Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 54-1 (2021) 570–575

PREFAB Framework - PRoduct quality towards zEro deFects for melAmine surface Boards industry

Rui Correia Dias*[a], Pedro Pinho Senna*,**, Artur Freitas Gonçalves***, João Reis***
Nikolaos Michalaros****, Kosmas Alexopoulos****, Miguel Gomes*****

* Centre for Enterprise Systems Engineering, INESC TEC, Porto, Portugal (rui.c.dias@inesctec.pt; pedro.senna@inesctec.pt)
** Faculty of Engineering, University of Porto, Porto, Portugal (up201708818@fe.up.pt)
***SYSTEC - Research Center for Systems and Technologies - Faculty of Engineering, University of Porto, Porto, Portugal (afreitas@fe.up.pt; jpcreis@fe.up.pt)
**** Laboratory for Manufacturing Systems and Automation, LMS, University of Patras, Greece (michalaros@lms.mech.upatras.gr; alexokos@lms.mech.upatras.gr)
***** Sonae Arauco, Maia, Portugal (miguel.gomes@sonaearauco.com)
[a] Corresponding Author

Abstract: Zero Defects is one of the ultimate targets for manufacturing quality control and assurance. Such systems are becoming common in advanced manufacturing industries but are at an initial stage in more traditional industrial sectors, such as wood panels, laminates production, pulp and paper processing and composite panels production. This paper proposes the PREFAB framework, applied to the wood-based panels industry, to minimize rejected products using AI, machine learning and IoT devices. The framework was built through action research with a Portuguese wood-based panel manufacturing. This framework delivered an innovative decision support system that provides relevant and timely recommendations for shopfloor decision making and to support process/product engineering.

Keywords: Zero-defects Manufacturing, Defect Prediction, Quality Predictive Monitoring, Business Process Modeling, Decision Support System.

1. INTRODUCTION

In the wood-based panels industry, the product complexity is constantly growing, and stricter industrial clients' requirements demand a smarter, data-driven approach to managing surfaced panels production and engineering product development (Thoemen, Irle and Senek 2010, Myklebust, 2013). Over 8 billion m² of surfaced wood panels are expected to be consumed in Europe by 2022 (Sauter, 2018). Manufacturing of wood-based panels is done in a continuous process involving the feeding of raw materials, processing through heat and pressure, and finishing of the panels. Panels are then supplied to industrial clients, large or small, to satisfy a wide variety of end uses, particularly in the building products and furniture industries (Nemli and Usta, 2004). The high-volume production and combination of different materials sets up the challenge to ensure the quality and reliability of the product (Raabe, Myklebust and Eleftheriadis, 2018). The adoption of decision support strategies aims to improve product quality, and additionally, reduce resources consumption, with consequent environmental impacts, and economic benefits (Myklebust, 2013).

The solution to this problem can be given partially by the Zero-defects Manufacturing (ZDM) concept, which aims to increase the production capabilities and, therefore, to make the manufacturing process more efficient (Psarommatis et al., 2019). ZDM seeks to directly reverse the attitude that the number of mistakes a worker or equipment makes does not matter since they are detected in the quality inspection phase, thus avoiding defective products reaching customers. On the other hand, zero-defects manufacturing, aid to reduce the number of rejected products, and respective costs, therefore ensuring economic benefits and positive environmental and ecological impacts (Myklebust, 2013).

This paper presents the PREFAB Framework - PRoduct quality towards zEro deFects for melAmine surface Boards industry - based on action research to support decision making involving digitalization and smart production control.

2. LITERATURE BACKGROUND

The literature review herein depicted begins with the description of the melamine surfaced boards' manufacturing, followed by an overview of the zero-defects concept, and culminating in a brief review of AI-based solutions for defect prediction and prevention.

