Digital Twin for Automated Industrial Optimization: Intelligent Machine Selection via Process Modelling

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***Abstract*—Digital Twin (DT) is an emerging paradigm that enables a virtual model to effectively represent a physical process. In this paper, we present the adoption of the DT scheme by an offset printing company towards industrial optimization. The considered DT model is a virtual representation that serves as the digital copy of the physical printing process within an industrial unit. A virtual model for selecting the optimal machine line was developed to ensure cost-efficient printing. The machine line selection process was modeled as a decision process and then analyzed through simulations in a safe and cost-efficient digital environment, provided by the DT. Moreover, Machine Learning (ML) models were exploited to extract knowledge for the machine selection task, taking full advantage of the DT experiment. Based on real data and selection policies of a printing enterprise, the results revealed an improvement during the selection process, followed by a 5% cost reduction on the examined dataset.**

***Index Terms*—Digital Twin, Digitalization, Machine Learning, Industry 4.0, Business Process Management**

I. Introduction

Living in a digital era, all modern and competitive companies, understand that digitalization is key for moving towards the new age of business and commerce. The digitalization process is of paramount importance for an organization to improve its production line. One of the most successful paradigms of digitalization is the Digital Twin [1]–[3]. The Digital Twin scheme offers the possibility of creating a digital copy of the physical resources and production line and presents a number of advantages like being able to simulate facilities in a protected environment, with minimal risks and costs. Digital Twin also enables Artificial Intelligence (AI) and Machine Learning (ML) methodologies that can be utilized as major instigators in Industry 4.0 to enable automation in the manufacturing process, as well as provide defect detection and real-time decision-making functionalities.

Offset printing is one of the most extensively used printing methods, capable of handling a wide range of printing projects such as newspapers, magazines, brochures, labels, books, and many more. Currently, the traditional printing process presents a number of issues: (i) lack of real-time decision-making and data analysis, (ii) the amount and diversity of order characteristics make it difficult to standardize the operations, (iii) important decisions on resources are taken by humans and (iv) an increased environmental impact due to absence of optimization. Digitalizing any step of the printing process could be an enormous advantage for any offset printing company and address multiple of the aforementioned issues. Monitoring, process optimization, and proactive maintenance can be possible thanks to the digitalization of the printing process through the Digital Twin. More specifically in this experiment, the Digital Twin is intended to assist human operators in the difficult machine selection process, which is: finding the available production lines capable of printing a given order, respecting the order's features, and then selecting the optimal line which minimizes the cost.

Selecting the most suitable machine line to print orders is one of the most critical decisions in the production process. The company currently has three (3) different lines of printing: one 5-colour printing line (hereinafter referred to as 5-col), one 8-colour printing line (hereinafter referred to as 8-col), and one 4-colour printing line (hereinafter referred to as 4-col).

In this work, we present the Digital Twin experiment, as conducted within the company's environment. The key contributions of the proposed experiment can be identified as: (i) reporting and modeling the examined physical processes, (ii) the exploitation of historical knowledge extracted by a real printing industry environment to obtain accurate and reliable data, (iii) the proposition of an automated machine selection policy, which can be easily simulated, and (iv) the utilization of Machine Learning (ML) classification models to further analyze and optimize the machine selection process.

This work has been partially supported by the OASEES project, funded by the European Commission under Grant Agreement No 101092702 through the Horizon Europe Program (https://oasees-project.eu/).

II. Related work

Optimizing industrial production lines has been a well-studied problem with many proposed methodologies [4]. Digitilizing the planning process within the printing industry has also been extensively studied [5]. Machine learning and artificial intelligence tools were also used for industrial digitalization and optimization. Deep learning-based approaches were introduced for bearing fault diagnosis [6]. Moreover, deep learning has been an established approach also for the printing industry. Deep learning has also been leveraged for industrial vision quality control in the printing process [7]. Artificial intelligence has also been utilized for creating mechanisms for IoT, edge and cloud computing-based industrial applications [8]–[10]. Last, a comparative study of the impact of classifiers on the drift detection problem has been presented [11]. Industrial digitalization has also been studied extensively on the subject of Zero Defect Manufacturing (ZDM) [12], which takes advantage of Industry 4.0 technologies. Recently, the Digital Twin scheme has also been proposed for Zero Defect Manufacturing (ZDM) [13].

