Neural Networks for Predicting Industrial Paper Press Condition

Subjects: Engineering, Electrical & Electronic
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Forecasting has extreme importance in industry due to the numerous competitive advantages that it provides, allowing to foresee what might happen and adjust management decisions accordingly. Industries increasingly use sensors, which allow for large-scale data collection. Big datasets enable training, testing and application of complex predictive algorithms based on machine learning models.

maintenance neural networks XGBoost forecast

1. Introduction

Advanced sensing technology, combined with high performance computing, help industries run with increasing reliability and competitiveness.

Industries are striving to constantly improve industrial processes and equipment. Maintenance plays a fundamental role in this field, being very important to prevent disruptions in production chains.

1.1. The Importance of Maintenance

Maintenance is a combination of technical and administrative activities required to maintain equipment, facilities, and other physical assets. The goal is to maintain those assets in the desired operational condition, or restore them so that they can fulfil their function with quality [1][2][3]. The main objectives of a good maintenance policy are: safety, quality, cost reduction, and availability [4]. The optimization of those four objectives at the same time is challenging, since they often conflict with each other. In those cases, it is the maintenance management's responsibility to find the best compromise solution based on the company's strategic objectives.

Predictive maintenance is one of the fastest growing types of maintenance in the industry nowadays [5]. It aims to predict the occurrence of failures before they happen, using data from sensors and state-of-the-art augmented intelligence algorithms. The algorithms are trained based on historical data, the operating condition of the assets is monitored, and the trends are predicted in near real time.

Industrial systems currently use tens, hundreds, or thousands of sensors to collect data to be used primarily to monitor processes and equipment condition [6][7].

Due to developments in data processing, along with storage algorithms and hardware, it is currently possible to store and process large quantities of data to predict the future behaviour of equipment, thus making it possible to forecast failures in advance [8].

The asset's behaviour, after being observed and analyzed, can be predicted with state-of-the-art algorithms. Such techniques have a positive impact on production reliability, security, availability and quality [9]. It should also be noted that predictive maintenance promotes environmental sustainability, as it contributes to reduce industrial downtimes, unnecessary maintenance interventions, production surpluses, and non-conforming products [10].

1.2. Industry 4.0 in Maintenance

Industry 4.0 is a consequence of scientific and technological advances, including predictive maintenance.

The amount of data extracted from industrial processes has exponentially increased due to the rise of non-invasive sensing technologies and decreasing hardware costs. However, it is essential to calibrate the sensors correctly, so that the acquired data are reliable [7][11]. Poor or incorrect data do not add value and can lead to prediction errors [12][13].

Analysis of reliable data with predictive computational techniques can avoid unnecessary equipment changes, save costs and improve safety, availability, and efficiency of processes [14].

1.3. Predictive Maintenance from an Economic Point of View

Maintenance was often seen as a source of unnecessary cost by industry, so it was often overlooked by companies. Nowadays, the role of maintenance is better understood. It is considered a key factor for the success of companies, helping them to reduce production costs and, consequently, increase profits [15].

Although applying predictive maintenance policies may involve significant costs, those costs are often less than the benefits generated from a well-planned system [16].

Most devices involve an expensive hardware network, formed by many sensors for data collection and storage. In addition to hardware, predictive maintenance requires additional costs for training staff, as well as analysing data and developing and training prediction and classification methods.

By enabling more efficient, sustainable, and higher quality production, the application of predictive maintenance also affects the company's image in the market and contributes to increase its value.

Predictive maintenance can be applied to almost all industrial equipment. However, due to its high implementation costs, technical and economic analyses must be performed before proceeding to modelling and deployment, namely determining the criticality of the equipment in case of failure or anomaly, and the potential economic losses for the company.

According to François Monchy, the more expensive the unavailability of an equipment, the more important its maintenance [17]. In other words, direct and indirect costs of equipment unavailability along with the value generated by the equipment are the most important factors to consider when choosing a maintenance policy.

