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Deep learning enabling quality improvement in rotogravure manufacturing

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Abstract

Advances in Computer Vision have helped the manufacturing industry achieve superior quality norms with a minimal inspection time due to optical quality surveillance systems. These inspections most often take place at the end of the value chain, insuring the quality standards of the manufactured pieces. The downside to this approach is that defective parts can still continue through the value chain. Wasting a lot of resources and increasing the lead time. To avoid this drain, the machines in the value stream should only produce error-free parts or at least detects them. An optical quality inspection system at every production step would add a high price cost. For this reason, existing sensors should detect unwanted states. With structured data, a person with specific domain knowledge could rate this. This is a tough task, as a lot of unknown factors can influence each step. Therefore, this paper proposes steps to improve quality in rotogravure manufacturing using deep learning. Further research will be conducted in the coming months to expand these results. The proposed procedures will be applied to live data of a rotogravure manufacturing site and the effectiveness of this approach will be analysed.

Keywords: Quality improvement; Quality control and inspection; Jidoka; Industry 4.0; Machine learning

1. Introduction

Today's manufacturing industry is increasingly subject to an international competition, because of falling transit and communication costs, and a faster transportation of goods [1]. Products have become more standardized, as has the technology to produce these [2]. Adding to this, it is becoming more and more important for companies to cut the environmental footprint by reducing energy and material usage. Only through this is a sustainable use of resources achievable [3]. These conditions intensify the pressure to reduce the costs, but also to increase the speed of the delivered goods. An enormous factor to fulfill these demands will be that only high-quality items are produced.

Optical quality control systems have helped improve the delivered products condition in many fields of manufacturing in the last years. Through the possibilities of digitalization, advances in imaging hardware, and Computer Vision (CV). The sectors concerned include a wide range from food [4, 5] to solar cell [6] and fabric [7] inspection. The check is usually only performed at the end of production. Based on the generally high costs of an optical quality control system. Therefore, a defective part still travels along the value stream, and is remade or if possible fixed. Depending on the defect and the point during the production, this can have significant effects on the lead time and the waste.

While the general belief is common, that higher automation naturally improves the quality in manufacturing, the effects aren't always positive and at least on its own shouldn't be seen as a sufficient step towards a higher quality in manufacturing [8]. Sometimes when the complex interplay between machine and human operator isn't fully taken into consideration, this can even expand the problems because of the complexity of the task [9]. This allows two general strategies on how to handle the complexity to improve the quality that don't demand to and shouldn't be applied on their own.

The first is to reduce the complexity of a process step by analyzing it and using tools such as lean management (LM) [10, 11, 12]. The aim of LM is to find less complex ways of achieving the planned results [13, 14, 15, 16, 17, 18, 19]. The non-value adding steps are removed and continuous improvement becomes a focus.

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Another approach is to use tools such as artificial intelligence (AI), which can handle a higher complexity as the problem it controls. AI aims to show intelligence by machines [20]. This includes a wide range of sub-fields with an even wider range of goals. A big sub-field of AI is machine learning, through which it is possible to learn correlations and patterns from sample data. Within machine learning, deep learning has seen an immense surge in the last years. Through it, it has been possible to solve many complex challenges that assumed to be impossible to solve even with earlier AI tools [21].

The third option is to view LM and AI not merely as side-by-side approaches, but as complementary and integrated parts of each other. In this hybrid, both contribute their strengths. AI can improve the decision-making process by offering new insights. The LM framework is used to incorporate these results. Through this, the human still stays in the focus and prevents the system from becoming a black box.

As AI has become an ubiquitous tool in production, it is becoming an essential building block for many current improvements. One of these developments can be found under the term smart manufacturing [22]. In simple terms, it can be summarized as methods that use resulting data from manufacturing to improve the performance. This also comprises several subareas such as predictive maintenance, quality control [23] and quality improvement, which will be the key focus in this paper.

