

Machine Learning-Based Predictive Optimisation in Cyber-Physical Manufacturing Systems - A Review

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Abstract - The adoption of cyber-physical manufacturing systems (CPMS) have been facilitated by the rapid changes brought about by the fourth Industrial Revolution, integrating digital technology (such as IIoT, sensors, and cloud technology) into the manufacturing process. There are emerging complexities in the optimization of manufacturing processes caused by the dynamic nature of varying production processes and the extensive information generated from connected manufacturing systems. Machine learning (ML) is able to create predictive optimization and intelligent decision-making, from in-depth analysis of large-scale data generated from the manufacturing processes. This article provides an extensive analysis of the various ML predictive optimization methods of the CPMS. This review investigates the use of various ML techniques such as supervised learning, deep learning, and reinforcement learning, to predict the behavior of systems and to optimize the operational variables. This review evaluates the combination of ML and heuristic optimization such as genetic and swarm optimization, to illustrate some hybrid intelligent optimization. This review focuses on predictive maintenance, process parameter optimization, energy management, production scheduling, and tool condition monitoring. This review will also describe the main challenges that are involved during the optimization process, such as data interactivity, interpreter models, scalability, and real-time implementation within an industrial system. To conclude, this paper proposes future research avenues focusing on integrating digital twins, explainable AI, and autonomous frameworks of decision-making within next-gen smart manufacturing systems. It aims to assist researchers and practitioners in understanding the state of the machine learning-based predictive optimization of cyber-physical manufacturing systems and the emerging avenues it presents.

Keywords: - *Machine Learning; Predictive Optimization; Cyber-Physical Manufacturing Systems; Smart Manufacturing; Industry 4.0; IIoT; Deep Learning; Reinforcement Learning; Predictive Maintenance; Intelligent Manufacturing Systems.*

1.0 INTRODUCTION

The digital revolution has greatly impacted today's manufacturing systems. Industry 4.0 has brought the IIoT, AI, cloud computing, and analytics to the forefront. These emerging technologies have shifted the paradigm to develop cyber-physical manufacturing systems (CPMS) [1]. In CPMS, physical manufacturing processes are integrated with digital systems to enable better monitoring, control, and decision-making. Cyber-physical systems are integrated with physical processes through the use of smart sensors, and communication networks to develop smart manufacturing systems that are adaptive and capable of Intelligent Manufacturing[2].

Optimization is essential in enhancing productivity, quality of output, energy utilization, and resource efficiency in complex environments. The vast scale and dynamic nature of modern manufacturing systems produce vast amounts of high dimensional data that traditional methods of optimization cannot manage. Intelligent optimization is needed to adapt and learn from previous data, forecast future behaviors of systems, and provide support for real-time predictions. Manufacturing systems that incorporate Machine learning (ML) can optimize and predict the dynamic processes efficiently[3].

Predictive system performance and operational parameter optimization within cyber-physical environments can be achieved through a variety of machine learning methods, including supervised and unsupervised learning, deep learning, and reinforcement learning. The traditional data analytical models filter and miss valuable performance-illustrating data and instead, machine learning can be applied to large datasets and uncover performance data and its hidden dependencies[4]. The combination of predictive models and optimization algorithms provides manufacturing systems with predictive optimization (PO). It transforms system behavior through operational changes and provides optimization in not just a reactive but also proactive nature.

Predictive maintenance, production scheduling, energy consumption optimization, process parameters optimization, and tool condition monitoring are a few of the predominant areas of machine learning predictive optimization within manufacturing. For instance, a machine learning model can predict failure of a piece of equipment by analyzing its historical data, leading to proactive scheduling of maintenance. Additionally, in machining operations, predictive optimization can be applied to determine the optimal

process parameters to improve the quality of the products and decrease the cost of production. Overall, the applications demonstrate the importance of machine learning in achieving smart, fully automated systems in manufacturing.

