Learning Systems for Manufacturing Management Support

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ABSTRACT

Highly optimised assembly lines are commonly used in various manufacturing domains, such as electronics, microchips, vehicles, electric appliances, etc. In the last decades manufacturers have installed software systems to control and optimise their shop floor processes. Machine Learning can enhance those systems by providing new insights derived from the previously captured data. This paper provides an overview of Machine Learning fields and an introduction to manufacturing management systems. These are followed by a discussion of research projects in the field of applying Machine Learning solutions for condition monitoring, process control, scheduling, and predictive maintenance.

CCS Concepts

•Social and professional topics → Automation; •Computing methodologies → Machine learning approaches; •Applied computing → *Enterprise applications;* **•Information systems →** *Enterprise resource planning;*

Keywords

Machine Learning; Manufacturing Management Systems; Advanced Manufacturing; Industry 4.0

1. INTRODUCTION

Highly optimised production lines coordinated by information systems are a major aspect of modern manufacturing environments. These systems provide a high degree of software support at various stages of a production lifecycle [32]. In high-volume and high-throughput manufacturing environments information systems are vital for planning, coordinating, controlling, and evaluating the fully- or partly-automated manufacturing processes. Nowadays such environments are commonly applied in the mass production of goods, such as cars, electronic parts, electric appliances, and toys etc. [11] Although initially these systems where only used for planning and did not collect telemetrics from the production process, soon the telemetric data began to be fed back to the information system. While at first the focus was on the monitoring of the manufacturing process, Machine Learning offered the potential to implement self-adapting manufacturing management systems which constantly improve based on the collected data. [31]

Machine Learning applications gained additional momentum due to the US Advanced Manufacturing Initiative in the United States [6] and the Industry 4.0 program of the German government [3]. One aspect of both initiatives is the use of Internet of Things (IoT) solutions in the manufacturing domain to create so-called Cyber-Physical Systems (CPS) [16]. Another important idea in both programs is gathering intelligence based on the collected data. This implies that the measurements are not only recorded (i.e. for reporting purposes) but also actively used to monitor, forecast and optimise the manufacturing process [10]. Traditionally, this often implied the desire to achieve higher degrees of automation. Nowadays, complete automation is not the only goal and other aspects can become similarly or even more important, including [29, 12, 26]:

High equipment utilisation is vital to economically operate expensive equipment forming a shop floor. Hence, a high utilisation is important to be competitive in cost-sensitive markets. High utilisation requires low idle times and low downtimes due to failures and maintenance [22, 14]

Predictive maintenance (PdM) is key to achieving low equipment downtime by optimising repair cycles and predicting failures in advance. [29] PdM can be used as a tool to reduce unexpected downtime, maintenance, and repair costs, as well as to maximise overall throughput performance via scheduled and predictable downtime windows for tools, equipment and shop floor line setups [28]. Hence, PdM helps to achieve a high availability of equipment and higher equipment utilisation.

High production yield is an issue in the manufacturing of complex products, such as microchips consisting of billions of semiconductors. Reducing the scrap rate directly influences the earnings of a manufacturer. [14] PdM makes it possible to detect deteriorating tool quality and increase the production yield.

For *small lot sizes* and customisable products, adaptive production lines are required. The individualisation and optional features make a selling point that can attract new customers. Adaptive production lines are

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used for manufacturing small batches of individualised products that derivate from a common main product. This often collides with the desired equipment utilisation since the manufacturing process becomes more complex and might need specialised tools. [27, 12, 26]

Information systems *supporting shop floor workers* are a bridge between the automated machinery and human workers. Workers who are well informed about the production goals and receive personalised information for their tasks can excel in various working stations and are empowered to make the right decisions. [26]

Machine Learning can be one way to master these manufacturing challenges. Although research in Machine Learning in the manufacturing domain has been performed for many years [15], recent trends, such as deep learning [25], offered new solutions. Machine Learning algorithms can be trained on the basis of data collected on shop. Depending on the available data and the problem to be solved, various Machine Learning approaches can be applied.

