A Practical Experience of AI Solution Used to Improve Varnishing Process Efficiency in Furniture Manufacturing

Juan Del Agua [1] and Gabriel Modia [1]

[1]AIDIMME Metal-Processing, Furniture, Wood and Packaging Technology Institute, Benjamín Franklin Str, 13, 46980 Paterna (Valencia), Spain

Abstract

This paper shows the results of an R&D project where artificial intelligence techniques were applied to improve the efficiency of a varnishing process for flat parts in the furniture manufacturing sector. Specifically, a predictive model of the amount of varnish that the machine deposits on a piece has been developed. With the use case presented, it is shown how the datasets have been generated with the data, the type of algorithm training carried out, and the result of the precision of the different models tested. The model based on random forest has been the one that has shown the best calculation precision. Finally, the barriers to the algorithm learning process suffered in the use case have been identified, relating to the lack of interoperability between the capture systems involved.

Keywords

Artificial intelligence, machine learning, Industry 4.0, furniture manufacturing

1. Introduction

The number of research and developments in the field of Artificial Intelligence (AI) applied to manufacturing processes has increased in recent years. Predictive maintenance or defect detection solutions based on the application of AI techniques have been identified. However, there are still numerous manufacturing processes where there are information gaps that cause low production efficiency, where AI has great potential to be applied.

The furniture-manufacturing sector traditionally follows a process design known as "batch manufacturing" where machinery adjustments are required prior to each manufacturing batch. These adjustments directly affect production efficiency, reducing the available time of the machines and generating a waste of defective parts processed during the adjustments.

This document shows an application scenario in a manufacturing environment of an AI solution that allows reducing the configuration time and the waste of defective parts, in the process of varnishing flat parts in the manufacture of furniture. The AI solution, which allows predicting the amount of varnish applied to a piece of furniture, has been developed by AIDIMME within an R&D project at regional level in the Valencian Community.

After the introductory section, the rest of the document is organized as follows. In chapter two, a brief analysis of the state of the art related to the application of AI in manufacturing processes in general and in the furniture sector in particular is made. In chapter three the use case is presented, explaining the current problem of the varnishing process. In chapter four, the developed solution is detailed as well as its results. Three different models (neural networks, random forest, and linear regression) were trained. The random forest-based model obtained the best prediction accuracy both in the training phase and in the test phase. The conclusions are collected in the last chapter of this work, emphasizing one of the main barriers detected to adopt AI in real industrial environments: interoperability between different information source provider systems.

Proceedings of the Workshop of I-ESA'22, March 23–24, 2022, Valencia, Spain
EMAIL: jdelagua@aidimme.es (J. Del Agua); gmodia@aidimme.es (G. Modia)
ORCID: 0000-0003-4324-0533 (J. Del Agua); 0000-0001-6662-0569 (G. Modia)
© 2022 Copyright for this paper by its authors.
Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).
CEUR Workshop Proceedings (CEUR-WS.org)
CEUR-WS.org/Vol-3214/WS5Paper3.pdf

2. Related work

Today's manufacturing plants are forced to design production systems which combine high flexibility (to adapt to increasingly volatile environments) with a high level of efficiency (to maintain an adjusted cost level). To achieve this type of process where these two traditionally opposed concepts are integrated into manufacturing systems, industries are changing towards the concept of intelligent manufacturing. Within the concept of intelligent manufacturing, AI is one of the main enablers [1].

The ability of AI techniques to provide predictive insights has enabled discerning complex industrial patterns and offers a pathway for an intelligent decision support system in different industrial tasks: inspection, predictive maintenance, process optimization, supply chain management, and task scheduling [2]. In addition to the manufacturing processes where it has already been applied, AI opens the possibility of designing new processes, models and ways of working that will improve the efficiency of current systems [4].

After analyzing specific applications of AI, it has been identified that in Supply chain processes, genetic algorithms and intelligent agents are the most used techniques for supply chain planning processes, with an approach that incorporates uncertainty in supply [5].

In manufacturing AI methods have begun to find application in manufacturing systems for automated visual inspections, fault detection, and maintenance [6]. Within AI, Machine Learning (ML) techniques have been the ones that have had the greatest application so far [7].