Interest in predictive optimisation using machine learning has increased over the years, however, research on this topic is still scattered over different manufacturing domains and different computational methods[5]. Most studies are either focused on a particular optimisation method or a single applicational study, and are unable to provide a holistic view of the role machine learning plays in predictive optimisation of cyber-physical manufacturing systems. In addition to this, there are still challenges regarding data, quality, model interpretability, scalability, and real time industrial system integration[6].

This is the reason why there is a need for a comprehensive analysis of the existing research on the machine learning predictive optimisation of cyber-physical manufacturing systems, to be able to clear the current research gaps and improve the understanding of new patterns. This research attempts to offer a holistic analysis of the branches of machine learning that have been employed on predictive optimisation in cyber-physical manufacturing systems, focusing on the different uses, advantages and drawbacks[7]. The paper also addresses the fusion of machine learning and sophisticated optimisation methods and the opportunities to conduct research that warrant the damaged areas. The essence of the paper is to help both researchers and practitioners structure the development of intelligent and efficient manufacturing optimisation methods.

2.0 LITERATURE REVIEW

A systematic literature review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency, reliability, and reproducibility in article selection. The PRISMA approach provides a structured method for identifying, screening, and selecting relevant studies for review. PRISMA Image analysis is given in Figure 1

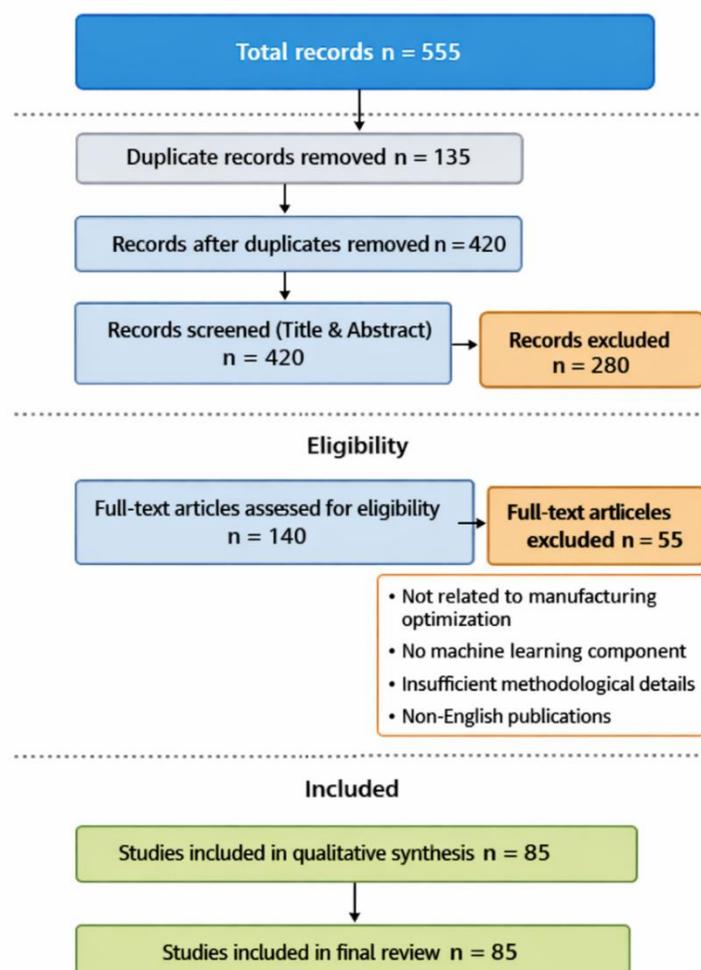


Figure 1 PRISMA Analysis for the Literature collection

Optimisation and machine learning have become increasingly popular in modern manufacturing due to the rapid evolution of industrial frameworks and large quantities of production data[8]. In cyber-physical manufacturing systems (CPMS), real-time data processing and intelligent machine learning facilitate predictive analytics and the intelligent optimisation of systems. Many scholars have applied machine learning models to forecast system behaviour and to stimulate the optimisation of manufacturing processes, ultimately elevating system productivity, efficiency and reliability[9].

