Application of Machine Learning for Failure Prediction in Manufacturing Process

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Abstract – This paper deals with research and development of an autonomous system for multicriterial predictive diagnostics which allows us to respond quickly enough to emergence of defects in the production process. It describes the diagnostic methods used in the designing of a Machine Learning system that uses neural network to process data from the production line. We focus on analyzing the vibrations in the production line that adversely affect the quality of the final product and development of a model that can predict the emergence of these vibrations and their mitigation by proactively controlling parameters of the production line. Our diagnostic and prediction model was integrated into the industrial control system of the production line, and we evaluated the performance of the developed control code.

1. Introduction

As part of our cooperation with industry, we carry out research and development of a multi-criteria diagnostic system of the production line at our research center. This diagnostic system works on the principles of online diagnostic systems. We focus in our research on the analysis of parameters of a production line that affect the quality of the product being manufactured. Direct collaboration with the manufacturer of the equipment provided us with direct access to the implementation of their know-how. This allowed us to amplify our knowledge of production equipment and processes. Our intention is to create a predictive diagnostic system that will allow the analysis of emerging defects that adversely affect the quality of production in real time. Therefore, allowing for effective corrections to prevent or suppress the creation of defects that negatively affect the quality of production in real time.

The production line for which our multi-criteria diagnostics system is being developed is designed for the production of a motor vehicle tire component. The resulting product is a tire bead. A prerequisite for a successful application of the product on the market is to ensure its high quality. The basic quality parameters are the stability of the diameter and the shape of the rubber layer on the metal wire of tire bead. At the same time, the stable thickness of the rubber coating that is created without interruption is required for the desired quality of the tire bread.

The simplified manufacturing process can be described as follows: the metal wire (support wire) is unwound from the coil at the start of the production line then the wire is guided thru production line and kept under appropriate tension by pulleys. Then the coating process is carried out by an extruder in which rubber mix with a composition according to customer specification is mixed under high pressure. This results in heating of the mixture to a temperature that must be kept below the vulcanization temperature. The rubber layer is applied by passing the wire through the extruder die. At the end of the production line, a rubberized wire is stored in a gravitational buffer that ensures uniform feed rate. The final step is to wound and form the rubberized (coated) wire to the desired shape by using a mold. After loosening the wire of the mold, the handling device takes the final product - the tire bread from the production line. The manufacturer has several types of production lines some variants can simultaneously coat several wires and wind them onto a mold with different cross-section according to requirements defined by the customer.

Based on the know-how of the manufacturer, we were able to determine the factors directly affecting the quality of the rubber coating. In particular, the parameters are: vibration, temperature of the metal wire, feed rate of the wire through the production line, chemical composition of the rubber coating, pressure inside the extruder, shape, and length of the extruder die. However, despite the knowledge of the above-mentioned factors, phenomena arise in the process of production, where defects significantly reducing the quality of the product occur even without an obvious cause. Reduced quality is caused mostly by the disruption of the integrity of the rubber coating, the instability of the geometric characteristics of the rubber layer on the surface of the carrying wire and the instability of the thickness of the rubber layer on the surface of the wire.

Based on our initial analysis conducted in collaboration with a production line manufacturer, we found that the occurrence of the problems with quality seems to be due to several distinctive causes.

The feed rate of the wire in the production line: When using higher feed rate uneven or discontinuous coating can suddenly occur. In certain cases, even rupture of the wire can occur as it passes through the production line. In the event of a production defect or a rupture of the wire, the production line must be shut down. Due to the fact that the rubber extrusion needs to be carried out continuously without sudden fluctuations in measured parameters, shut down of the production line will cause irreversible changes in the extruded rubber mixture. Extrusion system must be disassembled and cleaned after every production line shut down. In the case of wire rupture, it is necessary to wound it across the production line, this operation is very time-consuming.

Feed rate instability: The characteristic of feed rate instability is very similar at both low and high speeds. The speed instability in the production line occurs only after the first production defect occurrence in the coating process.

The inconsistency and lack of homogeneity of the rubber mixture: When the rubber mixture is not homogenous across its entire volume, or when it is contaminated by unwanted agents defects in the coating can occur. Unfortunately, we do not have the ability to correct these inconsistencies and therefore we will not investigate them in our research.

The shape and length of the extruder nozzle: Extruder nozzle has some influence on the quality of the rubber coating. Increasing the length of the output nozzle of the extruder will provide greater stability to the wire coating layer thickness, however, the disadvantage of extending the output nozzle length is a reduction of the resulting rubber coating thickness.

