Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Artificial Intelligence Platform Proposal for Paint Structure Quality Prediction within the Industry 4.0 Concept

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Abstract: This article provides an artificial intelligence platform proposal for paint structure quality prediction using Big Data analytics methodologies. The whole proposal fits into the current trends that are outlined in the Industry 4.0 concept. The painting process is very complex, producing huge volumes of data, but the main problem is that the data comes from different data sources, often heterogeneous, and it is necessary to propose a way to collect and integrate them into a common repository. The motivation for this work were the industry requirements to solve specific problems that cannot be solved by standard methods but require a sophisticated and holistic approach. It is the application of artificial intelligence that suggests a solution that is not otherwise visible, and the use of standard methods would not give any satisfactory results. The result is the design of an artificial intelligence platform that has been deployed in a real manufacturing process, and the initial results confirm the correctness and validity of this step. We also present a data collection and integration architecture, which is an integral part of every big data analytics solution, and a principal component analysis that was used to reduce the dimensionality of the large number of production process data.

Keywords: artificial intelligence, automotive, big data analytics, industry 4.0, knowledge discovery, neural networks, prediction, principal component analysis.

1. INTRODUCTION

The painting process in a car producing company is a complex one with various sub-processes. There are many other factors and influences affecting the individual sub-processes that have impact on the quality of the production process as a whole.

It is the problem of the quality of key indicators, its retention as well as the prediction of results that is the fundamental problem that companies face in the production process. This article therefore provides a proposal for quality of key indicators prediction using Big Data analytics methodologies. The whole proposal fits into the current trends that are outlined in the Industry 4.0 concept.

Our previous research Kebisek et al. (2018) and Kebisek et al. (2019) has shown the impact of external influences, i.e. non-process values, influencing the quality of the painting process. This research provides a base line for this proposal that incorporates the impact of process parameters on paint quality.

Three main topics are relevant to this research. These include Big Data and Data Mining technology, Industry 4.0 concept and utilisation of artificial intelligence for prediction of key production quality parameters.

2. STATE OF ART

Big Data definitions have evolved rapidly, which has raised some confusion. Gandomi et al. (2015) describe differences of Big Data understanding, where some definitions are focused on what it is, while others tried to answer what it does. Gartner, Inc. IT Glossary (2015) defines big data in these terms: “Big Data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation”. Several other publications deal with Big Data issues, including the use of Data Mining methods and techniques. Cheng et al. (2018) reviewed the development of Data Mining techniques in the Big Data era and have created discussion on the applications of Data Mining techniques in smart production. Grady et al. (2017) describe the implications of an agile process for Big Data analytic in cleansing, transformation and analytics. Zhu et al. (2018) give a systematic review of various state-of-the-art data pre-processing tricks as well as robust principal component analysis methods for process understanding and monitoring applications and Big Data perspectives on potential challenges and opportunities. Liu et al. (2019) provide insights on Data Mining and information retrieval behind its demonstrated growth in the recent past, with the ultimate goal of revealing its potential of driving scientific innovation in the future.

The German Federal Government presents Industry 4.0 as an emerging structure in which manufacturing and logistics systems (in the form of the Cyber Physical Production System) intensively use the globally available information and communications network for an extensively automated exchange of information, in which production and business processes are matched Vaidya et al. (2018). Ahuett-Garza et al. (2018) discuss the trends in some of the smart technologies and smart manufacturing within the Industry 4.0 concept. Lu et al. (2017) outline the critical issue of the interoperability of Industry 4.0, providing a conceptual framework of interoperability regarding Industry 4.0 and provides challenges and trends for the future. Frank et al. (2017) show that the Industry 4.0 is related to a systemic adoption of front-end technologies, where smart manufacturing plays a key role. They however, note that Big Data and analytics are still poorly implemented in manufacturing companies. Miskuf et al. (2016) present strengths of deep learning algorithms and present possibilities of its application in an industrial environment, utilising fundamental pillars of Industry 4.0. Dalmarco et al. (2019) synthesize the challenges and opportunities of adopting Industry 4.0 from the perspective of technology provider companies and recommend that companies who want to adapt themselves for Industry 4.0 should first incorporate technologies such as Big Data and analytics, which will provide companies with enough information to observe and analyse its manufacturing process. In similar manner, Pacchinia et al. (2019) propose a model to measure the degree of readiness of a manufacturing organization with regard to the implementation of Industry 4.0.