The first studies in manufacturing optimisation relied heavily on certain statistical and mathematical traditions. Nevertheless, these frameworks faced restrictions with high-dimensional, dynamic, and nonlinear manufacturing systems. In line with immense progress in machine learning, the optimisation of manufacturing processes have been greatly enhanced by the use of control parameters in the modelling of complex relations of process variables and system performance with predictive models such as artificial neural networks (ANNs), support vector machines (SVMs), and decision trees[10].

Supervised machine learning techniques have been used for predictive optimization in manufacturing systems. As an example, regression-based learning models are often used to predict process outputs (e.g., product quality, tool wear, energy consumption) based on input data collected by sensors and manufacturing systems. Once models are sufficiently accurate, optimization algorithms can be applied to obtain operating conditions that enhance the performance of the manufacturing systems [11]. Many studies have demonstrated that the integration of predictive models with optimization methods improves the quality of decisions made in manufacturing systems.

The use of deep learning techniques has extended the frontier of predictive optimization in cyber-physical manufacturing systems. For example, deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have been used for industrial data analysis, capturing complex patterns in the data that are often missed by conventional models. These deep learning architectures are especially valuable in the fields of image-based inspection, vibration analysis, and sensor-based monitoring[12]. The integration of deep learning models and optimization methods has enhanced performance in fault detection, predictive maintenance, and optimization of process parameters.

Reinforcement learning (RL) has also started gaining traction as a viable method for dynamic optimisation within cyber-physical manufacturing systems [13]. While traditional machine learning techniques fail without pre-existing labelled data for the optimisation task, reinforcement learning enables a system to learn optimal strategies for decision making through environmental interactions. In the context of manufacturing, RL algorithms develop the operational strategies themselves through the feedback that they receive from the manufacturing operation(s). This feedback also enables the real-time optimisation of scheduling, robotic movement, and the allocation of resources. With these advantages, reinforcement learning facilitates the autonomous self-optimising manufacturing systems[14].

Beyond standalone machine learning models, metaheuristic optimisation algorithms coupled with machine learning have also been extensively researched. When searching for optimal solutions to a complex optimisation problem, metaheuristic algorithms, like genetic algorithms (GAs), particle swarm optimisation (PSO), and ant colony optimisation (ACO), are a common choice. In conjunction with machine learning models, these algorithms prove to be effective in locating the optimal process parameters and strategies[15]. Numerous manufacturing applications, including the optimisation of machining parameters, production scheduling, and the promotion of manufacturing with reduced energy consumption, have benefitted from the hybrid ML-optimisation frameworks[16].

An active area of study is the use of machine learning and digital twin technology in cyber-physical manufacturing systems. Digital twins create a virtual model of a physical asset or process in a manufacturing system so it can be monitored, simulated, and optimized in real time. By adding machine learning to the digital twin model, researchers can create systems that optimize predictions by continuously analyzing operational data and providing recommendations for the best next steps [17]. The result is a model that assists in proactive decision making and improves the agility of the manufacturing system in a changing production environment.

Despite the above advancements, in real production environments, the implementation of machine learning predictive optimal systems still faces a number of challenges. In the industry, data is often incomplete, inconsistent, or noisy, and it is a major issue for the implementation of predictive systems based on machine learning[18]. On the other hand, the problems that systems of deep learning have, in terms of processes, are still a setback, when it is required to have a transparent and clear model, as is the case in the industry. On the other hand, the integration of machine learning with real time control systems poses the problem of having to process the data and the computational systems that allow for real time control of the system[20].

The current body of research indicates a significant role of machine learning within the cyber-physical manufacturing systems predictive optimisation domain. Many intelligent optimisation methods have been proposed, yet the optimisation community continues to face challenges regarding the practical implementation, scalability, and dependability of these systems. Such obstacles

need to be clearly understood, as they are crucial for the progression of smart manufacturing and the ultimate goal of a fully autonomous manufacturing system[21].

