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Building a Digital Twin -features for veneer production lines - observations on the discrepancies between theory and practice

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Introduction

The utilization of digital twinning (DT) in large scale industrial applications has been extensively discussed in academic literature. However, only a few publications provide real-life case descriptions on building a digital twin model from scratch. This chapter aims to fill that gap by providing a case example from the veneer and LVL (laminated veneer lumber) industry, discussing the applicability of the DT concept, and identifying central pain points observed from simulation and data perspectives that are likely to be generalizable for many process industrial organizations undertaking DT projects.

The brief history on the idea of digital twinning can be traced back to aeronautics and the need to forecast the performance and structural life of individual operating aircrafts (see discussion, e.g., (Madni et al., 2019; Rosen et al., 2015; Stark et al., 2017; Tuegel et al., 2011)). Some scholars, such as (Min et al., 2019; Negri et al., 2017; Qi & Tao, 2018), say that the digital twinning of the whole industrial system is still at its beginning and many ways conceptual. For the purposes of this paper, we use digital twins in a meaning, stated by (Alam & Saddik, 2017), of highly detailed computer models that interact with physical reality.

The production of veneer involves various physical phenomena that require adequate consideration in the DT-model. In the past, one of the most widely used ways has been randomly selecting sheets and evaluating them manually. Today, the quality inspection is done online in the separate processing equipment by automated imaging and the physical flows of material are steered

accordingly. Nevertheless, plant-wide optimization solutions remain a challenge due to the complexity of the production process, which involves multiple pieces of equipment interconnected in a veneer production line that requires dynamic optimization. To address this challenge, the veneer/LVL manufacturing industries are investing in process automation and digital twinning of manufacturing lines to enhance product quality standards, reliability, and efficiency (Urbonas et al., 2019).

Despite the advances in computerization of industrial processes since the 1950's, the idea of using digital twin model for automated communication and operation multiple intelligent machines in concert is relatively new. That is, the previous generations of industry automation have relied on human operator wisdom in the overall production line optimization while focusing on the computerized optimization of single equipment at a time. In the case of complex and multi-phase industrial processes, such as veneer and LVL introduced below, this sometimes leads to situations where the production line optimum is not reached due to lack of automated communication between equipment and the inability of humans to continuously change production settings “on the fly” within the timeframe of minutes or hours. In this chapter, this gap of real time optimization is addressed with digital twinning.

The chapter continues with a background on industry 4.0 followed by the case description. Then key findings of the project are given and their generalizability to other applications are evaluated within the I4.0 / digital twinning framework. The chapter closes with conclusions and discussion.

Background

In 2013, a German initiative labelled the fourth industrial revolution as *Industry 4.0* (I4.0) that has later emerged as a prospective technological paradigm. One of the areas most impacted by I4.0 is manufacturing, with a focus on enhancing production processes to optimize operational performance, product or service development, and supply chain planning (Zheng et al., 2020). The underlying technology behind I4.0 is Cyber-Physical Systems (CPS), which makes manufacturing systems modular and flexible, allowing mass production of highly customized products (see, e.g. (Veza et al., 2015) (Li, 2018)).

(Ishwarappa & Anuradha, 2015) write that the integration of information technology with the industrial systems, and enterprise data has become increasingly rich consisting of various types of datasets. In addition, the amount of data generated by industrial systems has been rapidly increasing. (Zhong et al., 2017) say that IoT-enabled manufacturing transforms traditional manufacturing devices into smart manufacturing objects (SMOs) that can connect, communicate, and interact with one another to execute manufacturing logic automatically and adaptively.

The interconnectedness of equipment and mutual communication brings with it new challenges. Therefore, as observed by (Wang et al., 2022), data analytics as a whole is the vital component in the development of intelligent industrial systems. One of the objectives of I4.0 -paradigm can be considered to include the gathering of all the available data to make traditional factories and manufacturing processes more intelligent and thus achieve higher levels of operational efficiency and productivity. By gradually incorporating additional sensors, autonomous systems, and actuators into the manufacturing process, the factories are made smarter, more dynamic, and adaptive enabling machines and equipment to self-optimize their actions (see, e.g. (Roblek et al., 2016)).