The company has already experience in exploiting machine learning models towards optimizing a production process. Specifically, the R&D department has investigated both supervised and unsupervised approaches for the machine allocation task [14], [15]. The proposed methodologies were introduced in the context of ZDM and were used to minimize defective outputs and waste as well. While the previous studies have been extremely helpful, they mainly constitute approaches that work on an offline dataset, that do not reflect or mirror the actual printing process.

In this paper, we propose the Digital Twin scheme, a virtual copy of the printing process, deviating from the ZDM context. The Digital Twin will serve as a live, interactive, and efficient way of modeling and observing the physical process of printing, analyzing via machine learning models, while selecting the optimal machines to print orders, minimizing cost and resources. To the best of our knowledge, this Digital Twin experiment is one of the first to be studied within the offset printing industry, combining also state-of-the-art process modeling and machine learning tools.

III. Materials and Methods

A. Dataset

The company keeps records of jobs for each month, grouped by the assigned machine line ID. For each printing job, we get 14 values, representing the job's features. Each of the collected data samples follows the process of a particular printing order with specific characteristics. In order to have a representative dataset of the printing lines, a number of orders for each individual machine were selected, leading to 5117 samples. The dataset covers a time period of 12 months. We point out that an order could include multiple jobs printed in multiple machine lines, for example, a book includes the cover and the pages. For simplicity, we keep only the machine line with the highest frequency for a single order.

Each order when given by a customer is characterized by a number of features. Afterwards, the order is enriched with some additional information coming from multiple departments. The ones that we exploit for the Digital Twin are presented in the following bullets:

- ID: auto-increment integer identifier of a printing order.
- Delivery time (days): the number of days that the order shall be printed and delivered to the customer.
- Ink Varnish: the ink varnish selection is considered as a boolean attribute with True or False possible values.
- Colour (4 or >4): This categorical variable denotes the color requirements of the particular printing assignment. In offset printing, the most requested color requirement is the 4-colour printing (class 1), followed by 4+1 colour printing (class 2 that involves the use of special / pantone colors, for example gold and/or silver) and grayscale printing (class 3 entailing only black and white colors).
- Quantity: the number of paper pieces requested in this specific order. Quantity takes integer values extending to up to large numbers, depending on the type of printing assignment (e.g. newspaper, poster, etc.).
- Type: Each specific printing order has an associated discrete type category, also denoting required specifications related to the post-press procedure.
- Quality: The quality of the paper associated with the specific printing order. The Quality parameter takes string values depending on the properties of the requested paper. The most used ones are 'Velvet' (the most frequently used), 'Uncoated', and 'Illustration/Gloss' paper quality.
- Job name: each job comes with a small description, including the customer's name, and requested type.
- Sides: a job may be required to be 1-side or 2-side.
- Weight (gr): the weight of the paper to be used in the printing process, measured in grams.
- Press sheets: it is a larger than-requested sheet that fits multiple smaller printed sheets. For example, a press sheet may include multiple pages of a book, which are then cut to create single pages. Its maximum size may be 70x100 cm.
- Dimension: the dimensions of a printing order come in the following format: 350x280 mm - 500x280 mm.
- Cost 4-col: the cost of 4-col line to print the order.
- Cost 5-col: the cost of 5-col line to print the order.
- Cost 8-col: the cost of 8-col line to print the order.
- Machine ID: the machine line to print the order.

B. Proposed Digital Twin Architecture

The following Figure 1 is an abstractive high-level illustration of the Digital Twin architecture. On the left side, an abstractive illustration of the physical production flow is shown. A customer arrives, giving a specific order. Then the order is passed to the Sales department. Given an order, the Sales department proceeds with the order analysis and outputs the paper type, quantity, size, and format. The total cost is computed by the Finance department and then the order is given to the Production department.