This paper aims to further examine the possibilities how Deep Learning (DL) can be employed for quality improvement by proposing steps in rotogravure manufacturing using DL. The results are produced on the example of the rotogravure manufacturing industry but can also be adapted to other areas of manufacturing.

2. Rotogravure manufacturing

2.1. Overview

Rotogravure cylinders are one of the most important printing methods in the packaging industry and were developed in the early 1890s [24]. Belonging to the family of intaglio printing, which has an even longer history dating back to the fifteenth century, making them one of the oldest printing technologies [25]. The cylinder has cells in the cylinder (Figure 1), that fill with ink. This ink gets released during printing, as seen in Figure 2, by being pressed against an impression cylinder. In its current form, rotogravure cylinders still work through the same principle as they did in the beginnings. Yet, manufacturing rotogravure cylinders has experienced many advances through the help of digitalization.

This has allowed the rotogravure cylinder to keep its place as the most important printing method when high print quality and long print runs, starting at a run of at least 100.000 units [26], are needed. These cases have been decreasing. More printing designs are only used for shorter times. This in turn increases the need to also become relevant for smaller printing runs.

Although manufacturing rotogravure cylinders has this extensive history, the production processes are still prone to errors

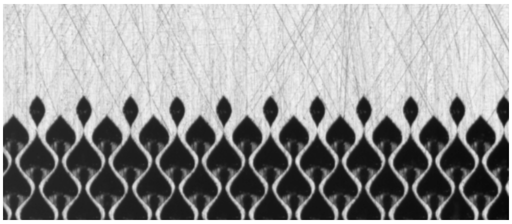

Fig. 1. Surface of an electromechanically engraved cylinder.

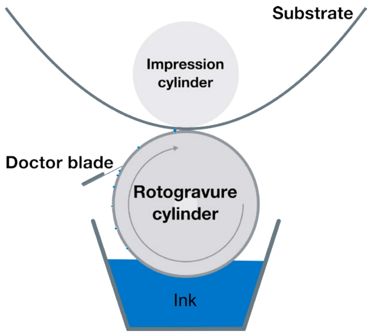

Fig. 2. Rotogravure printing.

because of the many influencing parameters and the required high accuracy. Therefore, there is enough room for Machine Learning (ML) techniques, and DL in particular to be applied and to help improve the processes. As the first step to the analysis, the production steps are described.

2.2. Production process

The general production process is highly standardized. The key steps can be seen in Figure 3. Although the core of the printing cylinder is made of a steel plate that is enclosed by a copper layer, the standard process usually starts with used printing cylinders. These get dechromed and decoppered (3-1). After this, the new production can start. Before a fresh copper layer can be added, the cylinder is degreased (3-2) to remove any kind of contaminant that could have negative effects on the further production steps. If this doesn't happen correctly or if any dirt remains on the cylinder surface, this can lead to defects.

In the next step, a layer of copper is added in a galvanic process (3-3). Because of the earlier production step, and through a multitude of influencing parameters of the coopering machine, holes in the copper surface can emerge. These are already visible in this step. Still many more difficulties can arise in this process step, that aren't visible by the eye. The major points are the copper hardness or a contamination of the copper that could lead to further problems in the next production step.

The following step adds the desired illustration to the printing cylinder (3-4). Depending on the requirements, a multitude of methods are available to achieve this goal. The most used method is the electromechanical engraving, that uses a diamond stylus to remove small cells of varying sizes of copper from the

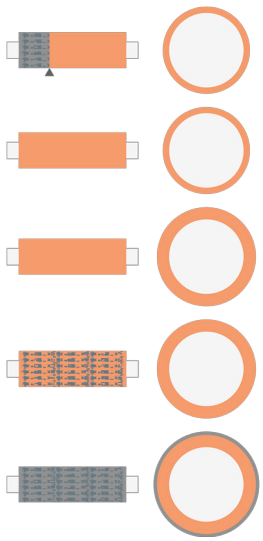

Fig. 3. The main steps of rotogravure cylinder manufacturing. On the left the on-top view of the cylinder. In the middle a cross section of the cylinder and on the right the description.

surface, that fill with ink during printing and release it on the printing substrate with the help of a doctor blade and a rotary press. Also, other methods are available, from which many use a laser directly or indirectly to form cells on the cylinder surface. In scarce cases, engraving can even be done by hand. During the process, many kinds of defects can emerge. For the electromechanical engraving this could, for example, be a broken or fractured stylus or defects of the cylinder surface.

