Scheduling predictive maintenance with production tasks: A steel industry case study

Nikolaos Nikolakis[a], Xanthi Bampoula[a] and Kosmas Alexopoulos[a]

[a] *Laboratory for Manufacturing Systems and Automation, Department of Mechanical Engineering and Aeronautics, University of Patras, Patras, Greece*

Abstract
Production scheduling is essential for a production system, prescribing when and where each operation necessary to manufacture a product will be fulfilled. Interruptions in the production process, both planned and unplanned, may result in reduced productivity. Predictive analytics however estimating the failure probability of a certain production asset can create insight and consist another factor for production scheduling. This study investigates an approach for combining predictive analytics with a scheduling system. The proposed framework, a result of the SERENA project, is evaluated in a use case coming from the steel industry.

Keywords 1
Predictive maintenance, Production scheduling, Analytics, Restricted Boltzmann Machines, Prediction

1. Introduction

The financial profile of the modern markets mandate production systems to operate under increased efficiency. Hence, increased levels of are required. Towards this advanced information and communication technologies (ICT) along with artificial intelligence (AI) techniques can create insight over the production status and enable condition monitoring of production assets. In turn this may be used to transform maintenance activities from a necessary evil into a strategic business factor. In this context, this article presents an approach for predictive analytics aware production scheduling, for proactively introducing maintenance tasks in the production schedule. The proposed concept is implemented into a prototype software system and tested on a use case related to the steel industry.

2. Related work

In order to predict and avoid unplanned production downtime, predictive analytics can be applied in order to evaluate its condition based on historical data and forecast its degradation, using machine learning (ML) techniques. Support Vector Regression (SVR) is presented in [1] for calculating the Remaining Useful Life (RUL) value directly without the need for estimating degradation states. In [2] run-to- failure historical samples have been used for neural network based autoencoder training to calculate the Health Index (HI) of a system. Vanilla LSTM networks are suggested in [3] and compared to standard and Gated Recurrent Neural Networks (RNN, GRNN). The results indicate that Vanilla LSTM demonstrate increased performance in noisy environments. Kalman filters for RUL calculation on a complex dataset for an unspecified machine is reported in [4], while in [5] a hybrid deep neural network approach consisting of both Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) is discussed. Hybrid models fusing various algorithms and characteristics have increased the prediction accuracy advancing anomaly detection and RUL prediction [6]. Nonlinear

Proceedings of the Workshops of I-ESA 2020, 17-11-2020, Tarbes, France
EMAIL: nikolakis@lms.mech.upatras.gr (A. 1); baboula@lms.mech.upatras.gr (A. 2); alexokos@lms.mech.upatras.gr (A. 3)

AutoRegressive neural network with eXogenous input (NARX) have been proposed in [7] capable of indicating damage in advance in the components of a wind turbine being monitored.

In [8] the connection to a scheduling framework is discussed highlighting the benefits of connecting an early warning to the predictive maintenance planning towards increased availability of production resources. In fact, the use of RUL values for maintenance planning and scheduling hold the promise of achieving an optimal schedule with minimization of maintenance costs [9]. To that end, in [10], an integrated decision model coordinated predictive maintenance based on prognostics information is presented. In addition, a multi-criteria framework is proposed in [11] for improving the maintenance efficiency and effectiveness in a cyber physical production system.

2.1. Approach overview

The proposed approach includes two steps. First an RBM network is used to predict the failure probability of a monitored machine and for a specific time horizon. Next the probability-ies are mapped to a RUL value. Then the RUL value is used for scheduling a maintenance task within the existing production activities.

