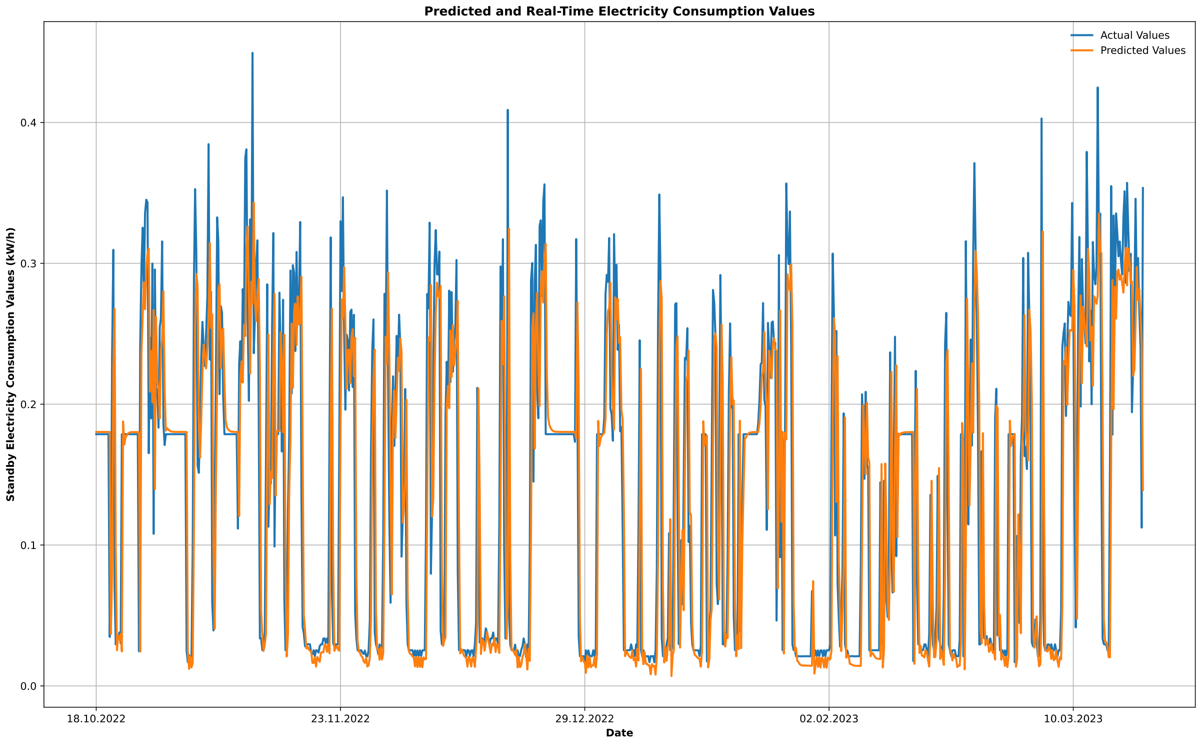

Figure 7. Real-time electricity consumption values and predicted threshold values using the proposed LSTM model

For testing the model performance, accuracy, success and comparison, the same data is also applied to RNN and GRU models using SW technique. In addition, this time series data is applied to the ARIMA model in order to compare the predictions obtained by the traditional methods with the results obtained by the DL methods. The real-time electricity consumption values and the predicted consumption threshold values by the GRU, RNN and ARIMA models are given in Figure 8, Figure 9 and Figure 10, respectively. According to the results, the proposed LSTM model predicts the threshold values closer to the actual values than the other DL models as RNN and GRU. On the other hand, it is observed that the ARIMA model obtains lower prediction results compared to DL models used in this study.