The CPS domain has a variety of classifications and implementations; however, optimization is always a key factor. The main CPS implementations are within the manufacturing and industrial sectors; without optimization and proper implementation of optimization techniques, the overall efficiency, reliability, and adaptability of the system are highly compromised [22]. CPS are designed to integrate a given set of physical processes with a great deal of computer-based processes, so that there are intelligent elements, sensing elements, actuating elements, as well as communication networks that are highly intertwined and cohesive. In these types of systems, optimization is crucial to ensure that operational decisions are made as efficient as possible, while also being adaptable to real time changes[23].

2.1 Improved Productivity and Efficient Use of Resources

One of the main benefits of optimization is that it allows cyber-physical systems to efficiently establish the ideal operational parameters for a given manufacturing process, including the speed of the machine, the path of the tool, the energy utilized, etc. The more efficiently the resources are arranged, the better the system will be at maximizing production output while also minimizing waste, energy consumption, and the time of the system [24].

2.2. Enhanced Quality of Products

Real-time sensors in CPS-enabled manufacturing can capture process alterations and changes in operational parameters. Defect reduction and meeting industry regulations concerning product consistency and quality can be achieved by optimisation algorithms adjusting and regulating parameters [25].

2.3. Downtime Minimisation and Predictive Maintenance

Malfunctioning of equipment can be decreased by optimised predictive maintenance scheduled with smart equipment CPS sensor data. Maintenance can be scheduled in advance and unpredicted downtime can be reduced and the operational life of the important machine can be increased.

2.4. Cost Impact and Environmental Effects

Through the collection of operational and energy consumption data, cyber-physical systems have the ability to optimize energy usage by improving operational efficiency and effectiveness, both of which are pivotal to the creation of sustainable systems [26]. Consider all the potential scenarios: the optimization algorithm will schedule and control the energy usage of all the machines in the factory in order to avoid and not interfere with the energy consumption peaks and thus in the end, will support the ecological improvement of the factory.

2.5. Control Strategies

Data processing of the dynamic cyber-physical systems (CPS) of the manufacturing systems, as well as the state of the machine systems and the systems of the supply chain, is done continuously and in a changing manner, in order to optimize the control systems in real time. This is done by identifying and determining the most optimal possibilities and thus, positively contributing to the improvement of responsiveness and flexibility of the entire system [27].

2.6. Autonomous Intelligent Systems Support

In order to make autonomous intelligent manufacturing systems operate, optimization is a prerequisite. Through the optimization combined with machine learning and artificial intelligence, cyber-physical systems (CPS) are in a position to automatically modify and/or adjust the operational parameters of the system, to control and manage complex systems of workflows, and to react to unanticipated and/or unpredicted situations in a proactive manner.

2.7. Trade-Offs

In manufacturing cyber-physical systems (CPS), it is not uncommon to have contradictory objectives like minimizing production costs, maximizing energy efficiency, improving the production and quickening the production. These contradictory objectives can be harmonized by optimization in a holistic way.

In conclusion, optimisation is fundamental to cyber-physical systems (CPS) and their ability to be used in intelligent, sustainable, adaptable, and efficient ways. The full potential of CPS in smart, autonomous, and predictive maintenance operations is dependent on efficient optimization[28].

3.0 ROLE OF MACHINE LEARNING IN OPTIMISATION

Machine learning (ML) plays a vital role in optimisation of CPS, especially in cyber-physical manufacturing systems, where conventional optimisation techniques are unsuccessful for high-dimensional, nonlinear, and dynamic data. When integrating ML into these optimisation techniques, systems become more adaptive, and the entire framework improves in predictive and decisional capabilities. The role of ML in optimisation is as follows:

3.1. The Ability to Learn and Adapt to Complexity and Non-Linearity

Many systems in the industry are complex and their processes are nonlinear. Because of the multitude of interrelated factors, it is very difficult to catch the aforementioned factors. Traditional optimisation techniques will probably fail. Various ML models, including neural networks, support vector machines, and ensemble techniques, learn complex dependencies in both historical and real-time data. These models result in accurate predictions of system behaviours, which provides the foundation for optimised decision making [29].