2.1 Manufacturing of melamine surfaced boards

Melamine surfaced boards are wood-based panels coated with impregnated decorative paper. The melamine process consists of coating raw board surfaces with melamine impregnated papers. Melamine papers are then pressed to the raw board surface using a combination of pressure and temperature. There are two categories of raw boards used for melamine impregnated papers: (i) the particle board; and, (ii) Medium Density Fibreboard (MDF). Both are manufactured

10.1016/j.ifacol.2021.08.065

under pressure and heat from particles of wood with the addition of an adhesive mix of resins (Liu and Zhu, 2014). Impregnated decorative paper is a high-quality special paper, widely used for surface protection and decoration (Mustafa et al., 2016). The decorative paper is impregnated with thermosetting synthetic resins which include urea formaldehyde (UF) and melamine formaldehyde (MF) resins, converted into a technologically sensitive cellulosic composite through an impregnation process, i.e. melamine impregnated (Nemli and Usta, 2004).

2.2 Zero-defects Manufacturing

The concept of Zero-defects Manufacturing (ZDM) was introduced in the early 1960s in connection with the United States Army (Halpin, 1996; Crosby, 1979). According to Myklebust (2013) the need for achieving ZDM is driven by the aim to minimize and eliminate product defects. The ZDM approaches became increasingly easier to implement given the availability of data, which are then fed into machine learning techniques for smart manufacturing (Psarommatis et al., 2019). ZDM can be implemented through two different approaches: (i) process oriented ZDM; and, (ii) product oriented ZDM. The process oriented ZDM lays within the predictive maintenance concept by estimating the degradation level of the manufacturing equipment to evaluate how it affects the product quality (Anagiannis et. al. 2020). On the other hand, the product oriented ZDM attempts to identify and define the defects on the products being produced (Psarommatis et al., 2019).

Four strategies are proposed for both approaches, which are interconnected (Psarommatis and Kiritsis, 2018): (i) detection; (ii) repair; (iii) prediction; and, (iv) prevention. Prediction and prevention strategies aim to avoid the production of parts with defect before the occurrence, as opposed to the traditional detection and repairing strategies, which focus on repairing it once a defect has already occurred (Psarommatis et al. 2019). From these strategies, prediction is the least studied and applied, and ZDM approaches are mainly implemented in the semiconductor and steel industries.

ZDM based on prediction strategy was observed as the most suitable approach for melamine surfaced boards industry, since it is focused on the product requirements, allowing adjustments on the production parameters and, thus, avoiding defects by forecasting its quality while it is being produced. To the best of our knowledge, this is an innovative approach on this particular manufacturing sector, which has not been tackled previously in the literature or by practitioners.

2.3 AI-based solutions for defect prevention in manufacturing

Data mining for manufacturing process modelling is on the rise, even amidst the worldwide pandemic situations, with companies focusing on digital innovation to leverage competitive advantages (Gartner, 2020). For the application of a manufacturing process modelling, literature presents various methodologies to be used in a data mining work (Mariscal et al., 2010). There are three well-known and used methodologies among these: Knowledge Data in databases (KDD); Sample, Explore, Modify, Model, and Assess (SEMMA), and Cross Industry Standard Process for Data Mining (CRISP-DM) (Azevedo and Santos, 2008).

From these, the most used methodology is CRISP-DM, followed by SEMMA and KDD (KdNuggets, 2014). When comparing the three methodologies, CRISP-DM was found to be the better option for our particular case given that it encompasses all methodological steps from KDD and SEMMA, complements these with an additional deployment step, and allows for scalable solutions for multiple AI-driven industrial applications (Azevedo and Santos, 2008; Mariscal et al., 2010). Therefore, we have elected to follow the CRISP-DM methodology as described by Shearer (2000). Its main steps are the following: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation and Deployment.

On Business and Data Understanding and Data Preparation steps, traditional statistical methods ought to be applied (Shearer, 2000). The goal is to understand the relationships between features and the tasks, identify outliers and potential data subsets, as well as to encompass a greater scope of data for analysis. Correlation statistics and dimensionality reduction can be used to handle data issues, such as anomalies, redundancy, or the size of dataset itself.