Within the maintenance area, as a result of the SIMBA project [8], mathematical models were obtained to predict when a machine entered abnormal working conditions, applying AI techniques.

In furniture manufacturing sector it has been identified a lack of practical experimentation of AI methods. With the SAIN4 [9] project, an AI system was developed that made it possible to predict whether the conditions of a manufacturing process were adequate to manufacture parts within quality parameters or not.

One of the resulting challenges of the evolution of the intelligent manufacturing concept is the increased need for interoperability at different levels of the manufacturing ecosystem. Successful implementation of interoperability in smart manufacturing would, thus, result in effective communication and error-prone data-exchange between machines, sensors, actuators, users, systems, and platforms [9]

Regarding the concept of interoperability of systems within the furniture-manufacturing sector, there is very little practical research. AIDIMME has participated in the EFPF project [13], where a pilot was developed integrating vision systems, data capture through sensors and human-machine interface (HMI), demonstrating a positive impact on the efficiency of the manufacturing process.

There are still a large number of tasks where the application of AI techniques can improve the efficiency of the production process. For this, pilot experiences are necessary to validate both the information systems and the data they offer, required for the learning processes. These pilot experiences should also serve to bring out the needs for interoperability between said systems.

3. Use case definition

The use case studied in this paper refers to a project that aims to improve the efficiency of the varnishing process for flat board pieces. This production process presents big information deficiencies that have an impact on quality and machine availability. A perfect piece will be one to which an exact amount of varnish has been applied which optimizes costs, while guaranteeing long-lasting aesthetics and mechanical properties.

The varnishing operation is carried out in a type of machine where rollers are soaked with varnish, and they are these that deposit it on the piece of board. In this type of machinery there are a series of parameters that can be manipulated by the operator: (1) speed of the conveyor belt, (2) speed of the applicator roller, (3) speed of the dosing roller, as well as (4) distance between rollers.

Another series of parameters are constant for a specific machine: for example the (5) hardness of the applicator roller. Finally, there are other parameters that do not depend on the machine, but on the coating varnish: viscosity which depends on the (6) temperature and the type of varnish (7) used. All these parameters have been identified as influencing the amount of varnish that is finally deposited on a piece.

Nowadays, a worker spends, in average, 30 minutes with every new order setting up the machine parameters (1-4) in order to obtain a furniture piece with the right quantity of varnish. The only way to check the amount of varnish applied is to weigh the piece before and after the varnishing process. It is a manual and iterative process that is labor intensive and does not guarantee the best possible combination of machine parameters. In addition, changes in the type of varnish or its temperature require new modifications of these parameters to be adjusted to the target varnish weight. In addition, with each new piece format, while these machine adjustments last, a waste of 10-15 varnished pieces is generated that do not meet the quality standard, until the exact amount of varnish applied to the pieces is adjusted.

With the present work, Artificial Intelligence (AI) techniques have been used to generate a model which allows real-time prediction of the amount of varnish applied in the process. This information saves the operator from having to manually weigh the pieces (before and after varnishing), and he will be able to adjust the machine parameters more quickly with each new manufacturing order, as well as detect immediately if there are variations in the target weight to be applied.

4. Implementation scenario

To carry out the learning process by applying AI, it is necessary to collect and integrate data and information from different sources and systems. On the one hand, sensor data to be installed in the coating machine: conveyor belt speed (1), applicator roller speed (2), dispenser roller speed (3), and distance between rollers (4). Also, it is necessary data from a sensor in the coating tank to measure varnish temperature (6). The parameter of the hardness of the applicator roller (5) is not taken into account in the experiment, since only one machine is used and, therefore, it is constant. On the other hand, information must be collected on the value to be predicted (applied varnish weight) and the type of varnish used (7). To do this, manual information is collected on the weighing of the pieces before (8) and after (9) being varnished. In Figure 1 green color represents data captured by sensors, red color data captured by a worker and black color is a constant.

