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Advancing Manufacturing with Machine Learning: Unlocking the Potential of Reinforcement learning in Industry 4.0

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Abstract. The ongoing Industry 4.0 revolution is transforming manufacturing environment to be smarter, empowering machines to comprehend processes, interact with their environment, and adapt intelligently, thus enhancing the productivity of manufacturing technologies. Within the realm of AI (Artificial Intelligence), Machine Learning (ML) has emerged as a pivotal force propelling these innovations in various industrial sectors, and leading digital transformation of operations and processes to Industry of the future. Particularly, ML, with a focus on Reinforcement Learning (RL), has demonstrated its prowess in successfully addressing diverse tasks and challenges across different complexities and performance levels in the industry. This paper provides a comprehensive overview of ML applications for smart manufacturing, highlighting several powerful ML algorithms capable of offering solutions to pertinent issues while averting potential challenges in the future of the industry.

Keywords: Industry 4.0 · Machine Learning · Reinforcement learning · artificial intelligence

1 Introduction

Over last two centuries, every industrial revolution has been propelled by a change in production methods through an emerging technology of that era. In this context, the steam engine was the flame that started the first revolution in industry, the second started by the application of electricity, and the third by the widespread use of information technology and electronics. In recent times, the popularity of the Internet of Things (IoT) [1] and Cyber-Physical Systems (CPS) has captured the attention of enterprise and academia. The use of these technologies promises to enable better connectivity between information, products, and people, thereby improving current production models. This phenomenon is known as Industry 4.0 [2]. It leads to several innovations, from digital technologies, advanced materials, innovative products to new manufacturing processes. Industry 4.0 is a revolutionary concept that is having a major impact on several areas of industrial manufacturing . It helps to enhance and improve development and growth through the use and adaptation of new technology and engineering tools, for creating intelligent products through intelligent processes. This evolution in industry is realised including various technologies such as : ML, Internet of Things, Big Data, and Cloud Computing (CC) which are driving together a revolutionary transformation in the fields of industry . Smart manufacturing, a key aspect of Industry 4.0, epitomize the forthcoming paradigm of manufacturing, wherein the uninterrupted transmission and meticulous analysis of shop floor data play a pivotal role in generating profound manufacturing insights. In this context of industry of the future a wide range of applications is envisioned, providing a solution that can help manufacturing companies to further optimise their processes and significantly increase their internal efficiency, thanks to the system's automated procedures, easy setup including simple, demand-driven installation and, finally, its high degree of scalability. Depending on theses application, a various of ML algorithms, have already been explored to achieve characteristics such as fault detection, prediction and autonomy.

AI and ML, gave a tremendous boost to Industry 4.0. Thanks to intelligent software, the large volumes of information and data being collected from the industrial environment through IoT devices. AI solutions can learn to read "between the lines", enabling the discovery of many complex interrelationships that human beings would not or no longer be able to grasp, this enhanced capability is made possible through the use of advanced ML analysis techniques. The increasing amount of real-time data generated in industrial environment has led factories to the adopt ML's techniques, algorithmes to respond specific industrial needs.

According to Arthur L. Samuel [35], ML refers to the ability of a system to behave in a smart way like human, in terms of performance and solving complex and hard problems. There are different types of ML models, which are categorised[36] as follows: **supervised learning** (include algorithms of classification and

regression such as Linear Discriminant Analysis (LDA) and Linear Regression(LR)), **unsupervised learning** (include algorithms of clustering such as K-Means), **reinforcement learning (RL)** (is based on agent, include algorithm such as Deep Q-learning, AlphaGo [37] is an example).

Recently ML applications have known a large expansion Not surprisingly, many works point to ML being the key to the development of the present industry towards industry 4.0 evolution .[38][39] The rest of this paper focus in section 2 on the methodology used to identify pertinent research and mention some related work to the use of machine learning in industry 4.0 . The section 3 contains a definition of Reinforcement learning approach and their application in industry 4.0 including some related work.

