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Conception of a new quality control method based on neural networks

Zoubaidi Z.[1], Herrou B.[1], Sekkat S.[2], Khadiri H.[2]

[1] *Industrial technique laboratory, FST, Sidi Mohamed Ben Abdellah University, Route d'Imouzzer B.P. 2626, 30000, Fes, Morocco*
[2] *IASI-ENSAM, Moulay Ismail University, Marjane 2, B.P. 298, Meknes 50050, Morocco*

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The prediction of failures in a factory is now an important area of industry that helps to reduce time and cost of non-quality from the data generated from the sensors installed on production lines, this data is used to detect anomalies and predict defects before they occur. The purpose of this article is to model an intelligent production line capable of predicting various types of non-conforming products. For that, we will utilize the neural network methodology within the specific context of a production line specialized in juice manufacturing. Firstly, we introduce the production line under study, along with its distinct manufacturing phases. Secondly, we evaluate the performance indicators of this line, enabling us to gain an overview of its efficiency and overall performance. Subsequently, we present common industrial solutions that are frequently implemented to address the issues identified during our analysis. At this stage, we propose a predictive model based on neural network methodology. This model will possess the capability to detect and identify defective products and potential hazards within a production line before they occur. Throughout this study, we compare between three models of neural networks: LSTM model using Stochastic gradient descend (SGD), Feed forward model using ADAM Optimization and Feed forward model using Levenberg-Marquardt back propagation (LMBP), in order to determine the most optimal method in terms of achieved results. Finally, we demonstrate the effectiveness, performance, and accuracy of the results through the testing phase of the neural networks.

Keywords: *OEE; ADAM; LMBP; LSTM; SGD; feed forward; neural networks; quality defects; root causes of defects.*

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1. Introduction

The global context of the manufacturing industry is characterized by a complex and eve revolving dynamic. This sector plays a fundamental role in the global economy, encompassing a diversity of industries ranging from automotive production to the manufacturing of consumer goods. The manufacturing industry serves as a driver for job creation, technological innovation, and economic growth on a global scale. However, it also faces significant challenges such as increasing pressure to reduce costs, the rapid adoption of new technologies, and the need to adapt to increasingly stringent sustainability standards. Industry 4.0 refers to the fourth industrial revolution, where a new technological development has occurred in production systems. This development has evolved as a result of the integration of the Internet of Things, cyber-physical systems, Big Data, artificial intelligence, and cloud computing into industrial systems. This integration has enabled new management capabilities to reach a higher level of excellence, efficiency, and effectiveness. Several issues can arise in a production line, such as high scrap rates, corrective maintenance downtime, inadequate production planning and scheduling, logistic problems. Industry 4.0 has proposed effective solutions by harnessing advanced artificial intelligence technologies to address these problems. Among these solutions, additive manufacturing, production-planning using a holonic approach, as well as predictive maintenance and defect prediction. In this article, we will specifically concentrate on the concept of predicting quality defects within a production line. Minimizing defects in the production process is of crucial importance for companies operating in the manufacturing sector. Production defects have a significant impact on the quality of finished products, potentially leading to a decrease in customer satisfaction and a deterioration of the company's reputation. Additionally, the costs associated with correcting defects after production can be substantial, encompassing expenses related to repairs, product recalls, and potential sales losses. Operational efficiency is also heavily affected, as defects can result in production delays, inefficient use of resources, and an increase in labor costs. In a competitive global market focused on quality and customer satisfaction, defect minimization becomes imperative to maintain competitiveness, retain customer loyalty, and ensure the long-term sustainability of the company. Thus, strategies aimed at preventing and predicting defects before they occur become essential elements of modern production management. Production defects have a significant financial impact on various crucial aspects within a manufacturing company. Firstly, the costs associated with correcting defects can be substantial, including expenses related to product recalls, repairs, and production rework. These costs not only directly affect the company's financial results but also result in inefficient use of resources. Additionally, defects compromise the quality of finished products, leading to merchandise returns, customer losses, and a deterioration of the company's reputation. Lastly, customer satisfaction is greatly affected, as defective products can result in negative experiences, complaints, and additional costs associated with managing dissatisfaction. Thus, the financial effect of production defects ripples throughout the entire value chain, emphasizing the imperative to implement effective strategies to prevent and minimize these defects. The prediction of scrap products aims to anticipate defects before they occur, enabling a reduction in waste costs and an improvement in customer satisfaction rates. The objective of this article is to introduce a novel approach for predicting defective products using neural network technology. This approach will be exemplified through the examination of a real case study on a production line specialized in juice manufacturing.