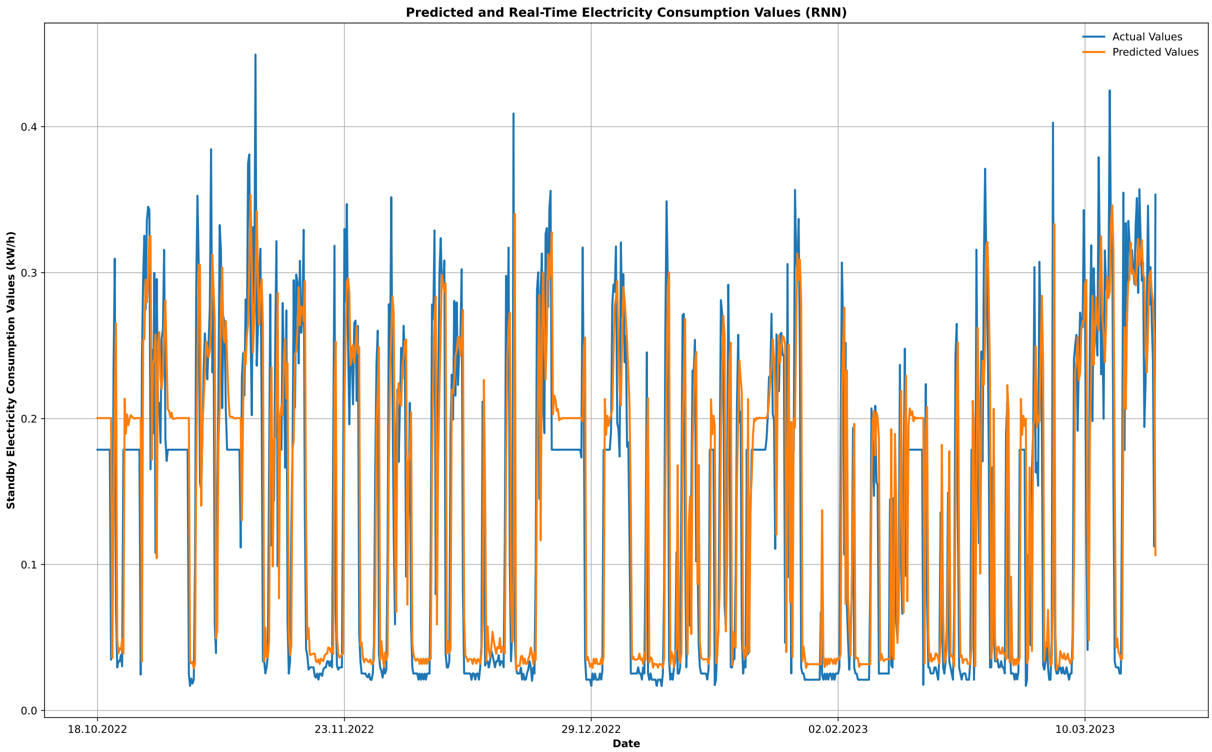

Figure 8. Real-time electricity consumption values and predicted threshold values using RNN