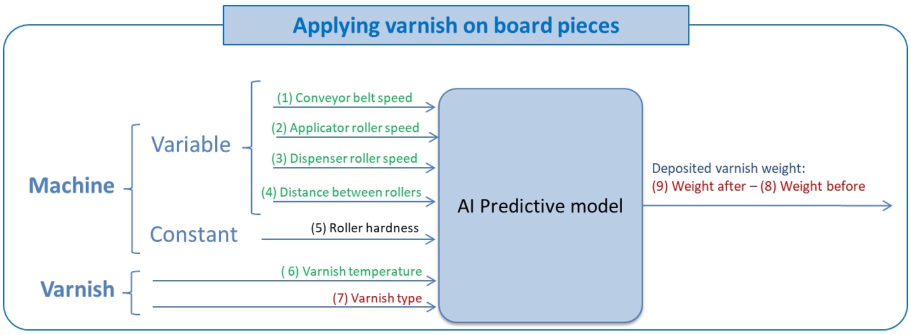

Figure 1: Data involved in the AI predictive model.

4.1. Data capture systems

In order to generate enough data to carry out the learning process through AI, the implementation of two data capture systems was carried out: an automatic and real-time data capture system with sensors (data sources 1,2,3,4 and 6) that were installed on the machine and a manual data upload system for those measurements not able to retrieve by sensors (data sources 7, 8 and 9).

In a roller coating machine located in AIDIMME, inductive sensors were installed to obtain a measurement of the speed of the conveyor belt, as well as the rotation speed of the dosing and applicator rollers. A sensor was also installed to measure the distance between the two rollers, and another sensor to measure the temperature of the varnish (Figure 2). These sensors are connected to a PLC (Siemens S7 1200) placed near the machine that governs the data capture cycle, and dumps them into a SQL database hosted on an industrial PC. An application was also developed to record the rest of data that could not be collected automatically by sensors. The user interface allows the operator to enter the type of varnish applied, the identification number of the piece being processed and the weight of the piece before being varnished, as well as the weight of the piece after varnishing.

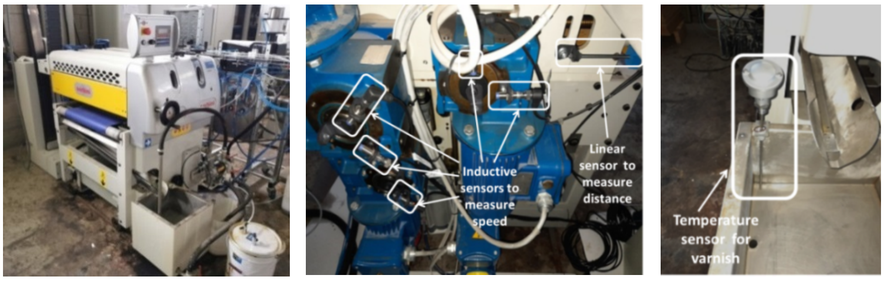

Figure 2: Sensors installed in the varnishing machine.

4.2. Datasets generation

First, a series of machine configurations were designed to be tested in terms of conveyor belt and roller speeds (Table 1). For the conveyor belt, the speeds to be tested were: 6, 8, 10 and 12 m/s. The speed of the applicator roller needs to be in sync with the conveyor belt, and therefore it was also tested at: 6, 8, 10 and 12 m/s. The dosing roller speeds were: 0 (stopped), 2 and 4 m/s.

The distance between rollers was manually modified each day of experimentation, with all values being within the 0-0’8 mm range. The temperature of the applied varnish varied in the range 5-45ºC, cooling and heating previously for the tests carried out.

Table 1
Sensor conditions tested

Conveyor belt speed (m/s)	Applicator roller speed (m/s)	Dispenser roller speed (m/s)	Distance between rollers (mm)	Varnish Temperature (ºC)
6	6	0	0 – 0’8	5 -45
8	8	2		
10	10	4		
12	12			

Two types of varnishes (with different viscosities) were used, manufacturing 60 pieces with each of them, with different configurations of speeds, distance between rollers, as well as varnish temperature. The pieces were weighed before and after processing. The data from the sensors was collected automatically by the PLC, but the data on the weight of the pieces (before and after being processed), the type of varnish, and the piece identifier were uploaded manually by the user through the developed interface.