2. Failure prediction model

2.1. Literature review

Predictive maintenance and defects prediction is a rapidly growing research field aimed at enhancing the efficiency and reliability of industrial systems. The use of neural networks for defects prediction has garnered increasing interest due to their ability to model complex data, such as time series, and capture subtle patterns. Reference [1] proposed an LSTM model for defect prediction in manufacturing systems, demonstrating improved accuracy compared to traditional methods. LSTMs are capable of retaining information over long time sequences, making them ideal candidates for capturing intricate dependencies within the data. Reference [2] presented a failure prediction of turbine blade coatings using feed forward network. The model exhibits better prediction accuracy on interface oxidation, damage evolution and failure region of TBCs on turbine vane. Reference [3] developed a new hybrid model for predicting air quality combining Holt-Winters and deep learning approaches. The results founded indicate a good finding with an index of agreement equal to 0.91 and a lower value of the error indices MSE $= 0.0032$. Reference [4] proposed a new intelligent and data-driven product quality control system of industrial valve manufacturing process using a BP neural network. This model shows that the new quality control system has good accuracy and practicability. Reference [5] reformulated a diabetes prediction using an Adam's algorithm and Tikhonov regularization. Then, they compared with the Stochastic gradient descend which approved a high performance of the proposed algorithm. Huang and Li (2023) introduced a Levenberg–Marquardt algorithm to realize a predictive control model of seismic responses of a novel seismic isolation and non-seismic isolation composite structure system. This method can effectively reduce the adverse effects of time lag on the structural control system.

2.2. Quality control

In a company, there are various sources of waste that can optimize operational efficiency and reduce profitability. Mudas refer to the forms of waste in production and management processes, and are primarily associated with the philosophy of Lean Manufacturing, which aims to eliminate any activity that does not add value to the product. The concept of Mudas was developed in Japan by Toyota in the 1940s and 1950s and has become a central element of the company's production system, also known as the Toyota Production System (TPS). Taiichi Ohno, one of the main architects of the TPS, popularized the term "muda" means "waste" in Japanese, and it. The primary goal of the TPS was to achieve a "just-in-time" production, where the quantity of products manufactured precisely matched the market demand, with no excess inventory or waiting time. There are seven types of wastes (mudas) within the framework of Lean Manufacturing:

1. Overproduction: Producing more than necessary or before the demand exists, resulting in excess inventory and high storage costs.
2. Waiting: Downtime or waiting time between different production stages, slowing down the overall process.
3. Transportation: Unnecessary movement of products or materials, which can increase the risk of damage or loss.
4. Over processing: Adding unnecessary features to the product, increasing costs without adding extra value for the customer.
5. Inventory: Having too much stock, which can lead to high storage costs.
6. Unnecessary Motion: Unnecessary movements of operators or machines, which can lead to fatigue or errors.
7. Defects: Producing defective or non-compliant products, resulting in additional costs for repair or rejection.

The Lean Manufacturing approach aims to identify and eliminate these forms of waste to improve efficiency, reduce costs, and deliver higher-quality products. This methodology has been widely adopted in the manufacturing sector and beyond, remaining a crucial tool for businesses seeking to optimize their operations and create value for their customers. The concept of quality always emerges as a major and relevant pillar to validate the performance and efficiency of a company. It is defined according to the ISO 9001 standard as the ability of the company to meet the requirements and expectations of its customers through appropriate policies and strategies that demonstrate and ensure its serious commitment [6].

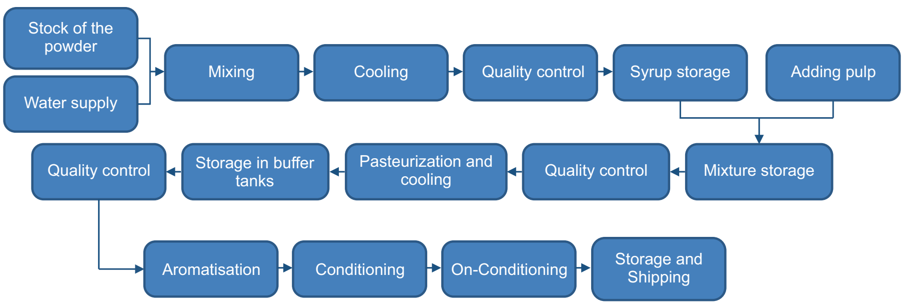

Fig. 1. Juice manufacturing diagram.