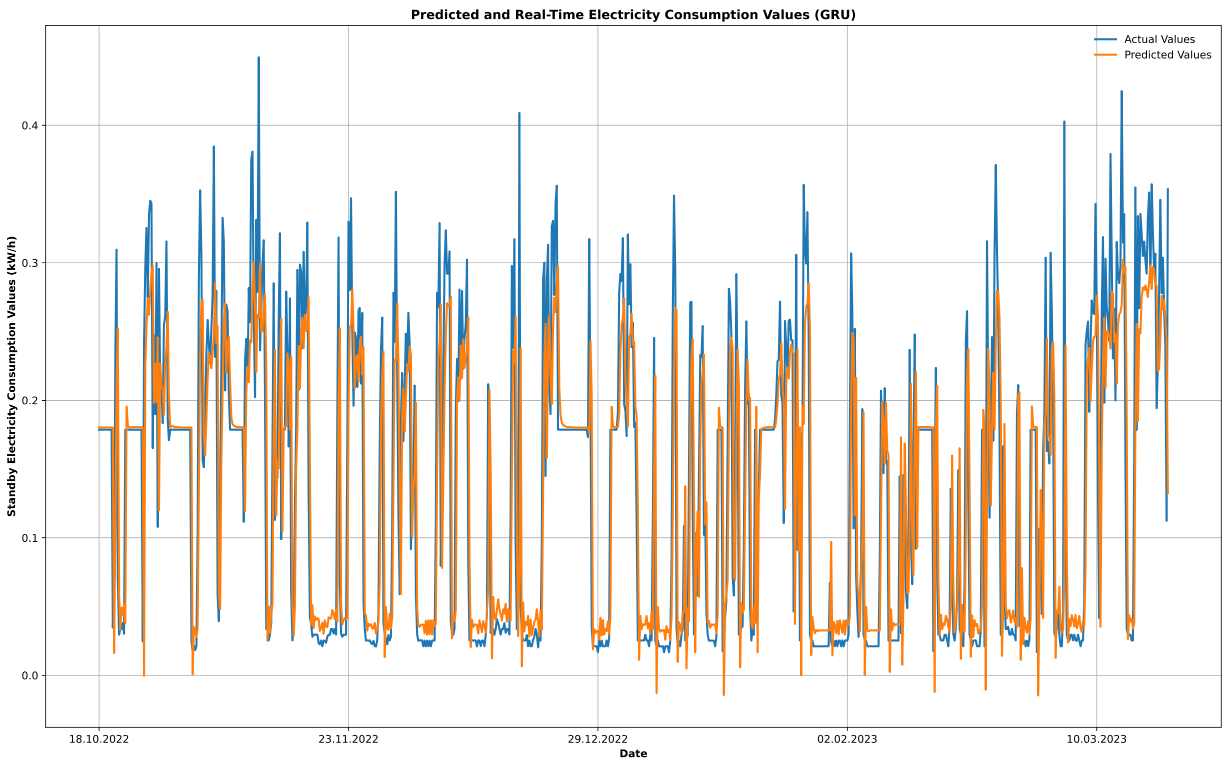

Figure 9. Real-time electricity consumption values and predicted threshold values using GRU

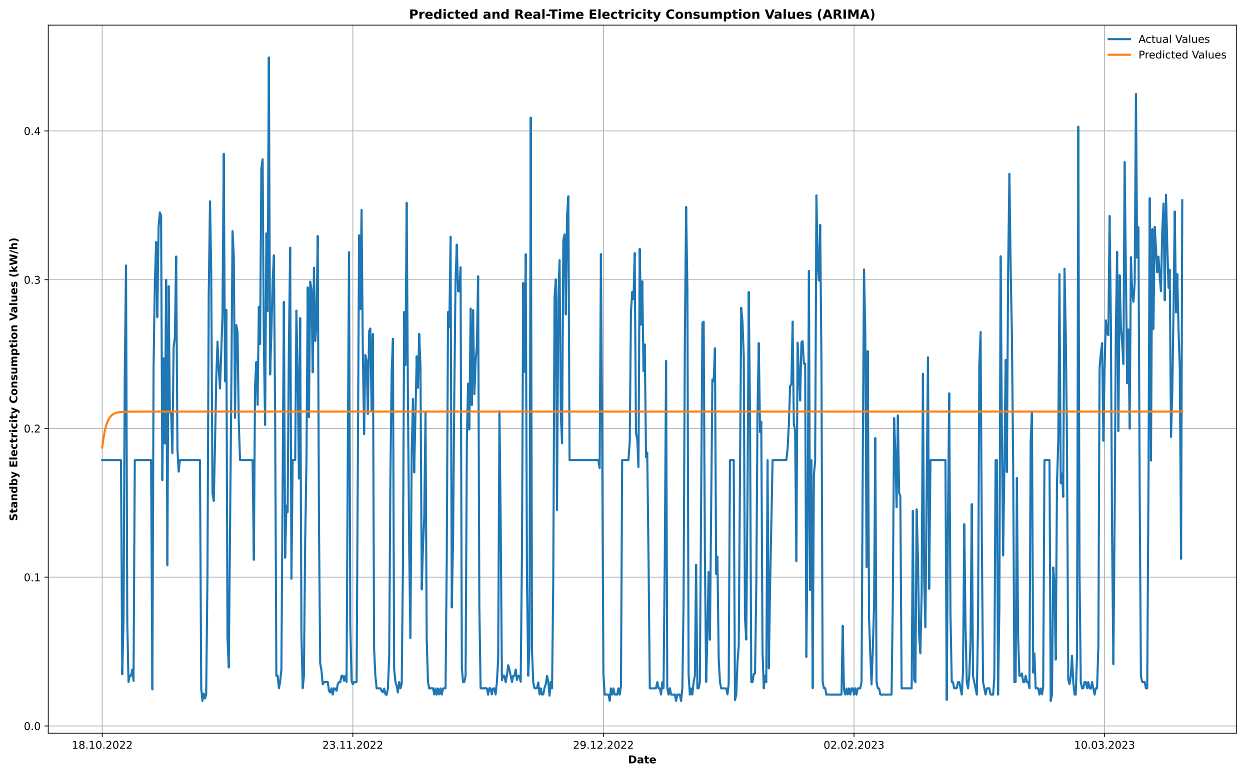

Figure 10. Real-time electricity consumption values and predicted threshold values using ARIMA