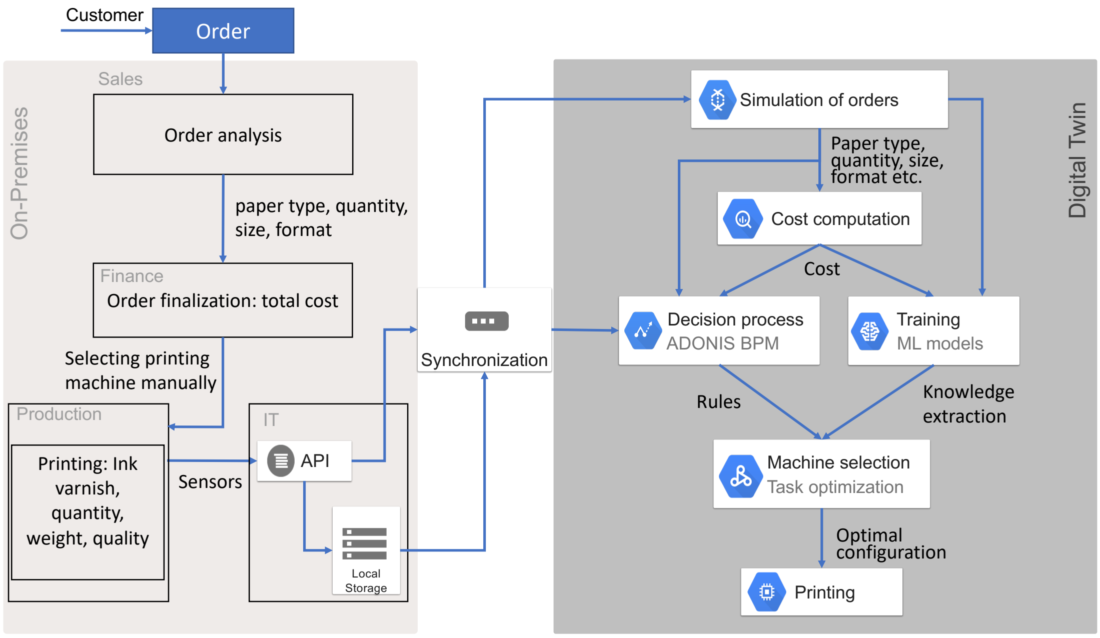

Fig. 1. The Digital Twin experiment design.

On the right side, the Digital Twin is presented. Older or simulated orders are first given for cost computation and then can either feed the designed decision process or be used as a training dataset for machine learning classifiers. Then the ML models can be trained to learn the optimal configuration for machine selection. Newly arrived orders can be given to the trained ML models and via the Digital Twin, we have access to the optimal configuration (best machine) for the specific order.

C. *Decision process modeling & simulation*

Modeling the physical processes that we wish to study through the Digital Twin experiment is the first objective of the development work package. The implementation of business process modeling (BPM) is done with a business process management tool, which is a full-featured business transformation suite created specifically for process management.

We point out that in our Digital Twin experiment, we attempt to model a specific production process: selecting the most suitable machine line to print an order (also referred to as a job). In addition to the multi-colour lines, there are also some digital printers, not considered as an additional line, and thus not shown in the current machine selection process.

Before we are able to model the decision process, we gathered the actual steps that the company follows during the physical process of selecting the printing machine line.

1) First, if the delivery date is less than 2 days, the digital printers are selected.
2) The next step is looking at the ink varnish, given by the job order. If the ink varnish selection is True, the order is printed on the 5-colour line. If the ink varnish is False we move to the next step.
3) Next, the job colour feature is checked. If the job colour is larger than 4 colours, the 5-colour line is selected. If the job colour is equal to or less than 4 colours, we move to step 4.
4) The next features to be used are Quantity and Printing sheet. If the product of quantity times printing sheets is less than 500, the 4-colour line is selected to print the order. If the value is equal to or higher than 500, we move to step 5.
5) Next, the paper's weight is checked. Books, journals, newspapers, and magazines fall under the category of weight equal to or less than 170 grams. On the other hand, posters, leaflets, business cards, and folders have a weight higher than 170 grams. If the weight is higher than 170g, the job is to be printed on the 4-color or 5-color lines, depending on the cost. The cost calculation is done by the pre-quotation department. If the weight is less than 170g, we move to step 6.
6) Dimension is the next feature to be taken under consideration. Here, the dimension is transformed to "True 4-col" or "False 4-col". This means that either the job is able to be printed on the 4-colour line or not. If the value is "True 4-col", a cost comparison between all the lines is performed. In the other case of the dimension being "False 4-col", a cost comparison between the 5-colour and the 8-colour lines is done. The line with the lowest cost gets to print the job.
7) Before reaching the final step of printing, a compar-