3.2. Predictive and Proactive Optimisation

As opposed to standard approaches that only respond to a situation, ML facilitates predictive optimisation by estimating system performance, possible failures, and performance deviations before they happen. Predictive models, for instance, can identify potential tool wear, energy spikes, and variations in quality. This will enable optimisation algorithms to adjust operational parameters to prediction, which will reduce downtime and improve operational efficiency [30].

3.3. Integration with Metaheuristic Algorithms

Machine learning can be integrated with certain metaheuristic optimisation methods (genetic algorithms, particle swarm optimisation, etc.) to develop hybrid intelligent frameworks. ML models can predict the areas of promising solutions and/or direct the search, which ultimately lowers the resource needed to reach an optimal or a near-optimal solution and improves the speed at which that solution is achieved.

3.4. Support For Decisions in Real-Time

With the aid of IIoT devices or sensors, ML models integrated within cyber-physical equipment can aid in the recycling of any process parameter, no matter how small, using large amounts of data within seconds, making them adaptable, flexible, and optimisable, essential for cyber-physical systems.

3.5. Optimisation for Multiple Objectives

Machine learning is being used in trade-off modelling. For example, using conflicting objectives such as optimising production and simultaneously optimising the energy used then balancing the cost. The objectives of multi-scenario optimising systems while maintaining sustainability, efficiency and performance can be achieved using system response prediction coupled with machine learning[31].

3.6. The Reduction Of Time and Cost Associated with Experimentation

Historically, a large amount of time was spent acquiring the data required for optimisation, and a great deal of money was expended acquiring the data required for the optimisation. The types of data ML models use to derive their conclusions are the same types of data that can lead to the establishment of a system that is optimally functioning to reduce the time of experimentation.

3.7. Increasing the Autonomous Nature of Intelligent Systems

Intelligent systems that are cyber-physical systems that incorporate ML and optimisation can create degrees of self-learning, self-adapting, and self-optimising without any need for human interactions. Such systems are essential for real time optimisation and adaptability that is often required in the manufacturing field within Industry 4.0 [32].

The combination of optimization and machine learning (ML) improves efficiency through real-time adjustments with regard to predictive and data driven techniques, lowering the overall computational cost, and alleviating the burden of manual adjustments for multi-dimensional objectives. When applied to optimization, ML allows for the transformation of cyber-physical systems from systems that passively follow rules to systems that think, act, and reason dynamically, proactively and autonomously.

4.0 MACHINE LEARNING, OPTIMIZATION, AND CYBER-PHYSICAL SYSTEMS

The combination of machine learning (ML), optimization methods, and cyber-physical systems (CPS) is at the core of intelligent manufacturing and Industry 4.0, offering the potential for systems to function autonomously, efficiently, and adaptively, even in evolving production settings. This combination allows for the evolution of CPS from simple automated systems to predictive, self-optimizing, data-rich systems [33].

In Figure 2, the block diagram showcases the optimization of a cyber-physical system.