The Modelling step focuses on a detection model approach (Shearer, 2000). Several established algorithms should be tested for the training process (e.g. Random Forests, Gradient Boosting Classifier, Support-Vector Machines, and Autoencoder). There are many benchmarking approaches that can be used: default parameters; grid search for hyperparameter optimization; random search for hyper-parameter optimization; oversampling using resampling; oversampling using SMOTE technique; and, oversampling using resample and grid search, among others. The relative rarity of defects occurring in manufacturing implies an unbalanced dataset, which favours a Recall metric approach in detriment of Precision and F1-Score approaches.

In a recipe recommendation process, a heuristic-based approach should be adopted (Shearer, 2000). The goal is to produce automated recommendations to change some key features values, whenever the prediction models infer that a defect is likely to occur, in order to reduce the likelihood of that defect effectively occurring. This implies the use of a generic cost function. Optimization methods available include Basin-hopping, Nelder-Mead, and Particle Swarm Optimization (Mariscal et al., 2010).

On product development, the main idea is to propose a recommendation for a product to come with specific and quantitative characteristics, based on the same philosophy as the previously described recommendation process. However, the key difference is that for new products, data is yet to be collected, so no recommendations can be done whatsoever. State-of-the-art approaches such as a Hyper-Process Model could be used (Reis et al., 2017), as it is a model of models whose capability of generating new models based on those product characteristics fits what we look for on this stage. Thus, a new predictive model for defects could be generated in accordance with new product characteristics, while recipe recommendations could be done as detailed in the previous step.

3. RESEARCH METHOD

To achieve this exploratory research we have applied action research, in the scope of the project Zero Defects 4.0 funded by EIT Manufacturing. Action research is appropriate to our study since it enables the development of solutions for real problems (Eriksson and Kovaleinen, 2008). For our study, researchers and operations managers have combined efforts to develop the solution (Coughlan and Coghlan, 2009), which is aimed at the requirements and interests of the organization in order to serve as validity assurance (Eriksson and Kovaleinen, 2008). For this purpose, data was gathered from the end-user organization from functioning sensors and by active involvement of researchers, generating historical data of the production process and of the product, which was used to feed the AI algorithms. This collaborative project involved three research centres, a technology company and the wood-based panel manufacturing company. This end-user company aims to improve production efficiency and reduce non-compliant products and the wastage of resources. The researchers aim to build and test theory in action on how to apply machine learning and AI into product manufacturing in order to reach the least amount of product waste while maximizing production efficiency. Additionally, researchers wanted to understand what is the best visualization method to portray the findings for practitioners in order to convey large volumes of information in a limited and seamless visual representation

4. PREFAB FRAMEWORK SPECIFICATION

This section describes the PREFAB framework, which is organized in three groups of activities: (i) process and production flow analysis; (ii) processes modelling; and, (iii) the specification and development of decision-making tool.

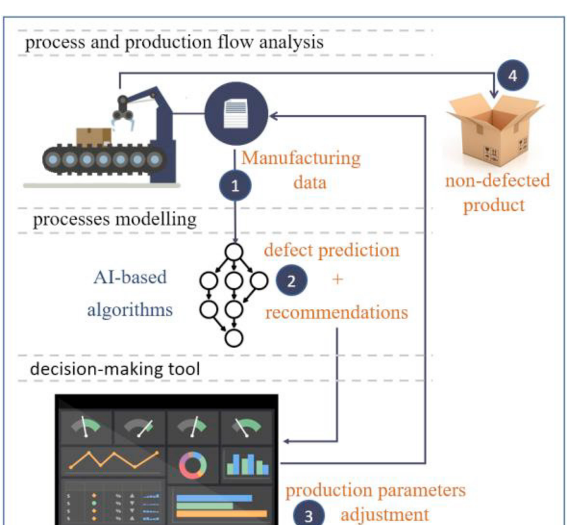

Fig. 1 PREFAB Framework

The first group focuses on the analysis of the manufacturing process and production flow, to identify key process parameters, as well as their impact in the production. The second group of activities is related to the manufacturing processes modelling, establishing the relation between parameter mix/recipes and their effect in product quality. The third group of activities lies in the development of a decision-making tool to be used by the shop-floor operators both for process monitoring and for parameters' recommendations. All of these activities are specified in the following sections and implementation results are presented in chapter 5, while the PREFAB Framework can be observed in **Fig. 1**.