In the last step, the imaged rotogravure cylinder receives a chrome plating (3-5). The reason being that a copper surface wouldn't be hard enough for the pressure needed during the printing process. In this last step, it is also possible that defects such as holes on the cylinder surface can occur. A contamination of the cylinder surface or chrome could cause such flaws.

2.3. Evaluating potential savings

The potential savings of energy, resources, and time depend on multiple factors. In rare cases it is possible that defects of a production step are found before the last quality check. For an easier comparison and as the percentage is currently small, in the following it is considered that the defects only get found after chroming in the last control step.

The two major factors for the environmental consequences are the impacts of a defect and how often it occurs. The cost of the defect can be measured by the impact on the various forms of environmental waste, but also on further kinds of drain used from a management point of view. To a specific degree, most include environmental waste. Perhaps every kind of waste found in LM to a certain extent impact the environmental waste, as it has been shown, that prior lean experience can be an important predecessor for environmental management practices [27]. Still, both environmental waste and lean waste can sometimes even stand in conflict [28]. Therefore, in the following, the view on the waste is through the lens of environmental waste.

The environmental waste of a defect needs to be measured by examining the impact it has on the production compared to a defect free item. Only viewing the environmental waste, it is composed of all the material and energy that is needed to fix the defect. For some types of defects, it's possible to fix a mistake by correcting the current production step. For other defects it can be necessary, that also earlier steps have to be repeated as the defect can not be fixed.

To get a complete picture, it can be an interesting challenge to estimate a realistic potential of how much a production step could be improved. As this can usually just be an educated guess and could lead to falsely dismissing production steps that have a high potential, the basis of deciding which production step has the highest potential to be improved, should only be based on the resulting waste of a production step.

2.4. Potential savings of the production steps

In the following, the results using the discussed methods for determining the potential savings of every manufacturing step are examined. Defects are usually found at the end. Therefore, the root cause for the defect can't always be determined. This raises the difficulty of finding the source of a defect, and in which production step it occurs. Also, it increases the difficulty of determining the exact potential waste savings for every production step. Because of this and to show generic data, in the following relative figures in the form of a proportion of the total waste of each production step between 0-1 are given.

During dechroming and decoppering, the risk for resulting defects are very low. Although imperfections in the resulting copper layer can exist, these neither significantly interfere with the next production steps nor directly lead to defects on the cylinder surface, as long as these aren't extreme. A rare defect could be that the decoppering hasn't been deep enough, and cells of the earlier engraving are still visible. Although a rare case, this would cause immense waste, as all production steps would have to be repeated to produce a defect free object. Therefore, the proportion of defective items through this production step are rated with 0.1 in the following evaluation.

The degreasing step is also a low risk production step. Nevertheless, big contaminations could lead to dramatic consequences, as the copper wouldn't be able to form a solid layer. The degreasing step still only contributes to 0.1 of the added waste.

The coopering phase has the highest associated risk for resulting defects. During this production step, the major risks are holes in the cylinder surface. This is also confirmed in [29] as the highest waste producing category for rotogravure manufacturing. Sizeable holes in the surface could print. Even if these are smaller or the copper hardness isn't consistent, this could lead to defects in the next production phase. Hence this production step adds a proportion of 0.45 to the total.

For the engraving phase, the complexity of defects is the highest, as the cells need to be placed with a very high accuracy and also with a consistent depth across the complete cylinder surface. As a result, the range of unique types of defects is very high whereas the most common is the fracture of the stylus [30]. But also other defects such as distortions of the engraved image in any direction or pin holes are possible. As a result, this production step comprises 0.25 to the total waste.