The companies are focused on exploring their requirements in terms of product or service compliance. This notion of compliance is explicitly exploited in the calculation of the company's performance indicators, specifically the Overall Equipment Efficiency (OEE) calculation. The NF E60-182 standard defines OEE as the ratio of fully productive time to planned productive time. We can further break it down as:

$$\text{OEE} = \text{Quality rate} \times \text{Performance rate} \times \text{Availability},$$

$$\text{Qualityrate} = \frac{\text{The yield produced}}{\text{The production quality}},$$

$$\text{Availability} = \frac{\text{Total hours planned-Lost time}}{\text{Total hours planned}},$$

$$\text{Performancerate} = \frac{\text{Acutal Machine Speed}}{\text{Design Machine Speed}}.$$

Over a period of six months, we calculated the OEE as illustrated in Figure 2.

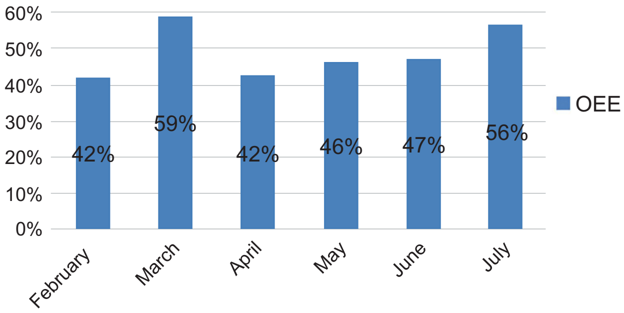

Fig. 2. OEE calculation.

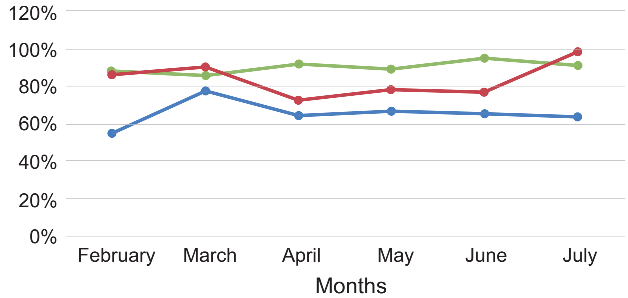

Fig. 3. KPIs calculation.

We observe an average value of the Overall Equipment Efficiency (OEE) rate equal to 49% during these 6 months of study. In the industry, the OEE is considered satisfactory if its value approaches 100%. Therefore, in our case, it is imperative that we implement methods aimed at improving this rate. On Figure 3, the quality rate shows the lowest values, necessitating a thorough analysis of the root causes of the defects in order to propose relevant corrective actions. The execution of this analysis begins with identifying the most frequent defects through historical data and consolidating them into a Pareto chart. Next, we determine the signatures of critical defects. This step helps us to collect various data and specifications that characterize each failure, which facilitates the development of relevant improvement actions. Subsequently, we reach the step of analyzing the root causes of defects. It is a systematic problem-solving method introduced by Taiichi Ohno.

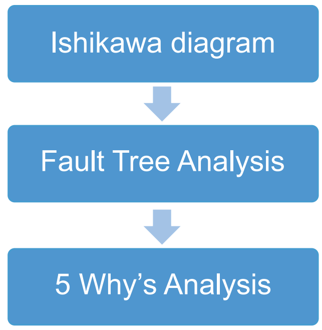

Fig. 4. Failure root causes analysis steps.

Through this analysis, we had the opportunity to access to the defect history that occurred on this production line over the past three years. This allowed us to collect more than 1000 data. Continuing with the steps mentioned above, we identified the most common defect types (16 defects identified) and matched them with their root causes (21 causes).

