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10. Machine Learning Can Maximize Efficiency in an Industrial Process

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ABSTRACT

A factory's production line is a series of consecutive processes designed to refine raw materials into a finished product that may be used for further processing. To ensure that the quality of the production process and the goods are met, it is critical to monitor production lines. The total production line process can now create a great deal of data due to the enhanced digitalization.

To improve quality control, evaluate risks, and save money, machine learning algorithms leverage the data provided by the production line. Industrial process monitoring and optimization can benefit greatly from new artificial intelligence (AI) and machine learning (ML) solutions that have arisen as a result of Industry 4.0's rapid development.

The proliferation of hybrid Internet of Things (IoT) architectures supported by polyglot data repositories and big (small) data analytics capabilities is one of the key elements of this new industrial revolution, which is enabled by the hatching of massive process monitoring data from CPS distributed along manufacturing processes.

KEYWORDS

Machine Learning, IOT, Industry, ML, AI.

Introduction:

For firms that lack the necessary resources to produce high-quality items, manufacturing may be a costly and time-consuming endeavour. Leaders in today's industry are already experimenting with more advanced uses of AI for digital transformation, such as machine learning-based solutions to automate decision processes.

Using machine learning, firms are able to enhance their revenue and improve customer happiness while enhancing staff engagement and reducing operational costs. Artificial

Intelligence (AI) is being used in a variety of ways by companies to improve customer service and retention, hire the right people, automate finance, assess brand exposure, detect fraudulent activity, and optimise supply chains.

It's no longer a question of whether or not managers should examine the adoption of AI, but rather how quickly they can implement it [1]. Organizations, on the other hand, need to be careful about how they use AI in their businesses, with a complete knowledge of the technology's advantages and disadvantages.

As the manufacturing process becomes more flexible, more adaptive to customisation, and more traceable, new industrial paradigms such as Manufacturing 2.0, Industry 4.0, Smart Factory, and the Internet of Things (IoT) are becoming increasingly popular.

Manufacturing has grown greatly in the previous decade as the use of IoT technology has developed significantly during the last several decades.

More and more real-time on-site data is being captured from production lines thanks to Industry 4.0 and IoT technology. Data-driven strategies can now be used to solve a variety of production line issues. [2-5]

Machine Learning:

Machine learning enables computer systems to do complicated tasks such as prediction, diagnosis, planning, and recognition by learning from previous data sets. The performance of machine learning models is dependent on the quality of the data and techniques used.

Machine learning models are more accurate when they have access to high-quality data and big data sets. It is also important to use the right methods to tackle a variety of problems, including datasets of various types. [6] Machine learning methods can be used to solve a wide range of problems, as seen in Fig.1.

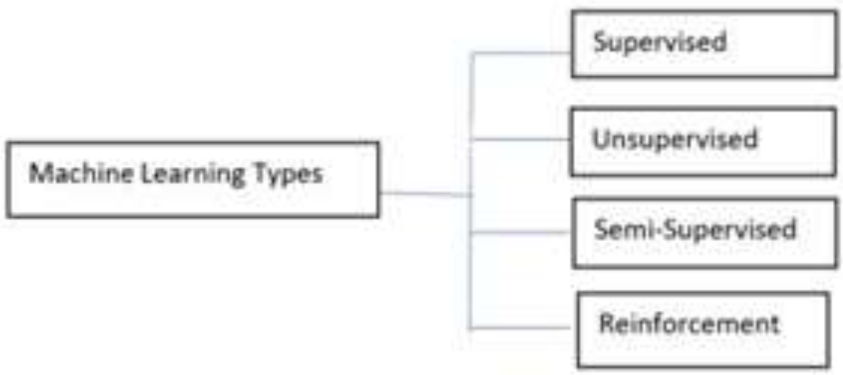

Fig.1: (a) Overview of machine learning types.