The greatest advantage of predictive maintenance is that it can assess the current condition of any machine and predict when it needs maintenance before a fault happens. With a properly implemented and updated maintenance policy, it is possible to schedule equipment maintenance for times that will have the least impact in production schedule and deadlines, minimizing disruptions in production lines and improving the quality of the items produced by the factory, contributing to the profitability and sustainability of any company's business.

1.4. Artificial Neural Networks

Artificial neural networks are machine learning models with interconnected nodes distributed over several layers. The networks can be trained to recognize hidden patterns, to classify input samples into a few classes and to perform predictions. This type of model was inspired by the human brain [18][19].

The neuron is the atomic unit of a neural network. When an input vector is given, the neuron provides an output which is a function of the weighted average of the input vector's coordinates. The neurons' outputs can then be fed as inputs to other neurons in the subsequent layers.

Optimization of neural networks is a challenging problem, and it has been the topic of many works [20][21].

Feed-forward (FF) neural networks are a type of neural network in which the data flow in a single direction, from input to output, without any feedback. On the contrary, outputs in recurrent neural networks (RNN) can be fed back into the network, allowing the network to remember past events and operate in non-episodic environments.

Multi-layer perceptron (MLP) is a type of FF neural network. It comprises three types of layers: one input layer, several hidden layers, and one output layer. The main applications of MLP networks are pattern classification, recognition, and prediction [22].

As the computing power and big data increase, deep learning models are becoming more popular in several fields of science. Deep models are characterized by containing several layers, while shallow models rarely have more than three layers. For instance, deep networks are the preferred architecture in object detection or classification problems. Shallow neural networks are more adequate for prediction problems. Despite many clear distinctions between deep and shallow neural networks, some techniques developed for deep learning can help improving shallow models, and vice versa [23].

The importance of the present work is reinforced by several authors that have emphasized the necessity to change the focus from short-term (15 days) maintenance policies to long-term ones (90 days). The importance of these contributions corresponds to the increase of equipment's availability, which permits increased productivity and, at last, the success of the company [24][25][26].

1.5. XGboost and Random Forest

XGBoost is a scalable and highly accurate implementation of gradient boosting that pushes the limits of computing power for boosted tree algorithms, being built largely for energizing machine learning model performance and computational speed [27].

Random forest is also a popular and effective ensemble machine learning algorithm. It is widely used for classification and regression predictive modeling problems [28].

2. Neural Networks for Prediction and Classification

This section reviews relevant works using neural networks for prediction and classification, namely in the field of predictive maintenance.

Rodrigues et al. used a neural network to predict and classify the degradation state of diesel engine oils from laboratory analysis data on 21 oil parameters, achieving an accuracy over 90% [29].

Effective maintenance is essential to keep assets at maximum availability and accident free. For these reasons, Bukhsh et al. developed a model to predict the need for railway maintenance [30].

Elhag and Wang presented an application of artificial neural networks to assess bridge risk by computing their risk scores and categories [31].

Balluff and his team developed a model to predict wind speed and pressure through recurrent neural networks [32].

Deepika and Prakash predicted the power consumption of a virtual machine with the help of backwards predictive analytics using a multi-layer perceptron, achieving a 91% accuracy [33].

Hongxiang et al. developed an algorithm using artificial neural networks (ANNs) to analyze spectroscopy data from lubricant oils. Results proved that ANNs can be used to classify distinct types of lubricants and to distinguish routine conditions of a diesel engine from operating conditions [34].

An algorithm based on a multi-layer feed-forward neural network model was developed to control a steel pickling process in several simulation cases [35].

Okoh et al. presented an approach to determine when a system needs to undergo maintenance, repair, and overhaul, before a failure occurs. One of the main innovations of this project is that forecasts were made in the long-term [36].

One of the main challenges of maintenance is to increase the availability of equipment and, hence, it is important to prognose failures before they happen. Makridis et al. presented a machine learning approach for detecting anomalies from data collected through sensors installed on vessels, predicting the condition of specific parts of the vessels' main engine [37].