4.1 Manufacturing process and production flow analysis

This analysis is comprised of three actions. In the first action, the manufacturing process for melamine surface boards is assessed aiming to identify the key manufacturing stages that impact "zero-defects" production. The assessment should involve senior workforce, given their lengthy experience and knowledge on the topic. Such collaboration allows for the identification of the need to install IoT devices aimed at collecting additional data. The second action consists of identifying the most critical production parameters and the method to collect them. Data can be gathered from shop-floor equipment, such as sensors and actuators, or from IoT devices. In this stage, it is important to identify the available data sources, which will be used to feed the manufacturing models. The third and final action consists of identifying and categorising the product defects registered in the quality inspection phase of the melamine process, as well as identifying the possible root causes. The result of this analysis will be the basis for subsequent activities.

4.2 Manufacturing processes modelling

The main objective of the manufacturing processes modelling is to build a process model where the selected parameters from previous steps should be considered as inputs and the expected quality and/or requirements are predicted. It consists in modelling the process phenomena, the relation between parameter mix/recipes, and effects in product quality. For this, an analysis on all process data associated with the product is performed. A more focused perspective on the product requirements should be considered to achieve improvements or to avoid defects. Thus, a material-tracking approach is used to isolate all the pertinent data from each production part so that possible deviations may be identified, and automatically calculate any required adjustment. Another objective is to provide assistance in the initial parametrization for new products. The introduction of a new product is usually followed by a calibration or ramp-up phase, which ends when the desired quality is met. However, the high number of parameters is often difficult to manage, and only highly skilled workers can provide a true contribution in ramping-up a new product. Therefore, a strategy must be explored to minimize calibration phases by finding the best process parameters (recipe for a certain product) according to quality and product requirements. By using heuristic-based and evolutionary algorithms, optimization will be performed to estimate the best machine parameters towards the target quality. Heuristic-based algorithms focused on local search strategies – such as Nelder-Mead – become suitable to work on limited solution search spaces, which correspond to the real-time restraints one has while modifying parameter values during manufacturing process. A similar rational is considered when selecting an evolutionary algorithm, as it searches for near-optimal solutions – a common end-result in such constrained spaces.

4.3 Specification of the decision-making tool requirements

As a final step, a decision-making tool that links manufacturing models to production performance and to decision making variables has been developed. Afterwards, these models are embedded in a system to support production plant operators and engineers in both their day-to-day (operational) production decisions at shopfloor level, but also their production planning when it comes to new product developments (strategic level). Decision-making tool includes a dashboard for process monitoring and recommendations for process parameters with the goal of zero defects. The dashboard provides customized views based on the different roles that exist in a manufacturing landscape such as shop-floor operators, production planners and data scientists.

5. IMPLEMENTATION AND RESULTS ANALYSIS

This section describes the application of the presented PREFAB framework on the melamine surfaced boards industry case, and the results' analysis.

5.1 Melamine process and production flow analysis

The process and production flow analysis consisted of understanding the manufacturing process for melamine surfaced boards manufacturing (**Fig. 2**). This process begins when wood-based panels and impregnated paper sheets are transported from warehouses to the supply table (m1 and m2). The bottom paper sheet, raw board, and upper paper sheet are overlapped in the confirmation table (m3), and then driven to the hydraulic press where they are coupled (m4). The product is finished in the scraper by removing excess paper (m5). Then, it is transported to the inspection equipment (m6), where the quality technician registers possible defects. Finally, the melamine surfaced boards are stored in the warehouse (m7).