The total number of parameters in the model summary determines the complexity of the model and the amount of information it can learn. If the model has more parameters, it can carry more learnable information and capture more relationships. But this also requires more computational power and needs to be trained with more data. The total number of parameters has an impact on the performance and accuracy of the model but is not a stand-alone indicator. However, the risk of over-learning should also be considered. RNN has 30401, GRU has 91601 and LSTM has 121301 parameters. The summary of the models is given in Table 3.

Table 3. Summary of the DL models

	RNN	GRU	LSTM
Model Parameters	30300	91500	121200
Dense	101	101	101
Total Parameters	30401	91601	121301

The results of learning performances per epoch of the proposed LSTM model, RNN model and GRU model are given in Figure 11 (a), 11 (c) and 11 (d), respectively. When the loss values of the models created with LSTM, GRU and RNN layers are compared according to the figure, it is seen that the best result is obtained from the LSTM model due to the decrease in MAE loss values between target values and predictive values in both training and test data sets. In addition, in LSTM model, the fact that the loss values in the training and test data sets are very close to each other makes the model performs better. Figure 11 (b) visualizes the relationship between actual values and predicted values in the LSTM model. According to the figure, the agreement between the actual values and the predicted values is understood from the distribution of the points. The points of the values are located symmetrically around the line dividing the graph in the middle.