2.3. Predictive approach based on neural networks

A predictive approach based on neural networks represents a cutting-edge methodology in the realm of data-driven forecasting and decision-making. Neural networks, inspired by the structure of the human brain, excel at recognizing complex patterns and relationships within vast datasets. In a predictive context, these networks are trained on historical data to discern underlying patterns and trends, enabling them to make informed predictions about future outcomes. The strength of this approach lies in its ability to adapt and learn from data, allowing neural networks to capture intricate nonlinear relationships that might elude traditional statistical methods. This predictive power finds applications in various fields, from finance and healthcare to manufacturing and marketing, where accurate forecasting is essential for strategic planning. Leveraging the capabilities of neural networks in predictive modeling not only enhances the accuracy of predictions but also provides valuable insights for informed decision making in dynamic and evolving environments. The proposed methodology involves training the machines installed along the production line to react intelligently to these issues. In other words, we will introduce the identified defect causes from the conducted analysis as input data, while the defect types will constitute the output data. This way, the machines will constitute a learning process concerning these defects, enabling us to predict these anomalies before they occur.

Table 1. Defects associated to causes.

Description of Defect	Cause of Defect
Development of pathogenic bacteria, yeasts, and molds	Storage of the finished product at a temperature $\geqslant 6°C$ Inadequate storage conditions
Foul odor in the finished product	Presence of volatile substances and impurities in the steam used for packaging closure
Contamination by pathogenic agents	Defective sealing of the packaging closure Use of contaminated steam for sealing the packaging jar
Microbial contamination	Contamination through compromised conduits conveying juice from the pasteurizer outlet to the temporary storage tank, or due to inadequate tank cleaning
Persistence of thermoresistant spores and pathogenic germs Partial degradation of enzymes (pectinases)	Non-compliance with pasteurization temperature scale: (89 to $94°C/18\,s$)
Proliferation of pathogenic and spoilage microorganisms in the mixture	Non-compliance with storage temperature ($\leqslant 4°C$) Usage of contaminated water or ingredients
Proliferation of pathogenic and spoilage microorganisms in the mixture	Non-compliance with nectar preparation quantities Insufficient acidity
Possible contamination of syrup by molds or fungi (Mucor)	Non-compliance with storage conditions (cooling, hygiene, and enclosure integrity)
Residues from cleaning and disinfection products	Insufficient rinsing of the mixer
Contamination of orange juice concentrate by cleaning solvents, detergents, and biocides	Presence of leaks in the packaging bags of juice concentrate within the cold chambers Inadequate rinsing of cold chambers after applying cleaning solvents, detergents, and biocides
Proliferation and persistence of microorganisms/ spoilage agents (yeasts and molds: Aspergillus, Fusarium)	Defects in refrigeration (proliferation due to non-compliance with storage temperature guidelines) Break in the cold chain Plastic bags used for packaging juice concentrate for refrigeration are contaminated or not properly sealed, allowing air entry and promoting bacterial proliferation
Development of pathogenic microorganisms	High water activity ($aw > 0.85$) due to issues with applying temperature and pressure parameters in the three-effect evaporation system (temperature and/or pressure drop)
Presence of pulp in the juice (risk of heat exchanger clogging in subsequent processing stages)	Centrifugation or clarification issues at the clarifier level
Presence of seeds (release of a bitter taste in the juice in case of their rupture)	
Proliferation of bacteria, yeasts, and molds (Aspergillus, Fusarium)	Elevation of juice temperature due to a malfunction in the plate heat exchanger operation

3. Neural networks

The neural network method is a sophisticated machine learning approach inspired by the functioning of the human brain. Comprising interconnected layers of nodes, neural networks are capable of performing complex tasks such as pattern recognition, classification, and prediction. What sets neural networks apart is their ability to learn from data. During the learning phase, the network automatically adjusts its weights and parameters based on patterns identified in the training data. These adjustments enable the network to generalize its knowledge and make informed decisions on new data. The advantages of neural networks lie in their ability to process complex and nonlinear data, adapt to changing environments, and deliver high performance in areas such as computer vision, natural language processing, and prediction. Their versatility and ability to model subtle relationships make them a powerful method for solving complex machine learning problems.