In the last step, the chroming can also add defects to the item. These could be small holes or an incomplete chrome plating. Due to it being the last step and as most of the defects resulting from this production step can be fixed be dechroming and rechroming the cylinder, the total waste is manageable. This step is responsible for 0.1 of the total waste.

Because of the analysis, the highest waste saving potential can be seen in the copper plating phase. This is the production step responsible for the highest amount of waste. Also, if defects are found at this stage, repairing the item has a much lower cost than in later stages. As an added benefit, it can help in analyzing the origin of a defect.

2.5. Methods for improving quality control

The previous analysis shows the best next target point for the future work. The implementation allows for various strategies. In this section three alternatives are described and rated based on the costs and saving potentials.

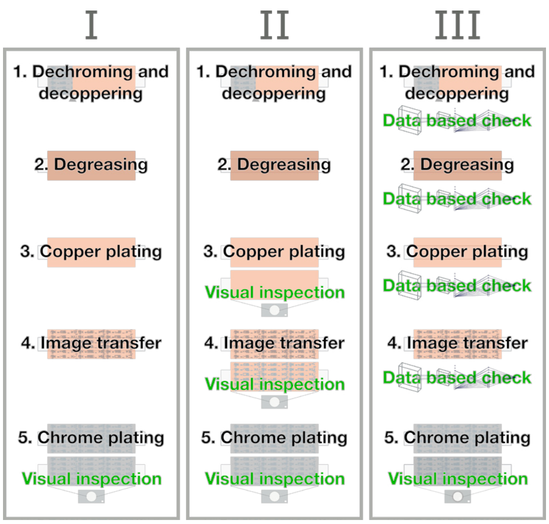

Fig. 4. Three different possible quality checks for rotogravure manufacturing. The currently deployed quality check on the left. An alternative with more visual inspections in the middle and a data based method on the right.

The different alternatives are visualized in Figure 4. On the left (I) the quality check deployed at the investigated manufacturing plant can be seen, where only one visual inspection at the end is used, that uses algorithms from computer vision and AI to detect defects [23]. This kind of quality check has its equivalents in other manufacturing areas, such as for laser welding [27] or metal additive manufacturing [31]. Though visual inspection systems show outstanding results for the final quality check, as discussed, this still doesn't prevent internal waste to accumulate, as defects are usually only found at the end.

The first alternative to the current workflow (Figure 4-II) uses multiple instances of the visual inspection system. Although it is possible to use a visual inspection system after every production step, only the three steps with high waste were chosen for this alternative. Nevertheless, a visual inspection system could be used for each step. The visual inspection system could ensure that only items with no defects are passed on to the next production step. This would make it possible to fix or discard an item without producing waste by adding the next production steps to the already broken item. A downside to this approach is the strong cost point for the visual inspection systems and that only the symptoms in the form of defective items are considered and not the root cause in form of a not optimized production step that only produces defect free items.

The second alternative (Figure 4-III) doesn't use any further visual inspection systems. Quality checks are data based. Details on feasible ways how this can be achieved are discussed in Section 3. Depending on the achievements of the data based checks, it would also be possible to replace the final visual inspection system. This alternative would reduce the costs for needed hardware and could help analyze the core problems in each process step.

In the long term, the correlation between the defects found by the inspection systems and the operational parameters will make it possible to address 4-III, following the LM culture.

3. Deep Learning for rotogravure manufacturing

3.1. Data based alternatives

DL appears to be a promising tool to improve the manufacturing quality. Still, other data based strategies should be taken into consideration. Through the rise of data generation and collection, many types have been developed over the years. All coming with advantages and disadvantages. Though in general terms this includes LM focused systems such as Six Sigma or Kaizen [32], the further focus lies on automated techniques that process data and give an output which is used to improve the quality.

A solution to a problem should never be more complex than it needs to be. Therefore, a first step should almost always be the visualization of the data and if possible simple models could be developed and the correlations of the factors checked. Through this, big influencing factors can already be determined. Domain-knowledge can be a huge plus in this stage. Unfortunately, this approach is not sufficient for most cases as a manufacturing system is usually dynamic, uncertain, and complex [33]. With the help of machine learning, it is possible to model more complex systems. This gives an enormous advantage as most processing steps have many influencing parameters that result in a high dimensional relation.