Vibrations of coated wire: One of the most important factors influencing the formation of defects in the process of coating are vibrations of coated wire. The aforementioned theory has been confirmed by test measurements and therefore we will focus on the impact of vibrations on the final product quality

The main goal of our research is to create an autonomous system of multicriterial predictive diagnostics system, which will allow us to respond to the occurrence of a defect in the production process with sufficiently early prediction. Based on this prediction, this system will automatically adjust production parameters in the production line control system (mainly feed rate of wire) and thus reduce or eventually eliminate the risk of occurrences of production defects.

2. Data gathering

The experiments were carried out on a used production line, that was installed in the testing hall on premises of manufacturers client, to avoid potential interference or measurement distortion.

In the measurement process, we focused on obtaining the necessary parameters with sufficient informative value to accurately characterize the production process. We focused on collecting the following data:

- Production line set feed rate (m / min)
- Production line drives speed (m / min)
- The feed rate of the wire in the production line - its value can be influenced by the action of gravitational buffers, the tension in the wire and by the vibrations of the wire. Therefore, there may be a difference between it and the set feed rate (m / min)
- Measurement of wire vibrations by Eddy current sensor
- Measurement of the diameter of the coated wire
- Single Axis Measurement with Micro Epsilon ODC 2600
- Biaxial measurement with Keyence LS-903D

We have acquired the data from the industrial control system of the production line and converted it into a structure suitable for subsequent processing by our system.

The vibration measurement data was gathered by a device that was developed at our university. The basic principle of measurement is the measurement of disturbances in a nonmoving electromagnetic field by vibrating wire that is sensed by our device.

Sensor Parameters:

- Measurement range 10Hz - 25kHz
- Measurement range with linear response 20HZ - 2kHZ
- SNR -67dB
- Sample rate 96kHZ
- 32bit AD interface

Vibration measurement positions in the production line were determined based on the estimation of the significance of measured value at that point.

Selected points were:

- Before the uncoated wire enters the extruder
- After the coated wire exits the extruder
- Before the gravity buffers

3. Preliminary analysis

Based on the analysis of vibration measurements, we have identified some of the causes of vibrations of the wire as it moves through the production line, namely:

- When wire reaches end positions on the stops on unwinding rollers
- When wire changes the direction of unwinding from coils
- When gravity buffer pulleys change the direction of their movement

We chose not to filter out these vibrations because it might introduce artifact in data. Despite their identification and preliminary rejection of their effect to defect formation they may still interact with other factors that affect the coating quality.

We decided to add synthetic data obtained from the operator by manual entry:

- wire breakage time
- time when the production defects begin to form

By a detailed analysis of the measurement data, which was performed after the measurements were completed, we found patterns that are clearly identifiable in the obtained data, but their source is unknown. Our hypothesis is that the aforementioned phenomena are a direct indicator of the immediate occurrence of rubber coating defects. Because the patterns appear at higher speeds and after their detection, rubber coating defects occur. After the first patterns appear their occurrence is repeated at regular intervals. The average vibration amplitude is only dependent on the line speed before first pattern detection. After the first patterns are detected, the average vibration amplitude increases.

Based on the above information, we expect to detect a direct correlation between the patterns and the emergence of defects in the coating process. We wanted to verify whether any successful prediction of these patterns and subsequent reduction of feed rate will be sufficient to eliminate the defects or reduce the number of their occurrences. If the reduction of feed rate is sufficient to decrease the number of coating defects, the result will be savings and improvements in the production process.

Our aim is to develop a system that will eliminate all or most of the manufacturing defects in the wire coating process by predicting their occurrence. The volume of the data from the production line does not allow us to obtain the necessary information about direct or hidden correlations between factors and their effects on vibration in a trivial way. Therefore, a high-performance data processing system is required. We have chosen an approach in which we applied the tools of artificial intelligence to analyze the obtained data by using a machine learning system for the analysis and processing of the diagnostic data.

The average time of recurrence of defects (Table 1) in wire coating is 3.2 hours, at a feed rate 180 m / min and 7.4 hours, at a feed rate of 120 m / min.

Table 1. The average time of recurrence of defects

Feed rate [m/min]	**80**	**100**	**120**	**140**	**160**	**180**	**200**
ATBD[a] 1 wire [h]	-	16.8	7.4	6.9	5.6	3.2	<1
ATBD[a] 4 wires [h]	>50	4.2	2.2	1.7	1.4	0.8	-

a. The average time between coating defects

The production line configurations allow the production of coated wires to be parallelized to up to 6 wires at the same time, that are formed at the molding station simultaneously. In the case of a production defect in the case of only one coated wire, it is usually necessary to stop the entire production line and cleaning of the extruder nozzle is required. This causes downtime in production and thus reduce the effective performance of the production line.