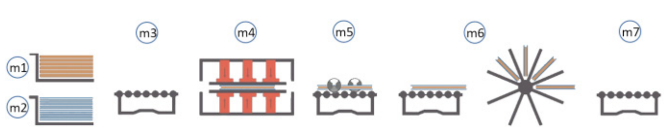

Fig. 2. Melamine surfaced boards manufacturing process

The second action of the manufacturing process analysis consisted in identifying the most important production parameters from the manufacturing process analysed before. In the manufacturing process for melamine surfaced boards, some of the key parameters identified are the resin content (RC) and volatile content (VC) of the impregnated paper, as well as the press parameters, such as: press cycles, press plates, thermo fluid temperature, thermal cycle and specific pressure.

The last action consisted of identifying and categorising the product defects registered in the quality inspection phase of the melamine process (**Table 1**).

Table 1 Defect groups of the quality inspection phase

Defect type	**Observations**
broken paper	Broken paper can occur both at the paper impregnation or in the melamine process.
dirt/dust	Dirt on the belts or rollers or even due to fingerprints, oil spots, or insects.
external impregnation	Nonconformities of the impregnated paper, such as, excess/lack of resin or wrinkles.
external MDF	Nonconformities of the MDF, such as, fractures, contamination with ashes.
external PB	Nonconformities of the PB, such as, fractures, pits, hulls, or porosity.
glued paper	Glued paper can occur both at the paper impregnation or in the melamine process.
logistic process	It can be related to lack of paper or lot bottom board damaged.
machine	Damages occurred due to equipment malfunction, or wrong configuration, such as, low pressure at the press causing melamine boards not completely pressed.
transport damages	Damages occurred during internal transportation activities causing broken corners or other transportation defects.

5.2 Modelling of the manufacturing processes

Following closely the CRISP-DM methodology explored in the literature review section, Business and Data Understanding procedures were undertaken. Due to the distributed nature of data available, first there was a merging effort to aggregate all data into a single corpus, by usage of cross-referencing timestamps. After this process was achieved, descriptive analysis and correlation techniques, as well as outlier detection were applied, and supported the preparation of data required on the following steps in the working methodology. Pearson correlation was used to identify and drop redundant features. Outlier detection focused on identifying and handling data inconformity and anomalies. In order to tackle the dataset size and considerable number of features available, Principal Component Analysis (PCA) was used to obtain a better understanding of the big picture.

For the modelling process, a unique subset for each defect was extracted from the main dataset. Each subset contained samples with one specific defect, along with normal production samples which were common to all subsets. A further split was performed, with 80% of each subset being used in model training, while the remaining 20% was allocated to model validation. These new datasets were highly unbalanced, due to the small volume of defect samples available for each defect. Among the algorithms previously discussed in literature review, the more promising results on the benchmark step were obtained from the Gradient Boosting Classifier. The algorithm was combined with an oversampling technique to improve the ratio of the under-represented class in each training subset, and a grid search to optimize the algorithm's hyperparameters. Following what was recommended earlier, the recall metric was selected for the benchmarking evaluation.

Concerning recipe recommendation process, we followed the heuristic-based approach detailed before. After identifying the critical features which could both impact the quality outcome of a sample and feasible to be changed in real-time, we optimized a cost function to approximate the defect sample's values to the ones observed in a normal production sample. The optimization method used was Nelder-Mead, while the function was the Euclidian distance as implemented in Python's SciPy package.

On product development, we moved forward with building a Hyper-Process Model capable of generating new predictive models for defects based on the characteristics of novel products, even if any data is yet to be collected on them. Recipe recommendations for these models were done as described on the previous process.

5.3 Development and implementation of decision-making tool

In order for predictive quality models and data to be utilized for decision making processes adequate Human Machine Interaction (HMI) concepts should be in place. Role centric dashboards have been developed to meet the needs of different types of users such as shop-floor operator, production planner and data scientist. In **Fig. 3** the dashboard provides an overview of the expected quality performance for the production lines.