One of the key challenges in manufacturing processes is improving the accuracy of quality prediction. Wang et al. (2019) propose a generative neural network model for automatically predicting work-in-progress product quality. This approach combines an unsupervised feature-extraction step with a supervised learning method. According to Chu et al. (2018) there are two main types of quality prediction methods commonly used at present, one is based on the mechanism model, and the other is based on the data-driven method. The modern industrial processes are becoming more and more complicated, so an accurate and reliable mechanism model is often difficult to obtain. Pacchinia et al. (2019) present a distributed parallel process modelling approach, based on a MapReduce framework, for Big Data quality prediction. A Big Data quality prediction scheme is developed and two case studies verify the effectiveness of the proposed method for Big Data quality prediction. Finally, Su et al. (2018) apply back-propagation neural networks to analyse real-time machine operation data transmitted from machine sensors for predictive purposes, leading to increase in production efficiency.

3. PROCEDURES OF SOLUTION

Several methods can be used to evaluate the quality of the paint structure. In our case, quality is evaluated at the end of the entire painting process using special spectrometers and measuring devices. These measure the basic parameters of the paint structure at exactly defined points on the bodywork. From the measured values there were calculated parameters that can be used for paint structure evaluation, like Long Waves, Short Waves, Parts of Wave Spectrum - W_a, W_b, W_c, W_d, W_e), Distinctness of Image and Dullness. The principle of measurement is shown on Fig. 1. Complete measurement of the entire bodywork takes approximately 60 minutes. Given the time required for this inspection and limited number of measurement devices, the number of bodyworks measured currently does not exceed 10% of the total bodywork production.

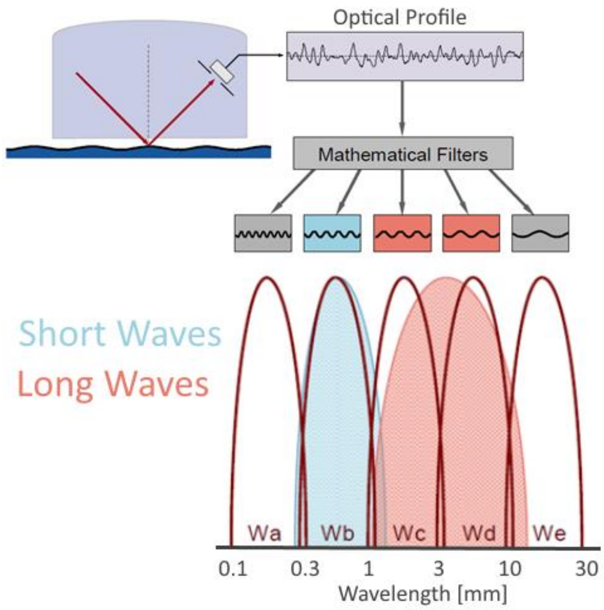

Fig. 1. Measurement Principle

From the measured values were calculated (1) other parameters for quality evaluation, such as a Balance Structure parameter BYK-Gardner GmbH (2010).

$$B = 10 * \frac{W_b - \left(6 * \sqrt{W_d} + 4\right)}{6 * \sqrt{W_d + 4}} \tag{1}$$

The quality of the paint structure is then evaluated based on the parameters W_d and B, which are used for an internal company evaluation. Intervals (2) and (3) define the satisfactory paint structure value ranges of these parameters.

$$W_d \in \left(0.0, 28.0\right) \tag{2}$$

$$B \in \left(-5.5, 6.0\right) \tag{3}$$

Other parameters that are used to evaluate the quality of the paint structure are Long Waves (LW) and Short Waves (SW). Intervals (4) and (5) define the satisfactory paint structure value ranges of these parameters. Unlike the previous parameters, the calculation formula for LW and SW is not known to the company, i.e. it is a trade secret of the system for evaluating the quality of the paint structure supplier.

$$LW \in (0.0,13.0) \quad (4)$$

$$SW \in (10.0,30.0) \quad (5)$$

Since the calculation of LW and SW parameter values is not available to us, we have focused on finding correlations between individual quality evaluation parameters. The correlation matrix analysis shown in Tab. 1 clearly shows that the SW parameter has a strong correlation with W_a, W_b and W_c and the LW parameter has a strong correlation with W_c, W_d and W_e parameter values. There is also a slight correlation between LW and SW parameter values. From this, it can be determined that the use of SW and LW parameters is sufficient to evaluate quality across a full spectrum of measurements. Nevertheless, it will also be necessary to consider the B and W_d parameters from the measurements as they are used in the internal evaluation of the paint structure quality in the company.