For effective application of the machine learning system on the data obtained from the production line control system, it is necessary to ensure the homogeneity of the entire data structure. Data from control system was in a form where it contained a global timestamp of the data point and the new data point value. Vibration sensor data was sampled with a sampling frequency of 700 Hz. Applying the sampling theorem allows us to measure vibrations up to 350 Hz. All data was encoded, and spline interpolated to occur at uniform time intervals across all measured factors, to align with data sampled from vibration sensors at sampling frequency 700Hz.

Our prediction was based on previously identified patterns that have an adverse effect on the quality of the coating. After the patterns begin to appear quality of coating rapidly decreases, and defect begin to occur.

Pattern types:

- pattern I. consists of two consecutive increases in the amplitude of the vibration component with an approximate frequency of 225Hz which is repeated periodically with time span dependent on feed rate with a variance of +/- 2sec
- pattern II. consists of two consecutive increases in amplitude with an approximate frequency of 25Hz with a timespan of approximately 0.5 seconds and at the beginning of the pattern components with frequency up to 60Hz are present
- pattern III. appears when the wire breaks

Figure 1. Pattern I.

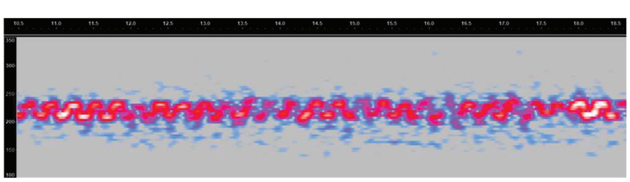
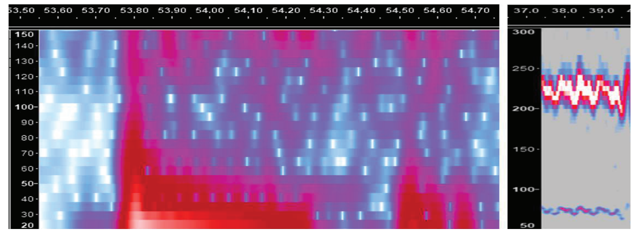


Figure 2. Pattern II. and III.



4. Training

The collection and pre-processing of diagnostic data were provided by a PC located in the production hall. The data collection configuration was set so that the system archived the data that was obtained 5 minutes before the first production defect detection and 3 minutes after. The size of each data set should be made up of 210,000 data points when a wire coating error occurs and 126,000 data points when the wire breaks. However, the collected dataset was smaller due to the presence of an error in the query used to request data from the production line control system as the export was in blocks and sometimes the last block was not exported, up to 700 samples (1 second) from the end might be lost. At the time of detection of this error, we already had the data in an aggregated form and therefore we were not able to add the missing data. Summary of the data is in Table 2.

Table 2. Characteristics of data

Feed rate [m/min]	**Data sets**	**Samples**	**Pattern I**	**Pattern II**	**Pattern III**
120	146	46 212 939	329	294	23
180	192	58 703 274	720	466	47

For the purpose of long-term data collection from the production line, we chose the feed rates 120 m/min and 160 m/min.

As input for machine learning following data was used:

- Time encoded as a number of 1/700 second intervals from the beginning of the data set
- Production line speed set in PLC (m / min)
- Measured feed rate (m / min)
- Measured vibrations after basic filtering
- Encoded pattern I. occurrence time
- Encoded pattern II. occurrence time
- Encoded pattern III. occurrence time

Output – prediction:

- Encoded time of pattern occurrence

Pattern occurrence time is encoded by the following formula

$$h = \begin{cases} e^{\frac{\log(2)\cdot(14000-s)}{14000}} - 1 & if\ s \leq 14000 \\ 0 & if\ s > 14000 \end{cases}$$

h - encoded value

s – number of samples (distance in 1/700 second intervals) from the detection of a pattern

Dataset was divided into 20% test data, 65% learning data, 15% validation data and we used 10-fold cross-validation. We compared two networks, nonlinear autoregressive exogenous model (NARX) and Long short-term memory (LSTM). Network parameters were determined empirically using experiments on a smaller subset of data.