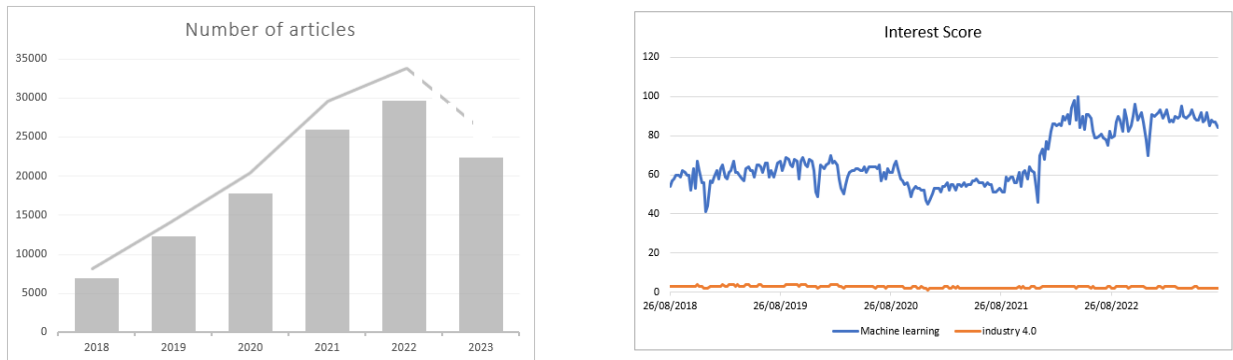
2 RELATED WORK

In this part, we discuss our used methodology and then we introduce some state of art in machine learning applications for industry 4.0 between 2018 and 2023 according to several criteria. First, we start with ML algorithms used in manufac- turing, then we mention their application in industry.

2.1 Used Methodology

In this part, we describe the methodology used to identify pertinent studies within the field of machine learning in the context of industry 4.0. We conducted thorough searches across Google Scholar database , focusing on English-language studies published between 2018 and 2023. Our search terms comprised a combination of keywords, including "ML/RL industrie 4.0", "industry of the future", "ML/RL smart industry" ,"ML/RL scheduling industry," "ML/RL computer vision industry" ,"ML/RL predictive maintenance industry" and "ML/RL could/edge computing industry". Our approach entailed scrutinizing titles and abstracts for the designated terms and additionally cross-referencing the complete bibliographies of located articles. We aimed for a comprehensive research process, culminating in a curated selection of articles that objectively encapsulate the existing literature on Machine learning and Reinforcement learning in industry of the future.

Most of articles included are recent publications (Figure 1.a). This reflects the trend of a sharp a sharp growth of articles published over recents years; Google Trends illustrated in Figure 1.b prove an increase interest score for Machine Learning and Industry 4.0 over recent 5 years.



(a) ML publications in industry 4.0 in the past five years (b) Machine Learning and industry 4.0 score Interest

Fig. 1: Machine learning application and Interest

2.2 Previous Survey Works

This part of paper focuses on giving a broad review of some ML algorithms employed in manufacturing processes. In order to carry out successfully our work , we are based on a systematic review (SR) approach described in [4] to identify relevant research and work on ML techniques[5] and application in industry 4.0. In recent times, the field of study related to ML applied in Industry 4.0 has attracted many contributions. The paper in [6][7] explained Successful machine learning algorithms in manufacturing including artificial neural

networks(ANN) , support vector machines (SVM), Naive Bayesian (NB) , LR, and other ensemble methods. Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) as example of deep learning algorithms have known recently good efficiency in terms of performance in areas involving images recognition, object detection and text processing/analysis [8]. The authors of Reference [9] propose for solving a production chain problem in manufacturing systems, the use of a machine learning method named Classification And Regression Tree (CART). The proposed approach used a decision tree based on supervised learning, to optimize delivery costs. Furthermore, an overview of a defect detection systems based on machine learning algorithm including a series of new digital manufacturing technology; was given in Reference [10]. A novel approach for fault bearing diagnosis was introduced in Reference [11], it based on a deep belief network (DBN) combining with Joint Distribution Adaptation (JDA) . This latest, plays a crucial role in the Joint Distribution Adaptation with DBN (JACADN) method, allowing feature transfer between samples from the source and target domains.