In this article, we work with:

a) Feed forward networks (case a), LSTM networks (case b).
b) 10 hidden layer with 18 neurons.
c) The input layer consists of 21 neurons (corresponding to 21 causes).
d) Output layer consists of 16 neurons (16 types of failures).
e) 600 data are used in the learning phase and 400 are allocated for the testing phase.
f) Forward propagation: We use the activation function as: Sigmoid, RelU, Tanh.
g) Optimization algorithm: SGD in LSTM model, ADAM and LVBM in feed forwards model.

LSTM model is presented like:

$$\begin{aligned}
\text{Forget gate: } & f_t = \sigma\big(W_{hf}h_{t-1} + W_{xf}x_t + b_f\big),\\
\text{Input gate: } & i_t = \sigma\big(W_{hi}h_{t-1} + W_{xi}x_t + b_i\big),\\
\text{Output gate: } & o_t = \sigma\big(W_{ho}h_{t-1} + W_{xo}x_t + b_o\big),\\
& c_t = f_t * c_{t-1} + i_t * \tanh\big(W_{hh}h_{t-1} + W_{xh}x_t + b_t\big),\\
& h_t = o_t * \tanh(c_t).
\end{aligned}$$

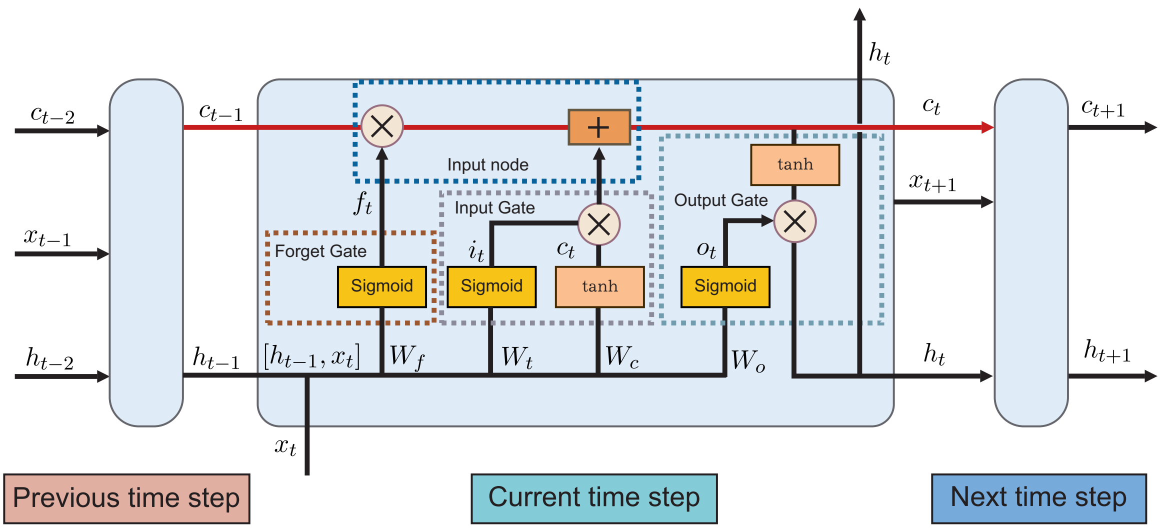

Fig. 5. LSTM model representation.

Stochastic gradient descent is presented like:

$$w^l_{i,j} = w^l_{i,j} - \alpha \nabla w^l_{i,j},$$
$$b^l_{i,j} = b^l_{i,j} - \alpha \nabla b^l_{i,j},$$

where α is the learning rate, $w^l_{i,j}$ is the weight of the i^{th} neural of the l^{th} layer that comes from the j^{th} neural of the previous layer, $b^l_{i,j}$ is the bias of the i^{th} neural of the l^{th} layer that comes from the j^{th} neural of the previous layer, $\nabla w^l_{i,j} = \frac{\partial J}{\partial w^l_{i,j}}$ is gradient descent of the cost function for the $w^l_{i,j}$, $\nabla b^l_{i,j} = \frac{\partial J}{\partial b^l_{i,j}}$ is gradient descent of the cost function for the bias $b^l_{i,j}$.