Most ML algorithms can be grouped into two major categories. Supervised and unsupervised learning. Unsupervised learning is used to detect patterns in unlabeled data sets and generally needs little supervision by a human. Supervised learning however depends on a labeled data-set and learns to find the connecting patterns between input and label. It learns from the examples provided. If the data and the use-case make it possible, supervised learning usually achieves better results.

Through the data won from the vision based systems it is possible to label the data with the information of existing defects. This makes it possible to use supervised learning if the use-case allows it.

The more concrete groups that are promising for the planned results are classification and regression. Though the exact use-case depends on the planned achievements, which will be further discussed in Section 3.2. Classification algorithms could be used to detect defective states. This would be the best choice if the factors resulting in a defect are only temporary. Through regression, prediction and forecasting could be implemented. This would be more useful if the influencing parameters are more continuous and need to be kept in check.

Since the 2000s DL, which belongs to ML, has seen a huge surge in popularity. Though more traditional ML approaches such as Support Vector Machines (SVM) have also shown successes in manufacturing [34] [35], DL are most often superior. The more traditional approaches require a manual feature extraction, while DL networks are able to learn more complex features in each layer which reduces the difficulty significantly [22]. The advantages of deep neural networks have been proven mathematically [36]. This is one of the reasons why it has seen many successful implementations in manufacturing for the last years [37] [38] and why it is chosen as the prime candidate for the future work.

3.2. Roadmap to improve rotogravure manufacturing using DL

To test which algorithm is most suitable for a problem, the required results and the data that can be used to train the neural network need to be examined.

The eventual goal is to find ways that reduce the waste in the production, which allows for distinct strategies. These can range from detecting, with a high probability, that a defective item was produced to further inspect the item for faults, to improving the production step by adjusting controllable variables that have an influence during the production through an automatic system. While the latter would be the ideal end state where every production step would adjust itself to only produce defect free items.

According to the Industry 4.0 maturity index from Schuh et al. [39], the steps visibility, transparency, prognosis and autonomy can be described as a path towards Industry 4.0 or in more general terms as an improvement to the manufacturing. This can also be adapted to this case of quality improvement with the help of DL as seen in Figure 5.

The first step increases the visibility of a system. Here this could, for example, be done by visualizing the interacting parameters through feature reduction with the help of autoencoders [40].

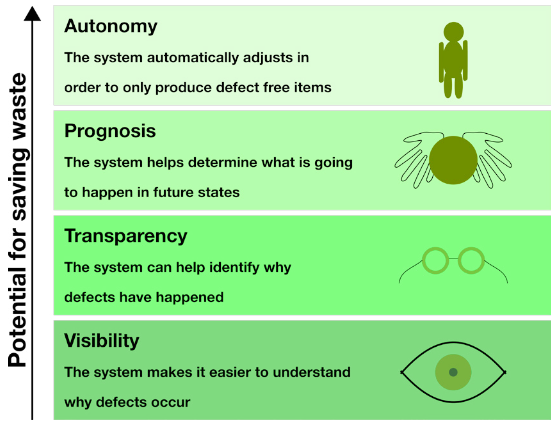

Fig. 5. Potential steps in order to improve waste saving through quality improvement aided by the possibilities of DL.

Creating transparency can achieve further potential. For example, showing which parameters have a negative influence on quality or how these parameters interact.

Making a prognosis can increase the potential. For example, the staff could see the influence of the current state on the system. With this knowledge, it's possible to know which parameters have the biggest influence on the quality and should be adjusted.

As the last step, a fully autonomous system can be imagined, that adjusts its own parameters to only produce defect free items.