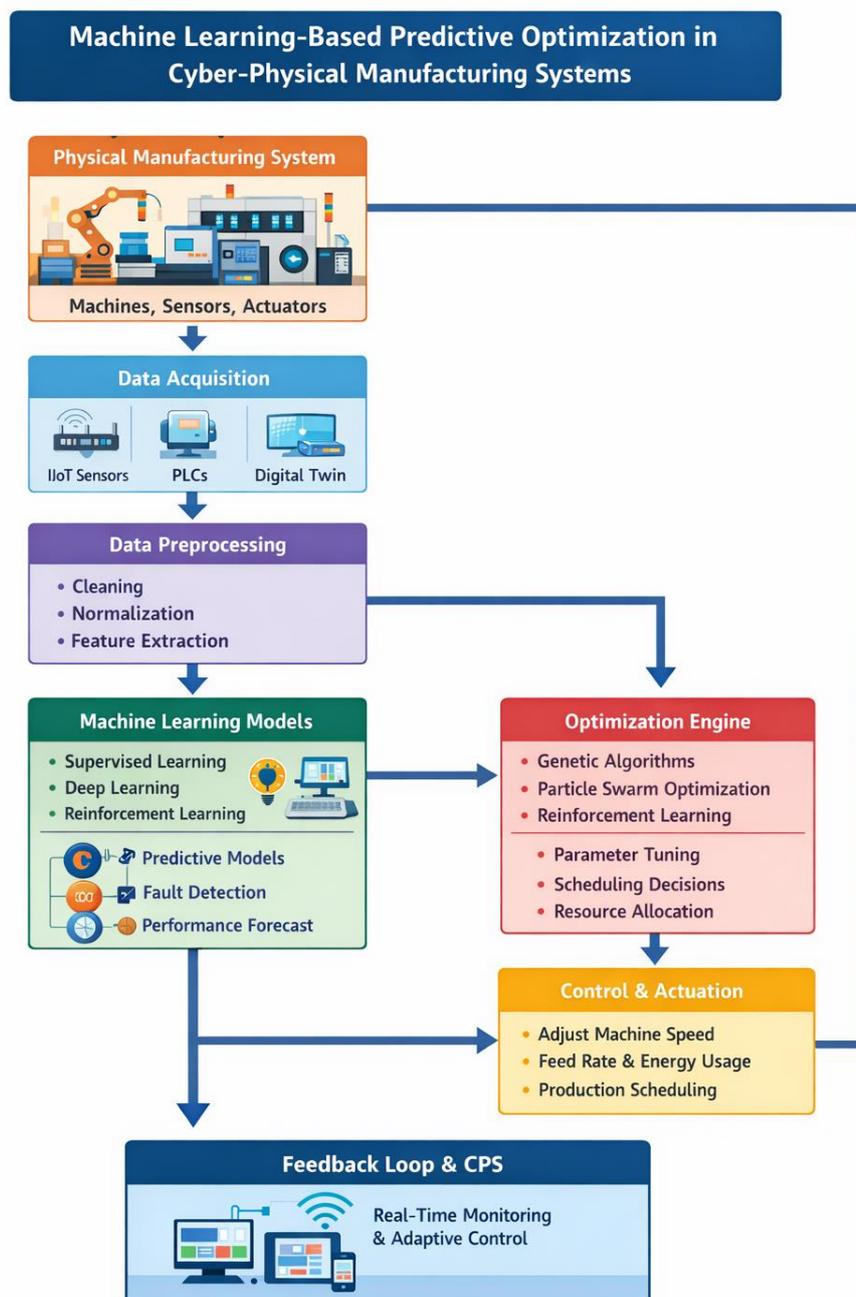


Figure 2: The block diagram for the optimisation of a cyber-physical system

5.0 RESEARCH GAPS AND KEY CHALLENGES

While significant strides have been made with ML based predictive optimisation for cyber-physical manufacturing systems (CPMS), numerous research gaps and challenges remain. Closing these gaps will be imperative for the continued progress of this field to permit fully intelligent and fully autonomous manufacturing systems.

5.1. *Quality and Availability of Data*

Industrial data is often noisy, incomplete and other inconsistencies exist which affect the quality of machine learning models constructed with this data.

Numerous studies have relied either on synthetic datasets or small scale datasets, and as a result the generalising of their findings to real phenomena present in manufacturing environments is limited [33].

Research Gap: Complete data acquisition, cleansing, and augmentation with relevant techniques in large scale CPMS.

5.2. *Real-Time Implementation and Scalability*

The nature of machine learning models and their optimisation algorithms means that they require significant computational resources; as a result, real time deployment is difficult, particularly in large-scale systems, or systems with multiple machines.

Research Gap: Edge computing and lightweight Machine Learning (ML) models that allow real-time predictive optimisation in manufacturing systems that are changing.

