Manufacturing Process Optimization Through Machine Learning and Analytical Prediction

Malinka Ivanova, Valentin Tsenev and Borislav Dimitrov
Technical University of Sofia

***Abstract*—A "smart" production is characterized with collection of a large amount of data and the application of machine and deep learning algorithms for the purposes of analytical prediction. The analysis supports the implementation of intelligent management and rapid response to changes in a manufacturing process. The paper proposes an approach for optimizing a robotic manufacturing line for electronic components through applying the failure mode and effect analysis and algorithm for deep learning. This approach is embedded in a software tool created through C#, Windows Forms technology and open source to assist identification of the potential risks by the responsible engineer.**

***Keywords*—big data, deep learning, FMEA, machine learning, optimization, statistics, "smart" manufacturing, robotic line.**

I. Introduction

Nowadays, the manufacturing process is considered in its dynamics, taking into account the influence of the factor time. With the time, various changes of some other factors can occur and this affect on the product quality.

It is known that the robotic manufacturing lines of electronic components collect a large amount of data, which makes it possible to monitor changes and take appropriate actions before failure.

The concept of "smart" manufacturing is discussed in [1] and it includes the use of new technologies, consideration of many parameters and a number of factors. An important part of a "smart" manufacturing is related to the techniques for processing and analysis of the collected data, including the application of statistical methods and algorithms for machine learning. Another paper points out the importance of large data sets for organizing "smart" manufacturing and using the advantages of predictive analysis for early detection of errors and shortcomings [2].

The most commonly used algorithms for machine learning in manufacturing processes and in the context of Industry 4.0 are discussed in [3]. Here they are summarized graphically and are presented through Figure 1. Also are shown the most commonly used algorithms for deep learning, which is summarized on Figure 2.

Deep learning is a part of machine learning and artificial intelligence, as the process of learning from data sets is based on artificial neural networks (ANNs) usage. The architecture of ANNs includes a number of layers depending on the specific task and on the requirement for finding a solution with high accuracy. Although artificial intelligence systems are currently part of "smart" manufacturing and certain techniques for data analysis are used, the researchers are still looking for solutions to improve and optimize manufacturing processes based on deep learning and analytical prediction.

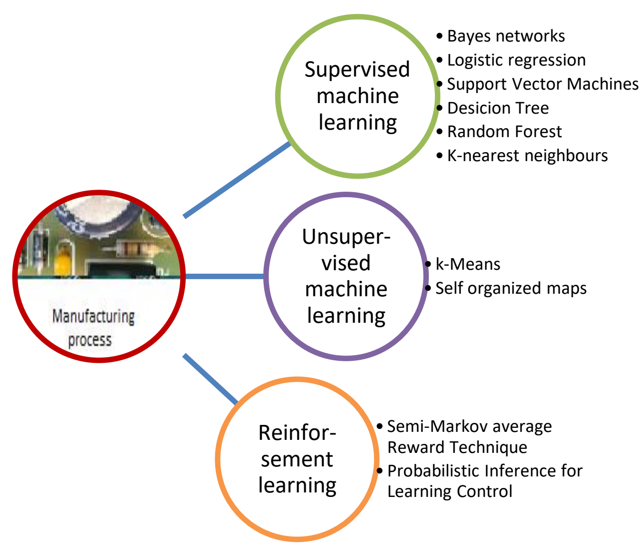

Figure 1. The most used algorithms for machine learning in a manufacturing process [3]

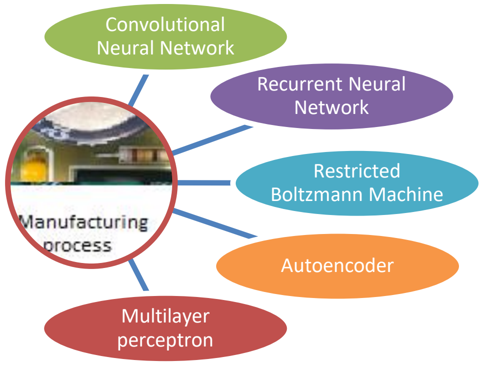

Figure 2. Deep Learning and its application in manufacturing process [3]

Statistical methods are also widely used for risk evaluation, control and optimization, as the most commonly used are: Gaussian process [4], [5], Failure Mode and Effect Analysis (FMEA) [6], [7], analysis of a tree with errors [8], repeatability and reproducibility [9].