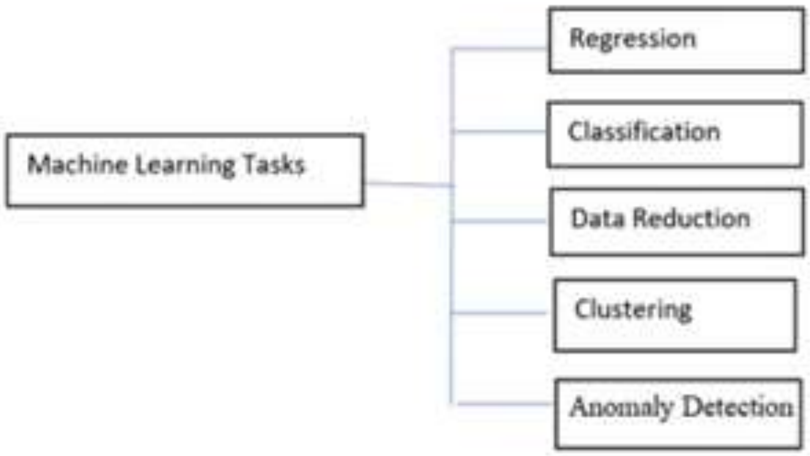

Fig.1: (b) Overview of machine learning tasks.

Machine learning types are explained as follows:

- **Supervised Learning:** Using labelled training data, the computer software creates a function between input and output. Supervised learning relies heavily on human involvement. Many assumptions about algorithms are made by people when they label the output for the training set as well as select the features, algorithm, and even the control parameters of algorithms.
- **Unsupervised Learning:** This method of machine learning does not require labelled data, unlike supervised learning. When the associations between input variables are unknown, unsupervised learning is typically employed. When compared to supervised learning, where an output value is provided, unsupervised learning shows the pattern of input variables and typically gives different clusters based on the input data themselves.
- **Semi-supervised Learning:** Nonetheless, the labelling process is expensive in supervised learning, which makes the model robust and accurate; however, the labelling procedure is costly. While the majority of the data points are labelled in some circumstances, only a tiny percentage is labelled in others. To train a model, semi-supervised learning algorithms can use both labelled and unlabeled data, which can lead to better accuracy than using only labelled data for training.
- **Reinforcement Learning:** Observing the environment, taking actions, and receiving rewards (positive or negative) depending on those activities are all part of reinforcement learning. The model is then modified accordingly. Using a feedback system, reinforcement learning rewards positive behaviour and punishes undesirable behaviour. [7-10]

Machine learning techniques are applied in numerous areas to solve different kinds of tasks. Five common tasks are explained as follows:

- **Regression:** Known as value estimation, regression maps input information to a continuous numerical variable. The coefficients of each independent variable are optimised using machine learning algorithms in order to minimise the prediction error. It is possible to use a floating-point number or an integer as the output variable.

- **Classification:** When a feature is classified, it is associated with a single discrete output variable. In the underlying problem, the output variable is a class.
- **Clustering:** Using clustering, data points can be grouped into appropriate subsets. It is based on the similarity of data points in this grouping. Data scientists can benefit from grouping together points that are statistically similar.[11]
- **Data Reduction:** It is possible to delete some rows (i.e., data points) due to the noisy data instances or the repetitive data points when performing data reduction operations. Some features that are highly linked or irrelevant may be omitted from the dataset in order to speed up the process of developing models. For other machine learning tasks, such as regression and classification, this task serves as an auxiliary approach.
- **Anomaly Detection:** In the majority of cases, an anomaly detection task is handled via unsupervised learning. Anomaly detection methods aggregate samples in a manner similar to clustering. Anomaly detection methods are used to locate the dataset's outliers.[12]

Impact of machine learning in manufacturing:

Machine learning has been used into all three phases of the manufacturing process—operations, production, and post-production—by manufacturers.