Table 1. Paint quality parameters correlation

Attribute	LW	SW	W_a	W_b	W_c	W_d	W_e
LW	1.00	0.48	0.47	0.50	0.82	0.92	0.77
SW	0.48	1.00	0.78	0.94	0.73	0.34	0.39
W_a	0.47	0.78	1.00	0.88	0.75	0.37	0.38
W_b	0.50	0.94	0.88	1.00	0.82	0.36	0.41
W_c	0.82	0.73	0.75	0.82	1.00	0.67	0.64
W_d	0.92	0.34	0.37	0.36	0.67	1.00	0.76
W_e	0.77	0.39	0.38	0.41	0.64	0.76	1.00

4. PROPOSAL OF THE ARTIFICAL INTELLIGENCE PLATFORM

4.1 Data Collection and Integration

One of the important conditions for the feasibility of designing the paint structure error prediction platform is the availability of real time production process data for knowledge discovery purposes. In order to obtain relevant results it was equally important to analyse and process historical process data. Due to these reasons, the existing company data collection infrastructure, as well as existing data sources within the company, were used.

Our proposal of paint structure error prediction platform, utilizes two main data sources.

- Manufacturing process data,
- Paint structure quality measurements.

The manufacturing process data (e.g. furnaces, paint cabins and filler cabins temperature and humidity, cooling system parameters, bath parameters etc.), originating from the sensors, IoT (Internet of Things) devices, PLCs and other field control level systems are collected using company's Field Level Bus platform, which provides various protocols, e.g. MQTT (MQ Telemetry Transport), OPC-UA (Open Platform Communications – Unified Architecture) and ODBC (Open Database Connectivity), to interconnect various production systems.

The manufacturing process data are collected using the MES system based on the Wonderware software platform. The MES system collects data from approximately 700 process tags, i.e. sensors, in intervals between 100 milliseconds and up to 10 minutes, based on the process value requirements. Although only the process tags' value changes are recorded, the total amount of data stored per month is around 200GB. Collected data are utilised for the MES system functionalities and further stored in the Wonderware Historian server that provides historical insight into the collected manufacturing process data.

The paint structure quality measurements, obtained using the spectrometers and measurement applications, are stored in the internal application database. The database contains all measured (W_a, W_b, W_c, W_d, W_e) and calculated values (B, LW, SW) of the individual paint structure measurement parameters. The database also contains additional essential data about the bodywork, its type, body variant, used colour and utilized supplements.

However due to the custom data format, these data are not available for external applications. Therefore the individual paint structure check reports were exported to MS Excel *.xlsx format for further analysis. For the purposes of this research, the data on a selected bodywork model (all colours, all parameters of paint quality and all measuring areas) were available from the whole year 2018 and for the first 8 months of 2019.

It should be noted that not all painted bodyworks are measured utilising this system. On average there are 18 bodyworks measured for paint structure quality each day. The approach of bodyworks selection for paint structure measurement is random, based on the current work shift and day production.

Two required data sources had to be integrated, for the following analyses and knowledge discovery processes, into the common data set. The proposed data collection and integration architecture is shown on Fig. 2.