The aim of the paper is to present an approach for optimizing a robotic manufacturing process for electronic components by comparing the FMEA and deep learning. The approach is implemented in a developed software tool to support timely informing the engineer in charge about the potential risks as well as to assist his decision-making process.

II. Research Methodology

The research methodology includes the following procedures: (1) A study of the FMEA and its applications for optimizing the manufacturing process of electronic components through the robot FANUC-M-10 is performed, which is documented through tables with information from experts. The activity *Component mounting* is discussed in more details as a demonstration example. Based on the collected information, data sets are formed, which are prepared for further processing by an algorithm for deep learning. Datasets are formatted according to the requirements of the .csv file. (2) A feed-forward artificial neural network with back-propagation is created, searching for the optimal neural network architecture according to the number of layers and neurons in each layer, as well as concerning the type of the activation function. Carrying out experiments in the environment of RapidMiner Studio on the data sets collected from the previous procedure as a deep learning is applied at the ratio of training and testing data: 70%/30%. Comparison between the FMEA results with deep learning is conducted. (3) Design and development of a software tool using C# programming language, Windows Forms technology and open source solutions for comparison of FMEA and analytical prediction is performed.

III. The Failure Mode and Effect Analysis

The FMEA is chosen as a statistical technique for performing risk evaluation in manufacturing using a FANUC-M-10 robot for placing and soldering electronic components on a printed circuit board. Failure regime means the situation in which a problem may occur. The problem is associated with errors, defects or outright failures. The analysis of the effects refers to the study of the consequences of these potential problems. Problems are prioritized according to how serious their consequences are, how often they occur, and how easily they can be identified. The purpose of the FMEA is some actions to be taken to eliminate or reduce failures, starting with those with the highest priority. FMEA is applied in order to prevent possible errors, defects and failures that may occur during the manufacturing. Thus, pre-identified problems at the earliest possible stage of the production process can save materials, resources and time. The advantages of FMEA are as follows: possibility for summarizing collective knowledge gained by experts; timely identification of risky manufacturing activities; reduction of the production cycle time; documenting possible risks of obtaining substandard or unusable products [10]. These benefits underlie the widespread use of FMEA to identify critical activities and priority risk.

This paper presents risk evaluation of manufacturing of electronic components, which includes activities for programming, starting, testing and stopping the robot, as well as the following main activities: component placing, soldering and external connections creation. All manufacturing activities are documented and evaluated according to three criteria: (1) *Severity* (S), indicating the influence of the failure effects on the subsequent manufacturing activities; (2) *Occurrence* (O), showing the probability of failure; (3) Detection (D), indicating how a particular control measure may contribute to the detection of a failure. Finally, the Risk Priority Number (RPN) is calculated as the product of above evaluated and described three criteria. RPN can take values from 0 to 100. If the value of the priority risk is higher, the greater is the probability of defect, error or failure occurrence. Then, activities are recommended, and after their implementation, the priority risk is recalculated. The resulting value of the risk is expected to be significantly lower, otherwise it is considered that the recommended activity has not led to reduction of the risk.

Tables document all activities related to this manufacturing process. Here is shown only one table (Table 1) with an evaluation of the manufacturing activity *Component mounting*. It consists of four potential failures: smaller diameter of the holes for the component mounting, larger diameter of the holes, no holes, no soldering square. Recommended activities to reduce the risk of potential problems are also shown. It can be seen that in this manufacturing activity the risk of failure is small and is minimized after the application of the recommended measures.

Data related to the rest of the main production activities (soldering and bonding) show that the priority risk may exceed 50 (from maximum 100 points). After the implementation of recommended activities, this risk can be significantly reduced.