- **Product Development:** Manufacturing organisations are reaping the benefits of big data in terms of product development. Using the data, businesses may better understand their customers, meet their demands, and satisfy their wants. That manner, it will aid in the development of new or improved products for your customers. With the use of important data, producers may create a product that is more valuable to customers and reduce the risks associated with introducing a new product to the market.[13] As part of the product's planning, strategy, and modelling, actionable insights are taken into consideration. Operational efficiency can be considerably improved with CRM application implementations.
- **Robot:** In production, robots can have a significant impact. They can assist in the ordinary chores that are too dangerous or complex for people to handle on their own. To meet demand and decrease human errors, firms invest more money in robotization.
- **Security:** ML platforms have made it possible to keep employees' mobile devices safe in the workplace. Ensuring the security of your processes and empowering business innovation is made possible through the use of machine learning (ML) algorithms. For Android and iOS devices, it allows for on-device security and remediation of device and network security issues.
- **Quality Control:** The quality of the manufacturing process can be improved thanks to the use of machine learning. An assembly line's strengths and limitations can be improved with deep-learning neural networks.
- **Supply Chain Management:** Improved logistics, inventory management, asset management, and supply chain management are all benefits of machine learning. Artificial Intelligence (AI) and IoT devices can assist ensure high-level quality through the use of Machine Learning (ML).[14]

Machine Learning for Product Optimization:

With a machine learning system that can forecast production rates based on the control variables you set, it's essential.

To find the best potential production rate, the multi-dimensional optimization algorithm traverses around this landscape. There are three primary components to a machine learning-based production optimization, which are as follows:

1. **Prediction algorithm:** Prior to anything else, make sure you've got an algorithm that can accurately estimate production rates given all of the operator-controllable factors you have in place.
2. **Multi-dimensional optimization:** Use the prediction algorithm as a foundation for an algorithm that investigates which control variables to alter in order to optimise production.
3. **Actionable output:** Your production rate can be improved by modifying the optimization algorithm's output, which includes advice on which control variables to modify. [15-17]

Machine Learning for Orduction Optimization:

1. **Predictive algorithem:**
   - Given historical data, learn model to predict the production rate given a set of operator controllable variables.
2. **Optimization:**
   - Utilizing the predictive power of the machine learning algorithm, perform a multivariate optimization with aim of increasing production rates.
3. **Actionable output:**
   - advice operators on which control variables to adjust in order to maximize production.

Control variable:	Pressure controller 4	Flow rate controller 17	Temperature controller	Control valve 9	Control valve 17	Control valve 22
Old settings	17 bar	230 m3/h	120 c	40 %	72 %	14 %
New setting	19 bar	240 m3/h	134 c	44 %	65 %	18 %

Fig.2: Machine Learning for Product Optimization

Objectives:

- Discuss how ML can be used to solve EE-related problems in industry.
- Use these tools to demonstrate how they might be utilised to gain valuable insights on EE issues.
- Manufacturing and process sectors can use machine learning (ML) tools to solve EE challenges.

Review of Research:

Using machine learning, a reduction in overall inventory of 20% to 50% is achievable, according to the consulting firm McKinsey. Even something as simple as taking a physical inventory can be made more efficient with artificial intelligence.

Advanced drones that fly through the warehouse and scan things, as well as check for missing items, may do tasks that take Wal-Mart personnel a month to complete in just 24 hours.

When it came to EM in industry, little attention was paid until the 1970s (Petrecca, 2014). Oil crises of the 1970s sparked concerns about energy security, which pushed for more energy-efficient technologies and procedures to be developed (Kaya and Keyes, 1980). The current energy landscape is vastly different from what it was in the 1970s.

The focus on reducing waste and inefficiency in the use of energy is shifting, driven by both economic and environmental considerations (Johansson and Thollander, 2018, Marimon and Casadess, 2017, Thollander and Ottosson, 2010), and this shift is being driven by both economic and environmental considerations.

Among the six topics proposed by May et al. (2017) are: Driving Forces and Barriers, Information and Communication Technologies, Strategic Paradigm & Tools & Methods, Manufacturing Process Paradigms & Manufacturing Performances are some of the topics covered in this book

Energy-efficient procedures can be developed in a favourable framework, but there is a dearth of awareness, expertise and experience among industry leaders on how to implement these ideas (Prashar, 2017, Thollander and Palm, 2015). EE is rarely a top priority for businesses, since they focus on more urgent goals (Sorrell, 2015, Reddy, 2013).

Manufacturing and process sectors face a major difficulty in this regard: how to use recorded data in a meaningful way. The proliferation of affordable sensors and the demand for better process monitoring and reporting has led to a massive increase in the volume of data in industry (Diez-Olivan et al., 2019, Shang and You, 2019).