2.2. Predictive analytics

Restricted Boltzmann Machines (RBMs) method is adopted for estimating the probability of a machine's failure within a certain period. RBMs are universal approximators of discrete distributions. The training of the RBM is performed by estimating the negative log-likelihood of the parameters, since it is less computationally expensive to the maximum likelihood even though less accurate. RBMs are used as a discriminative model learning the joint distribution for a labelled dataset. The probability distribution is determined by the parameters θ of the RBM including the connection weights and the biases. The RBM employs a Gaussian transformation on the visible layer and a rectified-linear-unit transformation on the hidden layer. The classification categories can be determined according to the specific requirements of the equipment owner and its supplier. One category corresponds to a condition close to the threshold set and another on the rest. The categories are based on experimental data and previous knowledge of the equipment condition in operation mode. The RBM's input is a vector with the category's value of each sensor at a specific timestamp. Let χ, with values in the range of $[0,1] \in N$, with $\chi = \{\chi 1, \chi 2, ..., \chi n\}$. Thus, each neuron in an RBM can only exist in a binary state of 0 or 1. After given an input vector χ, the probability of a visible or a hidden layer neuron to be in the state 1 is calculated.

In this study the RBM was implemented in Spyder IDE, using python 3.6 and TensorFlow 1.10.0. The RBM class object is trained upon a labelled dataset corresponding to a period of three months with the learning rate λ set to 0,01 and the size of hidden layer n to 100. The labels used for training include normal and abnormal operations. Abnormal operations consist of preventive replacements of the monitored part and unforeseen events, such as cracks and breaking of pieces.

The result is a vector consisting of seven failure probabilities, failurePDF, each corresponding to a day of the following week that is then mapped to RUL value. For a probability between 0.5-0.6 the RUL was set to 4 days, and then for each probability increase by 0.1 the RUL value was decreased by 1 day. The RUL value is then consumed by a scheduling framework for scheduling predictive maintenance activities with respect to the current production tasks.

2.3. Predictive maintenance scheduling

The scheduling framework implements a multi-criteria heuristic algorithm. At each decision point several alternatives are created and evaluated, selecting the highest ranked alternative. Two maintenance criteria, related to the RUL value and failure_PDF, are introduced as a function of time; a benefit (1) and a cost (2), and added on top of the two production criteria presented in [12]. The criteria are presented in the following equations:

$$Asset\ Utilization(t) =$$
$$1, if\ a\ new\ maintenance\ task\ is\ not\ introduced$$
$$1\frac{t}{RUL}, if\ a\ maintenance\ task\ is\ introduced, with\ 0 < t < 8,\ \ t\ \in \mathbb{N}^{*}$$
$$denoting\ the\ day \tag{1}$$

$$Asset\ risk\ (t)\ =\ failurePDF(t), with\ t\ as\ described\ above \tag{2}$$

As a result, the algorithm schedules the maintenance tasks as close to the machine's predicted end-of-life as possible. Furthermore, the purpose of combining predictive maintenance and scheduling is to guarantee that the proposed actions from analytics do not interrupt production or interrupt as little as possible because the failures are predicted advance and scheduling can be implemented based on the RUL.

The exposed scheduling service has been implemented in Java following a client- server architecture. The technologies used for the scheduling application are: (a) a Glassfish web server and the Jenna TDB for semantic data storage, b) a Tomcat server hosting the scheduling framework and the GANTT visualization service, and c) a Cassandra database, which is used to store time-based information. Moreover, the user interface and the Gantt chart, presented in the figure below, support interaction with the user, such as editing the generated schedule before dispatching it for execution.

Figure 1: Scheduler UI and Gantt visualization

3. Case study from steel industry

The prototype implementation has been tested in a use case coming from the steel production industry and specifically related to a highly automated trailing arm production line. The existing process can be modelled as a sequence of five steps; heating, rolling, eye-rolling, forming and hardening. The actual production numbers are not provided for confidentiality reasons. In the experiment a cycle time of 1 hour is assume, with each process having a duration of 20 min, with a maintenance activity on the monitored rolling machine taking 120 min. In the described scenario downtime can cause significant loss of heat resulting in production losses. Considering the actual preventive maintenance plan for a period of approximately one (1) month, a comparison is made between the actual maintenance activity and the one suggested by the proposed approach, along with a mapping to additional pieces produced.