Because the goal is to detect defects, it is necessary to know when a defect has occurred. After the copper plating, the cylinder is checked by scanning the cylinder surface with the help of a line-scan camera and an LED-light. Any holes, or other anomalies can be detected through a deviation to the cylinder surface. The check after the image transfer and the chrome plating is more difficult but also starts by scanning the cylinder surface. Now it needs to be compared with the engraving file through transformations and brightness adaptations as described in [23]. These results are the target for all supervised ML/DL algorithms in the training phase.

For the input data, it is necessary that it in more or less hidden form contains the information that a defect exists. It is desirable that no further delays or costs are added. These properties to the current knowledge should be able to be achieved by the data already produced by the machines in every production step. These are usually a mix of different outputs from sensors and parameters from the machine. In the case of the copper (Figure 4.3) and chrome plating (4.5) these would apply to the galvanization process such as the temperature, the amount of additives or the current strength. For the image transfer step (4.4) these would be related to the speed of the machine, the pressure to the stylus and any fluctuations in the electricity used. If it is not possible to achieve the wanted results, added sensors could be installed that contribute further information.

4. Discussion and Conclusions

This paper proposes steps that should make it possible to improve the quality in manufacturing and especially in rotogravure manufacturing for this case systematically. To verify the results, the authors aim to extend this work in the next months by applying these concepts to real-life data of a rotogravure cylinder manufacturer. This should help to show that a general systematic quality improvement and waste reduction strategy is possible by using data and DL algorithms.

A roadmap of the planned next steps is shown in Figure 6 to conclude this paper. It is not a simple transformation from 4-I to 4-III, but consists of multiple steps that build upon each other. The first step will be to have a visual inspection system after the copper plating. This gives the information if a cylinder has defects and will be the target data for the DL system in this part. The second step will be to record the data from the used machines for the copper plating. This will be the input for the DL system, from which it will learn which parameters influence the emergence of defects. In the next step, the DL system will add visibility to the copper plating by showing which parameters have the biggest influence on the emergence of defects. Adding to this, the next step will allow transparency by identifying why defects have occurred. Through integrating the prognosis in the next step, the ability will be added to determine the future outcome and gives the ability to take preventive countermeasures. These steps will be repeated for all the production steps until in the last step full automation for the quality control can be achieved.

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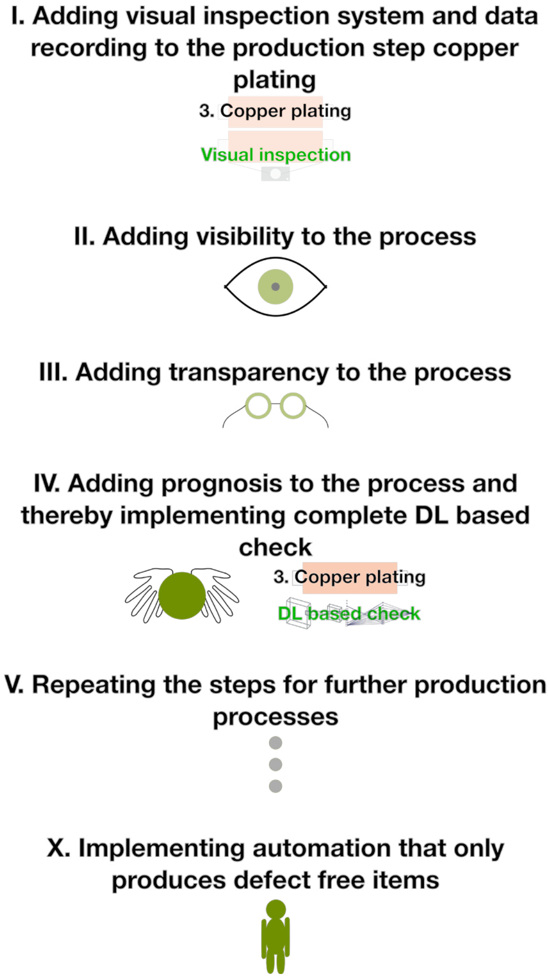

Fig. 6. The planned next steps for the DL based quality improvement in rotogravure manufacturing.

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