5.3. *Trust and Interpretability of the Models*

A significant number of ML models, particularly those employing deep learning and ensemble approaches, are opaque and act as black boxes, further reducing the ability to interpret these models to engineers and operators.

When a model is opaque this leads to a reduction in the likelihood the model will be used in a process, and in industry, decisions must be trustworthy and auditable; this is a sustainable barrier to the adoption of the model [34].

Research Gap: The addition of explainable Artificial Intelligence (XAI) to predictive optimisation models.

5.4. *Fusion with Optimization Algorithms*

Despite the existence of hybrid methods (e.g. ML + metaheuristics or RL), the absence of a systematic way of combining predictive models with optimization in CPS remains.

Research Gap: Focusing on real-time frameworks, combine ML predictions with multi-objective optimization in a more integrated way.

5.5. *Optimization with Multiple Objectives and Sustainability*

Most of the existing literature concentrates on single-objective optimization (e.g., cost or productivity), disregarding the other dimensions, such as energy, quality, and sustainability [35].

Research Gap: Multi-objective optimization that addresses production efficiency, as well as socio-economic and environmental sustainability.

5.6. *Fully Autonomous Decision Making in Dynamic Situations*

CPMS are expected to cope with unforeseen circumstances, e.g. machine failure, supply interruptions or demand peak.

Research Gap: Fully autonomous systems and self-optimizing systems in a dynamic industrial environment using reinforcement learning and adaptable ML.

5.7. Establishing Norms and Evaluating

There is no way to compare the results of various studies because of the absence of benchmark datasets, standardized measures, and evaluation methods for ML-based predictive optimization in manufacturing.

Research Gap: Due to the lack of public datasets, simulation tools, and evaluation frameworks, the pace of research and industrial utilization is hindered.

6.0 CONCLUSION AND FUTURE WORK

6.1 Conclusion

This review showcases the increasing importance of predictive optimisation using machine learning in cyber-physical manufacturing systems (CPMS). The use of machine learning with optimisation algorithms allows CPS to be smart, autonomous, and adaptive, which increases production, the quality of the product, the efficiency of the energy consumed, and the use of resources. Machine learning techniques such as supervised learning, deep learning, and reinforcement learning can be predictive and provide the ability to decide proactively. Optimisation algorithms, which can be genetic algorithms, particle swarm optimisation, and multi-objective, can provide operational strategies at the optimal level [36].

This review also shows that the hybrid frameworks, integrating ML and optimisation, outperform the existing approaches when dealing with industrial data that are complex, high-dimensional and dynamic. Furthermore, the combination of digital twin technologies with ML-driven optimisation enhances adaptive control and real-time monitoring, which brings smart manufacturing closer to the autonomous state [37]. The challenges of data quality, computational complexity, model interpretability, and integration with real-time control systems, however, are the challenges that remain to be solved for the industrial implementation to be widespread [38].

6.2 Future Work

There are many research opportunities that are predictive of optimisation using machine learning in CPMS that can be advanced.

Integration with Digital Twin and IoT: Broaden the use of ML models for real-time optimisation and simulation-based decision-making in digital twin frameworks.

Explainable AI (XAI): Building ML models that can be understood for industrial use cases to strengthen trust, transparency, and adoption at workplaces in the manufacturing industry.

Reinforcement Learning for Autonomous Systems: Focusing on the application of RL to completely self-optimising CPS, where the systems learn to adaptively implement optimal policies in the face of changing production conditions.

Multi-Objective and Sustainability Optimisation: Including variables such as energy use, costs, quality and sustainability in optimisation frameworks.

Edge Computing and Real-Time Analytics: Using ML-based optimisation at the edge for immediate, low-latency decision-making in CPS.

Robust Data Management Strategies: Developing strategies for the industrial domain that can deal with noisy, incomplete and heterogeneous data to achieve accurate ML predictions and optimal results for the frameworks.