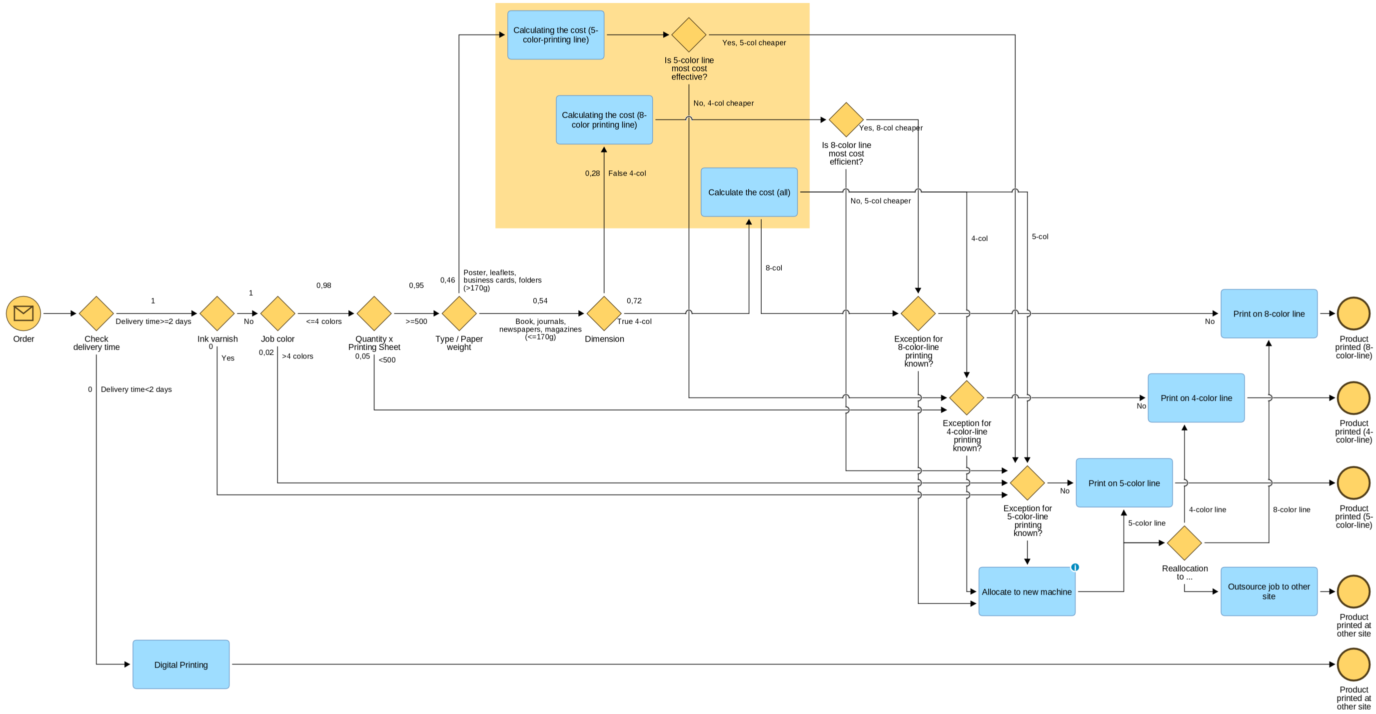

Fig. 2. The decision diagram as developed via the Business Process Management tool.

ison with previous jobs on similar lines is made. If no exception arises, the printing process begins. If an exception arises, the job is reallocated to a new machine. In the case of exceptional circumstances, a job can be outsourced to another site.

Figure 2 presents a digital representation of the physical process in full detail: features, inputs, outputs, and decision rules. Rectangles represent actions or processes, diamonds represent conditions and lines represent the flow.

D. Cost computation

A critical part of the decision process regarding the machine allocation task, which is also shown in the decision diagram, is the cost computation process. Each machine line has a different cost, and thus finding the machine line with the minimum cost, is vital to the company's economic well-being and growth. The cost computation is also dependent on other features, namely the requested quantity and the number of press sheets requested by the order. Next, we present the cost computation formulas of each machine line. For all formulas, q denotes quantity and p denotes the number of press sheets.

4-colour: regarding the 4-col machine line the cost follows a specific formula. We first need to check if the order requires 1-side or 2-side printing. In the case of 1-side, we have:

$$C^T_{4,1} = p \cdot C_4 \cdot (0.3 + q/1500) \tag{1}$$

where $C^T_{4,1}$ denotes the total cost of 4-color with 1-side printing and C_4 denotes the 4-col machine cost per hour. On the other hand, in the case of 2-side printing, we have:

$$C^T_{4,2} = p \cdot C_4 \cdot (0.3 + q/750) \tag{2}$$

where $C^T_{4,2}$ stands for the total cost of 4-color with 2-side printing.

5-colour: here the formula changes significantly. Again, we first need to check if the order requires 1-side or 2-side printing. In the case of 1-side we have:

$$C^T_{5,1} = p \cdot C_5 \cdot (0.2 + q/32000) \tag{3}$$

where $C^T_{5,1}$ stands for the total cost of 5-color with 1-side printing and C_5 denotes the 5-col machine cost per hour. On the other hand, in the case of 2-side printing, we have:

$$C^T_{5,2} = p \cdot C_5 \cdot (0.2 + q/16000) \tag{4}$$

where $C^T_{5,2}$ stands for the total cost of 5-color with 2-side printing.