4.3. AI techniques applied

The first step followed was to evaluate the machine learning approach that best fit the project. In this case, labeled data was available for both the parameter to be predicted and the parameters to be used in the model, so supervised learning can be applied. Also, since you are trying to predict a numerical quantity, you should select a regression method. Some of the most common in AI include linear regression, polynomial regression, neural networks, or support vector machines. In this project, artificial neural networks, linear regression, and random forest regression were used.

The next step was to study the data available in the two data sets (from sensors as well as from manual recording). A data cleanup was performed, inspecting the tables for erroneous data, duplicate data, or outliers that occurred by mistake. Once each data set had been cleaned individually, they had to be integrated into a single, unified data set. The rows of the two datasets were not connected one to one, which meant that it was required to find out which rows of one dataset corresponded with those of the other. For this task, a python script was programmed where the time field was used in both tables, eliminating the remaining records and being able to generate a single dataset.

Once the data were merged, their normalization was carried out, that is, transforming all the data into an interval [0,1] following a normal distribution. The data set was then divided into two parts; the first with 70% of the data (whit 104 records) is called the Training Set, while the second contains the remaining 30% and is called the Test Set (with 26 records). The algorithms learn from the first part, but then their performance is checked on both sets. With this technique, you are guaranteed that the resulting method works well not only with data that you already know, but also with new data.

To validate and compare its performance with the original data, three metrics were used: the mean absolute error (MAE) measuring the average deviation of the original and predicted data, the root mean square error (RMSE) measuring the same deviation but focusing on the large deviations, and the R squared (R^2) giving a measure of the similarity of both curves.

4.4. Results

For the training dataset, the predictive model which obtained the best precision indicators was the random forest (Table 2). Similar results were obtained with a neural network, but the model based on a linear regression model obtained results with considerably worse precision. For the dataset used as test, all the accuracy indicators of the three trained models worsen. But the error of the model based on random forest is still acceptable and consistent.

Table 2
Accuracy indicators of predictive models: Training and test phase

Training / Test	**Neural Network**	**Random Forest**	**Linear Regression**
MAE	3,52 / 5,65	1,84 / 4,9	5,68 / 9,43
RMSE	35,02 / 75,58	10,22 / 54,99	64,4 / 262,88
R^2	0,91 / 0,75	0,97 / 0,82	0,84 / 0,13

5. Conclusion

The mathematical models generated based on random forest have a high precision for the prediction of the amount of varnish deposited on the furniture piece. With this solution, the estimated amount of time adjusting the machine parameters to apply a specific amount of varnish is reduced from 30 (without the AI-based solution) to 5 minutes (with AI-based solution), increasing the availability of the machine for manufacturing activities, and therefore the efficiency of the process. This time saving has been obtained by measuring the time taken by the user of the machine to adjust the production to the target weight, before having the solution based on AI and after having it.

Therefore, AI has proven to be valid for its application in complex industrial processes. However, with the experimentation carried out, a series of barriers have been identified that must be previously resolved in order to achieve a satisfactory implementation of AI-based solutions in a real industrial environment:

- To generate a training dataset it is necessary to install external sensors on the machine. For this, the participation and consensus of production and maintenance workers is required, as well as a control of the working conditions to guarantee the stability of the data generated.
- Data aggregation must be done manually, which takes extra time. This way of proceeding can lead to human error, especially on a large dataset where even applying automation scripts could fail with some outlier examples.
- The retraining of the models, which must be carried out with each new type of varnish or repair on the machine that involves changes to the rollers or conveyor belt, implies carrying out the entire process again.

The lack of interoperability between the different systems in charge of collecting the data prevents the adoption of automated solutions to the barriers detected. With the interoperability of factory systems, since data would be automatically collected and processed, models could be retrained at pre-defined time intervals. Since all systems would be accessible, once the model is retrained, the AI system could communicate with the engineering team and report on the results and performance of the new model.