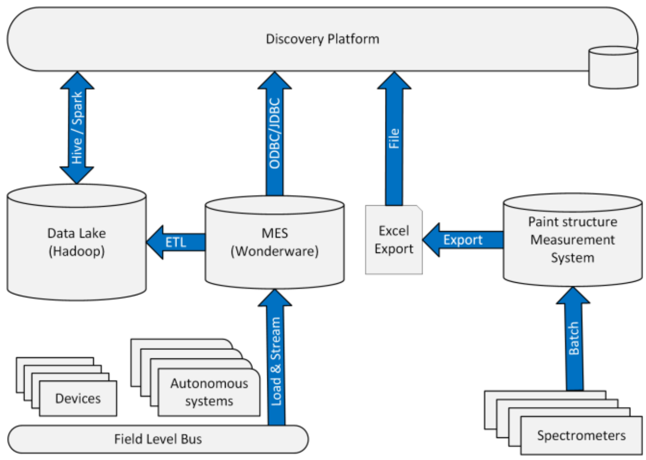

Fig. 2. Data collection and integration architecture

The proposed Big Data collection and integration architecture incorporates the Data Lake, based on the Hadoop platform that integrates process data and alarms from the Wonderware Historian server. This is needed mainly due to the fact that the Wonderware Historian server in the current configuration retains data only from the last 6 months and therefore is not a suitable data source for a historical data analyses. Currently, process data from the Wonderware Historian server from previous 31 months are stored in the Data Lake. Since the process data are stored in a form similar to the Wonderware Historian server data structure, they were suitable for interconnection with current process data for the sake of analysis.

For the data analysis process we have utilised the company's Discovery Platform, to obtain data sets suitable for machine learning. The discovery platform incorporates various data processing and analysis tools, to cover the whole knowledge discovery process.

For data processing we have utilised the RapidMiner data science platform with its Hadoop extension, to obtain a compact data set suitable for further analyses and knowledge discovery process.

The main challenge was represented by joining the paint structure quality measurements with the manufacturing process values, at the time of bodywork production. For this we have utilised RFID tag sensors that identify the bodywork movement through the paint shop process. Regardless, some of the time interval ranges needed to be estimated by the people from practice, due to incomplete process coverage by the RFID tags.

The final data set, including the paint structure quality measurement values for individual bodyworks with their associated production process values, was used in the TIBCO Statistica data science platform for data analyses and neural network learning process.

4.2 Principal component analysis

Principal component analysis (PCA) Eriksson et al. (2013) was used to reduce the dimensionality of the large volume of production process data that originated from the approximately 700 collected process values. Our data were processed using the data science platform TIBCO Statistica.

As a source for PCA we have used normalized variable values. Subsequently, we have applied a summary cross-validation algorithm on the pre-processed data set. This algorithm found a principal component model with 31 components. The first six significant components are shown in Tab 2.

Table 2. Principal component analysis summary

Comp.	R2X	R2X (cumul)	Eigen values	Q2	Limit
1	0.3621	0.3621	23.424	0.3248	0.0162
2	0.2169	0.5791	13.897	0.3003	0.0165
3	0.1675	0.7466	10.759	0.3704	0.0167
4	0.0731	0.8198	4.709	0.2231	0.0170
5	0.0531	0.8730	3.424	0.2657	0.0173
6	0.0286	0.9016	1.841	0.1256	0.0175

From the identified component eigenvalues we have calculated the average eigenvalue of 2.07672. For a better visualisation of found principal eigenvalues we have created a scree plot shown on Fig. 3. Based on an average eigenvalue we have selected five principal components. Using these five main principle components we have covered 87.3004% of total data variance.

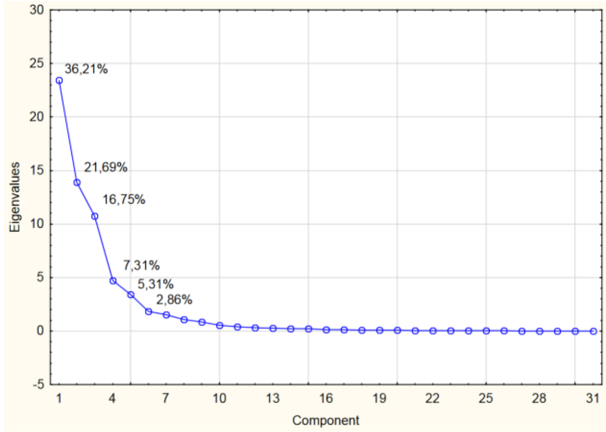

Fig. 3. Eigenvalue scree plot

After identifying significant components we have analysed the relationships between variables to determine which ones have the greatest impact on the PCA model. We have created a loading scatter plot, shown on Fig. 4, to better visualize component relationships.