2. MACHINE LEARNING

Machine Learning was first formalised and defined in 1950s as the concept of algorithms that can learn from data provided to them [9]. Learning in this context means that the algorithms derive a model from the data they have already received. This process is termed training and the data used for it is termed a training set. After the training, the derived model can be applied to make predictions for new data unknown to the algorithm. Depending on how training is organised and what kind of training set is required, Machine Learning algorithms can be categorised into the three groups: supervised, unsupervised and reinforcement learning. [1, 24]

In supervised learning the training sets consist of input and output data. Hence, the machine needs to find a mapping function between these two parts of the training set. A common subdivision in supervised learning is classification, whereby algorithms learn the assignment of observations to desired classes. If the target values are not discrete classes but rather continuous values, the process is termed regression. [33, 1] An example of classification is the assignment of emails to the two classes of junk or not junk mail based on examples of both classes provided by the user. An example of regression is predicting future temperature values based on current and past temperature readings. The obvious drawback of supervised learning is the effort required for generating good and comprehensive training examples consisting of input and output data.

In unsupervised learning the training data does not contain any desired output and the algorithm has to find hidden structures by itself [24].Clustering is a common example of data partitioned into groups by means of unsupervised learning. Elements assigned to the same group, or cluster, are thought to be more similar to each other than to elements assigned to other groups. Finding different representations and transforming data is also a common feature of unsupervised learning. Such transformations can be a pre-processing step for other Machine Learning algorithms. Principal component analysis or independent component analysis are examples of such transformations. While generating training data for unsupervised learning requires significantly less effort than for supervised one, the results of unsupervised learning are often difficult for humans to interpret. [33, 1]

In reinforcement learning algorithms have to interact with another party or system. Based on the feedback obtained from them, the algorithms can learn to make its own decisions. In other words, the algorithm determines good and bad actions based on the provided feedback. The feedback process can be continued during the operation, meaning that there is no clear boundary between the training and operational phases. Hence, reinforcement learning lies somewhat between unsupervised and supervised learning. Examples for reinforcement learning can be found in robotics and game-playing algorithms. [1, 24]

3. MANUFACTURING MANAGEMENT SYSTEMS

According to market researchers and consultants, applied Machine Learning has big potential in the manufacturing domain [18, 7, 8]. The highlighted scenarios have to be viewed in the context of Manufacturing Execution Systems (MES) and all the data they have stored to date. MES are information systems designed for planning, managing, controlling, and monitoring a manufacturing environment [23]. Traditionally MES were organised hierarchical, resulting in centralised management of production lines [4]. Due to the increasing complexity and additional requirements in terms of fault tolerance and redundancy, the effort to maintain hierarchical MES became a problem. This led to the creation of a heterarchical paradigm outlining a product-driven organisation of the shop floor and information systems. In a heterarchical environment products and machines are equipped with intelligent devices in order to interact with the planning and monitoring infrastructure. [30, 4] Such modularisation comes at a price, since each station only has information about its own context and can only plan ahead for a limited period of time or not at all. Providing each station with more autonomy and access to the state and scheduling information of other stations led to the development of holonic MES. They are modular and highly dynamic, meaning that hierarchies can be formed if needed. Due to a high degree of flexibility and modularisation, holonic MES can be viewed as an extension or generalisation of heterarchical MES. [2]

Although MES are important to modern manufacturing, they are not the only relevant information system in the production environment. Manufacturing execution systems (MES) help to track the manufacturing progress, trace products throughout the line and assess the quality or efficiency. To achieve this, MES receive product data from design and engineering computer systems termed Computer Aided Design (CAD) and Computer Aided Engineering (CAE) systems. Line monitoring systems (LMS) are used to evaluate the equipment efficiency, output, and bandwidth based on key performance indicators. Enterprise resource planning (ERP) and warehouse management systems (WMS) help to coordinate the management of production warehouses. Data distributed over all these individual systems fully describe the production process. Parts or all of these data can be the starting point for Machine Learning applications in the manufacturing domain. [5]

4. SELECTED APPLIED RESEARCH PROJECTS

Various manufacturing management systems collect large amounts of data from the planning and production phases of each product. Hence, an adaptive system equipped with machine leaning capabilities can use these data as a training set. Such rich databases are the basis for many Machine Learning applications in the manufacturing domain.