This allows production planning personnel to have a quick overview of the type of defects for the current and planned production orders. Additional dashboard views have been implemented that provide in-depth insight on the types of defects for a specific line, insight into the factors that contribute to the estimated defects' probabilities as well as recommendations to the operators on actions that could be taken in order to reduce the probability for producing defected parts.

Finally, statistical information on the success of the prediction model is provided that contributes to improving the trust between the user and the AI model that makes the prognosis.

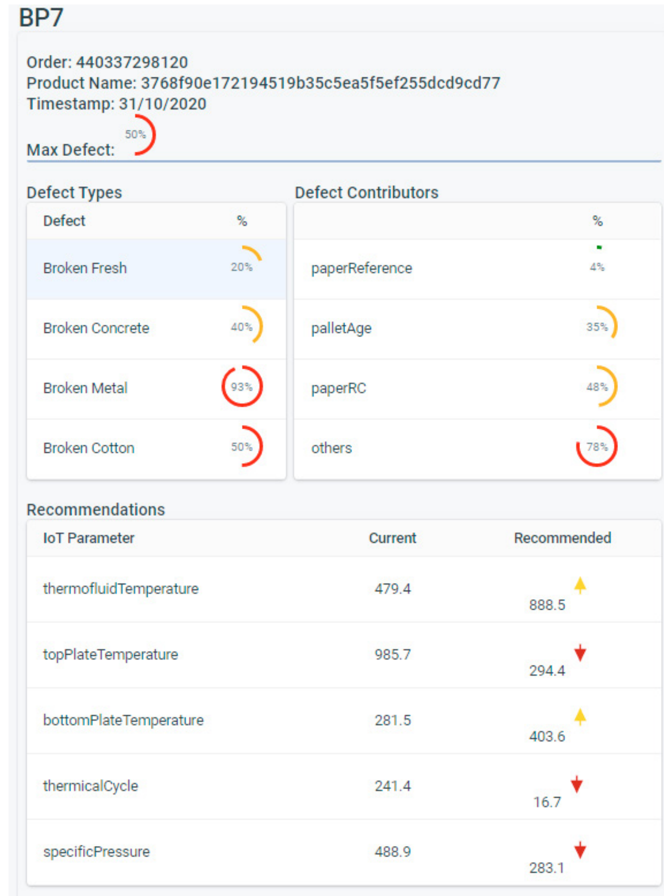

Fig. 3 Dashboard view for production planner in factory level

6. CONCLUSIONS

This research presents the PREFAB framework based on AI, machine learning and IoT devices applied to wood-based panels industry to ensure better product quality and higher production efficiency. The study has used action research to develop and apply the proposed framework for a Portuguese wood-based panel manufacturing. This framework enabled a Zero Defects approach for production of wood-based panels, particularly melamine impregnated paper, resulting in product waste reduction and production efficiency.

The proposed PREFAB Framework is the first attempt at developing and implementing an AI-driven, Zero Defects approach, to a process-based scenario considering a product-oriented quality management perspective. It contributes to the academic community by presenting an empirically validated AI-driven framework for the wood-based manufacturing industry and enhances the theory on Zero Defects manufacturing when considering a process-based scenario.

Future research on this field may apply the proposed implementation framework on other process-based industries such as laminates, composite panels or engineered wood panels, aimed at better evaluating the extension of this implementation framework. Outputs are expected to be scaled up to other product types and to similar manufacturing production sites in other countries.

7. ACKNOWLEDGEMENTS

The Zero Defects 4.0 project has received funding from the European Union's Horizon 2020 research and innovation programme under the grant agreement EIT/EIT Manufacturing/SGA 2020/1.

REFERENCES

Anagiannis, I.; Nikolakis, N.; Alexopoulos, K. Energy-Based Prognosis of the Remaining Useful Life of the Coating Segments in Hot Rolling Mill. Appl. Sci. 2020, 10, 6827, doi:10.3390/app10196827

Azevedo, A.I.R.L., & Santos, M.F. (2008). KDD, SEMMA and CRISP-DM: a parallel overview. IADS-DM European Conference on Data Mining: Amsterdam, The Netherlands.