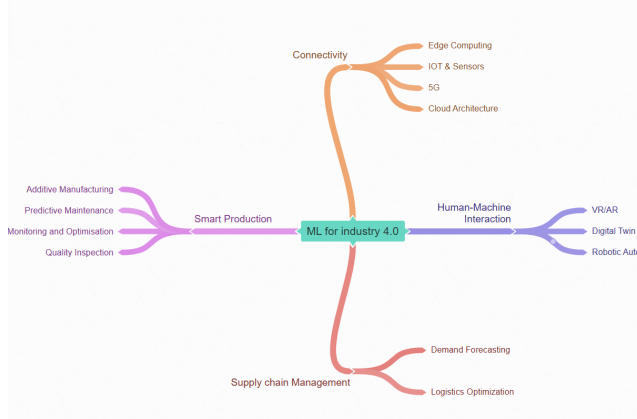
According to predictive maintenance, the work described in [12] proposes a model combining CNN and LSTM the first refer to convolutional neural networks, the second for long short-term memory it is a forecasting approach for predictive maintenance based on historical data Where the autors experiment the prediction of machine failures. Moreover, the Reference [13] provide a predictive and preventive maintenance model applicable to the industrial field using RNN. A stochastic dynamic programming solving approach is presented by authors in Reference [31] for solving the problem of machine's breakdowns, by scheduling jobs and implementing preventive maintenance, aiming to minimize the cost associated with earliness and tardiness. The study in the paper in Refrence [33] presents experimental findings that highlight the adaptive large neighborhood search algorithm's (ALNS) competitive performance to solve Hard scheduling problem with different specific time. It demonstrates a capacity to match or surpass the state of the art in 63% of cases. The aim of the study in reference[14] is to review several works on ML applications for the optimization production processes and for the improvement of products quality. in that regard, a method used for inspecting a quality of a product in manufacturing environment is proposed in Reference[15]. The model of inspection of quality product realised in this approach, is based on selecting data, then checking and controlling the quality, finally training the model to be adaptive to different cases, using supervised ML algorithms including Gradient Boosted Tree (GBT), Logistic Regression (LR) also , Support Vector Machines (SVM) then NB and Decision Trees (DT).

The study in Reference [16] highlight the application of ML in industry for anomaly detection. The paper compares various ML methods, including K-Nearest Neighbour (KNN), SVM, ANNs, and hybrid approaches. Essentially, all the objectives are aimed at maximising efficiency and minimising costs, we will present an example in Reference[34] of the use of an optimization model combing with ML to solve a manufacturing scheduling problem with constraints of time and ressources. The model is formulated as a mixed-integer linear programming (MILP) problem aimed at minimizing the total duration (makespan) of production while adhering to a set of intricate constraints. These constraints define conditions for the start, completion, and interactions among operations, machines, workers, and configurations. The objective is to achieve an optimal scheduling of production operations, accounting for Industry 4.0-specific constraints. Some assumptions are considered to simplify the problem: No operation preemption, Single worker and machine focus, Full initial information. The authors are based on parameters such as: set of jobs, machines, operations and configuration... In addition, authors in Reference [17] aim to introduce a prognostic method for predicting tool wear using random forests (RFs). They assess the effectiveness of RFs when compared to feedforward backpropagation-artificial neural networks (FFBP)-(ANNs) ,support vector regression (SVR) and in terms of performance for this purpose. The comparison is based on empirical data gathered from conducting experiments. The results indicate that RFs is better than FFBP-ANNs and SVR in terms of performance , showing precision in predictions for tool wear. The paper in [18] outline on a comprehensive approach of machine vision to automate processes for detecting material category, to enhance the capabilities of technological tools, such as robots, that are being used in manufacturing enviroment using method SVM. The paper in Reference [19] focuses on the topic of the human-robot collaboration (HRC), where authors propose a robot model represented in an interactive, dynamic interface using some deep learning algorithm of recognition and classification, including three modules speech, movement and body recognition.