8-colour: Lastly, regarding the 8-col machine line the formula the constants change slightly. Here, there is no need to check if the order requires 1-side or 2-side printing. In both cases of side printing, the cost is computed as follows:

$$C^T_8 = p \cdot C_8 \cdot (0.2 + q/14000)) \tag{5}$$

where C^T_8 stands for the total cost of 8-color and C_8 denotes the 8-col machine cost per hour.

As stated again, the cost of the printing process is very important for the overall product, as it points out the most efficient machine line. Currently, the company does not take into consideration the huge importance of cost computation, as it is mainly interested in time efficiency. Combining the cost computation and scheduling processes will be one of the greatest benefits of the company's digitalization activity.

E. Machine Learning for Classification

In a supervised learning scenario, a machine learning model, in our case, classifiers, are given a number of instances with information for training and their ground truth class as a label that we want to predict.

Setup: here we have a scenario of a multi-class single-label classification task, where we use the real machine ID as a class. For features, we use color, quantity, sides, weight, press sheets, dimension, cost 4-col, cost 5-col, and cost 8-col. The costs are precomputed and added as additional columns. We use 75% of the dataset for training the classification model and the rest 25% for testing after we shuffle them.

Metrics: as evaluation metrics, we shall use precision, recall, f1-score, and accuracy. In binary classification, the precision for a class is calculated as the ratio of true positives—that is, the number of objects correctly classified as belonging to the positive class—to the total number of elements classified as positive (i.e. the sum of true positives and false positives, which are items incorrectly labeled as belonging to the class). Recall in this context is calculated as the total number of components that truly belong to the positive class divided by the number of true positives (i.e. the sum of true positives and false negatives, which are items that were not labeled as belonging to the positive class but should have been). The f1-score can be interpreted as a harmonic mean of precision and recall, where an f1-score reaches its best value at 1 and the worst score at 0. The relative contribution of precision and recall to the f1-score are equal. Accuracy is the ratio of the number of correct predictions to the total number of input samples. For macro averaging we compute the metric for each label, and return the average without considering the proportion for each label in the dataset.

IV. Experimental Results

First, we want to know if we can correctly predict the actual machine lines by following our decision process. We managed to successfully predict 62.4% of the total orders. The remaining 37.6% is not predicted correctly due to scheduling, and the best suitable machine in terms of cost which are not available during the arrival of the order.

A. Cost

The total cost of the actually selected machine lines was 5514173. Since our decision process selects different machine lines in many orders, the total cost is also different. The new computed cost is 5249826. We observe a reduced cost of 264346 (5%) in just a year of printing orders.

In some cases, more than one machine lines are capable of printing a job. After running the first part of the simulation and before the cost computation process, we get the estimated machine line, which may include one, two, or all three lines. This is why we need to compute and compare costs. Table I presents an analytical overview of the cost computation process. We immediately observe that when the estimated machine line is either 4-colour or 5-colour, in most cases using the 5-colour machine is less expensive and this is why it is more frequent, as seen in the first row of the table. On the contrary, when the estimated machine line is either 5-colour or 8-colour the cost does not give us a clear view of which line will be selected. Last, we see that when the order is able to be printed in all machine lines, the most cost-efficient is again the 5-colour line.

TABLE I
ESTIMATED MACHINE LINES AND COST COMPARISON.

Estimated machine line	Cost comparison	Count
4/5 col dep cost	Cost 4-col≥Cost 5-col	1516
	Cost 4-col≤Cost 5-col	74
5/8 col dep cost	Cost 5-col≥Cost 8-col	388
	Cost 5-col≤Cost 8-col	354
4/5/8 col dep cost	Min cost 4-col	73
	Min cost 5-col	1227
	Min cost 8-col	688

B. Fitting machine learning models to initial dataset

In this part, we compare popular machine learning models for the machine allocation classification task. By fitting machine learning models, we are able to further analyze the dataset and extract rules in order to compare them with our decision diagram. ML also allows for scaling to millions of instances and making fast predictions. We chose standard and state-of-the-art classification models.