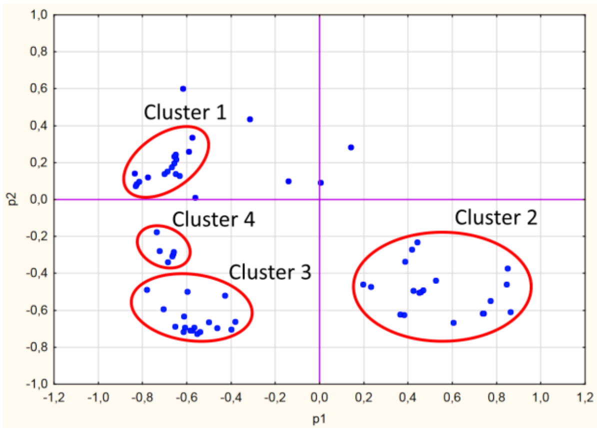

Fig. 4. Principal component analysis scatterplot of the first principal component vs. second principal component

In the loading scatterplot of the first two principal components, some clusters of similar variables were identified. We have identified some clusters of positive correlated parameters. Cluster 1 is located in the second quadrant and consists of data with parameters, i.e. production process sensors that mainly represent furnaces temperature in painting zone 3, 4 and 5. According to our analysis, the numerical values of these parameters tend to change in the same manner. On the opposite side of the plot origin, Cluster 2 is positioned with parameters that mainly represents temperatures and humidity in paint cabins. Dispersion of these parameters in the fourth quadrant suggests relatively weak positive correlation between them. Variables from these two clusters are negatively correlated to each other. Cluster 3 and Cluster 4 are located in the third quadrant. Cluster 3 consists of sensor data that mainly represents temperatures in filler furnaces, and the smaller Cluster 4 consists of sensor data that mainly represents furnaces temperature in painting zone 1 and 2. In consideration of its relative proximity to Cluster 1, a slight positive correlation with these parameters can be expected. There is no presumption of correlation between clusters from second and fourth quadrant and Cluster 3 from the third quadrant, i.e. they are not correlated with each other. On the contrary, according to the graph, the furthest parameters are the most influential.

4.3 *Initial Analysis*

Based on experience from experts and operators with practice, the temperature and weather in general has a significant impact on the quality of the painting process. Our previous research, noted in Kebisek et al. (2018) and Kebisek et al. (2019), has shown impact of the weather on the quality of the painting process. Despite the fact that the hypothesis of the weather effect could not be fully confirmed, there is a clear correlation between weather parameters and the number of paint structure errors. The trend is shown on Fig. 5, which is representing differences between the quality of painting in the summer months and during the winter months.

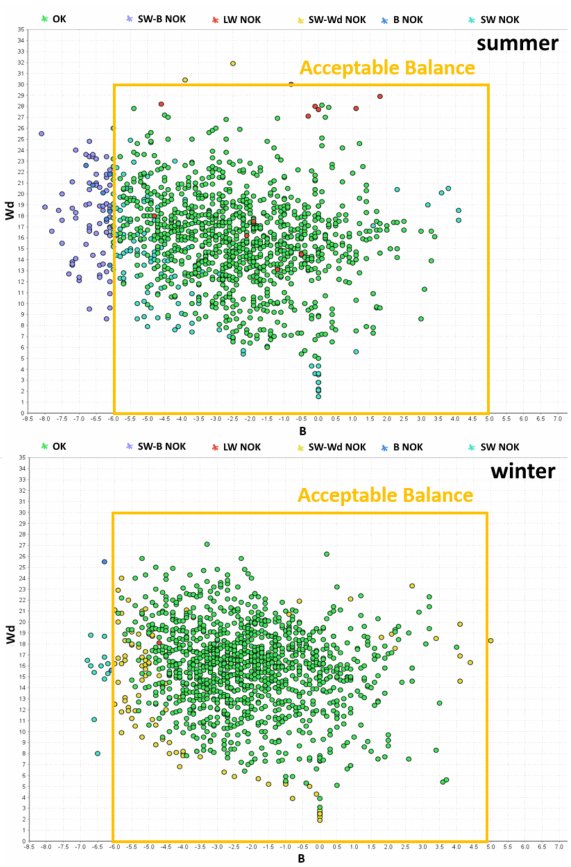

Fig. 5. Results of the paint structure evaluation

Each graph shows a paint structure quality evaluation, using W_d and B quality parameters that are used in the company for quality evaluation. Each coloured dot represents one bodywork paint structure measurement and its colour identifies the evaluation result. The graphs also include ranges for acceptable parameter values.