2.3 Major Application Areas of ML in industry 4.0

We present different application areas of Industrial ML: **Optimizing Processes, Ensuring Quality Control, Predictive Maintenance , Human-Robot Collaboration and Ergonomics**

These areas or topics were categorized, grouped and visualized in the mind map illustrated in Figure 2.



(a) Mind map of high potential value areas for ML in industry 4.0

	<i>ML method</i>	<i>Application</i>
ref[12]	CNN	failures prediction
ref[11]	DBN	fault diagnosis
ref[29]	KNN, ANN	Anomaly Detection
ref[15]	NB, DT, LR, SVM, GBT	Quality inspection
ref[9]	CART	Optimization process
ref[17]	SVR, RF	RUL and failures prediction
ref[19]	CNN, MLP	classification and recognition
ref[13]	RNN	prediction and preventive maintenance
ref[18]	SVM	Identification and classification
ref[14]	General approach for ML solutions	product's quality improvement

(b) the targets of ML solutions in Industry 4.0.

Fig. 2: the targets of ML solutions in Industry 4.0.

3 Reinforcement learning

3.1 Reinforcement learning approach

Reinforcement Learning (RL) algorithms concerned two essential elements, an agent operating in a space. The agent model interacts directly with the environment and manipulates it to perform a desired learning process. According to [5], the agent starts to receive the information about state called S of the environment. Based on this state and its probabilistic decision process, the agent selects an action A . Subsequent to executing the action in the previous state, the environment moves to a novel state, and the agent is rewarded R . This cycle of reinforcement learning persists, with the ultimate objective of maximizing, aiming to maximise the rewards by improving the choice of actions towards an optimal control policy. In essence, the agent strives to acquire the most effective control strategy for the environment.

RL holds great promise for achieving autonomous control in various industrial applications, such as processes, machines and systems. In addition, multi-agent RL is gaining attention in the research community and is showing potential for product control. Despite its potential, RL remains under-utilised in industry compared to other machine learning techniques.

3.2 RL application in industry 4.0

This part provides a review of related work in the application of reinforcement learning in the areas of industry 4.0. RL has been applied efficiently in different areas in industry

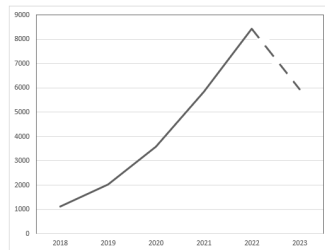


Fig. 3: RL publications in industry 4.0 in the past five years

Most articles included are recent publications (Figure3). The article in reference [21] propose a reinforcement learning (RL) method for tracking use, concerning an agent trained to choose the best optimal state based on an internal measurement to maximise the Rewards in each step. The applications of RL in industry 4.0 concerns often production scheduling and robotics. The study in Reference[22] propose an agent based on Reinforcement learning trained to solve a dynamic scheduling problem (DJSP) . A comaprasion study of performance for this proposed approach with other rules prove it efficiency and accuracy, depending on different scenarios and criteria for this comparison. Q-learning[23] is frequently employed in various papers, including the article in [24]. The article in Reference [25] shed light on scheduling optimization in manufacturing using a plenty reinforcement learning algorithms based intelligent. In other context related to robotics in smart manufacturing, some deepl RL methods such as Self-learning Processes are provided in [26], where authors expirement a RL model named Deep Deterministic Policy Gradient (DDPG) for the control of time and pressure injection. Moreover, authors in Reference [27] proposed a new neural network and Reinforcement learning method known as Reinforcement Learning Unit Matching Recurrent Neural Network (RLUMRNN) to solve a problem related to the performance control of neural network affected by the selection of hidden layers. This part provide a review of previous works in the application of reinforcement learning in the areas of industry 4.0. RL has have been used successfully in many applications.