- Gradient Boosting Classifier: this algorithm builds an additive model in a forward stage-wise fashion; it allows for the optimization of arbitrary differentiable loss functions.
- Light Gradient Boosting Machine: by including a sort of autonomous feature selection and concentrating on boosting cases with greater gradients, LightGBM expands the gradient boosting technique.
- Extreme Gradient Boosting: a more regularized form of Gradient Boosting. Extreme Gradient Boosting uses advanced regularization (L1 & L2), which improves model generalization capabilities.
- Random Forest Classifier: A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting (high training accuracy and low test accuracy).
- k-Neighbors Classifier: a non-parametric supervised learning method, used for classification and regression. The result of k-Nearest Neighbors (k-NN) classification is a class membership. The class that an object is assigned to based on the majority vote of its k closest neighbors is determined by the item's neighbors (k is a positive integer, typically small).
- Logistic Regression: The logistic model in statistics is a statistical model that depicts the likelihood that an event will occur by making the event's log odds a linear combination of one or more independent variables. In regression analysis, logistic regression estimates a logistic model's parameters (the coefficients in the linear combination).

- Naive Bayes: The family of straightforward "probabilistic classifiers" is based on the application of Bayes' theorem with strong (naive) independence assumptions between the features.

TABLE II
RESULTS OF MULTIPLE CLASSIFIER MODELS ON THE INITIAL DATASET.

Model	Accuracy	Recall	Precision	f1-score
Gradient Boosting	**80.51**	60.56	**79.76**	78.64
Light Gradient Boosting	80.26	64.47	79.37	79.30
Extreme Gradient Boosting	80.20	64.55	79.35	**79.33**
Random Forest	78.97	**65.02**	78.29	78.42
k Neighbors	74.31	52.97	72.14	72.39
Logistic Regression	70.87	35.69	61.20	61.24
Naive Bayes	54.96	46.42	61.55	54.18

Table II presents the computed metrics on the test set. We obtain an accuracy of 80.51% to predict the machine line which will print the order. The remaining errors are due to orders printed in alternative machine lines because of scheduling or malfunctions that do not allow a line to be used. Although some of the orders should be printed in specific machine lines, alternate lines are selected due to availability.

As the majority of the jobs are assigned to the 5-col machine line, the classifier also learns to assign most of the jobs to the 5-col machine line as well. This is why precision, recall, and f1-score are high regarding the 5-col class. On the other hand, 8-col comes with high precision and low recall. A system with high precision but low recall returns very few results, but most of its predicted labels are correct when compared to the training labels. Finally, 4-col presents low precision, recall, and f1-score because of the small number of 4-col instances in the dataset. An ideal system with high precision and high recall will return many results, with all results labeled correctly.

C. Fitting machine learning models to updated dataset

TABLE III
RESULTS OF MULTIPLE CLASSIFIER MODELS ON THE UPDATED DATASET.

Model	Accuracy	Recall	Precision	f1-score
Gradient Boosting	**93.19**	74.42	**92.96**	92.89
Random Forest	93.10	75.52	92.91	**92.92**
Light Gradient Boosting	93.10	**75.62**	92.91	92.90
Extreme Gradient Boosting	93.05	75.46	92.83	92.86
k Neighbors	87.63	67.60	87.36	87.33
Logistic Regression	74.98	36.66	70.10	68.20
Naive Bayes	64.12	61.42	70.40	61.53

Classification models were also fitted on an updated version of the dataset, with the estimated machine line, coming from the decision diagram, as the predicted class. Table III shows that our estimated machine lines are much easier to predict. All models present higher evaluation values in terms of accuracy, recall, precision, and f1-score.

Figure 3 also presents the reduced misclassification rates for all the classes in the test subset. In both problematic cases, the numbers of 4-col orders misclassified as 5-col and 8-col orders misclassified as 5-col orders have dropped.

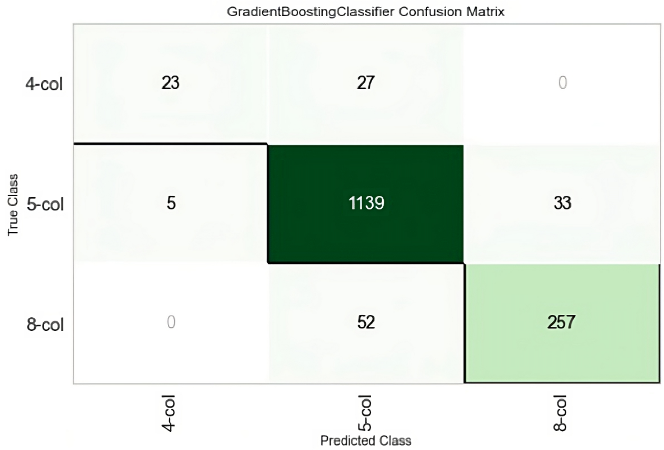

Fig. 3. Confusion matrix of Gradient Boosting on the updated dataset.