In our view, the self-optimization requires that the optimization software (or agent) is aware of *what happens next* and we propose that digital twinning could be the solution of accurate forecasting, once it is connected with the ability to simulate production process into the future which (Grieves & Vickers, 2017) refers to as “simulation front run”. The word “agent” is a process or entity designed to accomplish a task constantly and independently in a non-deterministic context with other processes and elements. The case example of digital twin dealt within this paper is a veneer production line with a vast amount of data from multiple individual processes that have stochastic elements. The simulation process should be able to weigh different courses of action with regards to maximizing a given value function of the digital twin model using policies that are either prescribed or explored by the agent during simulation. In intelligent manufacturing context, the agent paradigm is observed as one of the most effective ways of optimization (Lu, 2017) when the agent(s) are left to perform tasks in a condition from which they are separated and have their own knowledge and understanding of their surrounding environment; they employ preference in interacting within their environment, developing plans, making autonomous choices, and performing actions to change the environment (see discussion, e.g., (Adeyeri et al., 2015)).

Digital twinning of industrial processes requires, first, deep understanding on the physical processes and, second, the ability to analyse the data produced of these physical processes. This “model-driven” approach, based on the rigorous understanding of the scientifically proven relationships, enables one to extrapolate process values into the future by introducing, simulated, and possibly even unforeseen, variable combinations into the digital twin -model. On the other hand, a “model-free” approach may also be used, when the correlation or other numerical interactions between system parameters are to be unrevealed with data mining techniques which in general refer to the processes of determining correlations in large databases by applying multiple levels of analysis.

Machine learning means that no specific model is given for the computer to apply for the dataset but rather it should discover the patterns independently. A review of the commonly applied ML-methods is provided in (Kotsiantis et al., 2006). Before applying data mining methods in sensor data, outliers should be removed from the data as these can influence the model parameter estimation results and the data analysis process. These outliers can arise due to multiple reasons, including sensor failure and improper processing of missing data. Outliers are sometimes helpful providing information that can lead to the unearthing of new information (Cheng et al., 2018; Xu et al., 2015).

Data analysis has become much more complicated due to recent trends in gathering and utilizing diverse datasets. One of the characteristics of such large datasets is that they contain significant levels of redundancy, and the likelihood of unrelated data entities is high (Houari et al., 2016). The process of transforming a multidimensional data representation into a low-dimensional representation is known as dimensionality reduction. The idea of dimensionality reduction techniques is to transform multidimensional dataset into a low-dimensional dataset while preserving as much of the data’s original meaning. Data in low dimensions is simple to examine, process, visualize and interpret (Zebari et al., 2020). Principal component analysis (PCA) and partial least squares are some of the widely known multivariate statistical projection methods that can handle enormous volumes of data and compress the information into low-dimensional latent variable components, making monitoring and interpreting results more manageable (Kourti et al., 1996). In this chapter, we discuss the aspects of data availability, data types, dimensionality

reduction and simulation data analysis in the context of digital twins using the example case of veneer production line.

Data and Methodology

Any company's digital transformation is not only about investing in new technology, but it should be based on the business strategy and both internal and external business processes. (Rajnai & Kocsis, 2018) describe digitalization as an incremental advancement through steps including technological and organizational changes. In the case of veneer industry, companies are aligning their strategies towards extracting value from manufacturing processes through advanced data analytics and digital twinning.

The digital twin model of veneer production should have enough generalized, yet flexible, structure that enables not only the optimization of the original case factory but could be extended to other plants with new data and minor changes in the structure – such as adding / removing pieces of equipment from the process. Ideally, it would be a dynamic simulation model that utilizes the production data of separate process equipment in connection with their physical, computational model and thus would be able coordinate the veneer line in a manner that optimizes the use of different quality raw material. In other words, the ultimate aim is to produce on-target quality product from the available material stock and not spend the highest quality veneer sheets to meet order book targets at a specific timeframe given. The digital twinning project was started with a prototypical flowsheet of the veneer production line shown in *Figure. 1*