Furthermore, once the final predictive model is running, the lack of interoperability with the rest of the company's software dampens the positive impact of the AI-based solution. For decision making in the factory, it is necessary to connect order information, inventory level, quality, maintenance, etc. In this way, the AI core could be integrated with some other tools that would allow managers to access all the data in the factory. Systems such as MES (Manufacturing Execution Systems) or Business Analytics tools such as Power BI [14] or Tableau [15] could be potential candidates to use the result of the predictive model as input.

6. Acknowledgements

This work was fully supported by the "Instituto Valenciano de Competititividad Empresarial" (IVACE) through the "Proyectos de I+D en cooperación con empresas" Programme, through VIRTUALSENSE project with grant agreement IMDEA/2020/22.

7. References

[1] J. Lee, J. Singh, M. Azamfar, V. Pandhare, Industrial AI and predictive analytics for smart manufacturing systems, in: Smart Manufacturing, Elsevier, Amsterdam, 2020, pp. 213-244.

[2] X. Yao, J. Zhou, J. Zhang, C. R. Boër, From intelligent manufacturing to smart manufacturing for industry 4.0 driven by next generation artificial intelligence and further on, in: 5th International Conference on Enterprise Systems (ES), IEEE, New York, 2017, pp. 311-318. doi: 10.1109/ES.2017.58.

[3] R. Rai, M. K. Tiwari, D. Ivanov, A. Dolgui, Machine learning in manufacturing and industry 4.0 applications, International Journal of Production Research 59 (2021) 4773-4778. doi: 10.1080/00207543.2021.1956675.

[4] B. H. Li, B. C. Hou, W. T. Yu, X. B. Lu, C. W. Yang, Applications of artificial intelligence in intelligent manufacturing: a review, Frontiers of Information Technology & Electronic Engineering 18 (2017) 86-96. doi: 10.1631/FITEE.1601885.

[5] G. A. Icarte Ahumada, Aplicaciones de inteligencia artificial en procesos de cadenas de suministros: una revisión sistemática. Ingeniare, Revista chilena de ingeniería 24 (2016) 663-679. doi: 10.4067/S0718-33052016000400011.

[6] C. F. Chien, S. Dauzère-Pérès, W. T. Huh, Y. J. Jang, J. R. Morrison, Artificial intelligence in manufacturing and logistics systems: algorithms, applications, and case studies, International Journal of Production Research 58 (2020) 2730-2731. doi: 10.1080/00207543.2020.1752488.

[7] J. F. Arinez, Q. Chang, R. X. Gao, C. Xu, J. Zhang, Artificial intelligence in advanced manufacturing: Current status and future outlook, Journal of Manufacturing Science and Engineering 142 (2020) 110804. doi: 10.1115/1.4047855

[8] AIDIMME, SIMBA - Sistema inteligente de mantenimiento basado en el estado real del equipo, 2018. URL: https://www.aidimme.es/serviciosOnline/difusion_proyectos/detalles.asp?id=28698

[9] AIDIMME, SAIN4 - Sistemas avanzados de eficiencia productiva para la industria 4.0, 2017. URL: https://www.aidimme.es/serviciosOnline/difusion_proyectos/detalles.asp?id=28449

[10] A. Zeid, S. Sundaram, M. Moghaddam, S. Kamarthi, T. Marion, Interoperability in smart manufacturing: Research challenges, Machines 7 (2019) 21. doi: 10.3390/machines7020021

[11] R. Jardim-Goncalves, A. Grilo, K. Popplewell, Novel strategies for global manufacturing systems interoperability, Journal of Intelligent Manufacturing 27 (2016) 1-9. doi: 10.1007/s10845-014-0948-x.

[12] G. Weichhart, H. Panetto, A. Molina, Interoperability in the cyber-physical manufacturing enterprise, Annual Reviews in Control 51 (2021) 346-356. doi: 10.1016/j.arcontrol.2021.03.006

[13] G. Bhullar, S. Osborne, M. J. Núñez Ariño, J. Del Agua Navarro, F. Gigante Valencia, Vision System Experimentation in Furniture Industrial Environment. Future Internet 13 (2021) 189. doi: 10.3390/fi13080189.
[14] Microsoft – Power BI, 2021. URL: https://powerbi.microsoft.com/es-es/
[15] Tableau, 2021. URL: https://www.tableau.com/es-es