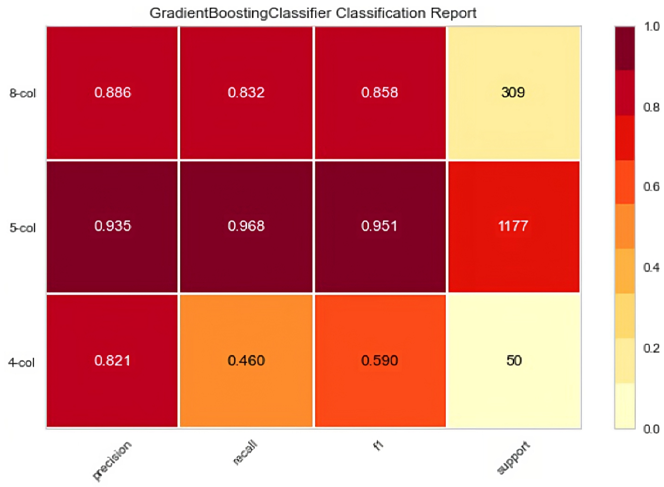

Fig. 4. Classification report of Gradient Boosting on the updated dataset.

Finally, if we look closely at Figure 4, a clear increase in all metrics can be noticed. Even the most troubled class, the 4-col machine line, has now an acceptable f1-score of 0.59 while predicting the 5-col orders is almost perfect.

In this section, we presented how machine learning models can help in the machine allocation task. After our detailed analysis, we observed that the actual machine lines selected to print the orders were not easily learned by a classification model. Thus, we experimented by fitting the algorithms of the classes of our suggested decision process, and instantly got improved models with higher prediction capabilities.

V. CONCLUSION

The digitalization process of the printing line brings many advantages. First of all, modeling the machine selection process, enabled the company to document, visualize and analyze the actual decision-making. The process can now be easily simulated in a safe and cost-efficient digital environment, provided by the Digital Twin. Given a new order, the simulation process can now show the estimated machine line to print it.

This is extremely helpful for operators as they can provide a large number of orders, and the system will output the most suitable and cost-efficient printing machine line for each one of the orders. Past orders can also be checked and validated. The new decision process also revealed that some orders could be printed in multiple machine lines. Moreover, the simulation process allows to parameterize of or tune both datasets and configurations for the machine selection task. Different setups can now be simulated and examined in a very efficient and inexpensive way through the business process management tool. Last but not least, the printing line will be ready to receive and integrate a new machine in a faster and more efficient way.

Another important benefit of the Digital Twin is reducing the cost of the printing process. Having analyzed the dataset, we quickly observed that for many orders, much more efficient machine lines should be selected with respect to cost. Comparing the actual lines that printed the orders with our decision process, a reduced cost of 5% was noticed. While this phenomenon could be attributed due to machines being already occupied with printing other orders, it serves as a clear indication that scheduling can be further improved to minimize cost. Consequently, the company is challenged to investigate additional ways of optimizing efficiency that could also assist in addressing other problems as well. For example, the scheduling process can be optimized via new digital tools that can automate and redistribute available resources when required, not only with regard to cost optimization but also human resource allocation.

Next, we exploited machine learning models to extract knowledge for the machine selection task, taking full advantage of the Digital Twin experiment. Our idea was to fit classification models in order to predict the actual machine line that prints an order. We also experimented by fitting the models to our simulated (estimated) machine lines. The newly estimated machine lines were much easier to be fitted as target values on a classification model given the orders, as well as to predict. Investigating machine learning for the machine selection task enables us to automatically extract rules or decisions from a large number of orders and optimize the printing costs by selecting alternative printing machine lines. The developed machine learning models are also capable of scaling to massive datasets with minimal effort by the operators in both training and test steps. The current study of machine learning models did not include state-of-the-art deep learning and neural network methods, as the size of the dataset is relatively small in order to get a significant improvement, as compared to traditional machine learning classification models. Classical machine learning models are also easier to interpret and visualize, in contrast to deep learning models that are not easily explained. A significant amount of time is also required to select the proper deep learning model, apart from configuration and tuning. We leave the study of neural networks as future work.

Last, by integrating the Digital Twin, and exploiting cutting-edge business process management tools and machine learning models, we have increased the innovation potential for the company and improved its competitiveness. The company is now more mature than ever to adopt additional technologies in other steps of the production phase.