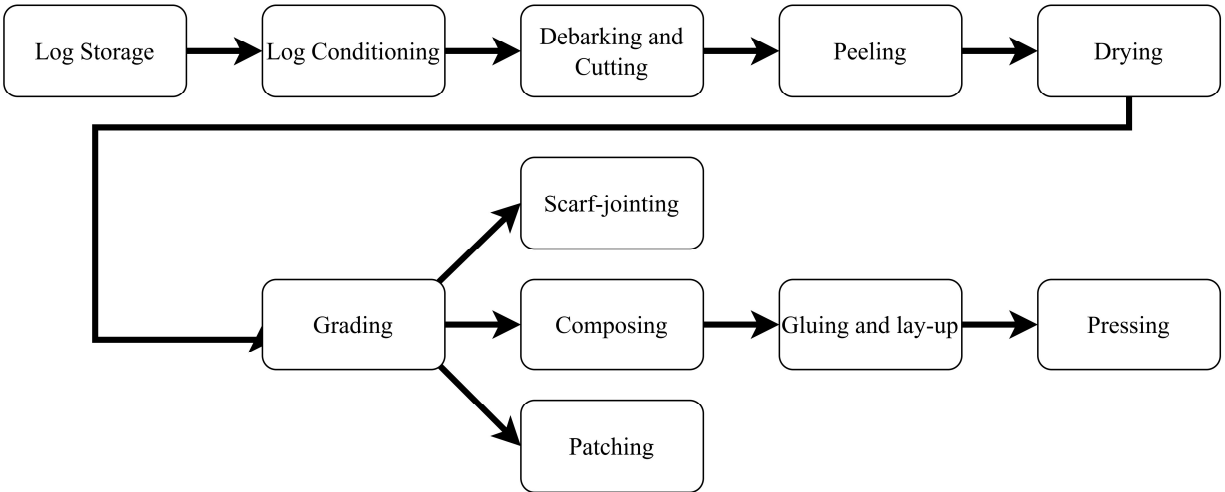


Figure 1. General process flowchart for the plywood and LVL manufacturing.

Building a fully applicable digital model is a huge technological and organizational effort. Therefore, the focus of the study was further narrowed down to the peeling and drying processes as a starting point of the modelling. It was figured that if these critical processes could be modelled adequately then, later on, the scope could be extended to cover the downstream processes as well using similar principles and level of modelling required for the digital twinning. For the sake of comprehensiveness, the process of veneer production is described below in full.

The production of plywood and LVL is based on multiple production stages illustrated in *Figure 1*. The above shown set of processes is required to convert wooden logs into veneer sheets and, further, to plywood or LVL as needed where veneer sheets are being glued together. In gluing, the wood grain directions of sheets vary by 90 degrees, making it strong in all directions and various dimensions of products – most commonly sizes 4 ft x 8 ft and 8 ft x 4 ft – are being made according to the customer requirements where the limiting factor is the woodblock length in the initial peeling process.

One of the major challenges from the production optimization point of view in veneer manufacturing is the varying wood quality which by nature varies a lot depending on the factors that are partly beyond the control of a veneer line operator, such as the habitat and growing conditions of trees. To control the quality of veneer sheets multiple automated measurements are taken from each sheet such as the moisture, temperature, and density. The main defining characteristic is the visual image of the sheet after the main process phases which inherently

dictates its quality class often indicated by letters, e.g., grades A-D and zero (“0”) for waste. The quality is decided by computer imaging where the defects such as knots, holes and splits reduce the grade evaluation.

The first step of the process is the “log conditioning” (see *Figure. 1*) where the logs are conditioned by soaking them in a hot water pool and spraying water over the bundles for about 12 to 24 hours. After log conditioning, the bark is removed from the log, length of the log has to be measured to properly cut the log into the required length (“debarking and cutting”) for the peeling process. The peeling phase is the critical phase from the point of view of the overall product quality as the quality further down the chain can only be made worse and not improved. Peeled veneer ribbons (meters long) are scanned and photographed to detect any defects in the veneer ribbon and the clipping of ribbon is done automatically in a way that maximizes individual sheet grades while maintaining appropriate sheet sizes. Visual defects are known to appear according to log diameter: the smaller logs have better grade veneers because the knots are still very small in the heartwood, and sometimes even without knots.

Peeling sheets are stored in stacks of sheets (few hundred sheets each) for hours to few days before they are fed to the dryer. The veneer sheet quality is ultimately defined by the effectiveness of the drying process where the drying parameters (such as speed and temperature) should be adjusted according to the input material (peeling sheet) quality, e.g., moisture and thickness. During the drying process, the width of the individual veneer sheets gets shrunked up to 10% due to varying shrinking properties on their surfaces. After the drying process, full-size sheets are stacked and transported directly to the lay-up or scarf jointing. Broken or defective veneers are stacked for the composing process and proceed to the further process of gluing, sanding, and trimming.