An approach using deep reinforcement learning based on multiple agent, is proposed by authors in [28] to solve Scheduling optimization model for energy system of a microgridpowered MEC network. Furthermore, the use of RL for anomalie Dectcion has succesful result presented in Reference [29], a framework combining RL and supervised learning, result a high intrusion prediction. In addition, RL is used in various other applications. In class of prediction and forecasting , there is a predominance of method of planning relying on value function approximation and decision processes of Markov. For detection policy gradient methods are prominent. For evaluation, assessment, assignment, and resource management, multi-agent methods are in the spotlight, signalling a shift towards distributing tasks to lower-level tools rather than centralised data processes.

Then, in the initial category, the allocation of various RL methods closely resembles the general distribution, while in the second category, policy gradient methods are predominant, as allocation-related problems tend to favour the creation of optimal policies. In the Clustering, Decision Making, Classification, Scheduling, and Planning classes, there is a contrasting pattern emerges: multiagent methods are underrepresented, suggesting that research in these operations still tends towards centralised solutions. The paper in Reference [32] tackles joint scheduling of tasks and optimizing cost. It explores machine learning vs. optimization methods, proposing a stochastic dynamic programming approach and an attention-based deep reinforcement learning model.

Figure 4 illustrates the core categories encapsulated by reinforcement learning methodologies.

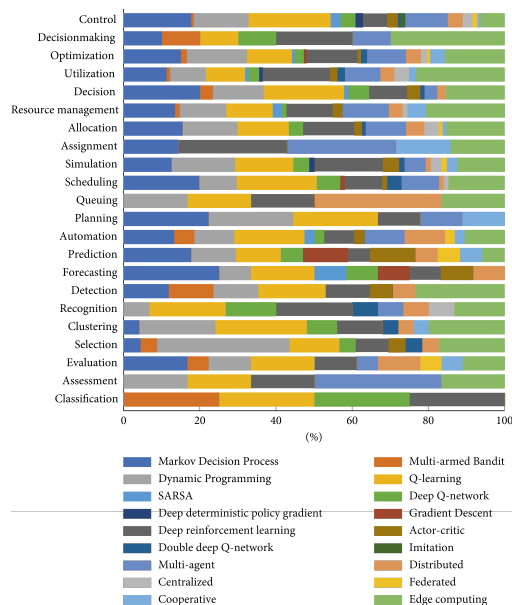


Fig. 4: Distribution of RL methods by principal captured classes on [30]

4 CONCLUSION

It is widely acknowledged that AI and ML are assuming increasingly pivotal roles in the digital transformation of manufacturing towards Industry 4.0, contributing to enhanced quality, productivity, and operational efficiency. In contemporary times, ML algorithms find extensive utility across diverse manufacturing domains, including optimization, control and security. The heightened transparency achieved within the manufacturing ecosystem through these technologies proves advantageous for cost reduction without compromising production quality. RL methods also hold substantial promise in Industry 4.0 applications. One key rationale is that new tools necessitate a level of optimization that surpasses what can be achieved through human intervention. The present paper has furnished a comprehensive survey of the state-of-the-art ML and RL methods developed since 2018. Recent trends reveal the ascendancy of RL-based approaches in the research landscape, largely propelled by advancements in smart manufacturing. Various machine learning paradigms, including supervised, unsupervised, deep learning, and reinforcement learning, are briefly introduced alongside their applications within the manufacturing sector. To address these explorations, we undertook a literature review, appraising the most recent scientific publications. As we delve into the potential of AI/ML and RL, we remain optimistic about their capacity to drive sustainable growth, operational efficiency, and innovation within the industries of the future.

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