The basis of future manufacturing systems that prioritise intelligent manufacturing is optimised Cyber-Physical Systems (CPS) combined with Machine Learning (ML) and optimisation algorithms. In combination, these systems demonstrate the importance of future-focused research. In order to create intelligent manufacturing solutions that are efficient, and in turn, sustainable, scalable, resilient, and autonomous, the manufacturing systems of the future will need more focus on interpretability and autonomy.

6.2.1. Framework

CPS are comprised of physical systems, and real-time intercommunication of sensors, actuators, and processors. Using historical and current data CPS are able to rethink processes and determine system behaviours. Optimisation algorithms achieve efficiency, quality, and sustainability through determining the best operational parameters, along with the best ways to organise and schedule the use

of resources and time. Data with algorithmic optimisation leads to better decision making. Predictive optimisation is the the aim of the CPS, and the combination of optimally data and algorithmic[39].

6.2.2. Predictive Decision-Making

Typical decision making models within CPSs revolve around fixed, pre-defined models. Predictive reasoning allows the integration of CPS and machine learning to anticipate system changes, production failures, machine failures, and energy supply changes. A predictive, proactive control loop increases reliability and reduces the amount of downtimes.

6.2.3. Hybrid Intelligent Optimisation

Hybrid frameworks combine elements of both approaches. Machine learning predicts the system's behaviour while optimisation algorithms such as genetic algorithms, particle swarm optimisation, or reinforcement learning, capture the operational strategies. For instance:

ML predicts tool failure in CNC machines.

While the optimisation algorithms modify the feed rate, spindle speed and cutting paths. This means a longer life for the tool and increased production [40].

The combination of the two approaches leads to better solutions, and also reduces the complexity of the calculations and the time required to obtain the solution, even if that solution is a sufficiently close approximation to the optimal one.

6.2.4. Real-Time Adaptive Control

The CPS system is characterised by a high rate of change, both in the production demanded and the state of the machines and the environment. This is the primary reason that the combination of machine learning and optimisation methods is fundamental for the real-time adaptive control of the system, that is, the system is able to operate on the basis of continuous learning and modification of operational strategies as a result of the integration of real-time data from sensors. Such functionality is a crucial component of autonomous and intelligent manufacturing systems [41,42].

6.2.5. Smart Manufacturing Applications

The integration of machine learning, optimisation, and CPS has benefited areas within manufacturing such as:

Predictive Maintenance: ML predicts machine failures, optimising the maintenance schedule to reduce downtime [43].

Process Parameter Optimisation: ML uses a model to anticipate the product quality from the process inputs. The optimisation model manages process input to sustain product quality and process efficiency [44].

Energy Management: ML predicts energy needs; Optimisation model controls process to reduce energy waste from the process while sustaining volumes of production[45].

Production Scheduling and Resource Allocation: Machine learning predicts customer demand and the availability of machines, while the integration of CPS with optimization technologies ensures the scheduling of tasks and the minimization of idle times.

6.3 Challenges and Considerations

The integration of CPS and ML and optimization are complicated by several challenges [46].

Data Quality and Availability: CPS produces large amounts of data that can be considered as noisy and/or incomplete, which would have a negative impact on the performance of the ML model.

Computational Complexity: In real time, optimization of the system can consume a large amount of computational power [47].

Model Interpretability: The application of deep learning methods creates large models that, accordingly, provide the model with a level of complexity that will create barriers to the adoption of the model in the industry.

System Integration: The seamless communication of different components of the system which consist of ML, optimization, and CPS is the main factor that affects the reliability of the whole system.

6.4 Summary

Combining ML and optimization with CPS, offers the opportunity to make manufacturing systems intelligent, adaptive, and autonomous. ML brings forecasting abilities, optimization algorithms provide the best option, and CPS applies the available best option in real-time. CPS, ML and optimization combinations are essential for achieving Industry 4.0 goals which are achieving higher efficiency and productivity, lower costs, improving quality of products and services, and achieving sustainable manufacturing.

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