Some of the studies dealing with the technical aspects of the veneer process include a research of (Çolak et al., 2007) who investigate log steaming and veneer drying conditions on technical properties and durability of LVL and solid sawn lumber suggesting partial least squares -method as effective method of quality control. (Han et al., 2015) apply non-linear programming and operational research theory to optimize the energy consumption during veneer drying. (Ahmed et al., 2020) provides a detailed study on the effect of drying temperature on the veneer sheet quality. They list several process parameters must be controlled, including airflow, gas usage, drying speeds (time), dryer zone temperatures, and chain side temperature. (Demirkir et al., 2013)

presented a method by applying ANN to predict the intermediate bonding strength values based on the peeling and drying temperature of the veneer sheets finding positive and negative correlations with the bonding strength depending on the bonding agent applied. Within the scope of the digital twin model here, the physical details were kept close to minimum and the main efforts were spent on image analysis which is discussed in detail later in this chapter.

Model description

Matlab Simulink was used for the purposes of model building as it provides a graphical, hierarchical model building environment with dynamic simulation where programmatic (“command line”) use of model objects is possible for the purposes of, e.g., optimization and random simulations. In the project, an Excel-flowsheet was constructed that enables an average model user can run the Simulink without any programming skills. Later, the Excel interface could be converted into a web-version (HTML) making the digital twin available over the internet. The flowsheet of the system model is provided in *Figure. 2*

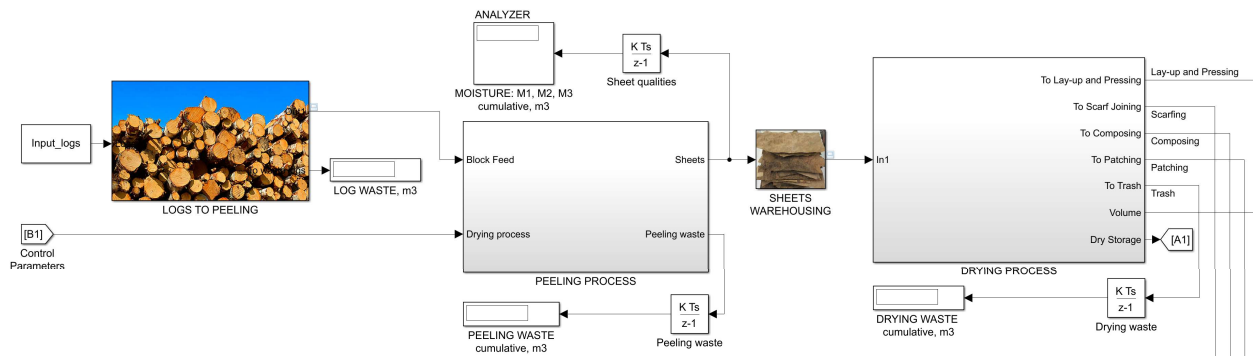


Figure 2. Model flowsheet in Matlab Simulink where each equipment block contains a detailed flowsheet diagram of the process.

Results

Despite the ongoing general discussion on the availability and accessibility of data sources, a lot of real life issues still persist regarding the data availability from the legal aspect as well as from the technical point of view. A key question to common to any DT-project is the data and result

ownership between the digital twin model developer and its customers: the sole ownership of raw data is seen as the data owners as something valuable whereas in the digital twin setting this is not completely accurate. In fact, the data becomes valuable if and only if one is allowed to utilize it inside the digital twin model whereas digital twin model cannot exist without the initial data for testing. This could be regarded as a *chicken and the egg* -problem where it is not clear which one comes first: DT or the data. It is evident, however, that neither the data nor DT-model alone is able to produce economic value and therefore, we suggest ensuring the data availability as far as possible first and secondly starting the model building which is the most time-consuming task.

In the veneer production, the tracking of individual sheets is not possible by humans which means that efficiency losses are incurred in the veneer production daily due to inadequate and/or ill-timed material flow planning. The sheet tracking with route planning and scheduling can be considered as (one of) the envisioned super-human abilities that, in the context of veneer production, would possibly justify the investments in digital twinning. However, tracking the location of individual veneer sheets which is not a straightforward task to implement in practice: first, and most importantly, it is not allowed to make any markings on veneer sheets which poses a risk of degrading their quality class. Second, the sheet order after peeling is continuously shuffled into multiple stacks due to quality classification and the stacks are stored varying time delays which makes it hard to apply the knowledge of sheet order in previous processing phases. And lastly, the visual changes in the sheets induced by the certain processing stages (such as drying) can be significant in terms of altering the colours, producing defects and shrinking the dimensions of the sheets.

Due to the constraints in marking or labelling individual sheets for tracking, the most important data for matching the sheets are the images taken at the different phases of veneer production. Based on matching images, the DT-model should be able to improve the control of both the inbound logistics and physical product quality: that is, if one was able to know the location and qualities of different sheets on a sheet-by-sheet basis it would open up new type of optimization possibilities to the current practice where some of the processes are mostly viewed as black-boxes where no statistical models exist on how different qualities of wood behave under given process conditions of the equipment.