4.1 Condition Monitoring and Process Control

Metz et al. [13] present a potential system design and a case study in a casting enterprise. Their approach was to collect data from events occurring at the shop floor and process events, e. g., from the supply chain management. Based on a predefined set of manually-entered rules, a classification-based rule-inferring system is described to deduct rules from the collected data. All rules are used to inform operators about the current process and to automatically control process parameters within predefined thresholds. Moreover, the authors pointed out that the system required a learning phase, which is problematic if products priory unknown to the system are introduced.

A similar approach was formalised by Gröger et al. [5], who designed an Advanced Manufacturing Analytics Platform holding data from an MES, process monitoring sensors, product design and development, and an ERP system. Pattern detection and decision tree induction were applied to all these data in order to derive rules for the optimisation of a steel spring manufacturing process in the automotive industry.

Peng [19] presented a fuzzy inductive-learning-based intelligent monitoring system for improving the reliability of manufacturing processes. It has been demonstrated that this method can successfully be applied to the conditions of a tapping process to improve the product quality.

4.2 Scheduling

Scheduling has many applications and can generally be NP (*n*on-deterministic *p*olynomial-time) hard [21, 17]. Production equipment under a job-shop-floor scenario requires planning strategies that consider routing alternatives, equipment utilization, parts on the shop floor and their respective routing, as well as a manufacturing operation plan. Priore et al. [22] used the mean tardiness and the mean flow time as criteria for Machine Learning algorithms trained to select dispatching rules. They evaluated various combinations of dispatching rules, such as shortest processing time (SPT), earliest due date (EDD), modified job due date (MDD) and shortest remaining processing time (SRPT). A generic algorithm was presented, which was trained to find better routing decisions in order to improve the overall manufacturing system's performance under various scenarios. By analysing earlier performance of the system, knowledge of the scheduling characteristics can be obtained and the correct dispatching rule at each particular moment can be determined. Three types of machine-learning algorithms were used and compared to gain the insights into the scheduling characteristics: inductive learning, back-propagation neural networks, and case-based reasoning (CBR). The results show significant improvements of the dispatching performance.

Noroozi et al. [17] presented an adaptive learning approach for optimising the job sequence and lot formation. Their work was inspired by neural networks using a weight factor to escape the local minima in the various tested optimisation settings.

Pickardt et al. [20] proposed a two-stage approach to generating scheduling rules. In the first stage a genetic programming (GP) algorithm derives rules and in the second one an evolutionary algorithm (EA) looks for possible assignments of the rules.

4.3 Predictive Maintenance

Susto et al. [28] presented a multiple classifier Machine Learning methodology for PdM. With that regard, the main challenge was to generate health factors and link the system status to a maintenance issue. The proposed methodology allows to adopt dynamical decision rules in the maintenance management and can be applied to multi-dimensional data problems. Susto et al. [28] show that this can be achieved by training multiple classification modules with different prediction horizons to elaborate different performance trade-offs in terms of unexpected breakdown frequency and unexploited lifetime. The proposed PdM methodology was tested for replacing tungsten filaments used in ion implantation, which is one of the most important processes in the semiconductor manufacturing. Implantation was used to modify the electrical properties of wafers by injecting doping atoms. This process equipment is often considered a bottleneck in production lines due to the operating and maintenance costs, making it a critical process step for the overall throughput. The methodology outlined by Susto et al. [28] outperforms the approaches that do not incorporate Machine Learning algorithms.

5. CONCLUSIONS

Machine Learning can help to handle the large amount of data collected during the product life cycle in the manufacturing industry. Machine Learning can provide solutions in the fields of optimisation, automation, and worker support by handling complex problems that cannot be solved via static, non-adaptive computer programs. Condition monitoring, forecasting, scheduling and predictive maintenance are examples of promising Machine Learning applications that are already in use today.

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