5. Results

NARX was configured to use 200 hidden neurons and 25 delays, it used Bayesian regularization. Performance characteristics were:

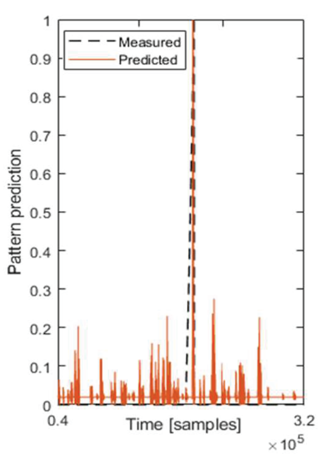
- Mean square error 4.075e-5
- R value 0.9982

LSTM was configured to use 200 hidden units and tanh activation function with sigmoid gate activation. Performance characteristics were:

- Mean square error 0.0982
- R value 0.9382

After comparing both networks, we selected NARX for further analysis and as a candidate for implantation in the industrial control system. The output from the network is on Figure 3. Because of the tendency to create many low value predictions we filtered out the predictions if the maximal value of prediction is less than 0.7. We consider a prediction to be successful if the pattern prediction predicts the pattern no sooner than 3 seconds and not after the pattern occurred. Results of prediction are summarized in Table 3, the success rate of pattern prediction is 36%. We can see that our model is less effective in predicting pattern II. and in predicting the breakage of the wire. From predicted times we can see that the worst ability to predict pattern II. is caused by predicting the defect after it occurs.

Figure 3. Output from network



The 36% success rate may not seem high, yet it represents considerable time and resource saving. For example, when coating four wires at the same time at a usual speed of 120 m/min, we can save approximately 13 hours per month per production line and save a lot of material in the form of scrap.

Table 3. Results of prediction

Feed rate [m/min]	Pattern I	Pattern II	Pattern III	Sum	%
120	28	14	2	44	36%
180	69	17	1	87	35%
Sum	97	31	3	131	36%

In deployment, we are considering slowing down the production line before fault will occur by 30%, which will allow us to achieve a higher average line speed. According to our simulations, this would allow, for example on 4 wire production line, to increase its average speed from 112 m/min to 115 m/min or additional 5760 m of coated wire can be produced per month. when set to 120 m/min feeding rate. For feeding rate 160 m/min the average speed 132 m/min is increased to 143 m/min or additional 21120 m of coated wire can be produced.

We also developed a diagnostic module implementation for the production line control system. The module performed following functions: data acquisition, pre-processing and filtering, modifying of the data to the required format for the model, continuous evaluation of the model, and generating requests to reduce production line speed when the defect is predicted.

We have done benchmarks of our developed model to find out whether the production line control system will have enough free resources to run the module. We found out that the module consumed 12MB + 2.1MB/per wire of RAM and ~ 20% single core CPU time per wire diagnosed on Intel Xeon E5-2670 v2. That means the module is suitable for deployment.

6. Conclusion

As part of our research, we demonstrated that by using NARX network we can successfully predict defects in the wire coating process. The prediction success rate is currently at 36%. Despite the seemingly low success rate, it represents significant savings in the production process.

Achieving the current level of defect prediction success rate is due to the relatively small set of training data and its small diversity since they are only from one production line.

In our next research, we will continue to expand the dataset used for training. At the same time, we will try to increase the accuracy of our mathematical models to increase the likelihood of a successful prediction of production defects.

7. Acknowledgment

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8. References

[1] S. A. Billings. "Nonlinear System Identification: NARMAX Methods in the Time, Frequency, and Spatio-Temporal Domains", Wiley (2013)

[2] Hochreiter S, & Schmidhuber J. “Long short-term memory”, Neural Computation, 9, 8, 1735–1780, (Nov 1997)

[3] Kuric I., at al "Analytical Intelligence Tools for Multicriterial Diagnostics of CNC Machines”, Advances in Science and Technology Research J., 10, 32, 59-64, online (2016)

[4] Sapietova A., Saga M., Novak P., “Multi-software Platform for Solving of Multibody Systems Synthesis”, Communication - Scientific Letters of the University of Zilina, 4, 3, 43-48, (2012)

[5] Sapietová A., Sága M., Kuric I., Václav Š., “Application of optimization algorithms for robot systems designing”, International Journal of Advanced Robotic Systems, 15, (2018)

[6] Tlach V., Císar M., Kuric I., Zajačko I., “Determination of the Industrial Robot Positioning Performance”, MATEC Web of Conferences, 137, EDP Sciences (2017)

[7] Frankovský, P., Ostertag, O., Ostertagová, E., Trebuňa, F., Kostka, J., Výrostek, M., “Experimental analysis of stress fields of rotating structural elements by means of reflection photoelasticity”, Applied optics, 56, 11, 3064-3070, (2017).

[8] Bozek P., Lozhkin A., Galajdova A., Arkhipov I., Maiorov K., “Information Technology and Pragmatic Analysis”, Computing and Informatics, 37, 4, 1011-1036, (2018)

[9] Monkova K., Monka P., Ungureanu M., Ungureanu N., “Modal Analysis as a Tool of Problem Identification of Gear Mechanism”, 9th ICMAE, 420-424, (2018)