In 2021, Zhagparov et al. proposed a solution to automate the prediction of grain yield based on machine learning using the XGBRegressor algorithm on the territory of the Republic of Kazakhstan. Comparisons were made with linear regression and decision tree regressor algorithms [38].

Dong et al., in 2020, developed a prediction model based on the XGBoost algorithm that considers all potential influential factors simultaneously; the objective of this model was to predict the electrical resistivity based on an experimental database [27].

In summary, according to the authors referred, among others, neural networks have high prediction accuracy and can improve support in decision making [39][40].

3. Condition Monitoring in Paper Press

Condition monitoring plays a central role in the maintenance of paper machines; the main objective is to maximize the availability and reduce the costs of these manufacturing units and to prevent unexpected damage or mechanical breakdowns.

The results of the tests by Suomela et al. in 2002 make it clear that thermal imaging combined with adaptive drive has great potential for monitoring paper machine components [41].

The work by Bissessur et al. features the ability to detect faults and provide early warning of impending problems based on collected vibration data and pre-processing spectra. These data processed by a neural network provide an instant decision about the state of the felt that is monitored. This method can be extended to diagnose faults in a wide range of mechanical and rotating equipment in industries [42].

Mateus et al. developed predictive models based on long-term deep memory neural networks applied to a dataset of sensor readings. The results show that it is possible to predict future behaviour up to a month in advance with reasonable confidence (errors in general inferior to 10%) using long short-term memory and gated recurrent unit deep neural networks [43][44].

References

1. Kumar, U.; Galar, D.; Parida, A.; Stenström, C.; Berges, L. Maintenance Performance Metrics: A State-of-the-art Review. J. Qual. Maint. Eng. 2013, 19, 233–277.
2. Standards, E. BS EN 13306:2017 Maintenance. Maintenance Terminology. Available online: http://hadidavari.com/wp-content/uploads/2018/12/BS-EN-13306-2017.pdf (accessed on 9 November 2021).
3. Rao, B.K.N. Handbook of Condition Monitoring; Elsevier: Amsterdam, The Netherlands, 1996; ISBN 978-1-85617-234-9.
4. Carnero, M.C. Selection of Diagnostic Techniques and Instrumentation in a Predictive Maintenance Program. A Case Study. Decis. Support Syst. 2005, 38, 539–555.
5. Selcuk, S. Predictive Maintenance, Its Implementation and Latest Trends. Proc. Inst. Mech. Eng. Part B: J. Eng. Manuf. 2017, 231, 1670–1679.
6. Patwardhan, A.; Verma, A.K.; Kumar, U. A Survey on Predictive Maintenance Through Big Data. In Proceedings of the Current Trends in Reliability, Availability, Maintainability and Safety; Kumar, U., Ahmadi, A., Verma, A.K., Varde, P., Eds.; Springer International Publishing: Cham, Switzerland, 2016; pp. 437–445.
7. Martins, A.B.; Torres Farinha, J.; Marques Cardoso, A. Calibration and Certification of Industrial Sensors—A Global Review. Wseas Trans. Syst. Control 2020, 15, 394–416.
8. Bousdekis, A.; Lepenioti, K.; Apostolou, D.; Mentzas, G. A Review of Data-Driven Decision-Making Methods for Industry 4.0 Maintenance Applications. Electronics 2021, 10, 828.
9. Rodrigues, J.; Torres Farinha, J.; Marques Cardoso, A. Predictive Maintenance Tools—A Global Survey. Wseas Trans. Syst. Control 2021, 16, 96–109.
10. Rodrigues, J.; Farinha, J.; Mendes, M.; Mateus, R.; Cardoso, A.J.M.; Rodrigues, J. Short and Long Forecast to Implement Predictive Maintenance in a Pulp Industry. Eksploatacja i Niezawodnosc—Maint. Reliab. 2021, 24, 33–41.
11. Carvalho, T.P.; Soares, F.A.A.M.N.; Vita, R.; da Francisco, R.P.; Basto, J.P.; Alcalá, S.G.S. A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance. Comput. Ind. Eng. 2019, 137, 106024.
12. Galar, D.; Stenström, C.; Parida, A.; Kumar, R.; Berges, L. Human Factor in Maintenance Performance Measurement. In Proceedings of the 2011 IEEE International Conference on Industrial Engineering and Engineering Management, Singapore, 6–9 December 2011; pp. 1569–1576.
13. Sahal, R.; Ali, M.I.; Breslin, J. Big Data and Stream Processing Platforms for Industry 4.0 Requirements Mapping for a Predictive Maintenance Use Case. J. Manuf. Syst. 2020, 54, 138–151.
14. Hashemian, H.M. State-of-the-Art Predictive Maintenance Techniques. IEEE Trans. Instrum. Meas. 2011, 60, 226–236.
15. Shrivastav, O.P. Industrial Maintenance: A Discipline in Its Own Right. World Trans. Eng. Technol. Educ. 2005, 4, 4.
16. Poór, P.; Basl, J.; Zenisek, D. Predictive Maintenance 4.0 as next Evolution Step in Industrial Maintenance Development. In Proceedings of the 2019 International Research Conference on Smart Computing and Systems Engineering (SCSE), Kelaniya, Sri Lanka, 28 March 2019; pp. 245–253.