Coughlan, P., & Coghlan, D. (2009). Action Research. In: Karlsson, C. (Ed.), Researching Operations Management, Taylor & Francis, Inc., New York, pp. 236-264.

Crosby, P.B. (1979). Quality is free: the art of making qualify certain. McGraw Hill, New York

Eriksson, P., & Kovalainen, A. (2015). Qualitative methods in business research: A practical guide to social research. Sage.

Erol, S., Jäger, A., Hold, P., Ott, K. and Sihn, W. (2016). Tangible Industry 4.0: A Scenario-Based Approach to Learning for the Future of Production. Procedia CIRP, 54, pp.13–18.

Gartner, Inc. (2020). Gartner Survey of Nearly 2,000 CIOs Reveals Top Performing Enterprises are Prioritizing Digital Innovation During the Pandemic. Available at: https://www.gartner.com/en/newsroom/press-releases/2020-10-20-gartner-survey-of-nearly-2000-cios-reveals-top-performing-enterprises-are-prioritizing-digital-innovation-during-the-pandemic Accessed on: October 31st, 2020.

Halpin, J.F. (1966). Zero defects: a new dimension in quality assurance. McGraw-Hill, New York

KdNuggets.Com (2014). What main methodology are you using for your analytics, data mining, or data science projects? Available at: https://www.kdnuggets.com/polls/2014/analytics-data-mining-data-science-methodology.html Accessed on: October 31st, 2020.

Liu, Y. and Zhu, X. (2014). Measurement of formaldehyde and VOCs emissions from wood-based panels with nanomaterial-added melamine-impregnated paper. Construction and Building Materials, 66, pp.132–137.

Mariscal, G., Marbán, Ó, & Fernández, C. (2010). A survey of data mining and knowledge discovery process models and methodologies. The Knowledge Engineering Review, 25(2), 137-166. doi:10.1017/S0269888910000032.

Mustafa Ç., Ahmet T. and Ferhat O. (2016). Resin impregnation of décor papers and comparison of physical properties. [online] ResearchGate. Available at: https://www.researchgate.net/publication/310249395_RESIN_IMPREGNATION_OF_DECOR_PAPERS_AND_COMPARISON_OF_PHYSICAL_PROPERTIES [Accessed 22 Oct. 2020].

Myklebust, O. (2013). Zero Defect Manufacturing: A Product and Plant Oriented Lifecycle Approach. Procedia CIRP, 12, pp.246–251.

Nemli, G. and Usta, M. (2004). Influences of some manufacturing factors on the important quality properties of melamine-impregnated papers. Building and Environment, 39(5), pp.567–570.

Psarommatis, F. and Kiritsis, D. (2018). A Scheduling Tool for Achieving Zero Defect Manufacturing (ZDM): A Conceptual Framework. Advances in Production Management Systems. Smart Manufacturing for Industry 4.0, pp.271–278.

Psarommatis, F., May, G., Dreyfus, P.-A. and Kiritsis, D. (2019). Zero defect manufacturing: state-of-the-art review, shortcomings and future directions in research. International Journal of Production Research, 58(1), pp.1–17.

Raabe, H., Myklebust, O. and Eleftheriadis, R. (2018). Vision Based Quality Control and Maintenance in High Volume Production by Use of Zero Defect Strategies. Lecture Notes in Electrical Engineering, pp.405–412.

Reis, J., Gil G., and Link, N. (2017) Meta-process modeling methodology for process model generation in intelligent manufacturing. IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society. IEEE.

Sauter, P. (2018). Decorative surfacing trends in Europe. Bürkle Forum 2018. Pöyry: Freudenstadt.

Shearer, C. (2000) The CRISP-DM Model: The New Blueprint for Data Mining. Journal of Data Warehousing, 5, 13-22.

Thoemen, H., Irle, M., & Sernek, M. (2010). Wood-based panels. An Introduction for Specialist. Brunel University Press: London