Since large amounts of data are being accumulated across all industries, businesses are increasingly turning to Machine Learning (ML) tools to explore its possibilities. Artificial Intelligence (AI) and Industry 4.0 have led to a revived interest in machine learning (ML) technologies, and there is a strong desire to explore its possibilities in many industries (Alcácer & Cruz-Machado, 2019, Lu, 2017).

Artificial Intelligence (AI) contains a wide range of strong technologies that may be used to extract important insights from raw data (e.g., class prediction, pattern recognition), which can then be utilised to assist organisations in improving their operations and strategic decisions.

A wide variety of products may be manufactured using a production line since it can be utilised to automate the process. The concept of a production line can be defined in a variety of ways. A production line is a manufacturing or assembly process where components are successively processed to produce a product at the end, as defined by Bierbooms (2012) in his study.

Research Methodology:

An crucial aspect of any scientific contribution is a literature review. A research field's linked works serve as a foundation for any such contribution, providing the necessary context and motivation for any such effort.

Here, we outline our study's research goals and search criteria, as well as our data gathering and synthesis methods. Numerous Internet databases were searched to gather a thorough picture of this topic.

Reading the abstract and introduction of each paper A single research question can be answered using one or more data gathered from the data extraction form. We use both qualitative and quantitative methods to address the study questions.

When it came to answering qualitative questions, we analysed the data from past studies. According to the definition of the United States Department of Labor, the industry domain is categorised (2019). For quantitative issues, we rely on the literature and tally the number of publications that are relevant to the subject at hand.

Machine learning algorithms related questions are answered based on the number of articles that have utilised this sort of methods, for instance.

Result and Discussion

For the industrial and process industries, one of the biggest issues is how to fully utilise recorded data. Due to the widespread availability of affordable sensors and the need for improved process monitoring and reporting, the volume of information generated in industry is increasing fast.

Machine Learning (ML) tools are rapidly being used by businesses to investigate the possibilities of vast volumes of data, which gives huge opportunity for many industries.[18]

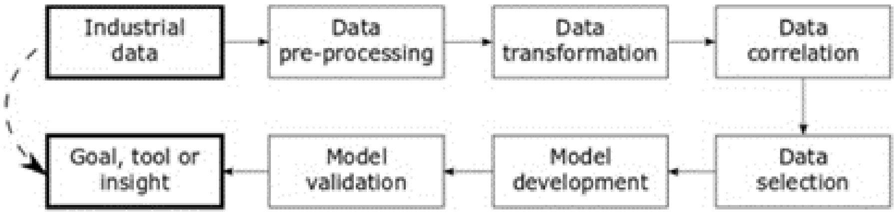

Fig.3: Typical steps used for insight extraction from data via ML tools.

Production Optimization:

A prevalent issue in many companies is product optimization. The term "optimization" refers to any action, process, or practise that aims to make something as good, functional, or effective as feasible. An example of this optimization is deciding on the best possible cost, quality, performance, and energy consumption. It's common for short-term decisions to be referred to as "daily production optimization." Most of the time today, the operators of the offshore production facility are responsible for optimising daily production. There are many variables that may be controlled that all effect the production in some way or another, making this optimization a very difficult endeavour. To get the best possible result, it is necessary to experiment with upwards of 100 distinct control parameters. Take a look at the picture below, which depicts a very basic optimization problem. Variable 1" and "variable 2" are the only two variables that can alter your manufacturing rate. Optimization is the process of determining the best possible combination of these variables to optimise production.[19]