Table 1. FMEA of manufacturing activity *Component mounting*

	Component mounting			
Activity	The component cannot be placed			
Potential failure	Smaller diameter of the holes	Greater diameter of the holes	Missing holes	Missing square for soldering
Potential effect	Another soldering cycle	Longer soldering time	Another soldering cycle	Another soldering cycle
S	2	4	3	5
Potential cause	Mistake of the programmer			
O	3	3	2	2
Current controls	Visual inspection			
D	2	2	2	3
RPN	12	24	12	30
Recommended activities	Preview of the printed circuit board			
	Proper selection of components before soldering			
	Corrections of the programming code			
Person in charge and date	Engineer production			
	Engineer production			
	IT expert			
Taken activities	Preview of the printed circuit board			
	Proper selection of the components			
	Programmer' training			
S	1	1	1	1
O	2	2	2	2
D	1	2	1	1
RPN	2	4	2	2

IV. Deep learning

Deep learning can be realized by applying a wide variety of algorithms and using ANNs with different architectures [11], [12].

In this work, a feed-forward artificial neural network with back-propagation is constructed, as shown in Figure 3. The ANN has 4 inputs: S, O, D and RPN and one output: the priority risk, which values can be: very low - at PRN = 1 ÷ 20, low - at PRN = 21 ÷ 40, medium - at PRN = 41 ÷ 60, high - at PRN = 61 ÷ 80) and very high - at PRN = 81 ÷ 100. The inputs are denoted with x_i and the output is y. Each neuron sums the input signals with a certain weight w_i and the result together with the deviation b is forward to the activating function AF, which can be linear or nonlinear [13]. Depending on this, linear or nonlinear regression or classification is performed. Our task here is a classification task to be solved. Then, the output y has the form: $y = AF(x_1w_1 + x_2w_2 + \ldots + x_nw_n + b)$.

The optimal architecture of an ANN is created after experimenting with the number of neurons and hidden layers with three different activating functions: tanh, rectifier and maxout (Table 2).

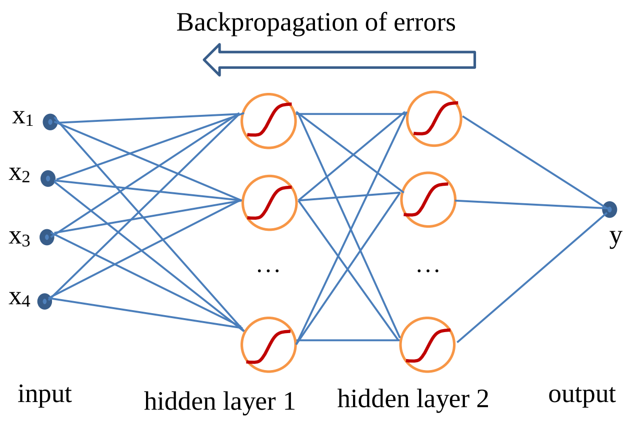

Figure 3. Feed-forward artificial neural network with back-propagation

Table 3 shows that with the highest accuracy of 96.81% is the ANN with 2 hidden layers, with 20 neurons in the first layer and 60 neurons in the second layer. The most suitable activating function for solving this classification problem is the hyperbolic tangent tanh.

Table 2. Activating functions

Hyperbolic tangent tanh	Rectified linear unit – ReLU	maxout
$\tanh(x) = (e^{x}-e^{-x}) / (e^{x}+e^{-x})$	$ReLU = \begin{cases} 0, & x<=0 \\ x, & x>0 \end{cases}$	$maxout = \max(w_1^T x + b_1 + w_2^T x + b_2)$
Range in (-1,1)	Range in $[0,\infty)$	Range in $(-\infty,+\infty)$

Table 3. ANN accuracy

	Accuracy		
Hidden layers/neurons	tanh	rectifier	maxout
2 layers /50/50	92.02%	85.11%	89.89%
2 layers /20/80	93.62%	91.49%	90.96%
2 layers /20/50	94.68%	83.51%	91.49%
2 layers /20/60	96.81%	82.45%	81.91%
2 layers /20/20	93.03%	87.77%	89.36%

V. INSTRUMENT FOR COMPARISON THE RESULTS FROM FMEA AND DEEP LEARNING

Comparison of FMEA results and deep learning is a possible approach for obtaining an objective evaluation and predictive analysis of critical activities in the manufacturing process of electronic components using the robot FANUC-M-10. This will support the responsible engineers to be timely informed about possible potential risks that can be avoided if appropriate measures are taken into account. Creating a software tool, implementing the proposed approach, could facilitate decision making and could prevent occurrence of critical problems.