During the painting process, most of the technological process is dependent on the weather. Due to this reason, more values, which depend on weather, like temperature, air pressure, humidity etc. have been taken into account for the analyses that followed. These data have been collected and stored by the MES system Wonderware.

Based on the results obtained from the principal component analysis we have identified 74 process parameters with the most significant impact on paint structure quality. This was confirmed by analysis of technological process scheme and also by experts and operators from practice.

After a detailed analysis of the selected parameters, we have identified disproportions between several process parameters during the summer and winter operation of the paint shop. One of the identified parameters is for example „temperature intake of filler layer cabin", shown on Fig. 6. This graph shows the course of temperature in the cabin aggregated by hours, during summer and winter operation. Each day on the horizontal X axis is synchronized to match the weekly period, i.e. Monday to Monday, weekend to weekend, etc. The vertical Y-axis represents the filler layer cabin temperature in °C.

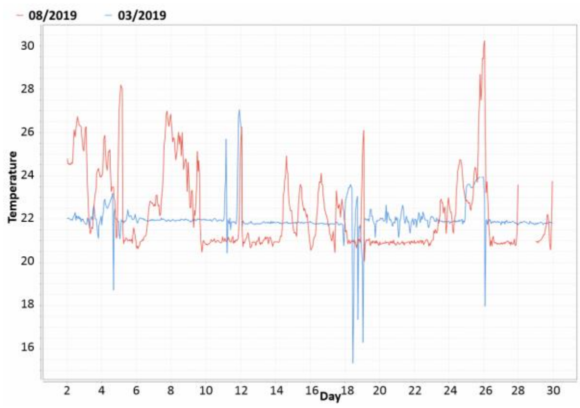

Fig. 6. Process parameter disproportion between cold and hot months

Due to these facts, paint process parameters have been taken into account for further analysis. These parameters allowed us to gain a detailed insight on their influence on the paint structure quality. Although, these datasets existed within the company, they were not previously interconnected and therefore not used for analysing the paint quality results.

4.4 *Neural Network Design for Paint Structure Quality Prediction*

Based on the results of our previous data analysis and principal component analysis, we have decided to design a neural network model for paint structure quality classification using paint process parameters. We have set the Complex Measurement Evaluation parameter as the target attribute for classification of the paint structure quality. This parameter aggregates all evaluations of individual measured parameters of the paint structure, which were obtained from the custom measurement system and are part of the integrated data set. The distribution of the Complex Measurement Evaluation parameter is shown in Table 3.

Table 3. Complex Measurement Evaluation Distribution

Parameter	Absolute count	Fraction
OK	13 744	0.914
SW NOK	882	0.059
SW-B NOK	225	0.015
LW NOK	69	0.005
B NOK	52	0.003
LW-SW NOK	21	0.001
LW-W_d NOK	13	0.001
LW-SW-B NOK	13	0.001
W_d NOK	12	0.001

In the integrated data set there is a large disproportion between the number of sufficient-valued bodywork and the number of insufficient-valued bodywork, from a quality standpoint. Therefore, it was necessary to use data sampling to obtain a subset of data that would have a smaller disproportion between them. This step was crucial for obtaining relevant results.

Subsequently, it was necessary to identify the key process parameters that will be used as input parameters for the designed neural network. Based on the results obtained from the principal component analysis, 74 process parameters were identified. These parameters should have the most significant impact on the painting process. This was also confirmed by the analysis of the technological process scheme and also during consultations with people from practice.

After determining suitable input parameters and the target attribute, it was possible to design the neural network itself. The multilayer perceptron neural network was designed using automated network search function, which has been provided by the TIBCO Statistica data science platform. Using this function it was possible to test several variants of neural networks with various number of hidden layer neurons, different activation functions etc. The parameters of the acquired neural networks are described in Table 4. It should be noted that the table shows only the five selected networks with the best parameters.