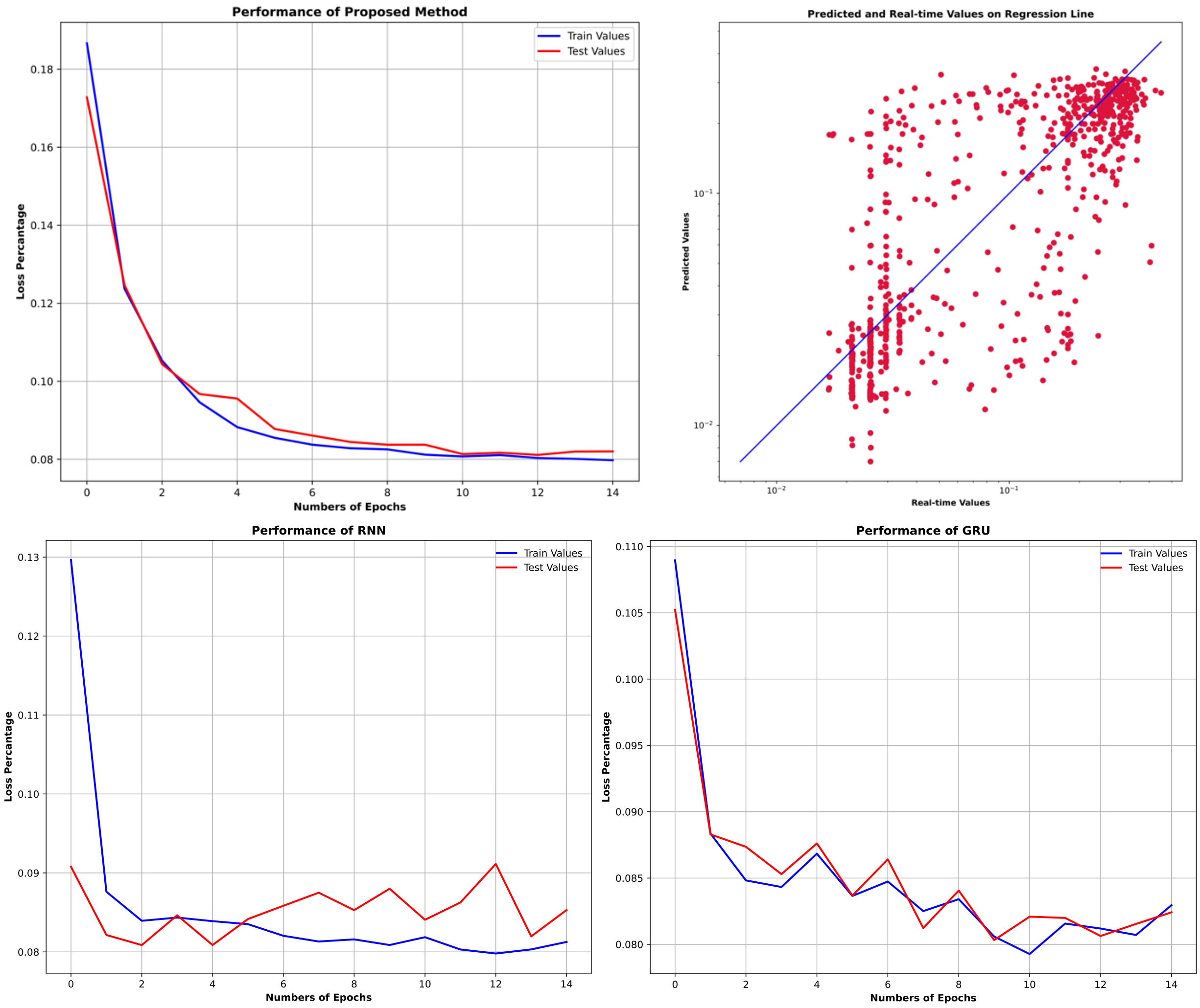

Figure 11. Learning performance results per epoch according to train and test values of LSTM, RNN and GRU and predicted and real-time values of electricity consumption on regression line of the proposed model

While the number of epochs increases, the loss percentage of the proposed model exponentially decreases by the train and the test values. The loss value measures how well the model fits the training dataset after each training epoch. A lower training loss indicates that the model better fits the training data and performs better. The training loss is expected to decrease over time, as the model aims to better understand the data and learn to make predictions more accurately. Test data is generally used to evaluate the generalization ability of the model. A lower test loss indicates that the model performs better overall and also fits well with the new data which is expected to decrease or remain the same over time. Average loss and error comparison results are given in Table 4.

Table 4. Average loss and error comparison results

	RNN	GRU	LSTM
Training Loss	0.0813	0.0830	0.0798
Test Loss	0.0853	0.0824	0.0820
RMSE	0.07149	0.0697	0.0728
MAE	0.0465	0.0449	0.0447

5. Result and Discussion

Recent technologies lead processes smarter in the manufacturing industry. While the production is continuous, these processes need more resource consumption. In recent years, free resources dramatically decrease therefore, their usage needs to be minimized. Thus, smart manufacturing should be optimized for resource consumption.

In this paper, LSTM with Sliding Window technique-based Deep Learning method is proposed for preventing the over-consumption of electricity in a textile factory as a case study. The proposed study offers a new perspective to the existing literature by focusing on the standby electricity energy consumption of textile machines and emphasizes that standby energy consumption is an overlooked area and long waiting times can lead to huge costs. The results of this study have the potential to contribute to the studies in the field of energy efficiency, as well as to reduce the energy costs of enterprises and achieve their sustainability goals.

The proposed method predicts upcoming 4-hour consumption thresholds of electricity, learning from the past 96-hour time series that helps the machines to stop manufacturing if needed by sending an interrupt signal to the PLC unit when the consumption levels reach these thresholds. The calculated thresholds are also compared with the results of RNN and GRU methods and the real-time resource consumption data in order to ensure the high accuracy of the proposed model. According to the results, the proposed model successfully predicts threshold levels of electricity values for preventing over-consumption. Additionally, the proposed model is a powerful tool for controlling the productivity of these textile machines.

On the other hand, in the textile industry, the resources are not limited to electricity. The other most important resources for textile machines are steam, hot water and natural gas therefore, the consumption of these resources should also be minimized. In future studies, the consumption values of these resources will be together taken into account.

Resource consumption in textile manufacturing depends on several parameters such as fabric type, machine type and process type that may change the resource consumption values thus making its estimation difficult. In this work, these parameters have not been included in the model. In order to predict resource consumption, these parameters will also be considered for future work. Additionally, the time spent and the performance of the proposed method in this case study should be also optimized. Therefore, the proper metaheuristic-based solutions will be implemented in the next model.

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Conflict of Interest

No conflict of interest was declared by the authors.

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