What makes the attempt of using sheet tracking exceptionally challenging from the computational perspective is that raw colour images are unstructured data that need to be somehow structured for the purposes of analysis by the computers. In other words, the question is how to reduce the data dimensionality in a way that enables identifying the whole variety of individual sheets while keeping the data size of the representation at the minimum. A trade-off between the presentation size and recognizability can be stated: one should be able to simplify the image representation enough to make compact and easy to analyse, but yet at the same time, it should remain distinctive of all the other (tens of thousands) images in the data. In practice, storing and using full images sized tens of megabytes for analysis is not an option as thousands of new images are being produced daily.

Admittedly, many advances on Artificial Neural Networks (ANN) in the current scientific literature have been reported that utilize raw image data but, noticeably, they are based on training image datasets of millions of labelled images. In the case of veneer production, manually labelling thousands of individual colour images into training dataset pairs showing peeling input (x) and drying output (y) is laborious – if impossible as tens of thousands of sheets may be processed daily in the largest operations. As an extra twist, there is a high level of randomness on how and where the new defects appear on individual sheets which makes it questionable whether even advanced deep neural networks would be able to generalize to veneer image data.

One documented effort on the use of ANN in matching veneer images is provided by (Jalonon et al., 2021) who use Siamese ANNs to match peeling sheets with drying. Their model is fitted on the data of approximately 2500 sheet pairs of manually labelled spruce sheets showing that the performance of matching is inadequate with realistically sized datasets. During the digital twinning project an alternative, much simpler, approach with gray-level correlation matrices (GLCMs; see, (Haralick et al., 1973) was adopted which is based on the textural differences in the raw images. The GLCM-method produced an excellent ~95% accuracy with the test dataset of ~2000 sheet images of spruce but it could not be verified if the method would generalize to less textured wood qualities such as birch.

From the software point of view, Digital Twins in the literature present themselves in the literature as computer programs, more or less, without further specifics on the actual hardware / software platform. Today, there are no off-the-shelf software for building digital twin models – or some

exists but they are usually tailored and restricted to specific equipment or industries. The unavailability of platforms is probably due to the immense list of requirements on what the DT should be able to do. In this study, the Matlab Simulink® was selected on the basis of the problem characteristics such as the need for dynamic simulation and ability to optimize. Matlab Simulink® is unfortunately a proprietary software and its licensing fees seldom justify its use for applications where the economic optimization potential is small or more uncertain than the case described here. From the scientific advancement point of view, we regard the unavailability of software platform as a serious handicap for developing generalized digital twin frameworks for industry applications.

The related, and higher level, question in the choice of software is the philosophical standpoint on the detail-level of the model which we see as a decision between top-down or bottom-up approach on the basis of what is the ultimately goal of the digital twinning. In the first option, top-down, the (managerial) interest may be in having an overall presentation of the production process with a model timestep of hours or days which should not be confused as a digital twinning project but rather it should be kept as a simulation model exercise due to the absence of real-time interplay with the real data feed. On the other hand, if the customer is genuinely interested in having a deeper, data-based insight to the process on a minute or second basis then the window of opportunity of DT implementation exists. Based on our research, the properties of modern simulation software (such as the one selected here) do have adequate capabilities for both cases as graphical interfaces, computational capabilities, and scalability (cloud computing) are available. However, utilizing modern simulation software requires at least a team of one or two highly skilled experts in the organization who are able to update, maintain and run the digital twin model.

Instead of software capabilities, the main problems of digital twinning seem to lie in the availability of data and technical details of physical processes. When it comes to data gathering, there are seldom too much digital measurements available that could be potentially beneficial for the DT-model. Probably, the default case in the heavy industry cases is such that a variety of measurement history data exist in the process automation system (DCS / digital control system) but the amount of metadata might be sparse. The metadata, in our perspective, is often something that exists outside the sight of the digital world that might affect, or even discard, the measurements taken from a given period of time.