17. Monchy, F.; Mirochnikoff, Y. La Fonction Maintenance: Formation à La Gestion de La Maintenance Industrielle. Engineering 1987.
18. Wang, S.-C. Artificial Neural Network. In Interdisciplinary Computing in Java Programming; Wang, S.-C., Ed.; The Springer International Series in Engineering and Computer Science; Springer: Boston, MA, USA, 2003; pp. 81–100. ISBN 978-1-4615-0377-4.
19. Nigrin, A. Neural Networks for Pattern Recognition; MIT Press: Cambridge, MA, USA, 1993; ISBN 978-0-262-14054-6.
20. Zhang, C.; Bengio, S.; Hardt, M.; Recht, B.; Vinyals, O. Understanding Deep Learning (Still) Requires Rethinking Generalization. Commun. ACM 2021, 64, 107–115.
21. Oymak, S.; Soltanolkotabi, M. Toward Moderate Overparameterization: Global Convergence Guarantees for Training Shallow Neural Networks. IEEE J. Sel. Areas Inf. Theory 2020, 1, 84–105.
22. Multilayer Perceptron—An Overview. ScienceDirect Topics. Available online: https://www.sciencedirect.com/topics/computer-science/multilayer-perceptron (accessed on 9 November 2021).
23. Impact of Deep Learning-Based Dropout on Shallow Neural Networks Applied to Stream Temperature Modelling. Elsevier Enhanced Reader. Available online: https://reader.elsevier.com/reader/sd/pii/S0012825219305549?token=CF6227805A1730A859BAEE2F77EBDCB50B400FCE09411CAF51B569500652A4EE3FA108283C5770F90F0470C4BF3EE5E west-1&originCreation=20211109021345 (accessed on 9 November 2021).
24. Jonsson, P. Company-Wide Integration of Strategic Maintenance: An Empirical Analysis. Int. J. Prod. Econ. 1999, 60–61, 155–164.
25. Carnero, M. An Evaluation System of the Setting up of Predictive Maintenance Programmes. Reliab. Eng. Syst. Saf. 2006, 91, 945–963.
26. Yamashina, H. Japanese Manufacturing Strategy Competing with the Tigers. Bus. Strategy Rev. 1996, 7, 23–36.
27. Dong, W.; Huang, Y.; Lehane, B.; Ma, G. XGBoost Algorithm-Based Prediction of Concrete Electrical Resistivity for Structural Health Monitoring. Autom. Constr. 2020, 114, 103155.
28. Qi, Y. Random Forest for Bioinformatics. In Ensemble Machine Learning: Methods and Applications; Zhang, C., Ma, Y., Eds.; Springer: Boston, MA, USA, 2012; pp. 307–323. ISBN 978-1-4419-9326-7.
29. Rodrigues, J.; Cost, I.; Farinha, J.T.; Mendes, M.; Margalho, L. Predicting Motor Oil Condition Using Artificial Neural Networks and Principal Component Analysis. EiN 2020, 22, 440–448.
30. Allah Bukhsh, Z.; Saeed, A.; Stipanovic, I.; Doree, A.G. Predictive Maintenance Using Tree-Based Classification Techniques: A Case of Railway Switches. Transp. Res. Part C Emerg. Technol. 2019, 101, 35–54.
31. Elhag, T.M.S.; Wang, Y.-M. Risk Assessment for Bridge Maintenance Projects: Neural Networks versus Regression Techniques. J. Comput. Civ. Eng. 2007, 21, 402–409.
32. Balluff, S.; Bendfeld, J.; Krauter, S. Short Term Wind and Energy Prediction for Offshore Wind Farms Using Neural Networks. In Proceedings of the 2015 International Conference on Renewable Energy Research and Applications (ICRERA), Palermo, Italy, 22–25 November 2015; pp. 379–382.
33. Deepika, T.; Prakash, P. Power Consumption Prediction in Cloud Data Center Using Machine Learning. Int. J. Electr. Comput. Eng. 2020, 10, 1524–1532.
34. Hongxiang, T.; Yuntao, L.; Xiangjun, W. Application of Neural Network to Diesel Engine SOA. In Proceedings of the 2011 Third International Conference on Measuring Technology and Mechatronics Automation, Shanghai, China, 28 January 2011; Volume 1, pp. 555–558.
35. Kittisupakorn, P.; Thitiyasook, P.; Hussain, M.A.; Daosud, W. Neural Network Based Model Predictive Control for a Steel Pickling Process. J. Process Control 2009, 19, 579–590.
36. Okoh, C.; Roy, R.; Mehnen, J. Predictive Maintenance Modelling for Through-Life Engineering Services. Procedia CIRP 2017, 59, 196–201.