The developed software tool incorporates the algorithm presented on Figure 4. Data from FMEA and deep learning can be entered manually via a form or via a pre-prepared .csv file. Numeric values for Severity - S, Occurrence - O, Detection - D, Risk Priority Number (RPNFMEA) are calculated after FMEA analysis and Risk Priority Number (RPNDL) is predicted by the neural network. Also, the evaluation is performed, as the risk is classified into five groups: very low risk, low risk, medium risk, high risk, very high risk.

The constructed software tool compares the results of FMEA and deep learning using two parameters RiskFMEA and RiskDL, and the comparison is presented in two ways: tabular and graphical. In the tabular and graphical representation, in addition to the parameters RiskFMEA and RiskDL, FMEAPoints and DLPoints are also shown, which provide statistical information on how many times the same risk priority number is obtained.

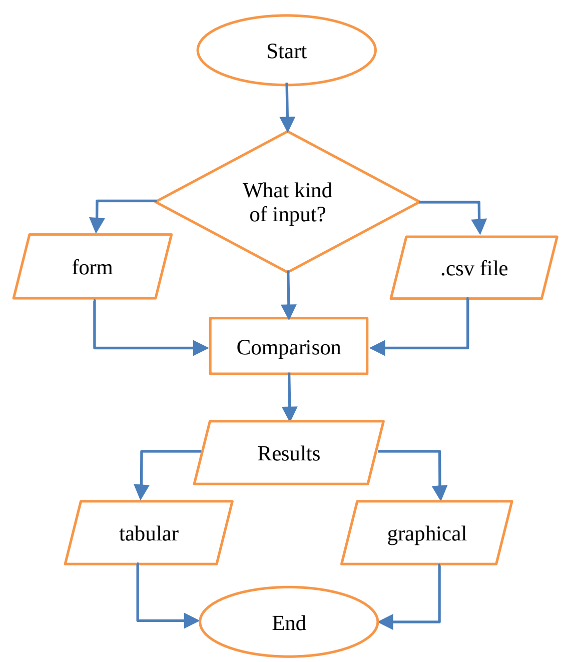

Figure 4. Algorithm behind the created software tool

Figures 5, 6 and 7 present screens from the implementation of the software tool with data taken from the demonstration example for the FMEA analysis concerning the manufacturing activity *Component mounting* and the four identified potential failures. From the obtained data, it can be seen that this activity does not carry a high potential risk of damage, defects or failures. However, there is a risk, which although minimal, must be taken into consideration. Using the *Add record* button, it is possible to enter data through the fields in the form, by the responsible engineer. Using the *Import .csv* button the engineer can read the data from a pre-prepared .csv file. The parameters Severity, Occurrence, Detection, RPNFMEA and RPNDL have a numerical expression, and the risk evaluation of FMEA RiskFMEA and the obtained prediction from deep learning RiskDL can be selected from five possible values. When the *Compare* button is clicked, a comparison is done between the results of the FMEA analysis and deep learning. The result of comparison is presented through tables and charts, showing the priority risk in the form of an evaluation in five groups: very low, low, medium, high and very high risk. According to the above mentioned demonstration related to the manufacturing activity *Component mounting*, the parameter RiskFMEA has values very low and low, repeated twice. The parameter RiskDL is characterized with very low values, repeated 3 times and low value predicted once.