Table 4. Neural networks parameters

Net	Train. perf.	Test perf.	Valid. perf.	Error func.	Hidden act.	Output act.
74-26-9	90.81	89.24	89.45	SOS	Logist.	Softmax
74-48-9	89.24	88.47	86.78	SOS	Identif.	Tanh
74-14-9	90.45	87.59	86.87	Entropy	Logist.	Expon.
74-21-9	87.58	89.57	85.29	SOS	Expon.	Logist.
74-35-9	87.24	86.74	86.41	Entropy	Tanh	Softmax

From the several acquired neural networks “MLP 74-26-9” was selected as the most suitable, due to the highest obtained performance value and the balanced ratio between training, testing and validation performance. The selected neural network comprises of 74 input neurons, 26 hidden-layer neurons and nine output neurons using logistic and softmax activation functions.

Based on the analysis of the prediction spreadsheet of selected neural network provided by the data science platform, we have evaluated the consistency and accuracy of the obtained predictions. Our conclusion is that the chosen neural network is suitable for classification of the paint structure in our use case.

4.5 Artificial Intelligence Platform Implementation

The acquired knowledge, represented by selected neural network, was used to implement a platform for paint structure quality prediction using real time process parameter values.

The implementation of our neural network has been performed in the TIBCO Statistica data science platform. The code generated by Statistica contains the configuration of learned neural network including its parameters such as the number of neurons in individual layers, synoptic weights, activation function etc.

The data source for the designed platform was available in the MES system Wonderware. Wonderware has been responsible for overall processing, collection and integration of process data from individual sensors and measuring points throughout the painting process.

The implemented operator panel of proposed artificial intelligence platform for paint structure prediction is shown on Fig. 7. The screen shot was anonymised to comply with the company security policy.

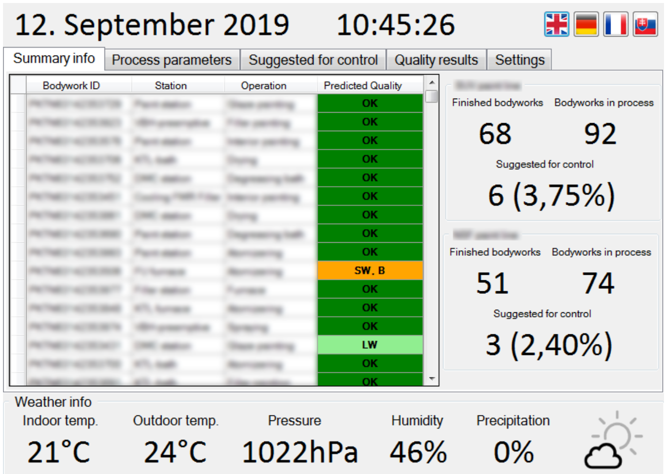

Fig. 7. Operator panel of proposed artificial intelligence platform for paint structure prediction

It should be noted, that the proposed platform is currently deployed as a proof of concept implementation in the paint shop. Efficiency is currently evaluated by employees in practice.

5. CONCLUSION

The proposed pilot solution of the artificial intelligence platform, for paint structure quality evaluation, serves to verify the suitability of using the neural network to predict the resulting quality from the selected process parameters. The artificial intelligence platform is currently in a multi-month proof of concept phase. The obtained results are continuously evaluated and used for neural network tuning. The proof of concept phase is scheduled for a minimum of eight months to ensure that the proposed platform will be used during hot and cold months, due to the different painting process behaviour at different temperatures. The suitability of the proposed solution that cannot be solved by standard methods, requiring a sophisticated and holistic approach, has been confirmed during the current proof of concept phase.

Our future work will enable us to realize the optimization of the paint structure process quality directly using real time modification of process parameters. This will allow us to create a support platform to achieve the highest possible quality of the paint structure.

ACKNOWLEDGEMENT

This contribution was written with the financial support of the VEGA agency in the frame of the project 1/0272/18: “Holistic approach of knowledge discovery from production data in compliance with Industry 4.0 concept”.

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