37. Makridis, G.; Kyriazis, D.; Plitsos, S. Predictive Maintenance Leveraging Machine Learning for Time-Series Forecasting in the Maritime Industry. In Proceedings of the 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), Rhodes, Greece, 20–23 September 2020; pp. 1–8.
38. Zhagparov; Buribayev, Z.; Joldasbayev, S.; Yerkosova, A.; Zhassuzak, M. Building a System for Predicting the Yield of Grain Crops Based on Machine Learning Using the XGBRegressor Algorithm. In Proceedings of the 2021 IEEE International Conference on Smart Information Systems and Technologies (SIST), Nur-Sultan, Kazakhstan, 28–30 April 2021; pp. 1–5.
39. Ayvaz, S.; Alpay, K. Predictive Maintenance System for Production Lines in Manufacturing: A Machine Learning Approach Using IoT Data in Real-Time. Expert Syst. Appl. 2021, 173, 114598.
40. Fonseca, D.J.; Navaresse, D.O.; Moynihan, G.P. Simulation Metamodeling through Artificial Neural Networks. Eng. Appl. Artif. Intell. 2003, 16, 177–183.
41. Suomela, J. Condition Monitoring of Paper Machine with Thermal Imaging; Maldague, X.P., Rozlosnik, A.E., Eds.; SPIE: Orlando, FL, USA, 2002; pp. 143–150.
42. Bissessur, Y.; Martin, E.B.; Morris, A.J. Machine Condition Monitoring for Consistent Paper Production. Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng. 1999, 213, 141–151.
43. Mateus, B.C.; Mendes, M.; Farinha, J.T.; Cardoso, A.M. Anticipating Future Behavior of an Industrial Press Using LSTM Networks. Appl. Sci. 2021, 11, 6101.
44. Mateus, B.; Mendes, M.; Farinha, J.; Assis, R.; Cardoso, A.J.M. Comparing LSTM and GRU Models to Predict the Condition of a Pulp Paper Press. Energies 2021, 14, 6958.