ACKNOWLEDGMENT

The authors warmly thank Mr. Christos Trochoutsos and PRESSIOUS Arvanitidis company for the dataset provision.

REFERENCES

[1] F. Tao, H. Zhang, A. Liu, and A. Y. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on industrial informatics*, vol. 15, no. 4, pp. 2405–2415, 2018.

[2] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, "Characterising the digital twin: A systematic literature review," *CIRP Journal of Manufacturing Science and Technology*, vol. 29, pp. 36–52, 2020.

[3] M. Liu, S. Fang, H. Dong, and C. Xu, "Review of digital twin about concepts, technologies, and industrial applications," *Journal of Manufacturing Systems*, vol. 58, pp. 346–361, 2021.

[4] Y.-Y. Chen, C.-Y. Cheng, L.-C. Wang, and T.-L. Chen, "A hybrid approach based on the variable neighborhood search and particle swarm optimization for parallel machine scheduling problems—a case study for solar cell industry," *International Journal of Production Economics*, vol. 141, no. 1, pp. 66–78, 2013.

[5] P. Baumann, S. Forrer, and N. Trautmann, "Planning of a make-to-order production process in the printing industry," *Flexible Services and Manufacturing Journal*, vol. 27, pp. 534–560, 2015.

[6] M. He and D. He, "Deep learning based approach for bearing fault diagnosis," *IEEE Transactions on Industry Applications*, vol. 53, no. 3, pp. 3057–3065, 2017.

[7] J. Villalba-Diez, D. Schmidt, R. Gevers, J. Ordieres-Meré, M. Buchwitz, and W. Wellbrock, "Deep learning for industrial computer vision quality control in the printing industry 4.0," *Sensors*, vol. 19, no. 18, p. 3987, 2019.

[8] A. H. Sodhro, S. Pirbhulal, and V. H. C. De Albuquerque, "Artificial intelligence-driven mechanism for edge computing-based industrial applications," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, pp. 4235–4243, 2019.

[9] A. Angelopoulos, E. T. Michailidis, N. Nomikos, P. Trakadas, A. Hatziefremidis, S. Voliotis, and T. Zahariadis, "Tackling faults in the industry 4.0 era—a survey of machine-learning solutions and key aspects," *Sensors*, vol. 20, no. 1, p. 109, 2019.

[10] P. Trakadas, X. Masip-Bruin, F. M. Facca, S. T. Spantideas, A. E. Giannopoulos, N. C. Kapsalis, R. Martins, E. Bosani, J. Ramon, R. G. Prats *et al.*, "A reference architecture for cloud–edge meta-operating systems enabling cross-domain, data-intensive, ml-assisted applications: Architectural overview and key concepts," *Sensors*, vol. 22, no. 22, p. 9003, 2022.

[11] A. Angelopoulos, A. E. Giannopoulos, N. C. Kapsalis, S. T. Spantideas, L. Sarakis, S. Voliotis, and P. Trakadas, "Impact of classifiers to drift detection method: a comparison," in *Proceedings of the 22nd Engineering Applications of Neural Networks Conference: EANN 2021*. Springer, 2021, pp. 399–410.

[12] B. Caiazzo, M. Di Nardo, T. Murino, A. Petrillo, G. Piccirillo, and S. Santini, "Towards zero defect manufacturing paradigm: A review of the state-of-the-art methods and open challenges," *Computers in Industry*, vol. 134, p. 103548, 2022.

[13] F. Psarommatis and G. May, "A literature review and design methodology for digital twins in the era of zero defect manufacturing," *International Journal of Production Research*, pp. 1–21, 2022.

[14] A. Angelopoulos, A. Giannopoulos, S. Spantideas, N. Kapsalis, C. Trochoutsos, S. Voliotis, and P. Trakadas, "Allocating orders to printing machines for defect minimization: A comparative machine learning approach," in *Artificial Intelligence Applications and Innovations: 18th IFIP WG 12.5 International Conference, AIAI 2022, Hersonissos, Crete, Greece, June 17–20, 2022, Proceedings, Part II*. Springer, 2022, pp. 79–88.

[15] S. T. Spantideas, A. E. Giannopoulos, N. C. Kapsalis, A. Angelopoulos, S. Voliotis, and P. Trakadas, "Towards zero-defect manufacturing: Machine selection through unsupervised learning in the printing industry," *Proceedings http://ceur-ws. org ISSN*, vol. 1613, p. 0073, 2022.