ADAM Optimizer is presented like:

$$V_{dw^l_{ij}} = \beta_1 \cdot V_{dw^l_{ij}} + (1 - \beta_1) \cdot \nabla J_{w^l_{ij}},$$
$$V_{db^l_{ij}} = \beta_1 \cdot V_{db^l_{ij}} + (1 - \beta_1) \cdot \nabla J_{b^l_{ij}},$$

$$S_{dw_{ij}^l} = \beta_2 \cdot S_{dw_{ij}^l} + (1-\beta_2)\cdot(\nabla J_{w_{ij}^l})^2,$$
$$S_{db_{ij}^l} = \beta_2 \cdot S_{db_{ij}^l} + (1-\beta_2)\cdot(\nabla J_{b_{ij}^l})^2,$$
$$V_{dw_{ij}^l}^{\text{corrected}} = \frac{V_{dw_{ij}^l}}{1-\beta_1^T},$$
$$V_{db_{ij}^l}^{\text{corrected}} = \frac{V_{db_{ij}^l}}{1-\beta_1^T},$$
$$S_{dw_{ij}^l}^{\text{corrected}} = \frac{S_{dw_{ij}^l}}{1-\beta_2^T},$$
$$S_{db_{ij}^l}^{\text{corrected}} = \frac{S_{db_{ij}^l}}{1-\beta_2^T},$$
$$w_{ij}^l = w_{ij}^l - \alpha \cdot \frac{V_{dw_{ij}^l}^{\text{corrected}}}{\sqrt{S_{dw_{ij}^l}^{\text{corrected}}}},$$
$$b_{ij}^l = b_{ij}^l - \alpha \cdot \frac{V_{db_{ij}^l}^{\text{corrected}}}{\sqrt{S_{db_{ij}^l}^{\text{corrected}}}},$$

where $v_{dw_i}^{\text{corrected}}$ is momentum of weight $w_{i,j}$ after the correction of β_1, $v_{db_i}^{\text{corrected}}$ is momentum of bias $b_{i,j}$ after the correction of β_1, β_1^T is momentum β_1 squared T iterations, $s_{dw_i}^{\text{corrected}}$ is moving average of squared gradients of weight $w_{i,j}$ after the correction of β_2, $s_{db_i}^{\text{corrected}}$ is moving average of squared gradients of bias $b_{i,j}$ after the correction of β_2, β_2^T is momentum β_2 squared T iterations.

Lmbp optimization: It is a method used to minimize the cost function of a neural network. LVBM utilizes an approximation of the Hessian matrix (the matrix of the second partial derivatives of the cost function) by combining the Gauss-Newton method with the SGD (Stochastic Gradient Descent) method. The weight is presented like:

$$w(t+1) = w(t) - \left(J_t^T J_t + \mu I\right)^{-1} J_t^T e,$$

where $e = A - Y$, Y is the value of expected result, A is the value of the result found, J_t is Jacobian matrix for the cost function.

3.1. Results and discussions

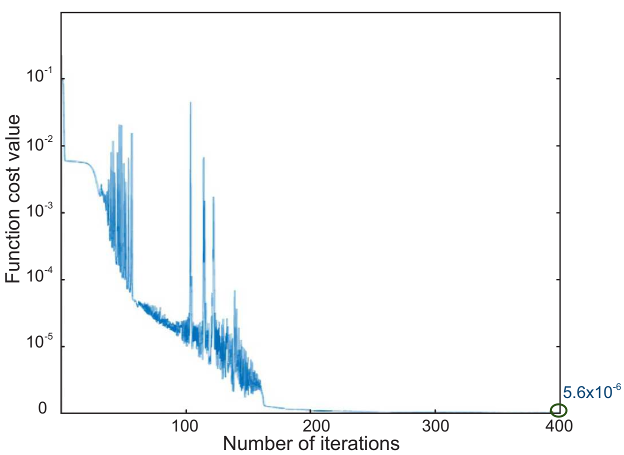

Fig. 6. Curve of MSE for the LMBP Optimization.

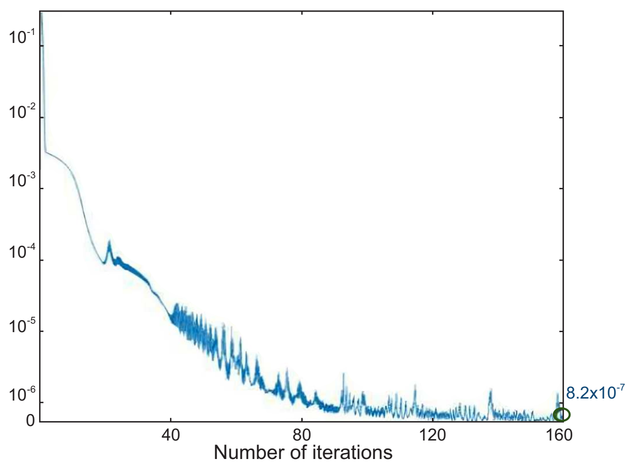

Fig. 7. Curve of MSE for the ADAM Optimization.