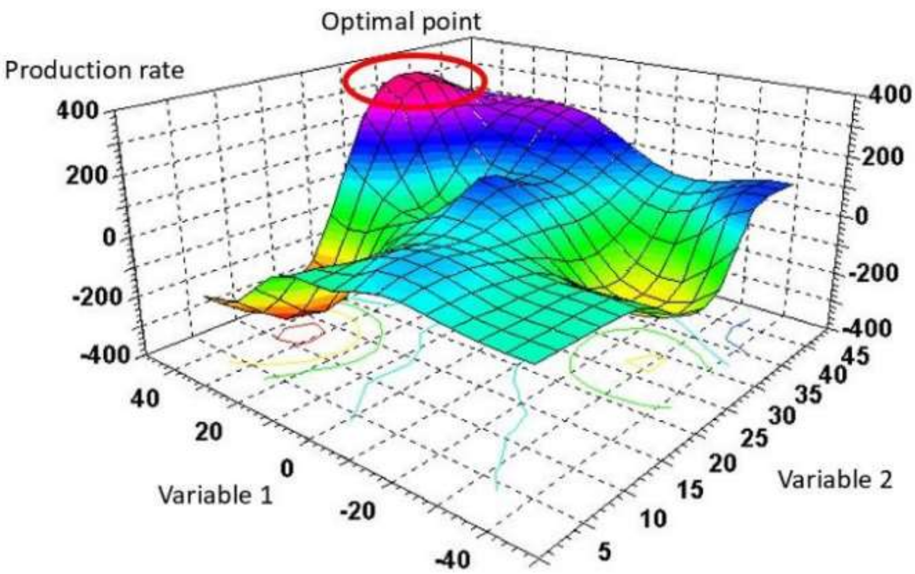

Fig. 4: Simplified Optimization Problem

Overall equipment effectiveness (OEE) as key performance indicators (KPI):

Product or part work orders that are more tailored are replacing high-volume ones without personalization, implying that effectiveness may not just focus on specific process optimization, but also on reducing changeover setup times or minimising scrap or increasing quality.

As a result, there is a clear need for all manufacturing processes to be improved and optimised, as well as the efficient adaption and use of production lines, to meet this demanding circumstance.

Because of its three core indications, OEE has become the primary KPI for most industrial businesses.[20]

- Availability: Percentage of time that an equipment can operate
- Quality: Percentage of good produced parts
- Performance: Percentage of maximum operation speed used

In Fig.5 OEE components are summarized and in Fig. 6, where a standard manufacturing process is compared with an AI-powered one.