Table 1
Preliminary results of combining predictive analytics with scheduling

Mounted	Unmounted	Fictional pieces produced	Probability	Suggested unmounted date	Theoretical pieces produced
9/13/2019 14:00	10/1/2019 12:00	250	68%	10/3/2019	280
10/1/2019 12:00	0/14/2019 17:00	200	80%	10/15/2019	215
10/14/2019 17:00	11/4/2019 12:00	200	72%	11/5/2019	215

Total pieces produced	650	710

4. Conclusion

Aim of this work is to discuss on the benefits arising from the combination of predictive analytics with production scheduling in a manufacturing system. Early warnings hold the promise of increasing the efficiency of a production system while considering maintenance needs, by optimizing the resources utilization.

Future work will focus on evaluating additional machine learning approaches, such as autoencoders which are a prominent replacement for RBMs, as well as evaluating the proposed concept in consideration to real world production and maintenance plans.

5. Acknowledgements

This research has been partially supported by the project "SERENA – VerSatilE plug-and-play platform enabling REmote predictive mainteNAnce" (Grant Agreement: 767561) (http://serena-project.eu/) funded by the European Commission.

6. References

[1] R. Khelif, B. Chebel-Morello, S. Malinowski, E. Laajili, F. Fnaiech and N. Zerhouni, "Direct Remaining Useful Life Estimation Based on Support Vector Regression." IEEE Transactions on Industrial Electronics, March 2017: 2276-2285.

[2] W. Yu, IY. Kim, C. Mechefske, "Remaining Useful Life Estimation Using a Bidirectional Recurrent Neural Network Based Autoencoder Scheme." Mechanical Systems and Signal Processing, vol. 129, 2019: 764–80.

[3] Y. Wu, M. Yuan, S. Dong, L. Lin, Y. Liu, "Remaining Useful Life Estimation of Engineered Systems Using Vanilla LSTM Neural Networks." Neurocomputing, vol.275, 2018: 167–79.

[4] L. Peel, Data Driven Prognostics Using a Kalman Filter Ensemble of Neural Network Models, in: 2008 International Conference on Prognostics and Health Management, Denver, CO, 2008, pp. 1–6. doi: 10.1109/PHM.2008.4711423.

[5] J. Zhang, P. Wang, R. Yan, RX. Gao, "Deep Learning for Improved System Remaining Life Prediction." Procedia CIRP, vol. 72, 2018: 1033-1038

[6] M. Huang, Z. Liu, Y. Tao, "Mechanical Fault Diagnosis and Prediction in IoT Based on Multi-Source Sensing Data Fusion." Simulation Modelling Practice and Theory, 2019: 101981

[7] P. Bangalore, LB. Tjernberg, "An Artificial Neural Network Approach for Early Fault Detection of Gearbox Bearings." IEEE Transactions on Smart Grid, vol. 6, no. 2, 2015: 980–87.

[8] N. Nikolakis, A. Papavasileiou, K. Dimoulas, K. Bourmpouchakis, S. Makris, "On a versatile scheduling concept of maintenance activities for increased availability of production resources." Procedia CIRP, vol. 78, 2018: 172–7.

[9] B. Einabadi, A. Baboli, M. Ebrahimi, "Dynamic Predictive Maintenance in Industry 4.0 Based on Real Time Information: Case Study in Automotive Industries." IFAC- PapersOnLine, vol. 52, no. 13, 2019: 1069–74.

[10] Q. Liu, M. Dong, FF. Chen, W. LV, C.YE "Single-Machine-Based Joint Optimization of Predictive Maintenance Planning and Production Scheduling." Robotics and Computer-Integrated Manufacturing, vol. 55, 2019: 173–82.

[11] M. Schreiber, K. Vernickel, C. Richter, G. Reinhart, "Integrated Production and Maintenance Planning in Cyber-Physical Production Systems." Procedia CIRP, vol. 79, 2019: 534–39.

[12] R. Salakhutdinov, A. Mnih, G. Hinton, Restricted Boltzmann machines for collaborative filtering, in: Proceedings of the 24th international conference on Machine learning, ACM, 2007, pp. 791–798. doi: 10.1145/1273496.1273596