On the first graph, we can observe that the cost function reached the value 5.6×10^{-6} after 400 iterations performed. On the other hand, the second graph, which refers to the model developed using ADAM optimization, reached the value 8.2×10^{-7} after only 160 iterations. The third graph achieved an error value of 5.13×10^{-7} after 120 iterations. Furthermore, we can see the difference in shape between three curves. The first one exhibited spikes after a regression towards an average value of 10^{-6}. Additionally, we can observe in the figure that during 200 iterations, the cost function's value did not undergo significant changes. On the other hand, we can see that the second and third method yielded a more optimal result in terms of the founded value and in terms of processing time. Thus, we can observe that the second and third model achieve a similar value of MSE. As a result, we can say that the ADAM optimization and the LSTM model had proved their performance and their efficiency to predict defects on a production line. We choose to adapt ADAM optimization in the phase of Test. As mentioned above, we divided the collected data into two parts: the first dedicated to training and the second devoted to the testing phase. The testing phase of a neural network is a crucial step in evaluating its performance. After being trained on a dataset, the network is exposed to data it has never encountered before, simulating real-world conditions. During this phase, the neural network generates predictions based on its previous learning. The primary goal is to assess the network's ability to generalize its knowledge and produce accurate results on novel data. The testing phase also helps identify potential overfitting issues where the network performs well on training data but less effectively on new data. Good performance during the testing phase indicates that the network can make precise and reliable decisions in real-world situations, reinforcing its applicability for practical use. The result obtained during this step is illustrated in a graph, which describes the value of the cost function for each data.

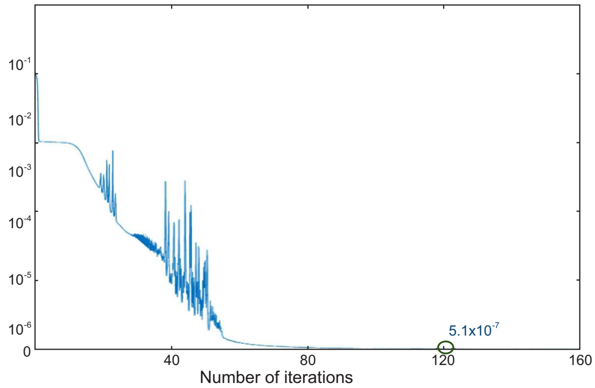

Fig. 8. Curve of MSE for the LSTM model.

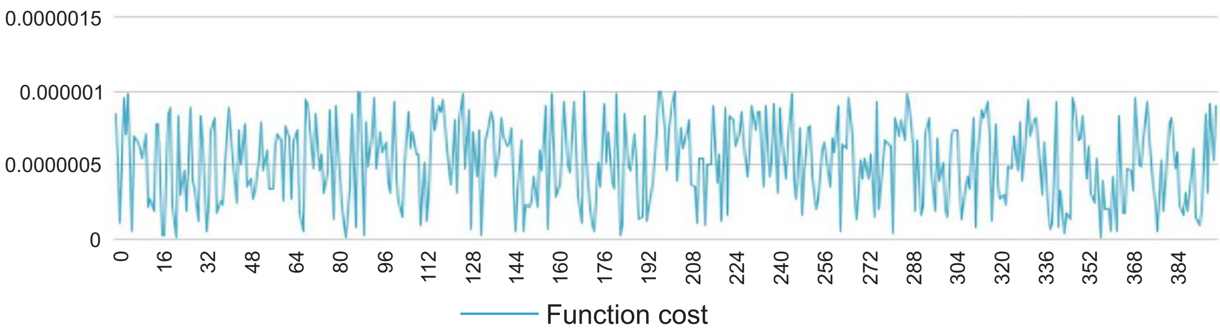

Fig. 9. Curve of the cost function during the test phase.