As an example of missing datapoints from the veneer industry, the stacks of quality-controlled sheets are often manually, i.e. with a forklift, transferred from peeling to a storage from where they are later on moved to the dryer based on the needs of the current order book of the production line. Therefore, there is no explicit knowledge on how the stacks are being moved on the factory floor as the decisions on feeding the subsequent processes are left for the human operator. A second example is the raw material feed which consists of logs that are stored outside in piles in the factory premises. Due to the sheer size of material stock, there are limited possibilities to optimize what type of size or quality distribution of logs is currently going into the process and if it were, there is still uncertainty of the real material quality is not revealed until the logs arrive to the peeling process. In this project, the missing knowledge of the input material quality was dealt with the idea that the previous logs (in peeling) represent the currently best guess on what is coming next and that would enable planning ahead.

Admittedly, it would be technically possible to automate some blind spots of the log storage-peeling-veneer storage-dryer logistics by, e.g., providing peeling stacks with IDs for improved traceability. From the economic perspective, however, this makes no sense unless the proof of monetary benefit can be given ex-ante to the management. In the case of heavy industries, many of the equipment have been installed decades ago before the emergence of new industrial automation paradigm. This means that the software is mainly built for running the machine's own proprietary pieces of code to perform desired task as efficiently as possible and "if it works, don't touch it". In other words, in many cases there are no in-built machine-to-machine communication abilities in the legacy equipment and even the question of synchronizing the clock of such a self-reliant machine regularly with the other processes may be a practical issue that needs resolving at the first place.

Conclusions and discussion

This chapter discussed the applicability of digital twinning paradigm in the context of veneer industry identifying several practical issues in the model building, data availability and the use of unstructured data. It was suggested that the key concerns in being able to build and implement

digital twins are related to the data availability and how to utilize it efficiently especially in the case of unstructured datasets that are traditionally utilized only by the human operators for high-level decisions. A second topic that the scientific literature is not addressing adequately, is the absence of computational models of physical processes that are used for day-to-day operations on factory floor that might be fitted as components of the larger, system wide digital twin. The summary of insights is provided in *Table 1* based on the project. It is suggested that many of the points raised are in common with other, established heavy industries as well.

“Insert Table 1 here.”

Table 1. Generalized take-aways on Digital Twin implementation based on the case-project in the veneer industry.

Topic / Issue	Proposed solution
Philosophical approach to modelling	Clarify whether the customer is looking for a top-down (fast to build; not completely accurate) solution or a bottom-up (accurate; slow to build) digital twin
Choice of software	Prefer hierarchical and flexible simulation software that does not create a bottleneck for the model properties; ensure reasonable costs of licensing (vs. expected benefits) and the customer commitment to the software platform in the long-term
Data / results ownership	Agree on who owns the (potential) results of the digital twin built on data and how the model can be utilized to cover similar applications with new sets of type data
Lack of formalization of physical processes	Even though many industrial processes have a solid physical theory and calculations but once taken into action they are treated as black boxes by the operators which means that the computational models may be non-existent at the start of the digital twinning project

Unavailability of digital measurements (and data) in critical parts of the process	Evaluate trade-off between the effort of automation versus human-effort and accept the fact that certain things are better to be left for human operators; be critical on assessing whether the case data available has the pre-requisites for digital twinning
Legacy equipment that are incompatible with the machine-to-machine communication paradigm	Start your DT-project using a bottom-up approach with the equipment that are sophisticated enough for model building. Proven results with tangible value serve as a motivation to upgrade weak spots of the overall process
Unstructured data formats (such as images) serve as a basis for humans' decision making	At the beginning of the project, explore ways to formalize unstructured critical data (assumed to be available) while preserving its distinctiveness and reasonable size. It is unlikely that ready-made solutions exist for context-specific industrial cases and therefore the data pre-processing and dimensionality reduction can take time more than budgeted
Data representativeness and data labelling	Be aware of the data gathering restrictions and (un)availability of metadata for historical data. Even big datasets have little to no value to algorithm development if they lack proper timestamps (or other metadata) and labelling
Reliability and validity	Due to uncertainty in the manufacturing process, dynamic changes in real-time data often cause volatility in the models and even declare the earlier obtained model invalid once new data is being introduced
Dimensionality reduction and de-noising	In the industrial manufacturing process, multidimensional data is ubiquitous. It provides ample information but also poses significant challenges to data mining and pattern recognition methods due to its sparseness and redundancy

Despite the practical challenges, the paradigm of digital twinning is worth of further research and (attempts of) application. It should be highlighted that within this research the focus of model building was on a prototypical veneer production line with an amount of automation that is typical for such systems. As a topic of future research or application, one could cover a state-of-the-art

veneer production line that would be, from the beginning, designed to meet the requirements of Industry 4.0 using the latest technological equipment available thus circumventing some of the foundational issues identified in this chapter.

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