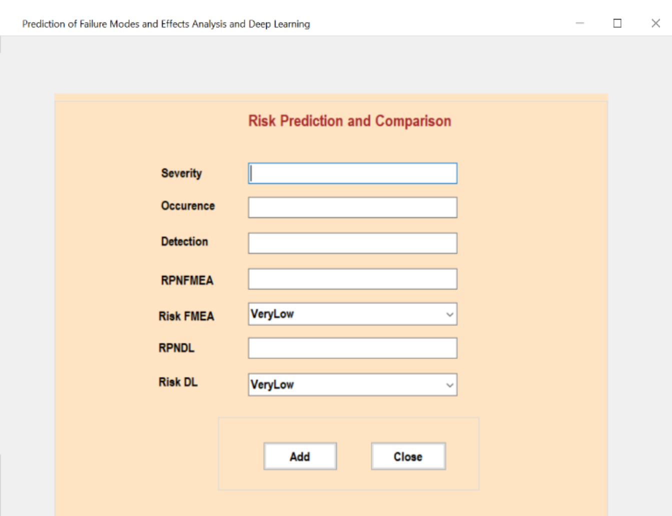

Figure 5. The form for data input

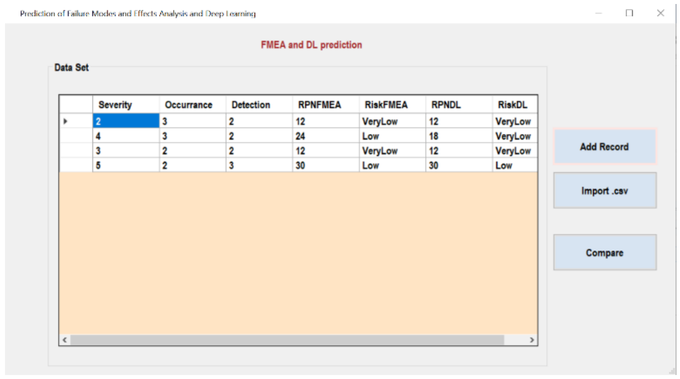

Figure 6. Entered data with possibility for comparison

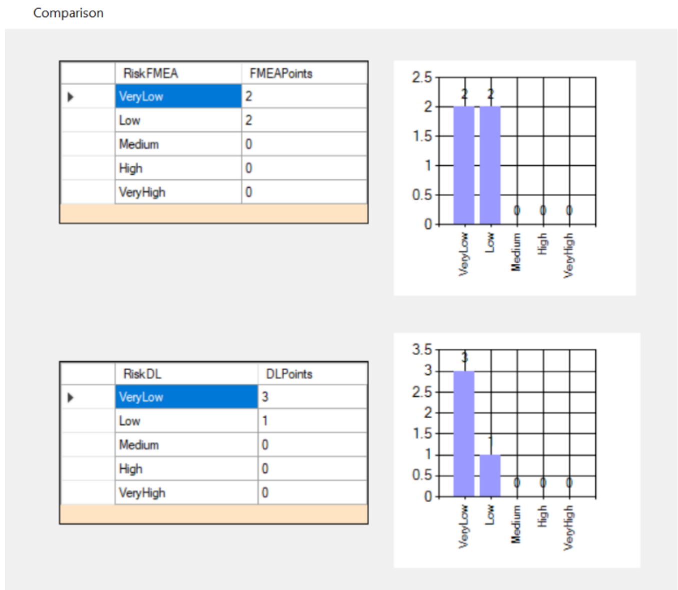

Figure 7. The results from comparison

VI. Conclusion

The FMEA is widely applied approach for evaluation of a manufacturing process and for identifyng potential failures. When the FMEA is combined with a deep learning algorithm it gives the opportunity for analytical prediction based on collected data during a dynamic manufacturing process. It is proved in this work that could be achieved very high accuracy of the predictive models and it depends on the constructed architecture of the ANN. Deep learning algorithm from supervised learning is tuned through usage of three different activation functions tanh, rectifier and maxout as the best accuracy 96.81% is obtained at ANN with 2 layers as the first one includes 20 neurons and the second one 50 neurons. The most suitable activation function for this classification task is tanh. Also, the developed software tool is presented, which compares the results from the FMEA and deep learning. There are huge possibilities for the FMEA to work in combination with deep learning algorithms in support of the responsible engineer, who can receive predicted analytics about potential critical manufacturing activities. This allows preventive actions to be taken and decisions to be made very quickly.