The results shown in Figure 6 demonstrate the effectiveness and performance of our system in predicting 75% of failures on the production line. The values are between 10^{-4} and 10^{-9}; as a result, we can validate the model developed.

4. Conclusion

The increasing complexity of production systems represents a major challenge for companies in the manufacturing sector. As technologies evolve and market demands intensify, production systems become progressively more sophisticated and interconnected. The integration of artificial intelligence, advanced automation, massive data collection, and the Internet of Things (IoT) contributes to heightened complexity. While this sophistication aims to improve operational efficiency, product quality, and flexibility, it simultaneously introduces challenges in terms of management and maintenance. Effectively coordinating the various components of the system, managing complex information flows, and ensuring seamless interoperability between equipment become crucial. The rising complexity of production systems calls for a strategic approach to ensure optimal performance while remaining adaptable to future market and technological developments. Proactive prediction of defects holds significant potential for enhancing operational efficiency and product quality in manufacturing environments. By anticipating and identifying potential defects before they occur, companies can implement corrective measures before major issues arise. A preventive approach helps minimize unplanned downtime, optimize production processes, and reduce costs associated with repairs and returns of defective products. Moreover, the ability to predict defects offers the opportunity to improve product quality by ensuring early detection of undesirable variations in the manufacturing process. By integrating advanced technologies such as machine learning and real-time data analysis, companies can create robust prediction models that contribute not only to the proactive resolution of issues but also to the continuous optimization of operations and the assurance of high product quality. Predicting failures using neural networks is a valuable and powerful approach in various industries. Neural networks have demonstrated their capabilities to analyze complex data patterns and identify potential failures before they occur. By training on historical data and learning from past failure instances, the neural network model using the gradient descent with ADAM Optimization proposed in this article was able to demonstrate and to prove its capability to occur 75% of failures. The neural networks can adapt and learn from new data, continuously improving their predictive accuracy over time. With their ability to handle large volumes of data and process it quickly, we will work on the optimization of the cost function value and time of training (number of iterations) to help industries to achieve higher reliability and productivity while minimizing unexpected downtime and associated costs.

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Концепція нового методу контролю якості на основі нейронних мереж

Зубайді З.[1], Херру Б.[1], Секкат С.[2], Хадірі Х.[2]

[1] *Лабораторія промислових технологій, FST, Університет Сіді Мохамеда Бен Абделлаха, Імоуззерська дорога, п.с. 2626, 30000, Фес, Марокко*
[2] *IASI-ENSAM, Університет Мулая Ісмаїла, Марджане 2, п.с. 298, Мекнес 50050, Марокко*

Прогнозування збоїв на заводі зараз є важливою галуззю промисловості, яка допомагає скоротити час і вартість неякісних даних, отриманих від датчиків, які встановлені на виробничих лініях. Ці дані використовуються для виявлення аномалій і прогнозування дефектів до їх виникнення. Метою цієї статті є моделювання інтелектуальної виробничої лінії, здатної передбачати різні типи невідповідної продукції. Для цього використовується методологія нейронної мережі в конкретному контексті виробничої лінії, що спеціалізується на виробництві соків. По-перше, представлено досліджувану виробничу лінію разом із її різними етапами виробництва. По-друге, оцінено показники продуктивності цієї лінії, що дозволяє отримати уявлення про її ефективність і загальну продуктивність. Далі подано загальні промислові рішення, які часто впроваджуються для вирішення проблем, що виявлені під час нашого аналізу. На цьому етапі запропоновано прогностичну модель на основі методології нейронної мережі. Ця модель матиме можливість виявляти та ідентифікувати дефектні продукти та потенційні небезпеки на виробничій лінії до того, як вони виникнуть. Порівняно три моделі нейронних мереж: модель LSTM з використанням стохастичного градієнтного спуску (SGD), модель прямої подачі з використанням оптимізації ADAM і модель прямої подачі з використанням зворотного поширення Левенберга–Марквардта (LMBP), щоб визначити найбільш оптимальний метод з точки зору досягнутих результатів. Нарешті, продемонстровао ефективність, продуктивність і точність результатів на етапі тестування нейронних мереж.

Ключові слова: *OEE; ADAM; LMBP; LSTM; SGD; передавання; нейронні мережі; дефекти якості; першопричини дефектів.*