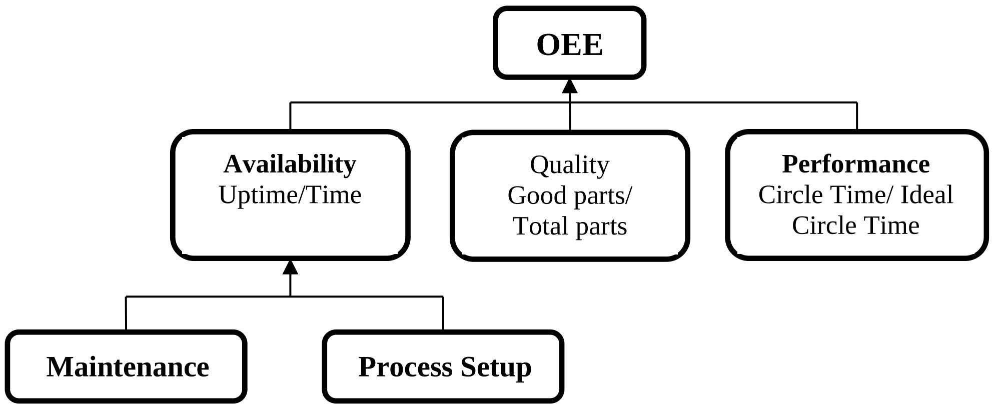

Fig.5: OEE Components and Focus

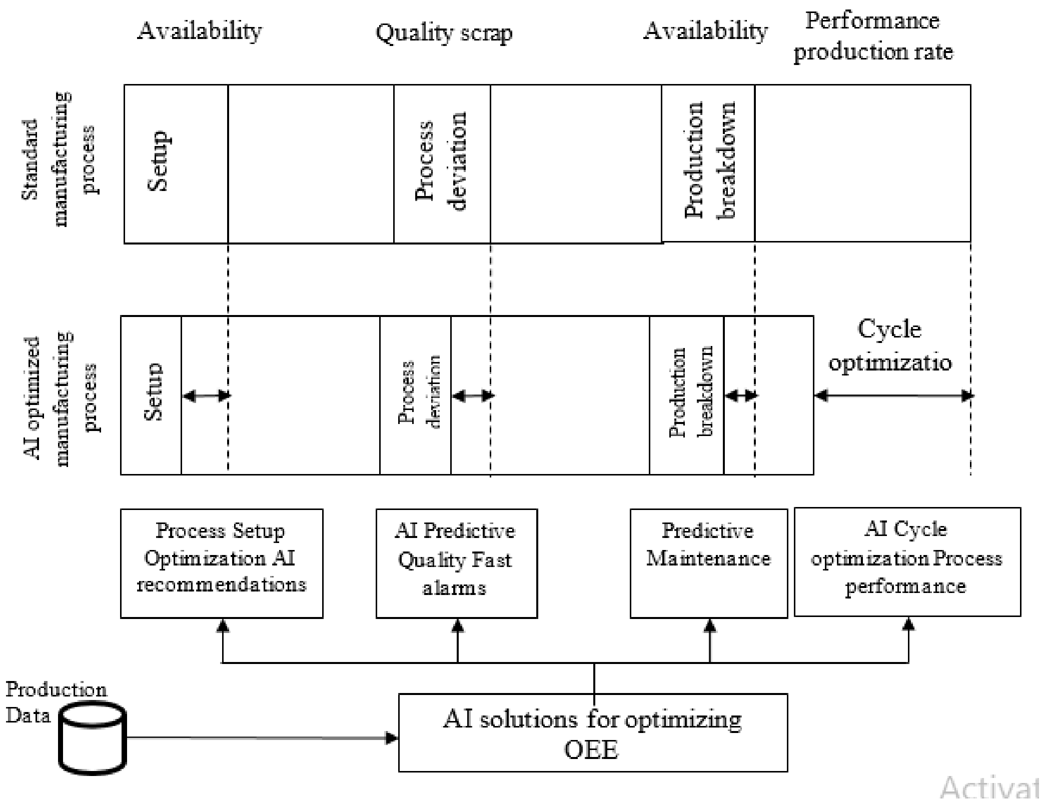

Fig.6: OEE optimization using AI.

When assessing a manufacturing process and gauging how AI and ML solutions may bring concrete benefits, other productivity indicators might be quite useful.

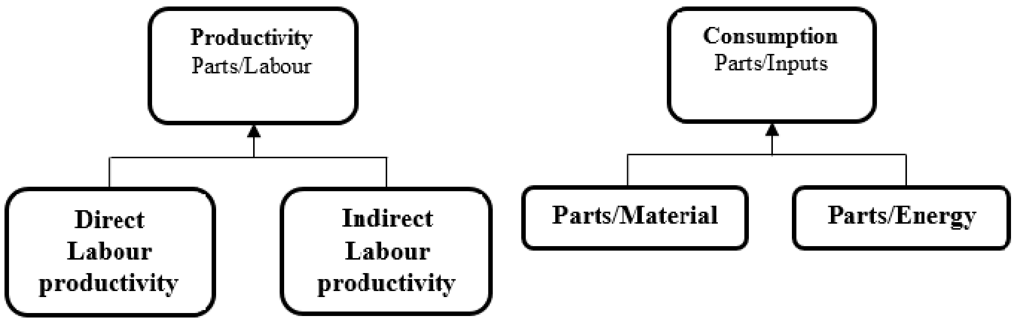

Fig.7: Productivity indicators.

Productivity indicators:

- Good produced parts/operator
- Good produced parts/total produced parts (scrap, setup, testing, etc.)

Consumption indicators:

- Material consumption (MC)
- Specific energy consumption

Conclusion:

Complex design methods and more advanced prototypes are generally accepted by the industry. Machine Learning (ML) models are fed data from products and processes in order to optimise the manufacturing process in real time. This means that the employees in the manufacturing sector will need new skills in order to keep up with the new technology, while older machinery will need an upgrade so that they can work in today's industry.

By discovering, monitoring, and evaluating the crucial system variables during the production process, Machine Learning is a vital enabler of sophisticated Predictive Maintenance capabilities. Operators can minimise costly unexpected downtime by being warned by ML before a system breakdown occurs, and in some situations, without the involvement of the operator. When it comes to productivity, quality, and efficiency, the smart exploitation of data is a crucial performance indicator of the Industry 4.0 paradigm (KPIs). Because OEE considers the availability, quality, and performance of equipment, it has become the primary KPI for most industrial businesses.

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