ACKNOWLEDGEMENT

This research is supported by Bulgarian National Science Fund in the scope of the project "Exploration the application of statistics and machine learning in electronics" under contract number КП-06-Н42/1.

REFERENCES

[1] Mittal, S., Khan, M. A., Romero, D., and Wuest, T., Smart manufacturing: Characteristics, technologies and enabling factors, *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 233(5), 2019, 1342–1361, https://doi.org/10.1177/0954405417736547.

[2] Moyne, J., Iskandar, J., Big Data Analytics for Smart Manufacturing: Case Studies in Semiconductor Manufacturing, *Processes*, 5(3), 39, 2017, https://doi.org/10.3390/pr5030039.

[3] Kotsiopoulos, T., Sarigiannidis, P., Ioannidis, D., Tzovaras, D., Machine Learning and Deep Learning in smart manufacturing: The Smart Grid paradigm, *Computer Science Review*, vol, 40, May 2021, 100341, https://doi.org/10.1016/j.cosrev.2020.100341.

[4] Civera, M., Boscato, G., Fragonara, L. Z., Treed Gaussian Process for Manufacturing Imperfection Identification of Pultruded Gfrp Thin-Walled Profile, *Composite Structures*, vol. 254, 15 December 2020, https://doi.org/10.1016/j.compstruct.2020.112882.

[5] Hensel, S., Marinov, M. B., Schwilk, T., Nikolov, D., Application of Gaussian Process Estimation for Magnetic Field Mapping, In: Perakovic, D., Knapcikova, L. (Eds,), Future Access Enablers for Ubiquitous and Intelligent Infrastructures, FABULOUS 2021. *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*, vol. 382, 2021, Springer, Cham, https://doi.org/10.1007/978-3-030-78459-1_21.

[6] Baynal, K., Sarı, T. Akpınar, B, Risk management in automotive manufacturing process based on FMEA and grey relational analysis: A case study, *Advances in Production Engineering & Management*, 13(1), 2018, 69–80, https://doi.org/10.14743/apem2018.1.274.

[7] Wu, Z., Liu, W. and Nie, W., Literature review and prospect of the development and application of FMEA in manufacturing industry, *The International Journal of Advanced Manufacturing Technologies* 112, 2021, 1409–1436. https://doi.org/10.1007/s00170-020-06425-0.

[8] Yahmadi, R., Brik, K. and Ammar, F. ben, Causal tree analysis for quality control of the lead acid battery manufacturing process, *International Journal of Energy Research*, 42(4), 2018, 1738-1759, https://doi.org/10.1002/er.3987.

[9] Runje, B., Novak, A. H. and Razumić, A., Measurement system analysis in production process, *XVII International Scientific Conference on Industrial Systems (IS'17)*, Novi Sad, Serbia, 4–6 October 2017, 274-277, http://www.iim.ftn.uns.ac.rs/is17.

[10] Liew, C. F., Prakash, J., Kamaruddin, S. and Ong, K. S. Deployment of an FMEA-Integrated Framework to Improve Operational Performance in Semiconductor Manufacturing: A Case Study, IOP Conf. Series: *Materials Science and Engineering* 530(1), 2019, doi: 10.1088/1757-899X/530/1/012040.

[11] Smys, S., Chen, J. I. Z., Shakya, S., Survey on Neural Network Architectures with Deep Learning, *Journal of Soft Computing Paradigm* (JSCP), 2(3), 2020, 186-194, doi: https://doi.org/10.36548/jscp.2020.3.007.

[12] Singaravel, S., Suykens, J. and Geyer, P., Deep-learning neural-network architectures and methods: Using component-based models in building-design energy prediction, *Advanced Engineering Informatics*, vol. 38, 2018, 81-90, https://doi.org/10.1016/j.aei.2018.06.004.

[13] Chigozie, N., Ijomah, W. L., Gachagan, A. and Marshall, S., Activation Functions: Comparison of trends in Practice and Research for Deep Learning, 2018, https://doi.org/10.48550/arXiv.1811.03378.